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Optimising Caregiver Engagement With a Digital Parenting Intervention to Prevent Violence Against Adolescents: An Investigation of Component Effects, Predictors, and Moderators in the ParentApp Optimisation Trial in Tanzania

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For my brother, Benjamin

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Abbreviations

Abbreviation	Definition
CAPE	Connect, Attend, Participate, Enact model
CONSORT	Consolidated Standards of Reporting Trials
CI	Confidence interval
CWBSA	Clowns Without Borders South Africa
FDR	False discovery rate
GPI	Global Parenting Initiative
HIC	High-income country
ICS	Investing in Children and Strengthening Their Societies
IDEMS	Innovations in Development, Education and the Mathematical Sciences (International)
INNODEMS	Innovations in Development, Education and the Mathematical Sciences (Kenya)
IPD	Individual participant data
IRR	Incidence rate ratio
JITAI	Just-in-time adaptive intervention
LMIC	Low- and middle-income country
MICE	Multiple imputation by chained equations
MOST	Multiphase Optimization Strategy
MR	Mean ratio
MRC	UK Medical Research Council
MRT	Micro-randomised trial
NGO	Non-governmental organisation
NIMR	National Institute for Medical Research Tanzania
PLH	Parenting for Lifelong Health
RCT	Randomised controlled trial
SMART	Sequential multiple assignment randomised trials
TIDieR	Template for Intervention Description and Replication
UNICEF	United Nations Children's Fund
VAC	Violence against children
WHO	World Health Organization

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Abstract

Background: Violence against children is a global public health issue with long-lasting consequences for individuals and societies. Parenting programmes are among the most effective evidence-based strategies to prevent such violence, and digital delivery has gained attention as a way to extend their reach in low- and middle-income countries (LMICs), where traditional in-person services remain limited. However, the effectiveness of digital parenting interventions depends on sustained caregiver engagement, which remains a critical challenge. This thesis investigates how caregiver engagement can be optimised in LMICs, focusing on ParentApp, a smartphone-based adaptation of the Parenting for Lifelong Health Teens programme. It is composed of three empirical papers, each analysing data from the ParentApp optimisation trial conducted in Tanzania between 2022 and 2023.

Objectives: The thesis had three primary objectives: (1) to evaluate the independent and combined effects of design and delivery strategies on engagement; (2) to identify caregiver characteristics associated with engagement and disengagement, including potential gender differences; and (3) to assess whether caregiver characteristics moderated the effects of the design and delivery strategies. Each objective was addressed in a separate empirical paper.

Methods: All three papers draw on data from a 2×2×2 cluster-randomised factorial trial of ParentApp, conducted within the Optimisation Phase of the Multiphase Optimisation Strategy (MOST). The trial enrolled 614 caregivers nested within 16 clusters, each corresponding to an urban or peri-urban community in Mwanza, Tanzania. Clusters were randomised across three factors: guidance (self-guided vs. guided), app design (structured vs. unstructured), and digital support (basic vs. enhanced). Engagement outcomes were automatically tracked via app usage metrics, while baseline sociodemographic and behavioural data were collected via an embedded questionnaire. Generalised linear mixed-effects models assessed component effectiveness (Paper 1), predictors of engagement and disengagement (Paper 2), and moderation effects (Paper 3).

Results: Paper 1 showed that both guided delivery and an unstructured app design significantly enhanced engagement across multiple metrics, including app launches, modules completed, time spent in the app, and self-reported positive behaviours logged. Digital support alone had no significant effect but demonstrated benefits when delivered alongside guided delivery. Overall levels of engagement, however, remained modest, suggesting that while low-intensity strategies can improve engagement, they may be insufficient to generate the sustained exposure required for behaviour change.

Paper 2 found caregiver gender to be the only significant predictor of engagement, with women completing significantly more modules than men. Women also reported greater socioeconomic and psychosocial adversity, which may have increased their motivation to engage. No baseline characteristics predicted disengagement, and gender did not moderate other associations. These findings suggest that ParentApp may be broadly accessible across diverse caregiver groups, provided gender-related barriers are addressed.

Paper 3 identified several moderation effects. Guided delivery increased engagement among older caregivers and those with higher baseline depressive symptoms or positive parenting practices. The unstructured app design increased engagement among women, while enhanced digital support improved engagement among older caregivers but was less effective for those with higher baseline parenting skills. No moderation effects were observed for financial stress, food insecurity, or child maltreatment. These findings highlight the value of tailoring digital parenting interventions to optimise engagement.

Conclusion: This thesis provides novel evidence on how caregiver engagement can be optimised, contributing both to the digital parenting intervention literature and to the development of ParentApp specifically. It offers a practical application of the Optimisation

Phase of MOST in an LMIC context, illustrating how optimisation methods can be used to evaluate multiple design and delivery strategies simultaneously under real-world delivery conditions. In doing so, it generates a series of evidence-informed insights and practical recommendations to guide the design, adaptation, and scale-up of digital parenting interventions in resource-constrained settings. As digital interventions are increasingly adopted to address scalability challenges in LMICs, the findings presented here are intended to inform future implementation within the Parenting for Lifelong Health programme suite and to contribute to the delivery of more inclusive, effective, and sustainable digital support for families globally.

1. Introduction

1.1 Summary of Thesis

This thesis investigates how to optimise caregiver engagement with digital parenting interventions designed to prevent violence against adolescents, with a particular focus on low- and middle-income country (LMIC) settings. It examines whether specific design and delivery strategies can increase engagement, and whether caregiver characteristics influence engagement patterns or moderate the effectiveness of these strategies. The research centres on the ParentApp optimisation trial, a cluster-randomised factorial experiment conducted in Tanzania between 2022 and 2023. The trial tested three discrete design and delivery components intended to increase engagement with ParentApp, an open-source, offline-first digital adaptation of the in-person Parenting for Lifelong Health for Teens (PLH Teens) programme.

Findings from the trial are presented in three interconnected papers, each addressing a distinct aspect of engagement optimisation. The first paper identifies which design and delivery strategies are most effective in promoting engagement, providing evidence to inform an optimised intervention package that is currently being evaluated in a large-scale trial in Tanzania. The second paper examines which caregiver characteristics predict engagement and disengagement, with a focus on barriers among underrepresented groups, especially men and fathers. The findings contribute to evidence on male engagement and inform more inclusive, gender-responsive strategies. The third paper investigates whether, and to what extent, caregiver characteristics moderate the effects of design and delivery strategies on engagement, to assess the potential for tailoring strategies to enhance equity and effectiveness. The study design and implementation plans of the ParentApp optimisation trial are summarised in a protocol paper published in *BMC Public Health* (Janowski et al., 2023) (see Appendix 1).

1.2 Focus of Thesis

Caregiver engagement is a critical determinant of whether digital parenting interventions can achieve population-level impact (Piotrowska et al., 2017). Engagement is shaped by two broad sets of factors: the design and delivery of the digital intervention, and the contextual factors of the individuals who use it (Perski et al., 2017). Guided by the principles of the Multiphase Optimisation Strategy (MOST) and framed within an implementation science lens, this thesis uses the ParentApp optimisation trial to examine how specific design and delivery strategies influence caregiver engagement, how these effects differ across caregiver subgroups, and how such insights can inform the development of more equitable implementation of digital parenting programmes in LMICs. This work is among the first to experimentally investigate strategies to improve engagement with a digital parenting programme in any context and, to my knowledge, represents the first optimisation trial of its kind in an LMIC.

1.3 Organisation of Thesis

This document is organised into nine chapters: Introduction (Chapter 1); Background and Rationale (Chapter 2); Review of Literature Underpinning the Methods (Chapter 3); Thesis Overview (Chapter 4); methods (Chapter 5); Paper 1, which has been published in the *Journal for Medical Internet Research* (Chapter 6); Paper 2, which is ready to be submitted to *JMIR Pediatrics and Parenting* (Chapter 7); Paper 3, which has been submitted to *Annals of Behavioral Medicine* (Chapter 8); and a Overall Discussion, including implications of the thesis, and strategies used to disseminate findings (Chapter 9). A Submission of Thesis Requirements Checklist is provided in Appendix 2.

2. Background and Rationale

This chapter presents the background literature and rationale that informed the development of the thesis. Section 2.1 outlines the rationale for focusing on parenting interventions as a strategy to prevent violence against children, reviews the global evidence for their in-person delivery, and examines the challenges of scaling these interventions in LMICs. Section 2.2 considers the potential of digital delivery to address scale-up barriers and identifies key gaps in the current evidence base. Section 2.3 explores conceptualisations and definitions of engagement from both the parenting intervention and digital intervention literature that informed the thesis. Drawing on this background, Section 2.4 introduces Parenting for Lifelong Health (PLH) and situates Papers 1, 2, and 3 within the context of the ParentApp Tanzania Project.

2.1 Parenting Interventions to Prevent Violence Against Children

Violence against children (VAC) is an urgent human rights and public health concern. The World Health Organization (WHO) defines VAC as "all forms of violence against people under 18 years old" (2022, p. 1). Globally, more than 50% of children experience some form of physical, emotional, or sexual violence, or neglect each year, and rates are estimated to be around 18% higher for children living in LMICs compared to those in high-income countries (HICs) (Hillis et al., 2016). Violence during childhood is associated with a wide range of adverse outcomes, including injury and death, cognitive impairment, mental and physical health problems, reduced academic attainment, and lower psychosocial well-being (e.g., Andersen et al., 2008; Cuartas et al., 2025; Fry et al., 2018; Hughes et al., 2017; Norman et al., 2012). At the societal level, these impacts impose enormous economic costs, estimated at 7 trillion USD annually (UNICEF, 2020). Preventing VAC is therefore a global health imperative and a core commitment within the 2030 Sustainable Development Goals, which call for the elimination of all forms of VAC (Colglazier, 2015).

The most common perpetrators of VAC are household members (Devries et al., 2018; World Health Organization, 2023). Global prevention strategies therefore increasingly prioritise efforts to support parents and other caregivers[1] to promote safe, nurturing caregiving environments. Parenting interventions are central to these strategies and are identified by the multi-agency INSPIRE framework as one of seven evidence-based strategies for ending VAC (World Health Organization, 2016, 2018). This thesis examines digital parenting interventions designed to prevent violence among 10- to 17-year-olds, who are referred to throughout as *adolescents* to distinguish them from younger children.

2.1.1 Defining Parenting Interventions

The terms *parenting interventions* and *parenting programmes* are used to refer to complex behavioural interventions designed to strengthen the knowledge, skills and understanding of those responsible for the care of children and adolescents, irrespective of biological relationship (Barlow & Coren, 2018). These interventions aim to support caregivers in creating safe, nurturing, and developmentally supportive home environments that promote children's health and well-being and reduce the risk of violence (World Health Organization, 2023).

Parenting interventions vary widely in their theoretical orientation, target populations, objectives, and modes of delivery. Many draw on social learning theory (Bandura, 1977), especially those developed for caregivers of older children and adolescents, while others are grounded in attachment theory (Bowlby, 1974), which is often emphasised in programmes for parents of infants and younger children. Programmes may be implemented as universal interventions (offered to all caregivers), selective interventions (targeting groups with elevated

[1] The terms “parent” and “caregiver” are used interchangeably in this thesis to refer to any person responsible for the care of a child or an adolescent, regardless of biological relation.

risk factors), or indicated interventions (designed for families already experiencing difficulties or exposure to violence) (World Health Organization, 2023). Despite these differences, most parenting interventions share a common set of core components. These typically include education on child development, techniques for managing stress and promoting caregiver well-being, skills to build positive caregiver-child relationships and improve communication, and strategies for replacing harsh discipline with non-violent, developmentally appropriate alternatives (Kaminski et al., 2008; Leijten et al., 2019; World Health Organization, 2023).

Programme content is usually delivered through a series of structured sessions or modules that combine didactic content with active learning techniques such as discussion, modelling, role play, and home practice activities to encourage application of skills in daily family life (Leijten et al., 2019). However, delivery models vary considerably (Barlow & Coren, 2018). Some programmes consist of a few brief sessions, while others span 20 or more. They may be offered in individual or group formats, and implemented in diverse settings including schools, health clinics, community organisations, faith-based centres, and family homes. Facilitation may be carried out by trained community workers or specialist professionals, depending on the context and resources available.

While parenting programmes have traditionally been delivered in person, the rapid expansion of mobile and digital technologies has led to growing interest in remote and digitally supported formats (Breitenstein et al., 2014). Digital parenting interventions deliver programme content through a range of digital platforms including mobile applications (apps), websites, videoconferencing, or messaging services. These interventions often incorporate established behaviour change techniques such as goal-setting, reminders, feedback, and self-monitoring, and may include interactive or personalised features to sustain engagement and support skill application in daily life (Michie et al., 2017; Orji & Moffatt, 2018). Digital delivery models vary in intensity and support, ranging from fully self-guided formats to hybrid approaches that include guidance from facilitators or peer interaction.

For the purposes of this thesis, a digital parenting intervention is defined as any digitally delivered intervention focused on parenting. This includes both fully digital programmes and hybrid models that combine digital and in-person components. In the literature, digital parenting interventions may also be referred to using terms such as *technology-assisted*, *online*, *internet*, *web-based*, or *remote* parenting interventions.

2.1.2 Global Evidence on Parenting Interventions

There is considerable evidence that in-person parenting interventions are effective in reducing VAC and improving a wide range of caregiver and child outcomes (e.g., Backhaus et al., 2023; Barlow et al., 2006; Chen & Chan, 2016; Gardner et al., 2016; Knerr et al., 2013; McCoy et al., 2020; Mikton & Buchart, 2009; Vlahovicova et al., 2017). Although much of the existing evidence has been generated in HICs, a growing number of trials in LMICs has contributed to more globally representative evidence syntheses in recent years. The most comprehensive of these is presented in the 2023 *WHO Guidelines on Parenting Interventions to Prevent Maltreatment and Enhance Parent–Child Relationships with Children Aged 0–17 Years* (World Health Organization, 2023). These guidelines are informed by systematic reviews of 435 randomised controlled trials (RCTs) conducted across 65 countries, including 131 trials from LMICs. The primary review focused on interventions for caregivers of children aged 2 to 10 years. Complementary sub-reviews examined programmes for adolescents aged 10 to 17 years in LMICs (30 RCTs), parenting interventions delivered in humanitarian settings (18 RCTs), and those targeting children in early childhood (0 to 3 years).

Across all reviews, parenting interventions were consistently associated with reductions in harsh and abusive parenting, along with improvements in positive parenting practices, child behaviour, and caregiver mental health (World Health Organization, 2023). These effects were observed across universal, selective, and indicated models of delivery, and were generally sustained 3 to 14 months post-intervention. Notably, outcomes did not differ consistently by child age, household poverty, caregiver education, or national income level. However, some variation was found in the primary review, where effects were slightly smaller among ethnic minority families and larger among children with elevated behavioural difficulties at baseline.

Within this body of evidence, the sub-review on adolescents is particularly relevant to this thesis. It found that parenting interventions in LMICs were effective in reducing violent discipline, improving communication between caregivers and adolescents, and strengthening caregiver–adolescent relationships (World Health Organization, 2023). These findings are notable given the distinct developmental needs of adolescents and the relative scarcity of adolescent-focused parenting trials in earlier syntheses (Edwards et al., 2023; Knerr et al., 2013; Marcus et al., 2021).

However, even where evidence of effectiveness is strong, interventions that succeed in tightly controlled trials do not always achieve impact when implemented at scale (Gottfredson et al., 2015). Implementation science seeks to address this gap between efficacy and real-world delivery by studying methods to support the uptake of research findings and other evidence-based practices into routine service delivery, with the goal of improving the quality and effectiveness of intervention implementation and outcomes (Eccles & Mittman, 2006, p. 1).

2.1.3 Challenges for Implementation at Scale in LMICs

As evidence of the effectiveness of parenting interventions has grown, so too has the imperative to scale these programmes in LMICs to achieve population-level impact (Mejia et al., 2017; Shenderovich et al., 2021). The WHO defines scale-up as "the deliberate effort to increase the impact of successfully tested health interventions so as to benefit more people and to foster policy and program development on a lasting basis" (World Health Organization, 2010, p. 2). However, efforts to scale in-person parenting interventions in LMICs remain limited in scope, reach, and sustainability due to a set of mutually reinforcing barriers, including fragmented governance, financing constraints, workforce limitations, and caregiver-level inequities. These challenges undermine the sustainability, equity, and overall effectiveness of scale-up in LMICs (Mejia et al., 2017; Parra-Cardona et al., 2021; World Health Organization, 2023).

At the system level, fragmented governance and weak institutional coordination hinder the integration of parenting support into national policy and service delivery systems (Mejia et al., 2017; Parra-Cardona et al., 2021; Weisenmuller & Hilton, 2021). In many contexts, responsibilities for child and family welfare are dispersed across the health, education, and social protection sectors, yet mechanisms for cross-sectoral coordination remain weak or absent (World Health Organization, 2023). Political instability and shifting policy agendas further constrain integration, as prevention-focused programmes are often deprioritised in favour of short-term or politically expedient initiatives (Parra-Cardona et al., 2021).

These challenges are compounded by persistent financing constraints, which limit the sustainability of scale-up efforts. In HICs, parenting programmes are often delivered through publicly funded systems (Weisenmuller & Hilton, 2021). By contrast, in LMICs, implementation frequently relies on non-governmental organisations (NGOs) operating outside of national financing structures (Mejia et al., 2017). These delivery models are typically short-term and vulnerable to political and donor funding cycles that make it difficult to transition to institutionalised, government-led service delivery (Mejia et al., 2017; Parra-Cardona et al., 2021).

Another critical barrier to scale-up is the capacity and structure of the workforce delivering interventions. Parenting programmes in LMICs are often delivered by paraprofessionals or community-based workers, a strategy promoted for its cost-effectiveness and scalability. When accompanied by adequate training, supervision, and quality assurance systems, this model can be highly effective (World Health Organization, 2023). However, in practice, many programmes face limited investment in workforce development, leading to inconsistent training, inadequate supervision, and drift from core programme content (Knerr et al., 2013; Mejia et al., 2012; Mejia et al., 2017). These challenges compromise implementation fidelity, which refers to the extent to which a programme is delivered as intended by its developers (Dane & Schneider, 1998). Strengthening workforce systems through sustained investment in training, supervision, and local capacity is therefore essential for ensuring quality delivery, impact, and long-term sustainability (Parra-Cardona et al., 2021).

Finally, structural and sociocultural barriers limit the equitable reach of parenting interventions at scale. Many families in LMICs face intersecting challenges, including poverty, precarious employment, insecure housing, and competing caregiving responsibilities, which make attendance at in-person sessions difficult (Pote et al., 2019). These barriers are compounded when programmes are delivered in distant locations, lack childcare provision, or are scheduled during working hours (McGoron & Ondersma, 2015; Pote et al., 2019). In addition to these logistical barriers, sociocultural factors also influence participation. Stigma associated with help-seeking, fear of judgement, and mistrust of service providers can reduce uptake and retention, particularly among historically marginalised families (Chacko et al., 2016; McGoron & Ondersma, 2015; Savard & Kilpatrick, 2022; Weisenmuller & Hilton, 2021). These dynamics raise critical concerns for equity in scale-up, as those most affected by violence and adversity are often least able to access support.

Collectively, these challenges underscore the limitations of relying on traditional in-person delivery as the primary model for scale in LMICs. Achieving large-scale, sustainable implementation will require delivery approaches that are cost-effective, adaptable to local systems, and responsive to the everyday realities of caregivers, including those affected by poverty, instability, and limited access to services (Mejia et al., 2017). In an increasingly digitalised world, digital approaches to intervention delivery may have the potential to address some of these challenges (MacDonell & Prinz, 2017). A deeper discussion of how digital parenting interventions can help address key barriers to scale, along with an overview of the current and emerging evidence base for their effectiveness, is provided subsequently.

2.2 Digital Parenting Interventions

2.2.1 Situating Digital Parenting Interventions Within Digital Health

While the primary focus of this thesis is on digital parenting programmes, it is useful to situate these interventions within the broader field of digital health. The WHO *Global Strategy on Digital Health 2020–2025* defines digital health as the field of knowledge and practice concerned with the development and use of digital technologies to improve health outcomes and strengthen health systems (World Health Organization, 2021). It encompasses the concepts of both mobile health (mHealth) and electronic health (eHealth), as well as wider applications of technologies for health such as artificial intelligence, robotics, and big data. Within this umbrella, *digital behaviour change interventions* are products or services that use digital technology to promote behaviour change (Perski et al., 2017). Parenting programmes delivered via mobile apps, websites, videoconferencing, or messaging platforms represent one such application and share many design and implementation features with other digital health interventions. As a more established field with a substantially larger evidence base, digital health provides theoretical and empirical insights that this thesis draws upon to guide its conceptual framing and analytical approach.

2.2.2 Why is Digital Delivery a Research Priority?

The WHO *Global Strategy on Digital Health 2020–2025* identifies digital health as a central strategy for achieving universal health coverage and the 2030 Sustainable Development Goals (World Health Organization, 2021). Within this global agenda, the recent WHO *Guidelines on Parenting Interventions to Prevent Maltreatment and Enhance Parent–Child Relationships with Children Aged 0–17 Years* similarly identify digital and hybrid delivery models as a potential means of expanding the reach of evidence-based parenting programmes. Although in-person delivery remains the recommended standard where feasible, the guidelines recognise that digital modalities may serve as a viable alternative or complement, particularly in settings where access, cost, or workforce limitations constrain implementation. At the same time, they caution that more implementation research is needed to establish the effectiveness, equity, and feasibility of these approaches, especially in LMICs where structural barriers may limit access and user engagement (World Health Organization, 2023). Addressing this evidence gap requires closer examination of digital delivery models for socioeconomically vulnerable families in LMICs, which is the focus of this thesis.

2.2.3 Emerging Evidence on Digital Parenting Interventions

A growing body of systematic reviews and meta-analyses provides encouraging evidence that digital parenting interventions can improve parenting practices, reduce harsh discipline, and enhance caregiver and child mental health (e.g., Baumel et al., 2016; Corralejo & Domenech Rodríguez, 2018; Florean et al., 2020; Flujas-Contreras et al., 2019; Hansen et al., 2019; McAloon & Armstrong, 2024; Spencer et al., 2020; Thongseiratch et al., 2020). Although this evidence base remains in its early stages, it is dominated by studies conducted in HIC contexts with caregivers of younger children. Research examining adolescent populations, and to a lesser extent families in LMICs, is beginning to emerge. These two areas are reviewed in the sections below.

Evidence on Digital Parenting Interventions for Adolescents

An early meta-analysis by Florean et al. (2020) synthesised evidence from 15 RCTs ($N = 1{,}668$) conducted in Australia, the United States, Sweden, and New Zealand to evaluate the efficacy of internet-based parenting interventions specifically targeting externalising behaviour problems in children and adolescents. Although the studies included caregivers of children aged 2 to 18 years, only four involved children older than 10. Compared to waitlist controls, digital programmes yielded small but statistically significant improvements in child behaviour (Hedges' $g = 0.40$), parenting behaviour ($g = 0.34$), parent distress ($g = 0.30$), and parenting self-efficacy ($g = 0.41$). Importantly, digital delivery was found to be as effective as in-person formats and effects remained stable at follow-up.

A broader meta-analysis by Spencer et al. (2020) synthesised 28 studies ($N = 3{,}979$) of online parenting interventions for caregivers of children aged 0 to 18 years, all conducted in HICs including the United States, Australia, the United Kingdom, Finland, the Netherlands, Singapore, Saudi Arabia, and Taiwan. Across the full sample, online parenting programmes were associated with large improvements in positive parenting behaviours (Cohen's $d = 1.00$) and modest reductions in negative discipline strategies ($d = –0.32$) and parenting stress ($d = –0.31$). No significant differences were observed between programmes with clinical support (e.g., therapist guidance) and those that were fully self-guided. This contrasts with findings from more recent reviews focusing on younger children, where the inclusion of professional guidance has been linked to greater improvements in outcomes (Lin-Lewry et al., 2024; McAloon & Armstrong, 2024).

Building on these earlier reviews, Morgan et al. (2024) conducted a recent structured review focusing exclusively on adolescents aged 10 to 18 years, which also identifies key gaps in the evidence base. The review identified 28 studies evaluating 22 unique digital parenting interventions, delivered via the internet, downloadable materials, text messaging, tablets, or video calls. Most programmes focused on strengthening parenting practices, while some addressed adolescent developmental concerns such as sexual health, substance use, mental health, and conflict reduction. Overall, the findings point to promising potential. All included studies reported at least one significant behavioural or feasibility outcome, with effect sizes ranging from small to very large.

At the same time, the review underscored persistent gaps in the evidence. Around half of the studies did not report feasibility, acceptability, or attrition rates; only one intervention was tailored for specific racial or ethnic minority groups; most were tested in high-income, urban settings with predominantly White samples; few included socioeconomically disadvantaged families or those in LMICs; and most programmes were not freely available outside research contexts (Morgan et al., 2024). These patterns echo a broader concern that digital parenting interventions remain largely developed and tested in high-income, urban contexts, with narrow demographic reach, limited cultural adaptation, and barriers to equitable access (Corralejo & Domenech Rodríguez, 2018; Harris et al., 2020; Morgan et al., 2024). Addressing this gap requires evidence from LMICs, where structural barriers to implementation and access differ markedly from those in high-income settings. Before turning to the limited literature in LMICs, the next section considers global and regional trends in digital access to contextualise the feasibility and equity challenges that shape implementation in LMICs.

Global and Regional Trends in Digital Access

Global trends indicate that the infrastructure for digital delivery is expanding rapidly. As of 2024, there were 5.8 billion unique mobile subscribers globally, representing 71% of the population, and 4.7 billion mobile internet users, or 58% of the global population (GSMA, 2025). While overall adoption remains uneven, particularly across and within LMICs, these regions are now the primary drivers of growth (GSMA, 2025). In Sub-Saharan Africa, mobile subscriber penetration reached 55% in 2024, while smartphone adoption reached 46% (GSMA, 2025). Despite remaining below global averages, both indicators are projected to increase to 71% and 81% respectively by 2030. The region is expected to contribute nearly one-quarter of the 800 million new mobile internet users anticipated by the end of the decade, a trend supported by declining handset costs, expanding infrastructure, and targeted affordability initiatives. Despite these advances, disparities persist. Women, older adults, and rural populations remain less likely to own smartphones or access mobile internet (GSMA, 2025). This suggests that while the feasibility of digital parenting interventions in LMICs is likely to increase over the coming decade, contextually responsive design and implementation strategies will be critical to ensuring equitable access.

Digital Parenting Interventions in LMICs

Against this backdrop of expanding yet uneven digital access, a small number of feasibility studies and trials have begun to explore how digital parenting interventions can be adapted and implemented in LMICs. Examples include programmes in Brazil (Solís-Cordero et al., 2023), Peru (Jäggi et al., 2023), El Salvador (Amaral et al., 2022), and Costa Rica (Hernandez-Agramonte et al., 2022). A recent scoping review by Jäggi et al. (2025), although focused on parents of children aged 0 to 5 years, provides a useful overview of the broader evidence base. The review identified only 13 LMIC studies, most of which were small-scale, short-term, and heterogeneous in design. While many reported positive impacts on parenting behaviours and parental wellbeing, common challenges included low caregiver engagement, limited cultural adaptation, and infrastructure barriers.

Alongside these small-scale studies, large-scale dissemination efforts have demonstrated the potential for digital parenting interventions to achieve unprecedented reach. One example is an inter-agency initiative led by Parenting for Lifelong Health (PLH) during the COVID-19 pandemic, which adapted existing, freely available, open-source parenting programme content (originally designed for in-person delivery) into formats suitable for remote dissemination, including social media, radio, SMS, and other low-tech channels, and translated it into more than 135 languages (Lachman, Nurova, et al., 2024). Promisingly, these resources reached an estimated 212 million people across 198 countries and territories, and were adopted by 697 organisations, including 43 national governments.

Together, the small-scale trials reviewed by Jäggi et al. (2025) and the large-scale dissemination achieved by PLH (Lachman, Nurova, et al., 2024) highlight both the potential and the current challenges of digital parenting provision in LMICs. Key uncertainties remain about how to design and implement such interventions to ensure equitable and sustained delivery. Addressing this need requires implementation research that can clarify what works for whom and under what conditions. This thesis responds by examining caregiver engagement as a central determinant of the feasibility and effectiveness of digital parenting intervention in LMICs.

2.3 Engagement in Digital Parenting Interventions

From an implementation science perspective, low engagement may signal challenges with programme acceptability (participant satisfaction), appropriateness (perceived fit), and feasibility (the extent to which delivery is possible in a given setting). These are key implementation outcomes that influence whether interventions are adopted and sustained in real-world contexts (Proctor et al., 2011). This section begins by examining how engagement has been conceptualised in the parenting intervention literature, including process models that describe its stages and forms (2.3.1), and then considers complementary definitions from the broader digital intervention literature that capture both usage patterns and subjective experience (2.3.2). It then reviews available data on engagement rates in digital parenting interventions (2.3.3) and discusses the relationship between engagement and intervention outcomes (2.3.4). Finally, it considers the implications of low engagement for effectiveness, evaluation, and large-scale implementation (2.3.5). Together, these perspectives provide the theoretical, empirical, and practical foundation for understanding engagement as both a process and an outcome in the implementation of digital parenting interventions.

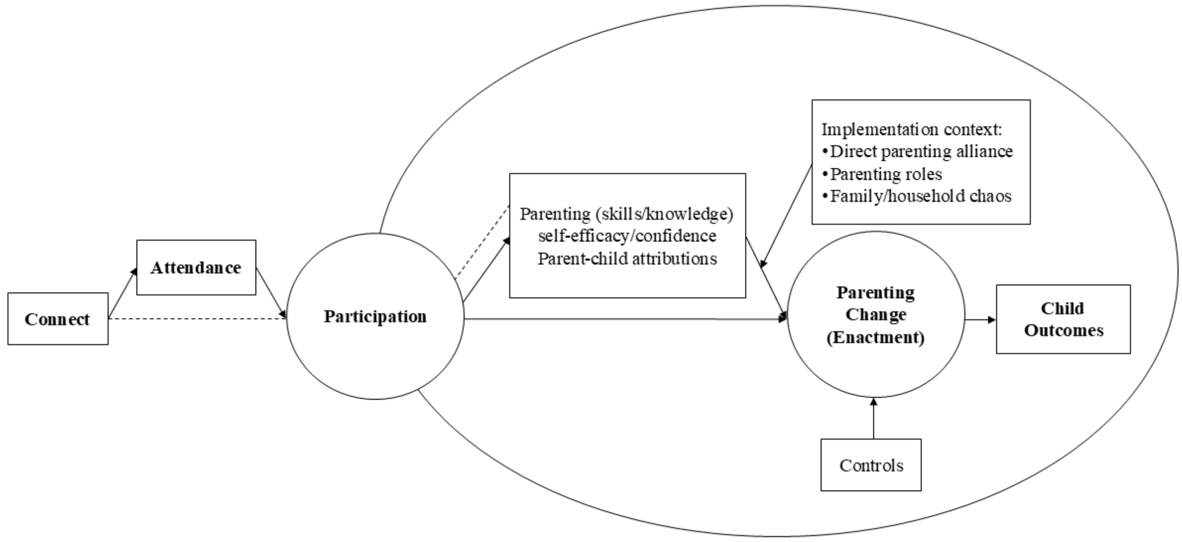
2.3.1 Conceptualising Engagement in Parenting Interventions

Engagement in parenting programmes is a complex and multifaceted construct that has been defined and measured in different ways across studies. Broadly, it refers to the extent to which caregivers interact with and participate in a programme (Chacko et al., 2016). To capture its complexity, researchers have distinguished between three interrelated components: initial engagement, ongoing engagement, and quality of engagement (Chacko et al., 2016; Ingoldsby, 2010). Initial engagement refers to both the intention to enrol and actual enrolment in the programme. Ongoing engagement refers to continued participation, such as attending sessions or completing online modules. This component is essential for ensuring that caregivers are exposed to core programme content. Quality of engagement, widely recognised as one of the most important mechanisms for behaviour change (Aldridge et al., 2024; Piotrowska et al., 2017), includes aspects such as completing home practice tasks and applying learned skills in daily family life.

Process Model of Engagement

Building on these interrelated components, Piotrowska et al. (2017) proposed the Connect, Attend, Participate, and Enact (CAPE) model (see Figure 1), which describes the process of engagement and links each stage to implementation processes and participant outcomes. The first stage "Connect", refers to how implementers establish rapport and trust with families, leading to their decision to enrol in the intervention. This step highlights the importance of establishing a meaningful and supportive connection between implementers and caregivers. The second stage "Attend", refers to caregivers' physical or digital presence at sessions. This is understood to be a fundamental aspect of engagement, as caregivers need to be present to benefit from programme content. The third stage "Participate", denotes active involvement in programme activities, such as contributing to discussions, asking questions, or interacting with content. The fourth and final stage, "Enact", involves applying learned skills from the programme to real-life parenting scenarios. This component focuses on translating programme learnings into daily interactions with their children. The CAPE model offers a framework for understanding the process of caregiver engagement and highlights the potential leverage points for implementation design. By addressing each of its four stages, developers and implementers can adopt strategies to strengthen caregiver engagement from initial contact through to the application of skills (Piotrowska et al., 2017).

Figure 1. *CAPE process model of caregiver engagement*



Source: Figure adapted from Piotrowska et al. (2017).

Theoretical Frameworks for Understanding Engagement

While process models such as CAPE describe how engagement unfolds, theoretical frameworks help explain why caregivers choose to engage in parenting interventions. The Health Beliefs Model (Salari & Filus, 2017) suggests that pre-existing values, attitudes, and beliefs shape intentions and behaviours. In the context of caregiver engagement, this theory implies that caregivers are more inclined to engage when they perceive the value of the programme's goals and believe that their participation will lead to positive outcomes for their families (Salari & Filus, 2017). Based on the Health Belief Model, engagement can be strengthened by clearly communicating the benefits of the programme and correcting misconceptions that might discourage participation.

The Theory of Planned Behaviour (Ajzen, 1991) emphasises that subjective norms, attitudes, and perceived ease or difficulty of a behaviour (e.g., participating in a parenting programme) determine intentions and behaviour. In the context of caregiver engagement, this theory implies that caregiver intentions to participate in parenting programmes are influenced by their perceptions of social norms (what others expect them to do), their attitudes toward the programme (whether they view it positively or negatively), and their perceived barriers and facilitators to participation. Researchers have applied this theory to improve caregiver engagement by reducing practical barriers, such as providing transportation and childcare, and by reshaping social norms through strategies like newsletters or community events that foster positive expectations and perceptions of support (Hill et al., 2021).

More recently, behavioural economics has provided a complementary perspective, challenging the assumption that engagement decisions are made in a purely rational, context-free manner (Hill et al., 2021). This approach considers how structural inequalities, poverty, and discrimination shape the cognitive resources available for engagement (Hill et al., 2021). The behavioural economics perspective views cognitive resources, such as attention, as limited and scarce (Hill et al., 2021). Allocating these resources to one aspect of parenting, such as earning money to buy food, may leave fewer resources available for another, such as attending a parenting intervention. Behavioural economics also views decision-making instances as cumulative (Hill et al., 2021). Micro-decisions such as reading a pamphlet about a parenting programme or opening reminders about the programme once enrolled reinforce the goal of participation and sustain parental motivation to engage. This model provides insights into promoting caregiver engagement through "nudges" that facilitate decision-making and help translate intensions into behaviours. These nudges might include sending timely reminders, streamlining enrolment processes, and minimising logistical obstacles. By accounting for the cognitive and contextual constraints facing caregivers, interventions can be designed to align with real-world decision-making processes and increase the likelihood of sustained participation.

2.3.2 Definitions of Engagement in the Digital Intervention Literature

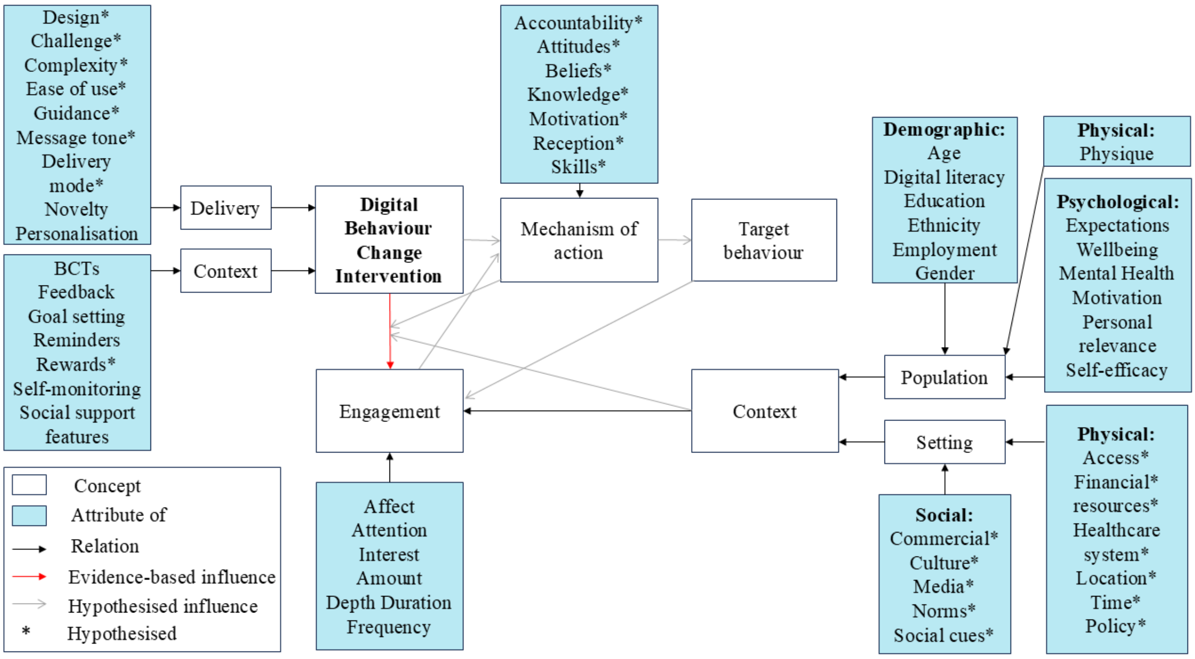
Engagement in digital interventions is defined differently across various fields and theoretical frameworks. A systematic review illustrates this variability, revealing 102 different definitions and 372 underlying theories of engagement among 351 research articles examined (Doherty & Doherty, 2018). Two main fields studying engagement in digital interventions are behavioural science and computer science. In behavioural sciences, engagement is often viewed as the process of achieving behavioural change through the use of digital platforms (Yardley et al., 2016a). This definition focuses on quantifiable use patterns, such as frequency and duration of use, as well as the utilisation of specific intervention content. Perski et al. (2017) describe this approach as equating engagement to the extent of usage or "dose" of the intervention over time. While this definition is efficient due to the ease of tracking digital activity, a major critique is that it fails to capture the depth of user involvement and the behavioural changes that occur beyond the digital environment (Yardley et al., 2016a).

To address this limitation, researchers have introduced distinctions between micro-level and macro-level engagement (Yardley et al., 2016a). Micro-level engagement refers to immediate, in-the-moment interactions with the digital intervention itself, such as navigating through an app or completing a module. In contrast, macro-level engagement encompasses broader, offline interactions with the intervention-mediated behavioural change, such as implementing learned strategies in daily life or maintaining long-term behavioural changes. Similarly, Cole-Lewis et al. (2019) proposed a framework that distinguishes between "Big E" (engagement with the target health behaviour) and "Little e" (engagement with the digital intervention itself). This framework provides a structured approach to understanding the relationship between engagement with the technology and engagement with the desired behavioural outcomes.

In computer science and human-computer interaction, engagement is more often defined in subjective experiential terms (Perski et al., 2017). This definition is rooted in flow theory (Csikszentmihalyi, 1990), where engagement is characterised by interest, focused attention, and enjoyment. This perspective acknowledges that engagement includes cognitive, emotional, and motivational components that users subjectively experience throughout their interaction with the digital intervention. Researchers often operationalise this definition through qualitative measures, observations, and sometimes physiological data (Doherty & Doherty, 2018).

Recognising the fragmentation of definitions across disciplines, Perski et al. (2017) conducted a systematic review of 117 qualitative and quantitative articles on engagement in digital behaviour change interventions. Their work culminated in an integrative definition that conceptualises engagement with digital behaviour change interventions as "(1) the extent (e.g., amount, frequency, duration, depth) of usage and (2) a subjective experience characterised by attention, interest and affect" (Perski et al., 2017, p. 258). From this integrative definition, Perski et al. (2017) proposed a comprehensive conceptual framework for understanding engagement in digital behaviour change interventions (see Figure 2).

Figure 2. *Conceptual framework of engagement with digital interventions*



Source: Figure adapted from Perski et al. (2017).

This framework distinguishes itself from earlier models of engagement by drawing insights from both theoretical predictions and empirical observations across various health-related fields. It depicts engagement as a complex, dynamic process influenced by three key elements: (1) the digital intervention itself (including its content and delivery methods), (2) the surrounding contextual environment (such as the usage setting and user demographics), and (3) the specific behaviour targeted by the intervention. Importantly, the framework introduces the concept of "mechanisms of action" and suggests that both these mechanisms and contextual factors can act as moderators, influencing the extent of the intervention's impact on engagement. In a departure from simpler, unidirectional models, Perski et al.'s (2017) framework proposes a reciprocal relationship where engagement itself moderates the intervention's impact on these mechanisms of action. This bidirectional interaction underscores the dynamic and evolving nature of user engagement in digital behaviour change interventions. By offering this multifaceted view, the framework provides researchers and developers with a valuable tool for analysing, designing, and improving digital behaviour change interventions. This thesis adopts Perski et al.'s (2017) integrative definition and conceptual framework as the basis for examining engagement in digital parenting interventions.

2.3.3 Engagement Rates in Digital Parenting Interventions

Reporting of engagement in digital parenting interventions is inconsistent, with many studies providing only partial or indirect measures and often failing to distinguish between overall study retention/attrition and actual interaction with programme content (MacDonell & Prinz, 2017). In an early review of digital parenting programmes, Hall and Bierman (2015) estimated intervention attrition rates between 30% and 50%, with higher rates in fully self-guided formats. However, a subsequent review by MacDonell and Prinz (2017) of 21 youth- and family-focused digital interventions found that 68% of studies did not report programme completion rates at all. Among those that did, completion ranged from 43% to 100% for parent/family-focused interventions and from 9% to 100% for youth-focused interventions. The authors note that these estimates likely overestimate actual engagement, as some studies reported the average proportion of content completed rather than the proportion of participants completing the full programme. Against this backdrop, the figures presented below reflect what is available in the literature, while recognising that inconsistent reporting and variation in measurement limit comparability across studies.

Encouragingly, several individual studies have demonstrated relatively high levels of engagement and retention. An early trial of the tablet-based ezParent programme with 83 low-income parent–child dyads in the United States achieved 95% retention (Breitenstein et al., 2016). Participants completed an average of 85.4% of programme modules, a rate significantly higher than attendance in the comparison in-person group-based programme. More recently, Feil et al. (2020) reported 90% retention in a trial of the Parenting and Learning Strategies programme involving 164 low-income mothers in the United States, which included the provision of laptops and weekly coaching calls. Comparable rates have been observed in other contexts. For instance, in a mixed-methods evaluation of the Afinidata parenting messaging programme in Peru ($N = 180$), 84% of participants reported using the programme at least once within the first two months (Jäggi et al., 2023). After five months, 42% continued to engage weekly, with little variation between urban and rural settings.

In contrast, large-scale implementations of digital parenting programmes frequently report substantially lower levels of engagement. For example, Ning et al. (2019) reported a 32% attrition rate in a trial of an app-based parenting programme for 2,920 caregivers in China. Similarly, in an evaluation of ParentWorks, a universal online parenting programme in Australia, more than half of the 2,967 caregivers enrolled never began the first module, and only 7% completed the full programme (Dadds et al., 2019).

These findings are consistent with broader trends in digital health interventions, where high attrition and limited engagement are widespread. In one of the largest datasets compiled to date, Pratap et al. (2020) analysed user engagement across eight digital mental health studies comprising over 100,000 participants. More than half disengaged within the first week, with a median retention of just 5.5 days and activity recorded on only two days. Similarly, a systematic review by Fleming et al. (2018) reported real-world programme completion rates for digital self-help interventions ranging from 0.5% to 28.6%, while Baumel et al. (2019) found a median 15-day retention rate of only 3.9% for mental health apps on Google Play. Collectively, these rates illustrate that achieving sustained engagement at scale remains one of the most significant challenges for translating the demonstrated efficacy of digital parenting interventions into population-level impact.

2.3.4 Engagement and Relationship to Intervention Outcomes

In the parenting intervention literature, engagement is conceptualised as a key determinant of intervention impact, influencing both the extent of exposure to, or “dose” of, programme content and the likelihood that caregivers will apply learned strategies in daily life (e.g., Menting et al., 2013; Piotrowska et al., 2017; Reyno & McGrath, 2006). Consequently, it is widely accepted that without sufficient engagement, caregivers are unlikely to acquire the skills necessary to improve their parenting practices and, in turn, enhance child and family outcomes.

Evidence from both in-person and digital parenting interventions supports a “dose-response” relationship between engagement and outcomes. Several systematic reviews of in-person parenting programmes have demonstrated correlations between higher session attendance and improved child and caregiver outcomes (Haine-Schlagel et al., 2022; Menting et al., 2013; Reyno & McGrath, 2006). In the digital context, a recent review found that module completion was positively and reliably linked to reductions in maladaptive parenting behaviours (Aldridge et al., 2024). However, the relationship between engagement and outcomes is not always straightforward. Reviews in the broader digital health intervention field have reported no significant associations, and in some cases even negative relationships, between app usage metrics and outcomes (Baumel et al., 2019; Torous et al., 2020). In response, scholars have emphasised the importance of examining how users engage, including which features they use and whether these meet their needs, rather than relying solely on usage metrics such as total time spent on the digital platform (Borghouts et al., 2021).

2.3.5 Implications of Low Engagement

Low engagement has important implications for both the effectiveness and the evaluation of digital parenting interventions. At the individual level, it reduces exposure to core programme content and opportunities to practise new parenting strategies. This limits the likelihood of meaningful changes in parenting behaviour or child outcomes (Chacko et al., 2016; Ingoldsby, 2010). At the population level, the impact of a parenting programme depends on both its effect size per participant and the proportion of the target population who engage meaningfully (Braver & Smith, 1996). Consequently, even a highly effective intervention will have minimal public health benefit if only a small fraction of the intended population participates at a sufficient level to experience its benefits. Moreover, from a pragmatic perspective, policymakers and funders are unlikely to invest in large-scale dissemination if reach and sustained engagement are too low to generate meaningful improvements in population outcomes (Sim et al., 2022). In addition, low engagement undermines research validity and reliability. It can introduce selection bias if those who remain engaged differ systematically from those who disengage (e.g., in motivation or access to resources), potentially inflating estimates of effectiveness (Druce et al., 2019). Conversely, disengaged participants may face unique challenges relevant to the outcomes being studied, leading to an incomplete understanding of the intervention's effects. Moreover, low engagement often results in attrition or early dropout, resulting in missing data that further complicate the analysis and interpretation of results (Druce et al., 2019).

In conclusion, engagement is a core determinant of whether digital parenting interventions achieve their intended impact and generate credible evidence to guide scale-up. Addressing low engagement is therefore essential to ensuring that these interventions can deliver meaningful benefits for families and communities, particularly in resource-constrained settings where their potential reach is greatest.

2.4 Parenting for Lifelong Health (PLH) and ParentApp

This thesis examines caregiver engagement within the context of ParentApp, a digital parenting intervention adapted from the Parenting for Lifelong Health (PLH) Teens programme. To contextualise this research, the following section provides an overview of the broader PLH programme suite, with a particular focus on the PLH Teens intervention from which ParentApp was derived. Specific methodological and design details related to the ParentApp optimisation trial, which forms the empirical foundation for the three papers in this thesis, are presented in Chapter 5 and within each respective paper.

PLH is a UK-based charitable social enterprise aimed at developing and scaling evidence-based parenting programmes in LMICs. The PLH suite includes multiple programmes designed for distinct developmental stages: PLH Infants (conception to 6 months), PLH Toddlers (1 to 5 years), PLH Young Children (2 to 9 years), and PLH Teens (10 to 17 years). These programmes are primarily grounded in social learning and attachment theory and were originally designed for in-person, group-based delivery. To date, PLH programmes have been implemented in over 35 LMICs, reaching an estimated 300,000 caregivers and children (Shenderovich et al., 2021; Shenderovich, Ward, et al., 2020).

2.4.1 Evidence Supporting PLH Teens

PLH Teens is a 14-session, group-based programme targeting caregivers of adolescents aged 10 to 17 years. It aims to reduce adolescent exposure to violence in the home and community by enhancing positive parenting practices, improving parent-child communication, promoting mental health, and mitigating risks of sexual violence victimisation (Cluver et al., 2018). The programme's efficacy has been evaluated through a pragmatic cluster RCT in South Africa, involving 552 caregiver-adolescent dyads across 40 rural villages and peri-urban townships (Cluver et al., 2018). Results demonstrated reductions in child maltreatment and improvements in positive parenting practices, monitoring, and parental involvement at five to nine months post-intervention. A subsequent cost-effectiveness analysis revealed that PLH Teens incurred a cost of $972 USD per prevented case of abuse, resulting in a total cost savings of $2,724 USD per abuse case (Redfern et al., 2019). These promising results have led to the rapid dissemination of PLH Teens to over 16 countries (Shenderovich, Ward, et al., 2020). Among these is the large-scale implementation of the programme in Tanzania, delivered to more than 75,000 caregivers of adolescents between 2017 and 2021 (Lachman, Wamoyi, et al., 2024; Martin et al., 2021). Evaluation of the pre-post results showed significant reductions in child maltreatment and school-based violence (Lachman, Wamoyi, et al., 2024). Additionally, there were improvements in sexual health communication and reductions in poor supervision, financial insecurity, parenting stress, as well as parent and child depression and conduct problems (Lachman, Wamoyi, et al., 2024).

2.4.2 ParentApp Tanzania Project

Building on the success of the in-person PLH programmes, the Global Parenting Initiative (GPI) was established to support the digital adaptation and scale-up of the PLH intervention suite. The GPI represents a global collaboration among universities, philanthropic foundations, and implementing partners across the Global South and North. As part of this initiative, ParentApp was developed as a smartphone-based adaptation of the PLH Teens programme for caregivers of adolescents aged 10 to 17 years. In parallel, the GPI also developed ParentText, a chatbot intervention that delivers parenting content via SMS and social messaging platforms to caregivers of children aged 0 to 17 years.

The development of ParentApp began in 2019 and followed a multiphase, iterative process. This included co-design with researchers, programme developers, and caregiver–adolescent dyads in South Africa (2019 to 2020); user-testing interviews with caregivers across nine African countries (2021); and feasibility pilot studies in South Africa (2021) and Tanzania (2022). The app was subsequently evaluated through a cluster-randomised factorial optimisation trial in Tanzania (2022 to 2023), followed by a large-scale evaluation RCT in Tanzania (2023 to 2024). Papers 1, 2, and 3 of this thesis analyse data collected during the optimisation trial in Tanzania. ParentApp's development and adaptation in Tanzania involved collaboration among the Universities of Oxford and Cape Town; PLH; Innovations in Development, Education, and the Mathematical Sciences (IDEMS International and INNODEMS Kenya); and Clowns Without Borders South Africa (CWBSA). Implementation support was provided by Investing in Children and Strengthening their Societies (ICS).

2.4.3 My Role and Contribution

I joined the University of Oxford ParentApp research team in August 2020 as a Research Assistant, contributing to pilot study protocols, ethics submissions, and early implementation in South Africa and Tanzania. During this period, I identified persistent patterns of low caregiver engagement, which informed my doctoral proposal and led to the design of the engagement-optimisation trial forming the basis of this thesis. I led the trial's conceptualisation, including selecting the experimental design, preparing the published protocol, and registering the study on the Pan-African Clinical Trials Registry. I worked closely with IDEMS International, INNODEMS Kenya, and CWBSA to co-develop intervention components and the app-based monitoring and evaluation system. Between October 2022 and March 2023, I spent two months in Mwanza, Tanzania, supporting trial implementation (Figure 3). This involved training research staff, overseeing data collection and management procedures, coordinating logistics with local partners, and troubleshooting data flow issues with the technical team. I also developed the statistical analysis plan and conducted all analyses for the three papers in this thesis, with early findings informing ParentApp refinements and a subsequent evaluation RCT in Tanzania (Baerecke et al., 2024). In addition to leading the optimisation trial, I contributed to broader GPI activities, including cross-study workshops, publications, conference presentations, and stakeholder engagement (see Chapter 9.8).

2.4.4 Positionality and Reflexivity

Although my research focus was primarily quantitative, it is important to reflect on how my identity, experiences, and education shaped this thesis. As a White South African woman who grew up in a rural community, I occupy both insider and outsider positions in relation to this work. My upbringing in a sub-Saharan African country sensitised me to intersecting structural, racial, and gendered inequalities, as well as the legacies of colonial power dynamics that continue to influence research relationships in these contexts. At the same time, I remained an outsider to the specific racial, cultural, linguistic, and social realities of caregivers in Mwanza, Tanzania. My academic training in psychology and evidence-based social intervention, combined with professional experience in violence prevention, also influenced the theoretical frameworks I prioritised, the operational definitions of engagement I adopted, and the trial design choices I made. I recognise that these decisions were not neutral and reflected my own assumptions about what is meaningful or measurable. To attempt to address this, I worked in partnership with Tanzanian colleagues and local organisations throughout the research process, not only to adapt study procedures and intervention components but also to critically reflect on and co-interpret the findings.

Figure 3. *Photographs during fieldwork in Mwanza, Tanzania*

Description (*top to bottom*): (1) primary school in Mwanza used for onboarding sessions; (2) implementation team members, including NIMR research assistants and ICS facilitators, at a fieldwork site; (3) view of Mwanza city, Tanzania (*Source: taken by candidate during fieldwork*)

3. Review of Literature Underpinning the Methods

This chapter reviews the literature underpinning the methodological aspects of the thesis. It is organised into four sections. Section 3.1 examines how engagement has been conceptualised and measured in parenting and digital intervention research, outlining key phases, dimensions, and challenges in assessment. This provides the conceptual basis for the engagement outcomes selected across the three empirical papers. Section 3.2 synthesises evidence on baseline predictors of engagement, spanning both contextual characteristics and intervention-level factors. These insights informed the conceptual model presented in Chapter 5 and guided the selection of design and delivery components tested in the optimisation trial. Section 3.3 situates the optimisation trial within the Multiphase Optimisation Strategy (MOST) framework and outlines the rationale for using factorial experiments to test discrete components designed to enhance engagement. This section also reviews applications of MOST in the public health literature. Section 3.4 considers the role of moderation in optimisation trials and reviews the existing evidence on moderation in parenting intervention research. Together, these sections establish the methodological foundations for the study design and optimisation strategies used in this thesis.

3.1 Measuring Engagement

The measures of engagement documented in the literature vary in terms of the phases and dimensions they focus on; the modes of data collection employed; and the digital delivery platform used. Broadly, engagement has been measured along two main axes: temporal phases, which capture how engagement evolves over time, and dimensions (behavioural and attitudinal), which include both observable actions and subjective experiences of users. The following sections will discuss the various phases and dimensions of engagement, modes of data collection, dominant measure types used in the literature, and challenges associated with measuring behavioural engagement in app-based interventions.

3.1.1 Phases of Engagement

Engagement is often viewed as a temporal process, with different phases marking a participant's journey through a digital intervention. These phases have broadly been described as initiation (e.g., scheduling the first session or expressing initial interest), progress (e.g., measured through ongoing activities such as session attendance and homework completion), and completion (e.g., finishing a full course of treatment or a prespecified number of sessions) (Georgeson et al., 2020). More detailed models, such as the CAPE model proposed by Piotrowska et al. (2017), add additional steps to these phases to capture the progression from the initial connection with the intervention (i.e., pre-enrolment activities) to the enactment of learned skills in real-life situations. Other researchers have proposed similar stage-based models. For instance, Brouwer et al. (2008) identified three distinct stages or levels of engagement in digital interventions: accessing the platform for the first time to decide if it is useful or relevant, extending the visit to use part of the intervention or content, and revisiting the platform to engage with the content and activities more fully. Similarly, O'Brien and Toms (2008) conceptualised engagement as a cyclical process involving stages of engagement, disengagement, and re-engagement. The latter models emphasises that users' interaction with digital interventions is not linear but rather fluctuates, with periods of high engagement potentially followed by disengagement and subsequent re-engagement.

3.1.2 Dimensions of Engagement

In addition to temporal phases, engagement is frequently measured along behavioural and attitudinal (or cognitive) dimensions (Georgeson et al., 2020). Behavioural engagement, often the most readily available measure, can be further subdivided into initial engagement, ongoing engagement, and quality of engagement (Aldridge et al., 2024). Initial engagement captures the user's first interactions with the programme, including measures such as recruitment rates, enrolment rates, expressions of interest, and first logins. Ongoing engagement focuses on sustained interaction over time, measured through metrics like logins, module completion rates, and retention or dropout rates. Quality of engagement assesses how users interact with specific components, examining factors such as time spent on particular modules, depth of interaction with exercises or components, completion rates of specific components, and adherence (Aldridge et al., 2024). Attitudinal or cognitive engagement, on the other hand, delves into users' mental interaction with the programme. This dimension focuses on aspects such as attention and focus, knowledge acquisition, and emotional investment (Georgeson et al., 2020). Measures in this dimension often include assessments of satisfaction, usability, acceptability, and therapeutic alliance. Additionally, it considers the perceived relevance and applicability of the programme content to users' specific parenting challenges and family situations.

3.1.3 Modes of Data Collection

Data collection methods for measuring engagement in digital parenting programmes can be broadly classified into objective and subjective categories (Perski et al., 2017; Yardley et al., 2016a). Objective measures typically rely on automated data collection through the digital platform itself, providing quantifiable metrics of user behaviour. These may include log data capturing frequency and duration of logins, number of modules completed, time spent on specific modules or topics, and interaction with various features such as videos watched or exercises completed. More advanced objective measures might include clickstream data, heat maps of user activity, or even biometric data if applicable (Pham et al., 2019). These objective indicators yield information on users' practical interaction with the digital platform and content.

Subjective measures, on the other hand, aim to capture users' qualitative perceptions, experiences, and attitudes towards the programme. These are often collected through self-report methods such as feedback forms and rating scales administered at various points during the intervention. More in-depth qualitative data can also be gathered through semi-structured interviews and focus groups, which are useful for capturing social and contextual factors that influence engagement with the programme (Aldridge et al., 2024). Recognising the complementary nature of these approaches, researchers have recommended mixed-method approaches to investigate both objective and subjective behaviour and attitudes of users (Michie et al., 2017).

3.1.4 Dominant Measure Types Used in the Literature

Although considerable inconsistency exists in both the measures employed and the terminology used to describe engagement constructs across studies, several dominant measure types have been identified through systematic reviews of digital parenting interventions (Aldridge et al., 2024; Georgeson et al., 2020). A recent systematic review by Aldridge et al. (2024) found that initial engagement, ongoing engagement, and quality of engagement were the primary components of behavioural engagement measured in digital parenting intervention studies. Initial engagement, most commonly assessed through enrolment and recruitment rates, was measured in 74.8% of the studies reviewed. The authors speculate that this high prevalence is likely due to the predominance of RCTs in the field, where reporting on recruitment rates is standard practice (Aldridge et al., 2024). Ongoing engagement, primarily assessed through session or module completion rates, was measured in 70.3% of the studies. Quality of engagement, often assessed through the use of specific programme components and time spent on these components, was only measured in 37.8% of the studies. This lower prevalence is noteworthy, given that the quality of parents' engagement is suggested to be a key mechanism for positive parenting change. The relative scarcity of quality engagement measures highlights a gap in the current research and suggests a need for more frequent evaluation of engagement quality to extend understanding of engagement and its association with target outcomes in digital parenting programmes. Attitudinal or qualitative measures of engagement, such as satisfaction ratings and feedback questionnaires, were assessed in 70.3% of the studies (Aldridge et al., 2024). However, more in-depth qualitative methods such as semi-structured interviews or focus groups were used less frequently.

Beyond the field of parenting, a scoping review by Pham et al. (2019) catalogued the range of analytic indicators being used to measure engagement in mobile health apps. Across the 41 studies reviewed, seven primary analytical indices were identified: number of measures recorded, frequency of interactions logged, number of components accessed, number of logins, number of modules started or completed, time spent on the app, and number or content of pages accessed. Most studies used a combination of measures to understand engagement, with an average of four measures per study (Pham et al., 2019). This multi-faceted approach to measuring engagement reflects the complex nature of the construct and the recognition that no single measure can fully capture all aspects of engagement. However, despite the use of multiple measures, the complementary value of these different indicators for understanding engagement remains unclear. There is limited prior research examining which combination of engagement measures constitutes valid, reliable, and meaningful engagement in digital interventions. This gap in knowledge presents a significant challenge for researchers and practitioners seeking to design effective digital parenting interventions.

To summarise, while dominant measure types have been identified in digital parenting intervention studies and digital health interventions more broadly, the field is characterised by a lack of consistency in both measures and terminology. This variability, coupled with the limited research on the complementary value of different engagement indicators, highlights the need for more standardised approaches to measuring engagement.

3.1.5 Challenges in Measuring Engagement

Measuring engagement in digital parenting interventions presents numerous challenges, both for behavioural and attitudinal measures. This section focuses on the specific challenges associated with behavioural measures in app-based interventions, as these form the core focus of this thesis's analysis.

Automated data tracking provides a wealth of quantifiable metrics, yet interpreting these data to gauge meaningful engagement is complex (Yardley et al., 2016a). Users might log in frequently but interact minimally, or leave the app open for extended periods without active participation. Such scenarios can lead to an overestimation of engagement. Conversely, passive engagement, where users consume content without interacting with features like quizzes or discussions, may result in an underestimation of engagement for those who prefer passive learning styles. Similarly, module completion rates, while providing insight into user progression, fall short in assessing the depth of understanding or practical application of content.

Technical issues further complicate engagement measurement in app-based interventions. Inconsistent internet connectivity can result in incomplete or inaccurate data capture. While offline usage options aim to mitigate this, they introduce new challenges in tracking engagement during disconnected periods and ensuring accurate data synchronisation upon reconnection. Device variability presents another layer of complexity. Older or lower-end devices may not fully support all app features, leading to compromised user experiences manifesting as slower load times, frequent crashes, or inaccessibility of certain interactive elements. This can result in artificially low engagement metrics for these users, not due to lack of interest, but because of technical limitations. Furthermore, resource-intensive apps can rapidly drain battery life or require substantial storage space, potentially leading to restricted or sporadic app usage. This intermittent usage pattern further complicates the differentiation between technical constraints and actual user disengagement. Additionally, in some households, especially in lower socioeconomic settings, devices may be shared among family members. This shared usage can lead to conflated engagement patterns, obscuring the true impact of the intervention on individual family members.

3.2 Predictors of Engagement

Having reviewed how engagement is commonly measured, this section considers the factors that influence it. Identifying these factors is essential for informing digital intervention design and delivery strategies that optimise engagement and, ultimately, improve programme effectiveness. While a substantial body of evidence exists on predictors of engagement in traditional, in-person parenting programmes (e.g., Chacko et al., 2016; Haine-Schlagel et al., 2022; Reyno & McGrath, 2006), comparatively little is known about the factors associated with engagement in digital formats. Given the limited evidence, this review also draws on studies from the broader digital health intervention literature. Furthermore, due to the inconsistent reporting and measurement of engagement across studies, engagement is conceptualised here as a continuum that includes recruitment, enrolment, active participation, adherence to intervention content, and attrition. Following the framework established by Perski et al. (2017), predictors of engagement have been grouped into two overarching categories: contextual factors, which include individual sociodemographic, behavioural, psychological, technical, and environmental influences; and intervention factors, which refer to the design, content, and delivery features of the intervention itself.

3.2.1 Contextual Factors

Sociodemographic Characteristics

Among caregiver demographic characteristics, emerging evidence suggests that digital delivery may attenuate the gender disparities typically observed in traditional, in-person parenting programmes (see Gonzalez et al., 2023; Panter-Brick et al., 2014). For example, in an evaluation of the ParentWorks programme, a free, self-directed online parenting intervention for childhood conduct problems targeting parents of children aged 2 to 16 years in Australia, Dadds et al. (2019) analysed data from 2,967 caregivers and found no significant differences in dropout rates between mothers and fathers. Fathers comprised 40% of the sample, and engagement patterns, including module completion and attrition rates, were comparable across genders. Similarly, a recent systematic review by Lin-Lewry et al. (2024), which synthesised evidence from seven digital intervention trials targeting the transition to parenthood, reported no significant differences in engagement between mothers and fathers.

Findings related to caregiver age as a predictor of engagement in digital parenting interventions have been inconsistent. A survival analysis of attrition among 3,261 expectant and new fathers in the SMS4dads programme in Australia found no significant association between paternal age and programme dropout (Fletcher et al., 2023). However, Horn et al. (2025), in a study pooling data from two pilot RCTs of the BEAM programme (N = 110) in Canada, found that older maternal age was significantly associated with higher engagement. The programme targeted mothers of children aged 6 to 36 months with elevated depressive and anxiety symptoms, and included psychoeducational videos, weekly telehealth groups, and asynchronous peer forums. Older mothers spent more time viewing video content and completed more sessions than younger participants.

Regarding child demographic characteristics, no known studies to date have examined whether caregiver engagement varies by the gender of the target child in digital parenting interventions. However, child age has been explored in two Australian studies, both of which suggest that caregivers of older children are less likely to engage. In the ParentWorks trial, Dadds et al. (2019) found that caregivers who enrolled but did not complete any modules tended to have older children. Similarly, in a study evaluating the Triple P Online Brief programme with 100 parents of children aged 2 to 9 years, Baker and Sanders (2017) reported that caregivers of older children were significantly less likely to complete the minimum recommended dose of the programme, which was defined as completing the introductory module and at least one core module.

Socioeconomic factors have been studied more extensively and show more consistent associations with caregiver engagement in digital parenting interventions. For example, in their study of the BEAM programme, Horn et al. (2025) found that higher income predicted greater forum activity, more frequent attendance at telehealth sessions, and more sustained weekly engagement. Similarly, Lin-Lewry et al. (2024) identified financial constraints as a barrier to ongoing engagement in their systematic review of digital parenting interventions. Caregiver education has also been linked to engagement outcomes. In a Finnish trial (N = 464) of the Strongest Families Smart Website, Fossum et al. (2018) found that lower maternal education was associated with nonparticipation among parents of 4-year-old children with disruptive behaviour. Similar associations have been reported in trials of digital parenting programmes conducted in Australia (Fletcher et al., 2023) and Germany (Wähnke et al., 2024), where lower educational attainment was associated with higher attrition and lower completion rates.

However, other socioeconomic indicators, such as family structure and household composition, have been less consistently associated with engagement. In the ParentWorks trial, Dadds et al. (2019) found that single parents were more likely to complete the programme. In contrast, Wähnke et al. (2024) found no significant associations between single-parent status, household size, or childcare arrangements and intensity of programme use. Beyond structural disadvantage, exposure to psychosocial stressors may also reduce engagement. For example, in a study of the eHealth Familias Unidas programme involving 113 Hispanic families of adolescents with behavioural problems in the United States, Perrino et al. (2018) found that higher levels of family stress and conflict predicted lower enrolment and reduced module completion. Broadening the scope to digital health interventions more generally, sociodemographic factors positively associated with programme uptake and user engagement include employment status, higher education, stronger language skills, and urban residency (Borghouts et al., 2021; Perski et al., 2017; van Kessel et al., 2023).

Behavioural Characteristics

A range of caregiver behavioural factors have been identified as potential predictors of engagement in digital parenting programmes, although the findings have been somewhat mixed. Day et al. (2021), in a large integrated analysis of seven RCTs (N = 985) conducted in Australia, examined predictors of the online version of the Triple P Positive Parenting Program for parents of children aged 2 to 12 years. The study found that higher baseline parenting confidence predicted greater programme completion, while lower confidence and greater parental adjustment difficulties were associated with early dropout. In contrast, Perrino et al. (2018), in their study of the eHealth Familias Unidas intervention in the United States, found that higher levels of effective parenting at baseline were linked to lower engagement. Dadds et al. (2019), on the other hand, reported that higher levels of dysfunctional parenting predicted early dropout in the ParentWorks programme, suggesting that caregivers experiencing more severe parenting difficulties may face practical or emotional barriers to sustained engagement.

Regarding child behavioural characteristics, Finan et al. (2018) conducted a systematic review of predictors of engagement across 23 parenting interventions delivered through both in-person and digital formats, although the majority were in-person. The review examined predictors of enrolment, attendance, and adherence. Child mental health symptoms were the only factor consistently associated with enrolment, while no variables were found to reliably predict ongoing participation or programme completion. However, several individual studies have reported that caregivers of children with fewer behavioural difficulties were more likely to disengage from digital parenting programmes (Dadds et al., 2019; Fossum et al., 2018; Perrino et al., 2018). Together, these findings suggest that while child symptom severity may prompt initial enrolment, it may not translate into sustained engagement.

Psychological Characteristics

Several digital parenting intervention studies have investigated the relationship between engagement and caregiver mental health. A study comparing self-guided, individual telehealth, and in-person group formats of a parenting programme for military families in the United States found that families with fathers reporting lower depressive symptoms were significantly more likely to enrol in the self-guided online format (Cai et al., 2024). Similarly, Dadds et al. (2019) found that higher baseline psychopathology was associated with early dropout. In contrast, Fletcher et al. (2023) found no association between psychological distress and dropout among expectant and new fathers. Likewise, Horn et al. (2025) reported no consistent associations between maternal depressive symptoms and engagement, although higher maternal anxiety was linked to a greater number of weeks engaged with the programme.

Findings from the broader digital health intervention literature suggest that mental health-related factors, including low mood, anxiety, and stress, can act as barriers to accessing and engaging with digital interventions, particularly those targeting individuals with clinical mental health conditions (Borghouts et al., 2021; Perski et al., 2017). Feelings of tiredness have also been reported to negatively affect participants' motivation and ability to use digital mental health interventions (Borghouts et al., 2021). In addition, low expectations of the intervention, and low trust in the professional may contribute attrition in digital health interventions (Jakob et al., 2022).

Technology Experience and Skills

Digital literacy and access to technology can significantly influence how caregivers interact with and benefit from digital parenting programmes. For example, in their integrated analysis of the Triple P online programme, Day et al. (2021) found that parents who reported more frequent internet usage at baseline completed a greater number of modules. Similarly, Jäggi et al. (2023), in one of the few digital parenting programme studies conducted in an LMIC, examined engagement among 180 mothers from Peru participating in a feasibility trial of the Afinidata programme. The study found that mothers who owned a smartphone demonstrated higher and more sustained engagement than those relying on a shared device. Qualitative findings further identified barriers to engagement such as difficulty reinstalling the app. These findings suggest that regular access to and familiarity with digital devices enhance engagement with digital parenting interventions.

This pattern is consistent with the broader literature. A scoping review of 244 studies found that internet access and perceived digital competence were key facilitators of uptake and engagement with digital therapeutic interventions (van Kessel et al., 2023). Individual characteristics associated with low engagement in digital health interventions include negative prior experiences with health services or mental health technology, poor health literacy, and limited digital literacy (e.g., Borghouts et al., 2021; Jakob et al., 2022). Likewise, a systematic review of 99 studies on attrition in health apps for noncommunicable diseases identified limited technical competence, poor health literacy, and lack of experience with digital intervention apps as contributors to higher attrition (Jakob et al., 2022). The authors of this review suggest that providing pre-intervention orientation and basic technical support may be an effective strategy to promote engagement, especially in self-guided programmes.

Intervention Setting

The social and physical environments in which digital interventions are delivered may shape engagement, although empirical evidence on these contextual influences remains limited. Perski et al. (2017), in their review of digital behaviour change interventions, identified a range of environmental factors hypothesised to affect engagement. These include social environments such as cultural norms, media influence, commercial settings, and social cues. Physical environment factors identified include financial resources, available time, material resources, location, physical cues, and the systems through which the intervention is delivered. Further research is needed to examine how these contextual variables interact with intervention design and delivery.

3.2.2 Intervention Factors

Usability, User-Friendliness, and Technical Stability

Usability and technical stability are frequently cited as key factors influencing engagement with digital parenting interventions. In particular, practical support for navigating the technology has emerged as an important facilitator of engagement. Aldridge et al. (2024), in a systematic review of 127 studies examining engagement strategies in technology-assisted parenting programmes for childhood adversity, found that interventions offering practical support for technology use were more likely to engage parents. These supports included low-cost strategies such as clear instructions, user manuals, and orientation sessions designed to build users' confidence in accessing and navigating digital components. However, the relationship between usability and engagement is not necessarily linear. In a study examining real-world user engagement with self-guided mobile health apps and websites, Baumel and Kane (2018) found no direct correlation between overall platform usability and user engagement. Instead, they identified user-friendliness, defined as the presence of an intuitive, simple, and reliable interface, as a stronger predictor of sustained use. These findings are supported by Jakob et al. (2022), whose systematic review of digital mobile interventions across six noncommunicable disease domains identified several usability-related features associated with higher engagement. These included user-friendly design, technical stability, and visually appealing layout. The review also highlighted the value of integrating onboarding tools, such as tutorials and audiovisual guidance, to facilitate early familiarity with the app. Together, this body of evidence suggests that while usability is essential, visual design features that prioritise ease, clarity, and aesthetic quality are critical to sustaining user engagement in digital interventions.

Guidance and Professional Support

Digital parenting interventions vary widely in the degree of guidance and professional support they offer, ranging from fully self-guided formats with pre-recorded materials to intensive models involving personalised coaching or therapist support. The impact of such support on user engagement has been debated in the literature, with findings remaining mixed. Several studies suggest that professional guidance may improve engagement. For example, Day et al. (2021), in an analysis of three RCTs of the Triple P Online programme, found that participants who received practitioner support via telephone or email were significantly more likely to complete both the introductory module and at least one core module. This aligns with systematic reviews in digital mental health, which have consistently reported higher engagement in guided formats compared to fully self-directed interventions (Baumeister et al., 2014; Borghouts et al., 2021; Leung et al., 2022). Similar conclusions have been drawn in the broader digital health literature, where professional guidance has been positively associated with uptake, retention, and adherence (Jakob et al., 2022; Szinay et al., 2020).

However, a recent systematic review of digital parenting programmes by Aldridge et al. (2024) challenges these findings. Their analysis revealed that professional support features, particularly those with a clinical orientation, such as coaching, therapist facilitation, or moderated discussion forums, did not consistently improve engagement outcomes. Moreover, guidance delivered through instructional videos, such as roleplays or vignettes, was not found to be more effective than unguided formats. Nevertheless, a qualitative study of parents from lower socioeconomic backgrounds in Australia found that professional guidance was perceived as important for sustaining motivation and accountability in digital parenting interventions (Broomfield et al., 2021). Building on this, Aldridge et al. (2024) emphasise the importance of user-centred design in shaping support features. They advocate for the involvement of target users in determining the optimal types and delivery modes of guidance, whether peer-led or professional, and whether delivered individually or in groups.

Social Support Features

Social support features, including online discussion forums and peer-to-peer groups, have shown potential to enhance engagement with digital interventions (Perski et al., 2017). However, their effectiveness appears to depend heavily on how these features are implemented and integrated within the intervention. In a systematic review of peer-based social media features, Elaheebocus et al. (2018) found that asynchronous communication components, such as message boards and online forums, were more commonly used and generally perceived as acceptable by users. These features offered flexible, low-pressure avenues for interaction, though patterns of usage were inconsistently reported across studies. In contrast, synchronous communication features, such as live chat rooms or scheduled video discussions, were less frequently employed and showed more mixed effects, potentially due to scheduling demands and user time constraints. The review also noted that some studies indicated that female users may be more likely to engage in peer-to-peer components compared to male users.

Other reviews have echoed the need for careful implementation. Oakley-Girvan et al. (2022), in a scoping review of mobile app interventions, found that social forums and media integration were often associated with lower engagement. By contrast, Biagianti et al. (2018) found that facilitator-moderated peer groups were associated with higher retention, engagement, and acceptability than unmoderated forums. Gamification elements that incorporate social features, such as contests and leaderboards, have also been associated with improved adherence (Jakob et al., 2022), although these may not benefit all users equally. Szinay et al. (2020) caution that while competitive gamification elements can drive engagement for some users, they may also induce stress or disengagement for others. These mixed findings underscore the need for careful consideration when implementing social support features in digital parenting interventions. Factors such as the type of communication (synchronous vs. asynchronous), user demographics, the presence of moderation, and the potential impact of competitive elements should all be taken into account to optimise engagement and avoid potential negative effects.

Control Features

Control features refer to aspects of intervention design that allow users to determine how and when they engage with programme content. These may include self-pacing, flexible access to materials, or the ability to choose modules in a preferred order. Although research on control features in digital parenting interventions remains limited, emerging evidence suggests that such features may enhance both subjective satisfaction and sustained engagement. In their systematic review of strategies to promote parental engagement in technology-assisted interventions, Aldridge et al. (2024) found that features enabling self-pacing and content review were associated with improved ongoing engagement. Notably, control features were also associated with enhanced subjective user experiences, including perceptions of flexibility, autonomy, and relevance. However, this finding was based on a small number of studies (n = 2), and evidence remains limited.

Supporting the role of user autonomy, Engelbrektsson et al. (2023) found that treatment preference matching significantly predicted both enrolment and programme adherence in an internet-based parenting programme in Sweden. Parents who received their preferred delivery format, whether internet-based or group-based, were more likely to complete the programme and adhere to homework. This suggests that enabling parents to shape the mode of their engagement may strengthen sustained use. These findings are consistent with studies by Broomfield et al. (2022; 2021), who examined parental preferences for digital interventions targeting youth mental health in Australia. In both qualitative interviews and a discrete choice experiment, parents (particularly those from lower socioeconomic backgrounds) emphasised the importance of flexibility, convenience, and autonomy in how they accessed and used intervention content. Together, this body of evidence highlights the value of incorporating user-centred control features into digital parenting programmes. While such features appear to support engagement and satisfaction, further research is needed to determine how they can be best implemented to optimise engagement.

Behaviour Change Techniques and Persuasive System Design

The use of behaviour change techniques and persuasive system design principles in digital parenting and broader digital health interventions has shown mixed effects on user engagement.

Aldridge et al.'s (2024) systematic review of digital parenting interventions found that common behaviour change techniques such as feedback and goal setting did not consistently improve engagement or users' subjective experience. However, these techniques were associated with improved target outcomes, suggesting their primary value lies in promoting behaviour change rather than enhancing engagement directly. In the same review, interactivity, including check-in questions, multiple choice quizzes, and problem-solving exercises, were more reliably linked to positive engagement outcomes (Aldridge et al., 2024). Additional behaviour change techniques, including logging/self-monitoring tools, goal-setting features, and action planning, have been associated with higher engagement in the broader digital health literature (Oakley-Girvan et al., 2022; Perski et al., 2017). However, monetary incentives such as vouchers, cash contributions, or lottery tickets have shown no significant effect on adherence compared to interventions without such incentives (Jakob et al., 2022).

Persuasive system design features have also demonstrated potential to enhance engagement. Baumel and Kane (2018) found that interventions incorporating interactive, targeted, non-irritating, and personalised or tailored features achieved higher engagement. Across multiple reviews, personalisation, especially when based on individual needs and characteristics, progress data, or user input, has been consistently linked to increased usage and retention (e.g., Jakob et al., 2022; Oakley-Girvan et al., 2022; Szinay et al., 2020). Similarly, in the context of digital parenting interventions, Hansen et al.'s (2019) systematic review of technology-assisted parenting programmes found that tailoring strategies were associated with higher study retention rates, although limited reporting of adherence outcomes made it difficult to assess their impact on engagement with the programme itself. More recently, Aldridge et al. (2024) found that personalisation or tailoring programme features were positively and reliably associated with user engagement. However, superficial personalisation, such as including a user's name, appears to have minimal impact (Graham et al., 2020).

Reminders and prompts, particularly when delivered via push notifications, have been consistently associated with improved engagement across various systematic reviews and meta-analyses (Alkhaldi et al., 2016; Jakob et al., 2022; Perski et al., 2017). In parenting interventions specifically, the timing of reminders appears to matter: messages delivered during evenings and weekends, when caregivers are more likely to be available, are perceived as more useful (Cortes et al., 2021). However, the optimal frequency remains unclear, as excessive prompting may overwhelm users and reduce engagement (Thakkar et al., 2016).

3.3 Optimising Engagement in Digital Parenting Interventions

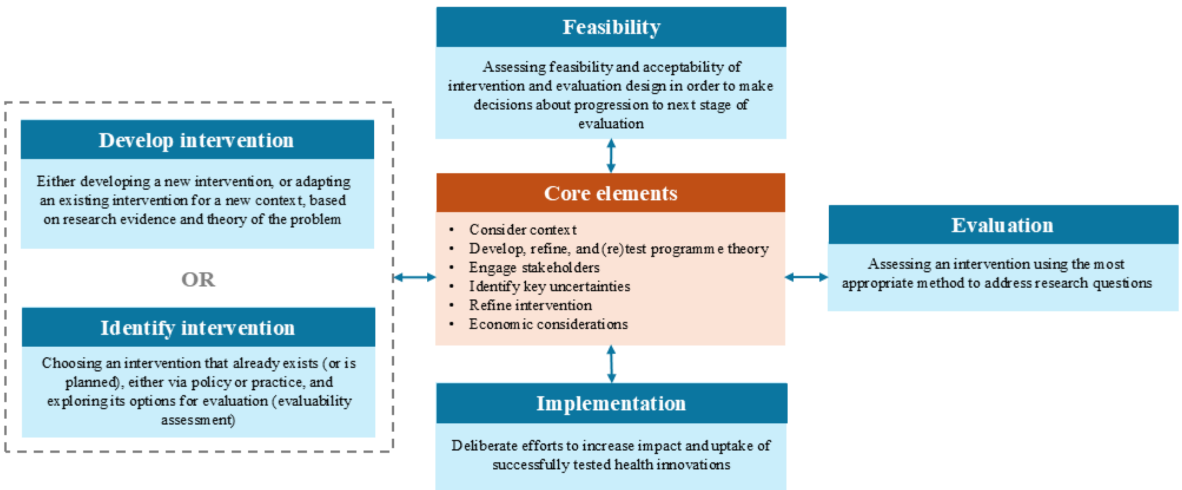
Building on the preceding sections on engagement measures and predictors, this section considers methodological frameworks for systematically optimising engagement in digital parenting interventions. The development and evaluation of complex behavioural interventions, including parenting programmes, have been shaped by a number of evolving methodological frameworks, most notably those developed by the UK Medical Research Council (MRC). Since its first publication in 2000 (Campbell et al., 2000), the MRC framework has been updated to reflect a shift from linear, evaluation-focused models towards more iterative, system-oriented approaches (Moore et al., 2023). The most recent guidance, introduced in 2021 (Skivington et al., 2021) and further contextualised in a 2024 update (Skivington et al., 2024) positions interventions within complex social systems, shaped by dynamic interactions between components, participants, implementers, and context.

The framework (

Figure **4**) identifies four interrelated phases of research: development, feasibility, evaluation, and implementation. Across all phases, six core elements are considered: context, programme theory, stakeholder engagement, uncertainty, refinement, and economic evaluation.

These elements should be addressed early and revisited throughout the research process (Skivington et al., 2021, 2024). The 2024 update also promotes a pluralistic approach to research. This means that researchers are encouraged to choose one or more complementary perspectives, such as efficacy (whether an intervention works under ideal conditions), effectiveness (whether it works in real-world settings), theory-based (how and why it works in different contexts), or systems (how it interacts with and changes the wider system), depending on the research questions that are most important for decision-makers. The 2024 update also positions the framework as meta-guidance, meaning that it should be used alongside more detailed, topic-specific methodological resources.

Figure 4. *MRC framework for developing and evaluating complex interventions*



Source: Figure adapted from Skivington et al. (2021, 2024).

The wider development and evaluation of the ParentApp programme was guided by the principles of the MRC framework. Within this broader research project, this thesis focuses specifically on optimising caregiver engagement with ParentApp. To address this aim, the

Multiphase Optimisation Strategy (MOST) was selected for its detailed methodological guidance on using systematic experimentation to identify which intervention components and implementation strategies are most effective and feasible within real-world delivery constraints (Collins, 2018; Guastaferro & Collins, 2021). This reflects a pluralistic approach encouraged in contemporary methodological guidance, which supports the use of targeted frameworks that best align with the research aim (Moore et al., 2023; Skivington et al., 2024).

The subsequent section begins by examining the limitations of the classical treatment package model in evaluating complex interventions (3.3.1), then introduces the MOST framework and describes its phases (3.3.2). This is followed by an overview of the experimental designs used in the Optimisation Phase of MOST, with particular focus on factorial designs (3.3.3), and a review of applications of MOST in public health, digital health, and parenting intervention research (3.3.4). Further discussion of how MOST was applied in this thesis is presented in Chapter 5.

3.3.1 RCTs and the Limits of the Classical Treatment Package Approach

Digital parenting interventions typically combine several interacting components, including core content (e.g., parenting skills), design features (e.g., app layout, navigation structure, content sequencing, personalisation, gamification), and delivery strategies (e.g., mode of delivery, level or type of guidance). When their primary purpose is to enhance implementation outcomes, these strategies can be broadly classified as implementation strategies, defined in implementation science as "methods or techniques used to enhance the adoption, implementation, and sustainability of a clinical program or practice" (Proctor et al., 2013, p. 2). In practice, however, intervention content, design, and delivery components are often interdependent and influence both implementation outcomes and the overall effectiveness of the programme (Perski et al., 2017; Proctor et al., 2013). This complexity presents specific challenges for evaluation, particularly when using traditional RCTs which test interventions as fixed packages.

Traditional RCTs have long been considered the gold standard for evaluating behavioural interventions (Collins, 2018). In this approach, researchers develop a complete intervention package and assess its overall effectiveness by comparing outcomes between intervention and control groups. This experimental design is well suited to answering the question of whether an intervention, as a whole, produces desired outcomes. However, it offers limited insight into which components are driving outcomes, how components may interact, or the conditions under which specific components are most effective (Guastaferro & Collins, 2021).

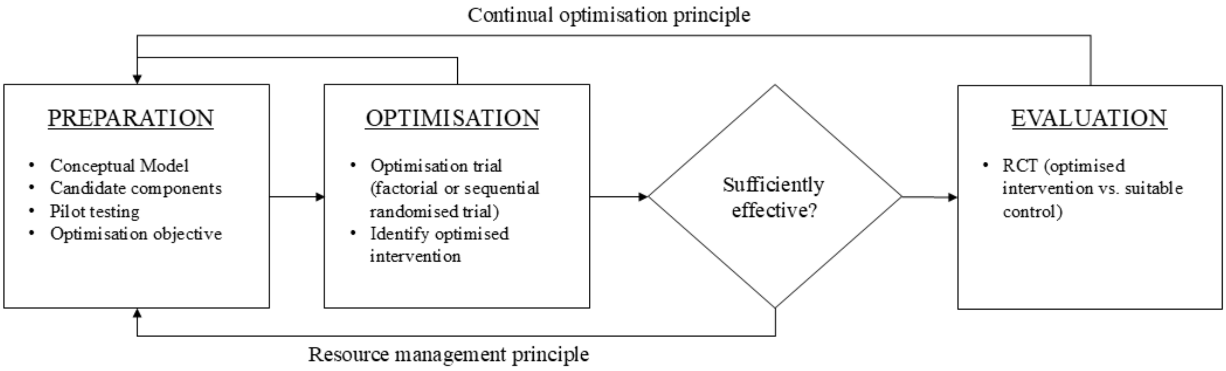
Three key limitations arise from the treatment package approach. First, researchers may be inclined to include multiple additional components in the hope that each will incrementally improve outcomes. However, each added component can increase complexity, cost, and delivery burden, often without a clear return in effectiveness. This can lead to interventions that are difficult to adopt, scale, or sustain, particularly in low-resource settings (Guastaferro & Collins, 2021). Second, when adaptation is necessary due to financial, logistical, or contextual constraints, it is often unclear which components can be removed without compromising effectiveness. This lack of clarity may lead implementers to discard or alter active ingredients, thereby compromising implementation fidelity and impact (Carroll et al., 2007). Third, because traditional RCTs do not estimate the individual or interactive effects of components, they do not advance understanding of how interventions work, for whom they work, or why. This limits the potential for theory refinement and weakens the evidence base needed to tailor interventions to diverse populations and settings (Guastaferro & Collins, 2021). In sum, these limitations highlight the need for alternative evaluation approaches that can disentangle the effects of individual components, support adaptation without undermining fidelity, and promote the design and delivery of interventions that are both effective and implementable in real-world settings.

3.3.2 Multiphase Optimisation Strategy (MOST) Framework

The Multiphase Optimisation Strategy (MOST) is a methodological framework designed to guide the systematic development, optimisation, and evaluation of multicomponent interventions, particularly in contexts where real-world implementation constraints need to be considered (Collins, 2018; Guastaferro & Collins, 2021). In the context of MOST, optimisation refers to the process of identifying the most effective combination of intervention components within specific constraints (Clapham & Nicholson, 2009). These constraints are formalised through the concept of intervention EASE, which refers to balancing *Effectiveness* against *Affordability*, *Scalability*, and *Efficiency* (Guastaferro & Collins, 2021). A complementary definition from the broader public health literature defines optimisation as a "deliberate, iterative and data-driven process to improve a health intervention and/or its implementation to meet stakeholder-defined public health impacts within resource constraints" (Wolfenden et al., 2019, p. 5). Together, these definitions underscore the dual aims of optimisation: enhancing intervention outcomes while ensuring their feasibility and sustainability in applied settings.

Unlike traditional evaluation approaches, which often treat implementation challenges as an afterthought, MOST embeds these considerations from the outset. It challenges the notion that more components necessarily lead to better outcomes and instead promotes the design of interventions that are both impactful and implementable (Guastaferro & Collins, 2021). This is particularly important in low-resource contexts, where interventions must be responsive to budgetary, infrastructural, and delivery limitations. MOST consists of three phases: Preparation, Optimisation, and Evaluation (see Figure 5). Each phase is described in turn below.

Figure 5. *Overview of the Multiphase Optimisation Strategy (MOST) framework*



Source: Figure adapted from Collins et al. (2018).

Preparation Phase

The Preparation Phase involves identifying a set of candidate components based on theory, evidence, and stakeholder input (Guastaferro & Collins, 2021; O'Hara et al., 2024). A key activity during this phase is the development of a conceptual model that articulates how each component is expected to influence the intended outcome. This model is typically informed by relevant theories and insights from community stakeholders to ensure that the intervention is both evidence-informed and contextually appropriate (O'Hara et al., 2024).

This phase may also include pilot or feasibility studies to assess acceptability of proposed components, refine delivery strategies, and inform decisions about which components should proceed to formal testing (O'Hara et al., 2024). These preliminary studies can take various forms, including non-randomised studies, randomised-experimental pilot studies, or mixed-methods approaches. They serve multiple purposes, including identifying practical issues that could hinder implementation, assessing preliminary evidence of effectiveness, and gathering qualitative feedback from participants and stakeholders (O'Hara et al., 2024). Findings from these preliminary studies may also inform refinements to the conceptual model.

A final step in the Preparation Phase is defining the optimisation objective. This objective specifies how effectiveness will be balanced against affordability, scalability, and efficiency. For example, researchers may aim to identify the most effective combination of components that can be delivered within a given cost threshold, time frame, or staffing model. Establishing this objective early helps ensure that the intervention developed through MOST is not only effective but also feasible to implement under real-world conditions (Guastaferro & Collins, 2021).

Optimisation Phase

The Optimisation Phase involves testing the candidate components through an optimisation trial (Collins, 2018). The aim of this trial is to estimate the individual and combined effects of selected components in order to determine which contribute most significantly to the target outcome while remaining within the predefined constraints. Target outcomes in this phase may vary depending on the intervention aims and the optimisation objective defined during the Preparation Phase. For example, they may focus on behavioural or clinical outcomes, cost-related outcomes, or engagement outcomes.

This phase typically begins with the selection of a suitable experimental design (O'Hara et al., 2024). The choice of design is informed by the nature of the components being tested, and any logistical or contextual constraints. Experimental designs commonly used in the Optimisation Phase include randomised factorial experiments or sequential randomised experiments, which are described respectively in 3.3.3. During this phase, intervention components may undergo iterative refinement based on real-time data, implementation feasibility, and stakeholder feedback (Guastaferro & Collins, 2021; O'Hara et al., 2024). The phase concludes with the selection of the most impactful and implementable set of components, which forms the basis for the final optimised intervention package. In this thesis, Papers 1, 2, and 3 report findings from an optimisation trial of the ParentApp intervention implemented in Tanzania, which was conducted as part of the Optimisation Phase of MOST.

Evaluation Phase

In the final phase, the optimised intervention package is tested in a traditional RCT to determine its overall effectiveness compared to a control condition (Collins, 2018). This step validates the combined impact of the selected components and informs decisions about broader implementation or further adaptation. Together, the three phases of MOST support the design of interventions that are evidence-informed, efficient, and aligned with the realities of implementation in diverse settings. Although this thesis does not focus on the Evaluation Phase of MOST, the findings from the optimisation trial informed the intervention package currently undergoing evaluation in Tanzania (Baerecke et al., 2024), which is discussed further in Chapter 9.5.

3.3.3 Experimental Designs Used in the Optimisation Phase of MOST

The Optimisation Phase of MOST relies on experimental designs that can test multiple intervention components simultaneously. The most widely used designs in this phase are factorial randomised experiments and sequential randomised trials.

Factorial Randomised Experiments

Factorial experiments are a type of RCT that tests two or more intervention components simultaneously by randomly assigning participants to different combinations of component levels at baseline (Kugler et al., 2018). Each component, also known as a 'factor', is tested at predefined levels (such as "active" versus "inactive"), allowing researchers to estimate the individual (main) effects of each component and their combined (interaction) effects on outcomes. Factorial designs can be either full factorial, which test all possible combinations of component levels, or fractional factorial, which test a strategically selected subset. Fractional designs reduce study complexity and resource requirements when many components are tested; however, they introduce planned confounding that limits the ability to estimate some effects independently (Gallis et al., 2018).

One of the key advantages of both full and fractional factorial experiments is their statistical efficiency. Unlike traditional RCTs, which require separate groups for each experimental condition, factorial designs randomise participants to combinations of component levels in such a way that each component is tested across the entire sample. In a balanced 2^k factorial design, where *k* denotes the number of components and each has two levels, half of participants are assigned to one level of a given component and half to the corresponding alternative level. This allows multiple components to be evaluated simultaneously without a proportional increase in total sample size (Collins, 2018).

When analysed using effect coding (i.e., coding component levels as 1 and –1, rather than the more common dummy coding of 1 and 0), balanced factorial designs produce orthogonal contrasts, that is, statistically independent comparisons between component levels. This results in uncorrelated estimates of main effects and interactions, and equal standard errors across parameters (Kugler et al., 2018). In the specific case of balanced 2^k factorial designs, this also ensures that the statistical power to detect an interaction effect is equal to that for a main effect of the same size. However, Collins (2018) notes that this point, originally made by

Cohen (1988), applies only to balanced 2^k designs analysed with effect coding and should not be assumed to hold in more complex or unbalanced factorial structures. Moreover, while power may be equal in theory, interaction effects are often smaller in magnitude than main effects in practice, and thus more difficult to detect without sufficient sample size.

Sequential Randomised Trials

Sequential randomised trials are experimental designs used to evaluate adaptive interventions, that is, interventions intended to change over time in response to participant behaviour, preferences, or other characteristics (NeCamp et al., 2019). In contrast to factorial designs, which assign participants to a fixed combination of component levels at baseline, sequential randomised trials introduce randomisation at multiple points during the intervention period (NeCamp et al., 2019). This allows researchers to assess how best to tailor interventions as individuals progress through different stages of engagement or respond to earlier intervention components.

Two types of sequential randomised trials are commonly used in digital intervention research: sequential multiple assignment randomised trials (SMARTs) and micro-randomised trials (MRTs). SMART designs involve an initial randomisation to one of several intervention options, followed by one or more subsequent randomisations at predetermined decision points (Collins, Nahum-Shani, et al., 2014). This design is particularly well suited for developing adaptive interventions, such as adjusting the intensity or mode of delivery based on early indicators of participant engagement. MRTs differ in that they involve frequent, often daily or momentary, randomisation of participants to receive (or not receive) specific intervention components, such as motivational messages, reminders, or prompts. MRTs are typically used to develop just-in-time adaptive interventions (JITAIs), which aim to deliver support precisely when individuals are most likely to benefit, based on their real-time behavioural or contextual data (Nahum-Shani et al., 2016).

Selecting the Appropriate Experimental Design

The choice between factorial and sequential designs depends on the intervention's aims, complexity, delivery context, and available resources (NeCamp et al., 2019). Factorial trials are relatively simple to implement and do not rely on continuous internet connectivity or real-time data to support re-randomisation. In contrast, SRTs are appropriate when the timing and sequencing of components are central to the intervention strategy, or when tailoring is expected to enhance effectiveness. However, they require more complex infrastructure, intensive data collection, and, in some cases, real-time decision support systems. These demands may limit their feasibility in low-resource settings with intermittent internet connectively, or for interventions with substantial offline or in-person components.

Given these considerations, the research presented in this thesis employed a full factorial experimental design to evaluate three design and delivery components hypothesised to influence caregiver engagement with ParentApp. This design was selected for its statistical efficiency, implementation feasibility, and alignment with the broader goals of the ParentApp research project of testing a hybrid human-digital delivery model.

3.3.4 Applications of MOST: Progress and Gaps

MOST has been applied across a wide range of public health domains, including digital mental health (e.g., Uchida et al., 2023; Uwatoko et al., 2018), substance use (e.g., Iscoe et al., 2025; Windsor et al., 2018), smoking cessation (e.g., Bernstein et al., 2018; Ostroff et al., 2022), weight management and nutrition (e.g., Lemacks et al., 2024; Thomas et al., 2021), and HIV prevention (e.g., Feelemyer et al., 2024; Mistler et al., 2023). In many of these studies, the

Optimisation Phase has focused on identifying combinations of intervention components that improve clinical or behavioural outcomes.

However, MOST can also be used to address key implementation questions (Guastaferro & Collins, 2021). For example, Broder-Fingert et al. (2019) conducted an optimisation trial in the United States to improve access to behavioural health services for underserved children. The trial tested four delivery strategies: standard versus enhanced care coordination technology, clinic-based versus community-based delivery, standard versus enhanced symptom tracking, and flexible versus structured visit schedules. Notably, the trial prioritised service access as the primary outcome, with secondary outcomes including feasibility, fidelity, acceptability, and cost.

A similar emphasis on implementation is evident in a planned multilevel optimisation trial by Lockhart et al. (2024), also based in the United States. This study aims to improve pre-exposure prophylaxis (PrEP) prescribing in primary care by testing both provider-level strategies (e.g., simulation-based training, best practice alerts) and patient-level strategies (e.g., tailored educational videos, HIV risk assessments). While implementation outcomes are not the primary focus, the planned study illustrates the versatility of MOST for identifying efficient combinations of service delivery strategies within real-world systems.

In addition to prospective studies, a recent proof-of-concept study by Aydin et al. (2025) applied a retrospective factorial design to examine implementation strategies for digital mental health programmes in Germany. Using non-randomised, real-world data, the study tested combinations of outreach strategies, including telephone calls, online meetings, and in-person visits, to assess their impact on programme uptake. This example highlights the methodological flexibility of MOST and its potential to support implementation improvements in routine care.

These selected examples demonstrate the growing versatility of MOST for evaluating delivery strategies and implementation processes across a range of public health domains.

However, a recent scoping review by McCrabb et al. (2020), which examined the use of MOST and other optimisation frameworks across public health interventions, found that implementation-related determinants, such as feasibility, uptake, cost, and scalability, are frequently overlooked, and that few optimisation trials have focused on outcomes identified as priorities by implementers, service providers, or users. Moreover, the geographic concentration of trials in HICs limits understanding of how optimisation frameworks might be applied in low-resource contexts. The following section examines a subset of studies that have specifically used MOST to optimise user engagement in digital health interventions.

MOST to Optimise Engagement in Digital Interventions

A handful of studies have applied MOST to optimise engagement in digital interventions. Most of these studies have focused on notification-based strategies, particularly the use of digital prompts. For example, Graham et al. (2020) conducted a 2×2×2×2 factorial screening experiment with 864 adult smokers enrolled in an internet-based smoking cessation programme in the United States. The trial tested four text message features: personalisation, integration with the web platform, dynamic tailoring based on user engagement, and message intensity. Integration and dynamic tailoring each produced significant main effects on engagement. However, the highest levels of engagement were observed when all four features were delivered together, suggesting a potential synergistic effect from combining multiple notification strategies.

In a similar study, Trinquart et al. (2023) conducted a 2×2×2 factorial trial in the United States with 655 participants to optimise adherence with a mobile intervention for cardiovascular self-monitoring. The intervention tested three message delivery strategies: personalisation (personalised compared to standard messages), timing (morning compared to evening), and day of delivery (weekday compared to weekend). Only personalised notifications, which referenced the participant's recent activity and included their name, significantly improved adherence to weekly blood pressure and heart rate monitoring at both three and six months. Neither timing nor day of delivery significantly influenced adherence, suggesting that message content may have a greater impact on sustained engagement than delivery scheduling.

Beyond notification-based strategies, some studies have examined the added value of human guidance. Lee et al. (2024), for example, conducted a mixed-methods 2×2 factorial experiment in South Korea with 12 outpatients managing atopic dermatitis. The study tested the effects of advanced versus basic push notifications, and the presence or absence of a human coach, delivered alongside core components such as self-monitoring and educational content. Findings indicated that the combination of advanced notifications and coaching was associated with the highest programme completion rates and improvements in clinical outcomes, although the small sample size warrants cautious interpretation of these results. Qualitative interviews indicated that perceived acceptability and satisfaction were important factors driving continued engagement.

In addition to factorial experiments, Bell et al. (2023) investigated momentary engagement using a micro-randomised trial involving 350 users of a digital alcohol reduction app in the United Kingdom. The study tested the short-term effects of receiving a standard notification, a novel motivational message, or no message at all. Both types of notification increased the likelihood of app use within the following hour. However, neither had an effect on long-term engagement or time to disengagement. These findings suggest that while notifications may effectively prompt immediate interaction, they are unlikely to sustain engagement without additional strategies.

Although relatively few in number, these studies illustrate how MOST has been used to optimise engagement strategies within digital interventions. However, most focused narrowly on notification-based strategies, targeted individual health behaviours such as smoking cessation, alcohol reduction, or chronic disease management, and were conducted in high-income settings. As a result, their applicability to other populations, including caregivers and families in LMICs, remains limited.

Application of MOST in Parenting Intervention Research

Shifting from the broader field of public health, a small but growing body of research has begun to apply the MOST framework to optimise parenting interventions. While these studies demonstrate methodological promise, few have focused specifically on caregiver engagement, and several remain at the protocol or early implementation stage. The following review summarises key examples identified at the time of writing, and considers the extent to which caregiver engagement has been addressed within this literature.

Notably, two studies stand out for applying the MOST framework to parenting programmes in LMICs. The first of these is the RISE study, which applied all three phases of MOST to adapt, optimise, evaluate PLH Young Children across Moldova, North Macedonia, and Romania (Jansen et al., 2022; Lachman et al., 2019). As part of the Optimisation Phase, a 2×2×2 cluster-randomised factorial trial tested three components: intervention length (5 vs. 10 sessions), facilitator supervision (structured vs. on-demand), and an enhanced engagement package including text messages, food parcels, and phone consultations. Although the trial design included delivery components designed to promote uptake and retention, engagement was not assessed as a primary outcome. The optimisation phase specifically aimed to identify the most effective and cost-effective combination of components to improve programme outcomes and inform future scale-up. At the time of writing, outcome data had not yet been published.

Building on this work, the FLOURISH study (Piolanti et al., 2025) extended the use of MOST to the PLH Teens programme. Also situated in Moldova and North Macedonia, FLOURISH included a 2×2×2 cluster randomised factorial trial during its Optimisation Phase to evaluate three add-on components: adolescent mental health tools, adolescent peer support, and an engagement booster. The engagement booster combined low- and high-intensity strategies, such as refreshments, attendance certificates, and monetary incentives for both adolescents and caregivers. Similar to RISE, the Optimisation Phase of FLOURISH was designed to inform the most effective and scalable package of components, but included engagement as a secondary or mediating variable in the study protocol. Overall, both studies reflect early progress in applying the MOST framework within LMIC settings and offer valuable methodological contributions to the emerging optimisation literature on parenting interventions.

A third example, although conducted in a HIC, offers insight into how qualitative methods and implementation science frameworks can inform optimisation trial design. A recent study preparing to optimise Floreciendo, a sexual and reproductive health programme for Latina adolescents and their female caregivers in the United States, drew on both the Preparation Phase of MOST and the EPIS (Exploration, Preparation, Implementation, Sustainment) framework (Merrill et al., 2025). The study used focus groups with adolescents, caregivers, and organisational staff to identify contextual barriers, delivery preferences, and strategies to support future optimisation. Participants emphasised the importance of culturally matched and bilingual facilitators, flexible scheduling, and logistical supports such as stipends to reduce barriers to engagement (Merrill et al., 2025). Although implementation components were not formally tested, the study highlights the value of integrating implementation science within the Preparation Phase of MOST to support adoption and scale-up in underserved communities.

Turning to digital parenting interventions, the Health4Life Parents & Teens study (Champion et al., 2025) represents one of the first known applications of MOST to a fully digital parenting programme. Conducted in Australia with socioeconomically disadvantaged families, the study used a 2×2×2×2 factorial design to test four digital components (text messages, tailored feedback, stress management, and health coaching) delivered alongside six core online modules targeting adolescent health behaviours. The primary objective was to identify a combination of components that maximises parental encouragement of healthy habits while minimising perceived burden. Although engagement was not a focal outcome, the study measured several implementation-relevant indicators, including component acceptability, perceived effort, and objective usage metrics. Trial results had not yet been published at the time of writing.

In summary, a small but growing number of studies have applied the MOST framework to optimise parenting interventions. Although some of these trials are ongoing, they demonstrate the feasibility of using factorial designs to test discrete components aimed at improving intervention outcomes and supporting scalability, including in LMIC settings. However, across the reviewed studies, implementation-related outcomes, and caregiver engagement in particular, have not been prioritised. While several trials have included delivery components intended to support engagement, such as reminders, facilitator support, or incentives, there is limited evidence on whether and how these strategies effectively enhance engagement.

3.4 Moderation Applied to Optimisation Trials

While the preceding section focused on literature that identified which intervention components are most effective on average, such findings do not capture variability in how different subgroups respond to specific components. Moderation analysis provides a methodological approach for examining whether, and to what extent, the effects of individual components differ across population subgroups (Collins, 2018).

3.4.1 Distinguishing Between Interaction and Moderation

Although the terms ‘interaction’ and ‘moderation’ are often used interchangeably, Collins (2018) draws an important conceptual distinction. In factorial designs, an interaction refers to the combined effect of two or more experimental components that are actively manipulated in the trial. These interactions are symmetric, meaning each component modifies the effect of the other. In contrast, Collins (2018) uses the term moderation to refer to cases where an observed (non-randomised) baseline variable interacts with an experimental factor. These observed variables are not manipulated by the researcher but may influence how participants respond to components. This type of interaction is referred to as effect modification in the epidemiological literature and moderation in behavioural science (Collins, 2018). In such cases, the observed variable is typically regarded as the moderator. This distinction helps clarify analytic goals: interactions between experimental components inform optimisation decisions, while moderation analyses identify subgroups for whom components are more or less effective, supporting tailored or precision implementation.

3.4.2 Moderation in Factorial Trials

Despite the potential of factorial trials to uncover differential effects across participant subgroups, few have tested moderation effects. One exception is a study by Piper et al. (2017), which used a fractional factorial design with 637 adult smokers to examine whether component effects varied by baseline characteristics such as psychiatric history and smoking intensity. Building on this early work, several published protocols of ongoing trials have indicated plans to incorporate moderation analysis. These include factorial trials targeting sexual health

(Shaffer et al., 2024), mental health (Sripada et al., 2023), obesity (Thomas et al., 2021), and viral suppression (Sauceda et al., 2023). However, most have yet to report findings, and to date, no published factorial trial has examined moderation in relation to caregiver engagement outcomes. Moreover, no known factorial trials in the field of parenting have investigated moderation. Together, these gaps highlight a critical limitation, particularly given the growing emphasis on tailoring digital parenting interventions to meet the needs of diverse users.

3.4.3 Moderation in Parenting Research: What We Know

In the absence of moderation evidence from factorial trials in parenting research, insights can be drawn from traditional RCTs, meta-analyses, and individual participant data (IPD) meta-analyses, although it should be noted that these approaches examine moderation at the level of overall programme effects rather than at the level of individual components. In RCTs, moderation is typically examined by including interaction terms between group assignment and baseline variables (Holmbeck, 1997). Meta-analyses assess moderation by first testing whether effect sizes differ significantly across studies (Hedges & Olkin, 1985). If heterogeneity is present, they then explore whether this variation can be explained by shared study-level characteristics (Huedo-Medina et al., 2006). In addition, IPD meta-analyses can test moderation effects at the individual level across pooled datasets (Gardner, Leijten, Harris, et al., 2019). The evidence reviewed below is broadly organised into three domains: moderation by child characteristics, caregiver characteristics, and sociodemographic factors.

Child Characteristics

Several studies have examined whether child characteristics moderate the effects of parenting interventions. Regarding child demographics, some individual trials have reported differential effects for boys and girls. In a Welsh-based trial of the in-person Incredible Years parenting programme with 153 preschool-aged children at risk of conduct problems, Gardner et al. (2010) found that boys in the intervention group showed greater reductions in conduct problems than boys in the control group, while girls improved regardless of condition. In the context of digital delivery, Creswell et al. (2024) reported similar findings in a UK-based trial of the Parent Positive app, involving 646 families with children aged 4 to 10 years. Boys in the intervention group showed significantly greater reductions in emotional difficulties than girls at the two-month follow-up. However, gender-based effects have not been reliably replicated in meta-analytic reviews (Florean et al., 2020; McCart & Sheidow, 2016). For example, Florean et al. (2020), in a meta-analysis of 15 trials ($N = 1{,}668$) of online parenting interventions for children and adolescents aged 0 to 18 years, found no significant moderation effects for child gender on behavioural outcomes.

Findings on child age similarly show no consistent evidence of differential effects in meta-analytic reviews (Florean et al., 2020; Gardner, Leijten, Melendez-Torres, et al., 2019; McCart & Sheidow, 2016). Gardner, Leijten, Melendez-Torres, et al. (2019) used two complementary meta-analytic approaches to examine age effects in parenting interventions. The first was an IPD meta-analysis of 13 European trials of the Incredible Years programme ($N = 1{,}696$; child age = 2 to 11 years), and the second a larger aggregate-level meta-analysis using robust variance estimation across 156 studies of parenting programmes ($N = 13{,}378$; mean child age = 2 to 10 years). Neither analysis found evidence that child age moderated intervention effects. Similarly, Florean et al. (2020) found no significant moderation effect of children's mean age on behavioural outcomes in their meta-analysis of online parenting interventions.

Child behavioural characteristics, particularly baseline severity of conduct problems, have shown consistent evidence of moderation effects. An early moderation analysis by Gardner et al. (2009), using data from a trial of the Family Check-Up parenting programme with 731 low-income families in the United States, found that children aged 2 to 3 with higher levels of problem behaviour at baseline showed greater reductions in externalising problems following the intervention. These findings have been supported by subsequent meta-analytic evidence (Leijten et al., 2020; Menting et al., 2013; Shelleby & Shaw, 2014). Shelleby and Shaw (2014) reviewed six parenting intervention studies involving children aged 1 to 10 years and found that in four of the studies, children with more severe behaviour problems at the start of the intervention derived greater benefit. Notably, none of the studies found reduced effects for children with more severe behaviour problems. Consistent with these findings, an IPD meta-analysis of the Incredible Years programme across 13 trials found greater intervention effects for children whose mothers reported more severe behavioural difficulties at baseline (Leijten et al., 2020).

Caregiver Characteristics

Caregiver demographic characteristics, such as gender and age, have shown inconsistent evidence as moderators of parenting interventions. One persistent limitation in the literature is the historical underrepresentation of fathers, which has constrained the ability to assess gender-based moderation robustly. Nevertheless, Lundahl et al. (2008), in an early meta-analysis of 26 studies of parenting programmes, found that trials involving fathers reported significantly greater improvements in child conduct problems and positive parenting practices. However, more recent evidence from digital interventions has not replicated these findings. Lin-Lewry et al. (2024), in a meta-analysis of seven trials of digital parenting interventions for parents in the first year after childbirth ($N = 1,342$), found no significant moderation effects of caregiver gender on parenting self-efficacy, social support, or depressive symptoms. Similarly, parental age has not been found to moderate outcomes in either in-person (Dedousis-Wallace et al., 2021) or digital formats (Lin-Lewry et al., 2024).

Other caregiver characteristics, including mental health, parenting style, and relational dynamics, have also been explored as potential moderators. Maternal depression, in particular, has been associated with stronger intervention effects in several studies of in-person parenting interventions (Gardner et al., 2010; Leijten et al., 2020; Shelleby & Shaw, 2014). Some of the most robust evidence comes from an IPD meta-analysis of the Incredible Years programme by Leijten et al. (2020), which found that children of mothers with higher levels of depressive symptoms at baseline experienced significantly greater reductions in conduct problems. However, the authors cautioned that the co-occurrence of elevated child behaviour problems in these families may partly explain this moderation effect.

In contrast to findings on caregiver mental health, there is less consistent evidence regarding other caregiver-related risk factors. While variables such as caregiver stress, family conflict, and broader relational functioning are often hypothesised to influence how caregivers respond to parenting interventions, a narrative synthesis of in-person programmes by McMahon et al. (2021) concluded that intervention outcomes were generally robust across a range of these risk factors. However, a recent non-inferiority trial conducted in Sweden by Engelbrektsson et al. (2023) compared group-based (gComet) and internet-based (iComet) versions of the Comet parenting programme for children with disruptive behaviour problems ($N = 161$). The study examined a range of demographic, clinical, and relational predictors and moderators of treatment outcomes. Although most variables did not show significant moderation, children from families with lower levels of coercive parent–child dynamics showed greater improvements in the group-based format. This finding does not imply that coercive dynamics reduce the effectiveness of digital interventions. However, it does suggest that relational context may influence which delivery format is most beneficial for particular families.

Sociodemographic Characteristics

Emerging evidence suggests that sociodemographic factors may moderate the effectiveness of parenting interventions differently across in-person and digital delivery formats. In the context of in-person interventions, Gardner, Leijten, Harris, et al. (2019) conducted an IPD meta-analysis of 15 European trials of the Incredible Years programme, finding no differential effects by family disadvantage, including poverty, low education, single parenthood, or household joblessness. The authors concluded that parenting programmes are unlikely to widen socioeconomic inequalities and may contribute to reducing long-term disparities in child outcomes. Similarly, Leijten et al. (2020), in an IPD meta-analysis of 13 trials, found no evidence that socioeconomic status or ethnicity moderated the effects of the intervention. In contrast, findings from digital parenting interventions suggest that certain sociodemographic factors, particularly caregiver education, may positively influence programme effectiveness. Florean et al. (2020), in a meta-analysis of 15 trials of online parenting programmes for children and adolescents aged 0 to 18 years, found that samples with a higher proportion of university-educated parents showed greater reductions in child behaviour problems Similarly, McAloon and Armstrong (2024), in a recent meta-analysis of 14 online, self-directed parenting programmes for families of children with behavioural difficulties, reported stronger outcomes among families with higher parental education levels. These findings highlight important equity concerns for digitally delivered parenting interventions, as they suggest that caregiver socioeconomic status may influence how parents access, engage with, and benefit from these programmes.

4. Thesis Overview

This chapter establishes the rationale for the thesis based on the evidence gaps identified in the preceding chapters and outlines how these are addressed through three empirical papers. The following chapter provides an overview of the methods and analytical procedures used across the three papers.

4.1 Thesis Rationale

Building on the literature reviewed in the preceding chapters, this thesis seeks to advance understanding of how to optimise caregiver engagement in digital parenting interventions, with a particular focus on LMICs. Although engagement is widely recognised as a key determinant of digital parenting programme effectiveness (Piotrowska et al., 2017), research in this area remains limited in two important respects. First, there is little experimental evidence on which specific design or delivery components most effectively increase engagement in digital parenting interventions (Aldridge et al., 2024), especially in LMIC contexts where barriers to technology access, digital literacy, and sustained engagement are distinct from those in high-income settings (Jäggi et al., 2025). Second, limited research has examined which caregiver characteristics predict engagement or disengagement in LMICs, or whether certain subgroups respond differently to specific engagement strategies. This is despite consistent evidence from HICs that demographic, socioeconomic, and psychosocial factors can influence engagement (e.g., Dadds et al., 2019; Day et al., 2021; Perrino et al., 2018) and moderate intervention outcomes (e.g., Creswell et al., 2024; Florean et al., 2020; McAloon & Armstrong, 2024).

This thesis addresses these gaps through the ParentApp optimisation trial, a cluster-randomised factorial trial implemented in accordance with the Optimisation Phase of the MOST framework. Findings from the trial are reported in three interconnected papers. Paper 1 evaluates the main and interaction effects of three discrete design and delivery components on caregiver engagement. It provides the first known experimental evidence on optimising engagement with a digital parenting programme in an LMIC context. Paper 2 examines baseline demographic, socioeconomic, and psychosocial predictors of engagement and disengagement, identifying which caregivers are most likely to drop out early or remain engaged over time. While retention is a well-documented challenge in digital parenting and mental health interventions (Baumel & Kane, 2018; Baumel et al., 2019; Dadds et al., 2019), little is known about its drivers in LMIC settings. Paper 2 also tests whether gender moderates the associations between these baseline predictors and engagement, contributing to the limited literature on male engagement in parenting interventions (Gonzalez et al., 2023; Jeong et al., 2023). Paper 3 investigates whether and to what extent caregiver demographic, socioeconomic, and psychosocial characteristics moderate the effects of the tested design and delivery components on engagement. By identifying for whom different components are most effective, this analysis responds to calls in implementation science for more tailored and responsive intervention delivery (Guastaferro & Collins, 2021).

Together, these three papers aim to generate actionable evidence on *what works, for whom, and under what conditions* to optimise caregiver engagement with digital parenting interventions in LMICs. They also provide practical guidance for the future implementation of ParentApp in Tanzania and beyond, contributing to global efforts to prevent VAC at scale.

4.2 Research Questions

This thesis aims to answer a series of interconnected research questions focused on optimising caregiver engagement with a digital parenting intervention:

1. What is the effect of design and delivery components (guidance, app design, and digital support) on caregiver engagement with ParentApp, and are there any interactions between these components? (Paper 1)

2. Which caregiver demographic, socioeconomic, and psychosocial characteristics predict engagement and disengagement with ParentApp, and do these predictors differ by gender? (Paper 2)

3. To what extent do caregiver demographic, socioeconomic, and psychosocial characteristics moderate the effects of design and delivery components on engagement with ParentApp? (Paper 3)

4.3 Overview of Papers

Paper 1 – Multi-Level Regression Analyses of Main and Interaction Effects

This paper presents the primary results of the ParentApp optimisation trial conducted in Tanzania. The trial tested three design and delivery components: guidance (guided vs. self-guided), app design (unstructured vs. structured), and digital support (enhanced vs. basic), within a cluster-randomised factorial experiment. Digitally tracked measures of caregiver engagement, including module completion rates and other in-app activity metrics, were analysed as primary and secondary outcomes. Generalised linear mixed-effects models were used to estimate the main effects of each component, with exploratory analyses investigating potential two-way interactions.

Paper 2 – Multi-Level Regression Analyses of Baseline Predictors

This paper examines baseline demographic, socioeconomic, and psychosocial characteristics that predict engagement and disengagement with ParentApp. It investigates both overall engagement (module completion) and early disengagement (time to first non-start and first non-completion). Predictors were selected based on prior literature and study data availability. Generalised linear mixed-effects models were used to assess associations, including interaction terms to test whether gender moderates these predictor–engagement relationships. The Benjamini–Hochberg procedure was applied to correct for multiple testing.

Paper 3 – Multi-Level Regression Analyses of Baseline Moderators

Building on the findings from Paper 1 and 2, this paper investigates whether baseline caregiver characteristics moderate the effects of the design and delivery components on engagement. Candidate moderators were selected based on contextual relevance as well as prior evidence on the predictors of engagement in digital parenting interventions. Generalised linear mixed-effects models with interaction terms were used to assess moderation effects, with engagement measured by module completion rates. The Benjamini–Hochberg procedure was applied to correct for multiple comparisons.

4.4 Hypotheses

In response to the research questions, the following hypotheses were developed. For Paper 1, it was hypothesised that participants receiving guidance would demonstrate higher levels of engagement compared to those in the self-guided condition. Participants assigned to the unstructured app design were expected to show greater engagement than those using the structured version, and those receiving enhanced digital support were hypothesised to engage more than those receiving only basic support.

Paper 2 adopted an exploratory approach, as evidence on predictors of engagement in digital parenting interventions remains limited in LMICs and has shown mixed patterns in HIC studies, which precludes the development of robust directional hypotheses for this context. It was hypothesised that caregiver demographic (age, gender), socioeconomic (financial stress, food insecurity), and psychosocial characteristics (positive parenting, child maltreatment, caregiver depression) would be significantly associated with engagement and disengagement. It was further hypothesised that these associations would be moderated by caregiver gender.

Paper 3 also adopted an exploratory approach, as no known prior studies have tested whether caregiver characteristics moderate the effects of specific intervention components on engagement outcomes in digital parenting interventions. It was hypothesised that the effects of the three components (guidance, app design, and digital support) on engagement would be significantly moderated by caregiver demographic (age, gender), socioeconomic (financial stress, food insecurity), and psychosocial characteristics (positive parenting, child maltreatment, caregiver depression).

5. Methods

This chapter describes the methods used across the three papers. It is organised into three sections. Section 5.1 provides an overview of the ParentApp optimisation trial, including its design, implementation context, participants, randomisation procedures, and sample size calculation. Section 5.2 outlines the development of ParentApp during the Preparation Phase of the MOST framework, detailing the co-design, user testing, and pilot studies that informed the conceptual model and guided the selection of the three design and delivery components tested in the trial. Section 5.3 explains the measurement and analytical procedures used across the three papers, including data collection systems, operationalisation of engagement outcomes, coding of experimental factors, and handling of missing baseline data. Together, these sections provide additional context and clarify methodological choices beyond those reported in each individual paper.

5.1 ParentApp Optimisation Trial

5.1.1 Trial Design and Implementation Context

Experimental Design

All three papers use quantitative data from the ParentApp optimisation trial, a 2×2×2 cluster-randomised full factorial experiment. The trial tested three experimental factors (also referred to as components in this thesis): guidance (guided vs. self-guided), app design (unstructured vs. structured), and digital support (enhanced vs. basic). These were selected based on insights from prior feasibility piloting and existing research, with a focus on addressing engagement challenges within low-income contexts and ensuring translatability to real-world implementation settings in LMICs. Further details on the development and rationale for these components are provided in 5.2.

Trial Registration and Protocol

The trial was preregistered on the Pan-African Clinical Trial Registry on 11 October 2022 (PACTR202210657553944). The full study protocol, which details the study design, methods, and planned analyses, was published in *BMC Public Health* (Janowski et al., 2023) (see Appendix 1).

Ethical Approval

The trial, including the analyses conducted for this thesis, received ethical approval from the University of Oxford's Departmental Research Ethics Committee (Ref: R69744/RE001) and from the National Institute for Medical Research in Tanzania (Ref: NIMR/HQ/R.8s/Vol.IX/-3856) (see Appendix 3).

Research Team

ParentApp was developed and adapted in Tanzania through a collaboration involving academic, technical, and implementation partners, including the Universities of Oxford and Cape Town; Parenting for Lifelong Health (PLH); Innovations in Development, Education, and the Mathematical Sciences (IDEMS International and INNODEMS Kenya); the National Institute of Medical Research (NIMR) in Tanzania; and Clowns Without Borders South Africa (CWBSA). Local implementation was led by Investing in Children and Strengthening their Societies (ICS), a Tanzania-based NGO with expertise in community-based programme delivery.

Study Site

The trial was implemented between October 2022 and May 2023 in 16 low-income urban and peri-urban communities in the Mwanza region of northwestern Tanzania. Mwanza, the country's second-largest city, lies on the southern shores of Lake Victoria and is predominantly inhabited by the Sukuma ethnic group. The region experiences high levels of poverty and limited access to formal services, with most livelihoods based on small-scale farming, fishing, and informal trade (Mwanza City Council, 2017). Prior studies suggest that environmental pressures, including the effects of climate change, are contributing to constraints on local economic opportunities in the region (Bjornlund et al., 2022; Magongo & da Corta, 2011). Trial sites were drawn from sub-wards within three wards characterised by high levels of socioeconomic disadvantage, following a two-week community engagement and assessment process led by NIMR.

5.1.2 Study Participants

Because the three papers draw on data from the same trial cohort, this section provides an aggregated description of participants to contextualise their circumstances and explain the scope of analyses reported in this thesis. Participants (N = 614) were parents or primary caregivers of at least one adolescent aged 10 to 17 years, with regular access to an Android smartphone. Analysis of data collected via an embedded baseline assessment revealed that 33.4% of the caregivers were male, which is comparable to male enrolment rates in the large-scale implementation of PLH Teens in Tanzania (Lachman, Wamoyi, et al., 2024). Caregivers' age ranged from 18 to 75 years, with a mean age of 35.94 years (*SD* 11.84). The sample reported experiencing a range of vulnerabilities, with 84% of caregivers reporting running out of money to pay for food in the past month, and 47.9% reporting that their adolescent had lost a primary caregiver during their lifetime. The post-intervention assessment completion rate was low (9.2%), and therefore this thesis does not examine caregiver behaviour change outcomes at post-assessment.

5.1.3 Randomisation

Randomisation was conducted at the cluster level, using the sub-wards identified during site selection (5.1.1). Community representatives first compiled lists of potentially eligible families within each sub-ward, and fieldwork coordinators from NIMR grouped geographically proximate sub-wards to form 16 clusters. An off-site researcher at IDEMS International (Dr Lily Clements) used a computer-generated sequence in R to allocate each cluster to one of the eight experimental conditions in a 1:1 ratio. The allocation list was then provided to the in-country research team. Although equal cluster sizes were planned, recruitment realities resulted in variation, with cluster sizes ranging from 32 to 49 caregivers (*M* 38.38, *SD* 6.20).

Cluster randomisation was chosen primarily for logistical reasons. Assigning all participants within a cluster to the same experimental condition allowed eligibility screening, informed consent, and baseline data collection to be completed in a single community-based session. This streamlined approach reduced participant travel and time burden, and conserved implementation resources by enabling more efficient coordination of in-person activities such as app installation and digital support. A secondary rationale, recommended by Tanzanian partners at NIMR, was to minimise the risk of contamination between experimental conditions. In densely populated communities with frequent social interaction, participants might inadvertently share details of their intervention experience. Assigning geographically proximate sub-wards to the same condition helped reduce this risk and protect the integrity of experimental comparisons.

While advantageous for the reasons outlined above, cluster randomisation required careful consideration of its implications for statistical power. Such designs typically need larger sample sizes than individually randomised trials because of intraclass correlation within clusters (Leyrat et al., 2018). Given the trial's focus on optimising engagement strategies rather than estimating clinical effects, and the in-person nature of some of the components, the logistical and contamination-control benefits were judged to outweigh potential losses in statistical efficiency. To partially offset this trade-off, all analyses accounted for clustering by including random intercepts in mixed-effects models.

5.1.4 Sample Size Calculation

Sample size calculations were led by Dr Lily Clements (IDEMS International), with methodological support from Dr David Stern (IDEMS International). I contributed by advising on trial design assumptions and interpreting outputs in my role as trial manager and in support of this thesis. A simulation-based approach was used to estimate the required sample size, accounting for the full factorial design and cluster-level randomisation. This method was selected as the trial focused on engagement outcomes rather than behavioural or clinical endpoints, and no established effect sizes existed for similar intervention components. Unlike conventional power calculations, simulation allowed for the inclusion of non-normal outcome distributions, variation in cluster sizes, and empirically grounded dropout assumptions, providing a more flexible and context-sensitive estimate of statistical power (Arnold et al., 2011).

Procedures

Two design scenarios were considered: one with 24 clusters and another with 16, each evaluated using varying average cluster sizes (25, 30, or 40 participants per cluster). For each configuration, 1,000 datasets were simulated. To reflect realistic variability in enrolment and differences in smartphone ownership, cluster sizes were modelled as normally distributed with a mean of 40 and a standard deviation of 8. Expected programme dropout rates were derived from a systematic review of digital mental health interventions implemented in real-world settings (Fleming et al., 2018), and followed a graduated model: 50% of participants were expected to disengage after module 1, 40% were expected to complete modules 2 to 4, 7% were expected to complete modules 5 to 8, and 3% were expected to complete modules 9 to 12.

Effect size assumptions for the three experimental factors were guided by study hypotheses: guided delivery was expected to produce greater engagement than self-guided delivery; the unstructured app design was expected to result in higher engagement than the structured design; and enhanced digital support was expected to yield higher engagement than basic support. For each simulated dataset, generalised linear mixed-effects models were fitted to estimate effects. Associations between baseline variables and engagement were informed by data from the in-person PLH Teens RCT (Shenderovich et al., 2018), which used measures comparable to those in the ParentApp baseline assessment. Covariates for inclusion were selected through backward elimination.

Simulation results indicated that a design with 16 clusters and a mean cluster size of 40 participants produced similar coefficients and model stability to a design with 24 clusters and smaller group sizes. The 16-cluster scenario was chosen as the most feasible option, given the logistical and financial demands of the guided condition. Larger clusters meant fewer WhatsApp groups, which was not only easier to manage but also more scalable and cost-effective for potential future implementation. This decision was further influenced by operational constraints, including the need to complete the trial and conduct data analyses within a limited timeframe to inform the design and implementation of a subsequent RCT.

While simulation-based power estimation offers a flexible and contextually appropriate alternative to traditional approaches, its accuracy depends on the validity of the underlying assumptions, particularly those concerning effect sizes, dropout patterns, and outcome distributions. These assumptions may not fully capture the complexity and variability of real-world implementation, and results should therefore be interpreted with appropriate caution.

5.2 ParentApp Preparation Phase of MOST

The Preparation Phase of MOST for ParentApp involved an iterative, multi-country process spanning from 2019 to 2022, during which the intervention was co-designed, developed, tested, and refined. Across these stages, the core PLH Teens curriculum remained intact, but design, delivery, and engagement features evolved in response to caregiver, implementer, and researcher feedback. This section first describes the programme tested in optimisation trial (5.2.1), then outlines the earlier development and feasibility work that informed it (5.2.2), and finally explains how these insights shaped the trial's conceptual model and component selection (5.2.3).

5.2.1 Overview of the ParentApp Programme

ParentApp is a smartphone-based intervention delivering a digital adaptation of the in-person PLH Teens programme. It was designed to address barriers to in-person programme delivery in low-resource settings, with features optimised for offline use and compatibility with low-end Android devices. Since its initial inception in 2019, ParentApp has undergone multiple iterations based on user testing and feasibility studies in South Africa, Tanzania, and other LMIC countries. The description below refers to the version tested in the optimisation trial, which incorporated lessons from all prior development stages.

Programme Modules

In the optimisation trial, ParentApp comprised 12 modules designed for weekly completion, accessible from the app's home screen. This structure reflected the pacing and content of the in-person PLH Teens programme in a condensed format. The modules integrated text, audio, and visual content to support learning and behaviour change. The introductory module focused on caregiver self-care and stress reduction, offering techniques to build confidence and reduce daily stress. It also included a welcome survey allowing users to customise their experience by choosing their preferred delivery format: *individual*, where content and activities were framed for the caregiver to complete alone, or *group*, where caregivers could use the app with family or friends and content and activities were framed for group participation. The survey incorporated an embedded baseline assessment capturing socio-demographic data and behavioural outcomes. Modules 2 through 11 addressed core parenting topics such as building trust between caregivers and adolescents, non-violent discipline, managing family finances, adolescent safety, and crisis management, with each building on prior content to support incremental learning. The final module reinforced learned skills and included a post-intervention assessment.

Programme Features

The app incorporated a range of features designed to enhance user experience, engagement, and skill development. An in-app navigation tutorial was presented upon first use and remained accessible through the settings menu. Push notifications were tailored to each user's engagement pattern, encouraging continued interaction with the app. Where appropriate, these messages were personalised with the user's name. In addition, brief, pre-programmed check-ins appeared at the start of each module to simulate the experience of a facilitator-guided programme. To support skill practice, modules prompted users to complete home activities and to review or problem-solve these practices via the "Home Practice Review" tab in Modules 2 through 11. A habit-tracking feature, "ParentPoints," encouraged users to log positive parenting and mental health-promoting behaviours, while the "ParentLibrary" tab provided additional parenting tips, activity suggestions, coping strategies, and information on local services and technical support.

5.2.2 Preparation Phase Part 1: Development and Early Testing

This section summarises the co-design, user testing, and mixed-methods feasibility pilots conducted between 2020 and 2022. These activities informed refinements to ParentApp's design and delivery and generated the evidence base for selecting the components evaluated in the optimisation trial.

Development and User Testing

ParentApp development began in January 2020 with a collaborative multi-day workshop involving the PLH research team, IDEMS International, INNODEMS Kenya, and representatives from CWBSA. Following the initial planning phase, co-design workshops in South Africa, engaged caregivers and adolescents who had participated in the in-person PLH Teens programme, to ensure that the proposed content, structure, and tone were relevant and acceptable for local families. The resulting minimum viable product was reviewed by CWBSA trainers for contextual and cultural fit and then tested in early 2021 with 24 caregivers and adolescents from nine countries (South Africa, Kenya, Nigeria, Malawi, Cameroon, Ghana, Democratic Republic of the Congo, Burkina Faso, and Trinidad and Tobago).

User testing participants engaged with all 12 modules, and 43 semi-structured interviews were conducted at the early, mid, and post-programme stages to explore satisfaction, usability, and engagement barriers (Awah et al., 2022). Content was viewed as highly acceptable, with parenting tips and strategies considered particularly useful. However, barriers to engagement included the absence of reminders or notification features, technical difficulties, and low digital literacy. A particularly notable area of feedback concerned the app's visual design. At the time of testing, ParentApp featured blue, gender-neutral characters, an animation style selected to allow easy adaptation across different cultural contexts. Reactions to this approach were mixed. Some participants appreciated the simplicity of the visuals, while others found them confusing or aesthetically unappealing. As one Cameroonian father explained, *"They would have made sense if they looked more like real people rather than inflated balloons."* This divergence in views highlighted a potential trade-off between contextual adaptability and user relatability. Consequently, the optimisation trial was designed to compare the original imagery with a locally adapted, more human-like visual style.

Feasibility Pilot in South Africa

Following user testing, the app was updated primarily to address technical bugs, refine content, and expand language accessibility through translation into two local South African languages. Other feature requests, such as the addition of push notifications, were deferred to later development phases. The resulting beta version of ParentApp was piloted with 107 caregivers across four implementing partners in the Western Cape and KwaZulu-Natal provinces of South Africa. This mixed-methods pilot study assessed the feasibility of recruitment, real-world delivery, and fully self-guided app use. Partner organisations received a one-day online training workshop from CWBSA and the research team, covering app content, recruitment strategies, and onboarding procedures. To support caregivers with limited internet access, recruiters were provided with data bundles and encouraged to follow up within one to two weeks of enrolment.

Initial uptake was promising, with 50% of participants completing the first module. However, sustained engagement declined steeply across the 12-week intervention period, with only 2% of users remaining active by programme end. Module completion rates dropped from approximately 47% in the first week to near zero by the twelfth week. To explore the reasons for this decline, qualitative interviews were conducted with eight caregivers purposively sampled by engagement level, language preference (English, isiZulu, isiXhosa), and implementing organisation. Nine staff members involved in recruitment and delivery also provided feedback via interviews and short surveys.

Findings echoed those from earlier user testing: content was acceptable, relevant, and easy to understand. However, sustained engagement was challenged by competing work and family responsibilities, limited phone storage, and frequent technical challenges. Participants and staff recommended structured reminders or push notifications to encourage consistent use, and many expressed interest in human support options, including peer interaction via WhatsApp groups. In addition, at the time of testing, a new module was released every seven days, meaning content was accessed sequentially rather than all at once. This weekly release schedule was perceived as too rigid, with several participants suggesting that more flexible access could improve engagement. Not all of these suggestions were implemented immediately. In the subsequent Tanzanian pilot, the main changes included the introduction of push notifications and the addition of human guidance via one-on-one phone calls and WhatsApp groups. Other recommendations, such as flexible content access, were tested in the optimisation trial.

Feasibility Pilot in Tanzania

A second mixed-methods feasibility study was conducted in Tanzania between April and December 2022 with 102 caregiver–adolescent dyads from urban and rural communities in the Mwanza and Shinyanga regions. Drawing on selected lessons from the South African pilot, the Tanzanian pilot introduced a more intensive delivery approach. Caregivers were provided with smartphones preloaded with the app and received weekly facilitator guidance, delivered either through individual phone calls or moderated WhatsApp groups. Recruitment and facilitation were led by ICS, with implementation and coaching support from CWBSA. Further refinements included language updates to Kiswahili, adjustments to the app's visual layout, and revisions to activity structures based on earlier feedback.

Although the pilot overlapped with the scheduled start of the optimisation trial, limiting full analysis of engagement and outcome data, implementation feedback was collected from facilitators and delivery staff. A prominent challenge was the low level of digital literacy among participants, which necessitated extensive onboarding and technical support. This finding highlighted the need for dedicated digital skills training in future delivery. Facilitators also reported that caregivers strongly preferred WhatsApp groups over one-on-one phone calls, viewing them as more engaging and conducive to peer support. These insights directly shaped the operationalisation of the guidance and digital support components tested in the optimisation trial.

5.2.3 Preparation Phase Part 2: Conceptual Model and Component Selection

This section describes the conceptual model and component selection process that underpinned the optimisation trial. The conceptual model clarified the hypothesised pathways through which candidate components could influence caregiver engagement with ParentApp and provided the framework for selecting the components evaluated in the trial.

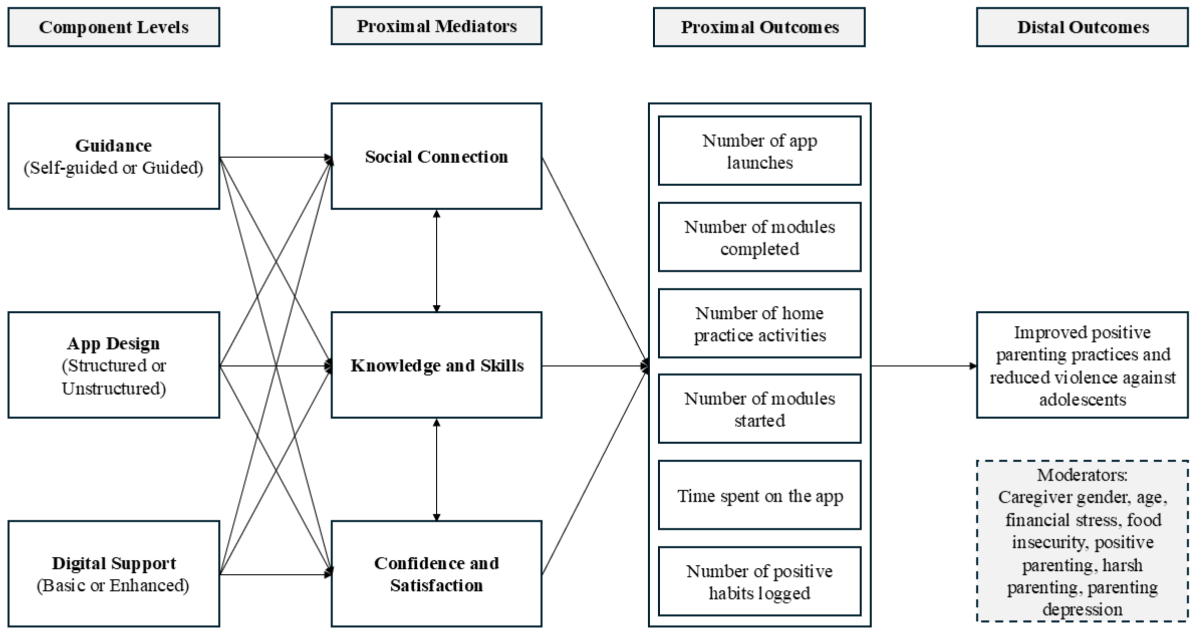
Conceptual Model

A conceptual model was developed during the Preparation Phase to (1) clarify the hypothesised pathways through which candidate components were expected to influence target outcomes, and (2) guide practical decision-making for the design and delivery of the optimisation trial. The model was specific to the optimisation objective of improving caregiver engagement with ParentApp while ensuring the intervention remained feasible, acceptable, and cost-effective in the context of LMIC delivery settings. It was not intended to represent the programme's full theory of change, but rather to support a focused, empirical investigation into how engagement could be maximised within the optimisation trial.

The model's development was informed by two main evidence sources: findings from user testing and mixed-methods feasibility studies (5.2.2), and the review of contextual and intervention predictors of engagement in digital parenting programmes, together with the broader literature on engagement with digital health interventions, presented in Chapter 3.2. Initial drafts were refined through an iterative, collaborative process involving the immediate research team, development partners (including IDEMS International and INNODEMS Kenya), Tanzanian research collaborators and implementation partners at NIMR, and stakeholders from the WHO Behavioural Insights Team. This approach reflected recent guidance on logic model development for complex interventions, which emphasises the value of staged, transparent, and stakeholder-engaged processes (Voss et al., 2025), and ensured that the model was grounded in empirical evidence while remaining responsive to the realities and priorities of delivery in Tanzania (O'Hara et al., 2024).

The final model (Figure 6) specifies the hypothesised pathways through which a set of candidate components might influence caregiver engagement. These components are theorised to shape a set of proximal experiences or mediators, such as a sense of social connection, increased confidence and skills, and satisfaction with ParentApp. These experiences are expected to lead to increased behavioural engagement with the app, the programme content, and the programme activities, which are treated as the primary proximal outcomes in the optimisation trial. In turn, increased engagement is hypothesised to contribute to improved parenting practices and reductions in child maltreatment. The model also incorporates potential moderators that may influence caregivers' responses to specific components. These were identified based on potential predictors of engagement in digital parenting interventions, given the limited evidence on moderators in this field. Pre-specified moderators include caregiver gender, age, socioeconomic status, parenting practices, and mental health. Including these factors in advance acknowledges the importance of understanding not only which components are effective, but also for whom they are most effective.

Figure 6. *Conceptual model guiding the optimisation of engagement in ParentApp*



Component Selection Criteria

The conceptual model outlined above served as a foundation for selecting the candidate components, also referred to as experimental factors in this thesis, to be evaluated in the optimisation trial. Component selection was guided by predefined criteria set out in the trial protocol (Janowski et al., 2023). Each component was required to: (1) address at least one theoretical mediator associated with engagement in digital interventions; (2) be clearly distinct from the other components in delivery mode, content, or structure; (3) have preliminary evidence of effectiveness; and (4) be feasible, acceptable, and cost-effective for implementation in low-resource settings.

In addition to these criteria, two considerations were introduced during the conceptual model development process in consultation with implementation partners and stakeholders. First, because ParentApp was adapted from the in-person PLH Teens programme, it was agreed that the optimisation trial would not test content-related components. Instead, it would focus on strategies intended to enhance caregiver engagement. In implementation science, these may be referred to as implementation strategies, defined as "methods or techniques used to enhance the adoption, implementation, or sustainability of a clinical program or practice" (Proctor et al., 2013, p. 2). For the purposes of this thesis, components intended to improve engagement, adherence, or other implementation outcomes are referred to as design and delivery strategies to acknowledge the overlap between purely digital strategies and hybrid human–digital delivery models. The decision to prioritise delivery over content components is consistent with the principles outlined in the ADAPT guidance, a consensus-informed framework for systematically adapting interventions to new contexts (Moore et al., 2021), which emphasises ensuring contextual fit while maintaining fidelity to an intervention's core functions. In this case, evaluating strategies aimed at enhancing engagement ensured responsiveness to local delivery needs without compromising fidelity to the programme's established theory of change.

Second, although a wide range of potential design and delivery components were considered, the number tested was deliberately restricted to three. This decision reflected practical constraints, including delivery complexity, time limitations, and the human resource demands of implementation. Many of the candidate strategies emerging from user testing and pilot studies involved hybrid human–digital delivery, which require more intensive coordination and oversight than fully digital components. To maintain feasibility, lower burden adaptations such as the inclusion of push notifications were incorporated across all trial conditions. The three strategies selected for evaluation were those judged most likely to address the most persistent barriers to engagement. These were tested within a 2×2×2 factorial design, yielding eight distinct experimental conditions (Table 1).

Table 1. *Overview of experimental conditions in the 2×2×2 factorial trial*

			Design and Delivery Components		
Condition	Clusters (n = 16) n (%)	Caregivers (n = 614) n (%)	Guidance	App design	Digital support
1	2 (12.5)	83 (13.5)	Self-guided	Unstructured	Enhanced
2	2 (12.5)	74 (12)	Self-guided	Unstructured	Basic
3	2 (12.5)	92 (15)	Self-guided	Structured	Enhanced
4	2 (12.5)	81 (13.2)	Self-guided	Structured	Basic
5	2 (12.5)	58 (9.4)	Guided	Unstructured	Enhanced
6	2 (12.5)	67 (10.9)	Guided	Unstructured	Basic
7	2 (12.5)	86 (14)	Guided	Structured	Enhanced
8	2 (12.5)	73 (11.9)	Guided	Structured	Basic

Note. ParentApp is a constant component across all experimental conditions.

Description of Selected Components

Full details of each component are presented in Paper 1; the summary below provides a concise overview for context. The first component addressed the level of facilitator involvement in programme delivery. In the self-guided condition, caregivers used ParentApp independently, as originally intended, whereas in the facilitator-guided condition, they participated in moderated WhatsApp groups that provided low-intensity weekly support from trained facilitators and opportunities for peer interaction. This component was designed to assess whether remote, group-based human support could address persistent engagement challenges identified in earlier testing.

The second component compared two structural and visual variants of the app. The structured version released modules weekly and used blue, gender-neutral illustrations intended to support adaptability across contexts. The unstructured version granted immediate access to all modules and incorporated more human-like, culturally adapted visuals. Although these structural and visual elements represent distinct design features, they were combined into a single component in this trial due to time constraints during development. The comparison was intended to assess the combined influence of visual relatability and content flexibility on engagement.

The third component addressed digital literacy barriers observed during piloting. In both conditions, support was provided in person during the orientation and onboarding session. The basic support condition offered an introduction to core app functions, while the enhanced support condition provided a broader orientation to smartphone use, including navigation, settings, and mobile data management. This component aimed to identify the minimum level of digital literacy support required to enable meaningful engagement.

5.3 Measurement and Analysis

This section outlines the procedures for data collection, pre-processing, and analysis used across the three papers. It covers the operationalisation of engagement outcomes, coding of experimental factors, and approaches to handling missing baseline data. Paper-specific analyses are described within each paper.

5.3.1 Data Collection

Quantitative data for all three papers were collected via an in-built data collection system managed by IDEMS International. The system combined two platforms, Matomo and Metabase, to record both app usage metrics and responses to pre–post assessments. Matomo, an open-source alternative to Google Analytics, captured information on device specifications, download region, and time-related data, including seconds spent using the app. This data collection required an active internet connection and was not stored locally on the device. Metabase collected prespecified app usage metrics, such as module and in-app activity completion rates, as well as self-report data on activity practice, progress, and challenges. Unlike Matomo, Metabase could operate offline, storing data on the device until it synchronised with the cloud server once an internet connection became available.

Socio-demographic and parenting-related outcome data were collected through app-embedded questions. These appeared during the setup and customisation process in the first module and again in the closing assessment of the final module. All questions were optional, and the app responded to users' answers with empathetic feedback and links to relevant tips. Only essential demographic items were included, and parenting-related measures focused on the programme's core outcomes. To minimise burden, abbreviated scales recommended by the GPI were used, with response options standardised to a simple frequency scale (0 = never to 8 = 8 or more times). All measures were translated into Kiswahili by the Tanzanian research team and back-translated for accuracy. Longer versions of these measures had been used previously in the large-scale implementation of PLH Teens in Tanzania (Martin et al., 2021). The abbreviated measures had been piloted in the Tanzanian feasibility study.

Linking usage data with participants' cluster allocation was done during the in-person orientation and onboarding. When ParentApp was installed, the system generated a unique device identifier. Research assistants scanned the QR code associated with this identifier, enabling researchers to match participants to their cluster allocation without storing allocation information in the app. Metabase data was then fed into a dashboard used by researchers and implementers to monitor engagement patterns, generate reports, and track app performance in real time.

5.3.2 Operationalising Engagement Outcomes

Engagement was the primary outcome of interest in the optimisation trial and formed the central analytic focus across all three papers included in this thesis. It was conceptualised as a multidimensional construct, informed by Perski et al.'s (2017) integrated definition. This definition includes both behavioural engagement, which is captured through four usage dimensions (amount, frequency, duration, and depth), and subjective experience, which includes factors such as attention, interest, and affect. In this thesis, the focus is on the behavioural dimension, as subjective experiences were not collected within the app. These experiential aspects were instead explored in post-intervention qualitative interviews, which fall outside the scope of this thesis. Two additional frameworks were applied to capture (1) the phase of engagement (initial, ongoing, or quality) (Aldridge et al., 2024; Georgeson et al., 2020), and (2) the level of interaction (with the app, the content, or the activities) (Brouwer et al., 2008).

Paper 1 Engagement Outcomes

Paper 1 operationalised engagement across six indicators to examine how specific design and delivery strategies influenced different forms of ParentApp use. These indicators were selected to reflect variation across usage dimensions, phases of engagement, and levels of interaction, as summarised in Table 2. Three indicators were designated as primary outcomes, representing the main behavioural patterns of interest, while three secondary outcomes provided complementary insights into the consistency, duration, and depth of use.

The primary outcomes were: (1) the number of app launches, which reflected ongoing engagement at the app level and measured how often participants accessed the platform; (2) the number of modules completed, which captured the amount of ongoing engagement with programme content; and (3) the number of home practice activities reviewed, which reflected quality engagement at the activity level and indicated depth of behavioural application.

The secondary outcomes were: (1) the number of modules started, which reflected frequency of content engagement by capturing initiation without requiring full completion; (2) total time spent on the app, which represented ongoing engagement at the app level and measured the duration of use; and (3) the number of positive parenting or mental health habits logged, which served as a self-reported indicator of quality engagement by capturing participants' proactive application of programme strategies. Together, these measures enabled a multidimensional analysis of not only whether participants engaged with the app, but also how consistently, for how long, and with what depth of interaction.

Table 2. *Paper 1 primary and secondary engagement outcomes*

Measure	Dimension	Phase	Level
Primary Engagement Outcomes			
1. Number of app launches	Frequency	Ongoing	App level
2. Number of modules completed (0-12)	Amount	Ongoing	Content level
3. Number of home practice activities reviewed (0-10)	Depth	Quality	Activity level
Secondary Engagement Outcomes			
1. Number of modules started (0-12)	Frequency	Ongoing	Content level
2. Time spent on the app (seconds)	Duration	Ongoing	App level
3. Number of habits logged	Depth	Quality	Activity level

Paper 2 Engagement Outcomes

In Paper 2, engagement was operationalised as the total number of modules completed (0-12). This measure was selected for two main reasons. First, module completion is a widely used and easily interpretable metric in digital intervention research (Aldridge et al., 2024; Pratap et al., 2020). Second, findings from Paper 1 highlighted reliability and validity issues with several other indicators. App launches and total time on the app contained small amounts of missing data, likely due to device restrictions or intermittent internet access. The home practice review variable was highly zero-inflated, suggesting low uptake or navigation difficulties, while the habits logged measure occasionally contained implausibly high values, potentially inflated by gamification effects or self-report bias.

Two secondary outcomes (first non-start and first non-completion) were included to identify early disengagement. Time to first non-start was defined as the first module in the sequence that a participant did not start. Time to first non-completion referred to the first instance in which a participant began a module but did not complete it. Each outcome was paired with an appropriate exposure variable to account for differences in participants' progression through the programme. For the module completion outcome, the exposure was the total number of modules. For time to non-start and time to non-completion, binary response variables were used (1 = disengagement, 0 = no disengagement), and the exposure was defined as the module number at which disengagement first occurred. Together, these three measures captured both overall content completion and early drop-off points.

Paper 3 Engagement Outcome

Paper 3 used module completion as the sole engagement outcome. This measure was selected because it was the most reliable and interpretable indicator available, showing complete data coverage and consistent patterns across participants. In contrast to other engagement metrics explored in Paper 1, module completion was unaffected by missing data, zero-inflation, or extreme outlier values, making it a robust choice for exploratory moderation analyses involving multiple interaction terms.

5.3.3 Effect Coding Experimental Factors

Because the analyses in Papers 1 and 3 relied on interpreting the main and interaction effects of the experimental factors, it is important to clarify how these factors were numerically represented in the regression models. Although the principles of effect coding were outlined in Chapter 3.3.3, this section briefly summarises the rationale for its use in the analyses.

In regression analyses, categorical variables must be converted into numerical form before they can be included in statistical models. This transformation, known as coding, creates numeric contrasts between levels of the factor. Two common coding methods are dummy coding and effect coding (Cohen & Cohen, 1983). Dummy coding assigns values of 0 or 1 and uses a reference category as the baseline for comparison. While this approach is widely used and straightforward to interpret, it can be limiting in factorial designs because main effects are estimated relative to a single reference group rather than the overall mean, and the resulting parameters may not be orthogonal (Kugler et al., 2018). Furthermore, it does not permit comparisons to the grand mean, and it can potentially create multicollinearity issues.

Effect coding, in contrast, assigns values of −1 and 1 to the two levels of a dichotomous factor. The key "rule" in effect coding is that the sum of the assigned values for each new variable must equal zero (Kugler et al., 2018). This removes the need for a reference group and allows effects to be interpreted relative to the grand mean. In balanced 2^k factorial designs, effect coding produces orthogonal contrasts, meaning that estimates of main and interaction effects are statistically independent, with equal standard errors (Collins, 2018; Kugler et al., 2018). Interaction terms can then be interpreted as deviations from the overall mean rather than from an arbitrary baseline, which can aid clarity in reporting. Given these advantages, effect coding was used for Papers 1 and 3. As discussed in detail in Chapter 3.3.3, this choice is particularly appropriate for balanced factorial designs, where it supports efficient estimation and interpretation of both main and interaction effects.

5.3.4 Handling Missing Baseline Data

Baseline caregiver data contained between 0% and 7.5% missing values at the item level (Appendix 4). Missing data can arise for various reasons and are typically classified as missing completely at random (MCAR), missing at random (MAR), or missing not at random (MNAR) (Rubin, 1976). Little's MCAR test ($\chi^2 = 545.73$, df = 491, $p = .044$) indicated that the data were not MCAR, suggesting that missingness may be related to other observed variables. In such cases, complete-case analysis risks introducing bias and loss of power, whereas multiple imputation can provide more reliable estimates when the MAR assumption is plausible (van Buuren, 2018).

On this basis, multivariate imputation by chained equations was used to address missing baseline data prior to analyses presented Papers 1, 2, and 3. The procedure was implemented using the *mice* package in R (van Buuren & Groothuis-Oudshoorn, 2011). Ten imputations were generated using predictive mean matching, which preserves the distribution of observed data by drawing imputed values from similar complete cases. The predictor matrix included all outcome variables except 'app launches' and 'time spent on the app' (both of which contained missing data), along with experimental factors, complete baseline variables, and cluster allocation. The cluster variable was specified as –2 so that imputations were conducted within clusters. For behavioural items contributing to total scores, imputation was performed at the item level, with total scores computed passively during the process.

Convergence was assessed by plotting the mean and standard deviation of imputed values across iterations, and density plots confirmed that the distributions of imputed and observed values were comparable (see Appendix 4).

6. Paper 1 – Optimizing Engagement With a Smartphone App to Prevent Violence Against Adolescents: Results From a Cluster Randomized Factorial Trial in Tanzania

The following chapter is published the *Journal of Medical Internet Research* and has been written using US spelling, in accordance with the journal's submission guidelines. Tables and figures are embedded within the chapter, with supplementary materials provided in Appendix 5. Figure and table numbering continues sequentially from previous chapters of the thesis.

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Statement of Authorship: I confirm that I carried out the majority of this research study. I conceptualised the study, led the writing of the protocol and trial registration, and planned and conducted the analyses. I trained staff for data collection, led project administration, and oversaw the data collection and curation process. I prepared the original manuscript draft and led the writing, review, and editing processes. Several co-authors contributed by supporting the analyses and by reviewing and approving the manuscript. All authors approved the final version prior to journal submission. Full authorship details are provided in Appendix 5 (Supplementary File 1).

6.1 Abstract

Background: Violence and abuse exert extensive health, social, and economic burdens on adolescents in low- and middle-income countries. Digital parenting interventions are promising for mitigating risks at scale. However, their potential for public health impact hinges on meaningful engagement with the digital platform.

Objective: The objective of this study was to evaluate the impact of three intervention design and delivery factors aimed at increasing engagement with a non-commercialized, offline-first smartphone app for caregivers of adolescents in Tanzania, in partnership with the United Nations Children's Fund, the World Health Organization, and the Tanzanian National Government.

Methods: Following Multiphase Optimization Strategy (MOST) principles, we conducted a 2×2×2 cluster-randomized factorial trial involving caregivers of adolescents aged 10 to 17 years. Caregivers were recruited by community representatives from 16 urban and peri-urban communities (i.e., clusters) in the Mwanza region of Tanzania. Each cluster was randomized to one of two levels of each factor: *guidance* (self-guided or guided via facilitator-moderated WhatsApp groups), *app design* (structured or unstructured), and pre-program *digital support* (basic or enhanced). Primary outcomes were automatically tracked measures of engagement (app launches, modules completed, and home practice activities reviewed), with secondary outcomes including modules started, time spent in the app, and positive behaviors logged. Generalized linear mixed-effects models assessed the impact of experimental factors on engagement.

Results: Automatically tracked engagement data from 614 caregivers were analyzed, of which 205 (33.4%) were men. Compared to self-guided participants, receiving guidance alongside the app led to significantly more app launches (mean ratio [MR] 2.93, 95% CI 1.84-4.68; $p <$

.001), modules completed (MR 1.29, 95% CI 1.05-1.58; $p = .02$), modules started (MR 1.20, 95% CI 1.02-1.42; $p = .03$), time spent in the app (MR 1.45, 95% CI 1.39-1.51; $p < .001$), and positive behavior logs (MR 2.73, 95% CI 2.07-3.60; $p < .001$). Compared to the structured app design, unstructured app use resulted in significantly more modules completed (MR 1.49, 95% CI 1.26-1.76; $p < .001$), home practice activity reviews (MR 7.49, 95% CI 5.19-10.82; $p < .001$), modules started (MR 1.27, 95% CI 1.06-1.52; $p = .01$), time spent in the app (MR 1.84, 95% CI 1.70-1.99; $p < .001$), and positive behavior logs (MR 55.68, 95% CI 16.48-188.14; $p < .001$). While analyses did not detect an effect of enhanced digital support on directly observed engagement, the combination of enhanced digital support and guidance positively influenced engagement across a range of outcomes.

Conclusions: This study is the first to systematically optimize engagement with a digital parenting intervention in a low- and middle-income country. The findings of this study offer important learnings for developing evidence-based, scalable digital interventions in resource-constrained settings.

Trial Registration: Pan-African Clinical Trial Registry PACTR202210657553944; https://pactr.samrc.ac.za/TrialDisplay.aspx?TrialID=24051

Keywords: digital health; engagement; parenting; adolescents; low- and middle-income country; violence against children; multiphase optimization strategy; randomized factorial experiment.

6.2 Introduction

Violence against children (VAC) has far-reaching individual and societal consequences. Beyond physical harm, violence during childhood negatively impacts brain development and increases risks of poor educational attainment, substance use, and adverse mental and physical health conditions (Fry et al., 2018; Hughes et al., 2017). These impacts cascade into broader societal costs, including reduced social participation, unemployment, crime, and intergenerational transmission of violence (Fry et al., 2018; Manchikanti Gómez, 2011; Norman et al., 2012; Roberts et al., 2011), with global economic costs approximating US $7 trillion annually (UNICEF, 2020).

While VAC occurs in many settings, it is most prevalent within the home environment, where it is typically perpetrated by parents or other caregivers (World Health Organization, 2023). It spans physical, emotional, and sexual abuse, with disproportionately higher rates in low- and middle-income countries (LMICs), particularly in Africa (Hillis et al., 2016; Know Violence in Childhood, 2017). In Tanzania, national survey data (UNICEF, 2011) revealed that >70% of respondents aged 13 to 24 years had experienced physical violence from parents, relatives, or guardians before the age of 18 years, including being slapped, kicked, beaten, pushed, or threatened with a weapon. Moreover, approximately 80% of those experiencing sexual violence reported physical violence, while emotional abuse was nearly universal among those who experienced physical violence (UNICEF, 2011). A more recent nationally representative study by Nkuba et al (2018) found even higher rates, with >90% of secondary school students reporting violent discipline from parents or primary caregivers and 80% of parents acknowledging such practices. This widespread prevalence is associated with limited knowledge of nonviolent parenting alternatives, high caregiver stress, and cultural norms emphasizing child obedience and respect, male honor, and family privacy (Nkuba et al., 2018; UNICEF, 2011).

Parenting interventions, identified by the World Health Organization as a key VAC prevention strategy (World Health Organization, 2016, 2018), aim to strengthen parent-child relationships and replace harsh, abusive practices with developmentally appropriate, nonviolent discipline strategies (World Health Organization, 2023). These interventions are effective in preventing VAC globally (Backhaus et al., 2023), particularly when they incorporate skill-building in nonviolent discipline, positive reinforcement, emotion regulation, proactive parenting, and protective relationship promotion (Gubbels et al., 2021; Leijten et al., 2019; Melendez-Torres et al., 2019). However, scaling traditional in-person delivery in LMICs, such as Tanzania, faces significant barriers, including prohibitive delivery costs, extensive human resource requirements, limited geographic accessibility for families, and competing work and childcare demands (Knerr et al., 2013; Mejia et al., 2012; Parra-Cardona et al., 2021).

Digital delivery via smartphone apps offers a promising solution to these implementation and access barriers, particularly in LMIC regions, such as Sub-Saharan Africa, where mobile phone penetration is rapidly increasing (World Bank Group, 2024). The success of mobile health interventions in delivering health care services in Sub-Saharan Africa (Bervell & Al-Samarraie, 2019) and improving health outcomes across LMICs (Fu et al., 2020; Marcolino et al., 2018) further supports this potential. However, systematic reviews (Baumel et al., 2016; Corralejo & Domenech Rodríguez, 2018; Florean et al., 2020; Flujas-Contreras et al., 2019; Hansen et al., 2019; Spencer et al., 2020; Thongseiratch et al., 2020) show that digital parenting research is almost exclusively concentrated in high-income countries (HICs), with interventions predominantly focusing on child behavior management rather than violence prevention. Moreover, these interventions typically experience poor participant engagement (Haine-Schlagel et al., 2022), defined as both the extent of program usage (e.g., amount, frequency, duration, and depth) and subjective user experience (e.g., attention, interest, and affect) (Perski et al., 2017).

Poor engagement undermines an intervention's impact at both individual and population levels. At the individual level, participants fail to acquire essential skills needed to prevent VAC and improve child well-being, while at the population level, governments and policy makers are unlikely to implement programs widely when only a small proportion of participants engage with and benefit from them (Sim et al., 2022). Consequently, poor engagement severely limits the potential public health impact of digital parenting interventions (Hall & Bierman, 2015; MacDonell & Prinz, 2017). Understanding and optimizing engagement in LMIC contexts is thus critical for establishing digital parenting interventions as a scalable violence prevention strategy.

Existing studies examining engagement with digital parenting interventions in HICs have largely been descriptive (e.g., Brager et al., 2021; Breitenstein et al., 2017) or focus on sociodemographic and behavioral characteristics associated with engagement (e.g., Baker & Sanders, 2017; Dadds et al., 2019; Fossum et al., 2018; Perrino et al., 2018). A recent review of technology-assisted parenting interventions has advanced this literature by identifying several potential engagement-promoting components, including practical technology support, interactive program features, tailoring, and control features (Aldridge et al., 2024). Similar components have been identified across the broader mobile health literature, such as personalized content and feedback (Jakob et al., 2022; Oakley-Girvan et al., 2022; Szinay et al., 2020), user-friendliness (Baumel & Kane, 2018), a visually appealing layout and the integration of a tutorial on how to use the app (Jakob et al., 2022), human guidance (Baumeister et al., 2014; Borghouts et al., 2021; Leung et al., 2022), peer-based asynchronous communication features (Elaheebocus et al., 2018), and reminders (Alkhaldi et al., 2016; Jakob et al., 2022; Perski et al., 2017). However, experimental evidence for these components remains limited; to date, only one known trial has experimentally evaluated engagement strategies for digital parenting interventions (Asher et al., 2022), with no such trials conducted in LMICs. This gap is particularly significant given that digital interventions and their delivery strategies comprise multiple components, each with potentially different effects on engagement. Furthermore, findings from HICs may not generalize to LMIC settings, such as Tanzania, where technological infrastructure, digital literacy, and cultural contexts differ substantially.

6.2.1 Objectives

In response to the need for scalable violence prevention in LMICs, the Global Parenting Initiative, a five-year research-within-implementation collaboration between universities, foundations, and implementing partners, is developing and evaluating open-source digital parenting programs based on the Parenting for Lifelong Health (PLH) intervention suite. One of these interventions is ParentApp, a smartphone app designed to address adolescent exposure to VAC. Using the Multiphase Optimization Strategy (MOST) framework (Collins, 2018) for systematic intervention optimization, we conducted a cluster-randomized factorial trial to identify optimal components for maximizing engagement with ParentApp among socioeconomically disadvantaged caregivers of adolescents in Tanzania. The trial examined three factors: *guidance, app design*, and *digital support*. Our primary objective was to determine the independent effects of these factors on primary and secondary engagement outcomes. An exploratory objective was to identify potential interaction effects between the factors.

6.3 Methods

6.3.1 Trial Design

The trial used a cluster-randomized factorial design with three experimental factors: (1) *guidance* (self-guided or guided; factor A), (2) *app design* (structured or unstructured; factor B), and (3) *digital support* (basic or enhanced; factor C). Each factor was varied at two levels (lower dose or inactive vs higher dose or active), yielding an eight-condition (2×2×2) trial. A full factorial design was used, allowing all clusters to potentially be randomized to all combinations of factors and their corresponding levels. Further details on the study design are provided in the published protocol (Janowski et al., 2023). The trial was preregistered on the Pan-African Clinical Trial Registry (PACTR202210657553944) on October 11, 2022. The CONSORT (Consolidated Standards of Reporting Trials) 2010 extension for randomized factorial trials (Kahan et al., 2023) and the CONSORT-EHEALTH (Consolidated Standards of Reporting Trials of Electronic and Mobile Health Applications and Online Telehealth) checklist (Eysenbach & CONSORT-EHEALTH Group, 2011) were used for reporting. The completed CONSORT-EHEALTH checklist can be accessed in Appendix 5, Supplementary File 2.

6.3.2 Setting and Participants

Target communities were urban and peri-urban sub-wards characterized by high rates of poverty in the Mwanza region, Tanzania. Eligible clusters were sub-wards that (1) were located within three selected low-income wards, (2) had no previous involvement in ParentApp testing, and (3) contained at least 40 smartphone-owning households. Within each cluster, participants were primary caregivers of at least one adolescent aged 10 to 17 years. Caregivers were eligible if they (1) were aged ≥18 years, (2) lived in the same household as their adolescent for at least four nights per week in the previous month, (3) had regular access to an Android smartphone, and (4) provided written informed consent. Participants were excluded from the study if they were unable to read or had a severe learning disability that affected their ability to provide informed consent.

6.3.3 Recruitment, Enrollment, and App Onboarding

Following a two-week community mapping period conducted by Tanzania's National Institute for Medical Research (NIMR) in October 2022, the fieldwork team, in collaboration with Tanzania-based nongovernmental organization (NGO) Investing in Children and Strengthening Their Societies (ICS), initiated recruitment procedures in three low-income wards. Centralized stakeholder meetings were held in two wards, while in the third ward, sub-ward-level consultations took place due to logistical constraints. A total of 31 community leaders, including ward executive officers, community development officers, and local representatives, were briefed about the study. Those who agreed to support the study were tasked with identifying and contacting potential eligible families within their respective sub-wards over an eight-week recruitment period. Community leaders invited interested families to attend orientation and onboarding sessions.

These sessions were organized by study cluster and held at accessible locations, such as schools and community centers. Sessions were co-facilitated by NIMR research assistants and ICS facilitators. Families first attended a group orientation where they received detailed information about the program objectives, study procedures, data collection requirements, and time commitments. Research assistants then conducted eligibility screening using an Open Data Kit checklist. Written informed consent was obtained from caregivers who met all eligibility criteria. The subsequent app onboarding lasted approximately 90 minutes and was conducted in small groups. This included guided assistance with app installation via Google

Play (Google LLC), technical troubleshooting, and an orientation to app features. Facilitators demonstrated key functionalities, such as module navigation, activity completion, and resource access. Participants then practiced these skills by completing the app's first module.

6.3.4 Intervention

ParentApp is a smartphone app adapted from PLH Teens, an in-person, group-based program originally developed in South Africa to address the need for cost-effective, culturally appropriate violence prevention (Cluver et al., 2018). Initial evaluations of PLH Teens demonstrated significant improvements in positive parenting practices, along with reductions in child maltreatment, parental depression, stress, substance use, and financial stress (Cluver et al., 2018). PLH Teens has since been adapted and widely implemented across >18 LMICs (Shenderovich, Ward, et al., 2020), including a large-scale delivery in Tanzania to >75,000 caregivers and adolescents (Lachman, Wamoyi, et al., 2024).

Building on this strong, emerging evidence, ParentApp was developed to address access and scalability challenges associated with in-person delivery. Its development and delivery in Tanzania were jointly led by the Universities of Oxford and Cape Town; PLH; Innovations in Development, Education and the Mathematical Sciences; Clowns Without Borders South Africa; NIMR; and ICS, in collaboration with the United Nations Children's Fund, the World Health Organization, and the Tanzanian National Government. The intervention content is described in accordance with the TIDieR (Template for Intervention Description and Replication) checklist (Appendix 5, Supplementary File 3 and 4).

ParentApp Development

ParentApp underwent systematic development through four phases: (1) initial adaptation and co-development with researchers, program specialists, technical experts, and PLH Teens participants in South Africa; (2) user testing with 24 participants across nine countries (Awah et al., 2022); (3) feasibility testing of self-guided delivery with 107 caregivers in South Africa; and (4) pre-and post-pilot testing with 103 caregiver-adolescent dyads in Tanzania, which included remote guidance via phone calls or WhatsApp (Meta Platforms, Inc). Iterative refinements to content, design, and delivery approach across these phases produced the version evaluated in this trial.

ParentApp Design and Content

ParentApp is an open-source Android app (compatible with version 5.5.1 or later) comprising 12 modules that integrate text, images, and audio to deliver a condensed version of the in-person program (Table 3). The introductory module focuses on parental self-care and stress reduction, concluding with a welcome survey that collects baseline data and enables users to select their preferred delivery format (individual or group) and engagement schedule. The core intervention consists of 10 modules covering evidence-based practices shown to effectively reduce harsh and abusive parenting (Cluver et al., 2018). A final module consolidates learning and includes a post-intervention assessment.

Each module uses recurring activities to reinforce learning and practical skill building. Modules begin with mindfulness activities featuring emotional check-ins and relaxation exercises, followed by comics that illustrate positive and negative caregiver-adolescent scenarios with reflection questions. Audio testimonials from Tanzanian parents share benefits and experiences, while “Essential Tools” summaries provide quick access to key skills and examples. Modules conclude with home practice assignments that include structured activities and a follow-up “Home Practice Review” for activity reflection. Throughout the app, users can log their skill implementation through “ParentPoints,” a behavioral tracking system for monitoring 10 evidence-based practices that promote positive parenting and mental health.

Beyond module activities, users have access to a library with essential parenting tips, local support resources, and technical support. To encourage ongoing engagement, automated push notifications are triggered at 1, 6, and 30 days following the user's last app launch.

Table 3. *ParentApp module content and learning objectives*

Module	Core skills and objectives	Home practice
1. Parental self-care and stress reduction	Developing essential mental and physical well-being skills to strengthen parents' capacity to support their families	Practice daily relaxation techniques, identify moments of achievement, and reward successes.
2. One-on-one time	Spending meaningful time with adolescents, using active listening to foster trust, communication, and positive relationships	Schedule and spend 5 to 20 min of focused time with adolescents daily.
3. Praise and positive reinforcement	Using effective praise techniques to encourage positive behavior in adolescents	Practice praising adolescents daily.
4. Positive instructions	Providing clear, specific, and positive directions to improve communication and cooperation	Use positive instructions with adolescents daily.
5. Managing stress	Enhancing emotional awareness and communication skills to support mental well-being and reduce the risk of violent reactions during challenging situations	Practice breathing exercises before reacting.
6. Family budgeting	Identifying strategies for managing and saving money to reduce financial stress and establish achievable family goals	Create a budget with adolescents and other family members.
7. Establishing rules and routines	Engaging adolescents in establishing household rules and routines to foster compliance and build a safe, supportive, and consistent home environment	Practice making rules together with adolescents.
8. Consequences and accepting responsibility	Promoting shared parent-adolescent responsibilities; applying realistic, appropriate consequences for noncompliance; and emphasizing positive discipline over punitive measures	Discuss negative and positive consequences with adolescents.
9. Problem-solving	Building family collaboration skills to identify, address, and resolve challenges through joint problem-solving	Teach adolescents 4-step problem-solving: know it, solve it, try it, and test it.
10. Teen safety in the community and online	Mapping risks in community and web-based environments to establish protective rules for adolescents	Map safe and unsafe spaces with adolescents and create a family safety plan.
11. Dealing with crisis	Remaining calm in crisis situations and developing immediate and long-term plans to respond effectively, using available support services	Discuss crisis scenarios with adolescents and create family crisis response plans.
12. Celebration and next steps	Reflecting on key learning and solidifying plans for ongoing peer support	Review key skills learned.

Note. Modules 2 to 11 include home practice assignments with follow-up reviews for activity reflection.

6.3.5 Experimental Factors

Table 4 presents an overview of the core features associated with each factor level. Justification for the selection of factors is also provided in the published protocol (Janowski et al., 2023).

Factor A: Guidance (Self-guided or Guided)

During formative testing, WhatsApp groups showed promise for enhancing app-based delivery. In this trial, half of the clusters received no human support after app onboarding, while the remaining half received guidance via facilitator-moderated WhatsApp groups. The purpose of these groups was to promote social connection and sustain engagement with ParentApp. Each cluster in the guided condition had a corresponding WhatsApp group, overseen by a female-male facilitator pair (8 groups and 4 facilitator pairs). Following a standardized manual, facilitators shared tips and reminders, monitored discussions, addressed questions, and led weekly 1-hour live-chat sessions to encourage discussion and reflection. The facilitators, who were locally recruited paraprofessionals with previous experience supporting caregivers remotely during the Tanzanian pilot, received training from Clowns Without Borders South Africa, an NGO experienced in training PLH program facilitators.

Factor B: App Design (Structured or Unstructured)

ParentApp was originally designed with a sequential progression to match PLH Teens' learning objectives and time frame. The original design also featured generic blue cartoon characters intentionally designed to facilitate global implementation. However, early testing highlighted that some participants found the fixed weekly module releases limiting, while others questioned the acceptability of the generic illustrations. In response, this trial evaluated two versions of the app's design (refer to Figures 7 and 8 for screenshot examples).

Half of the clusters received the structured design, which maintained sequential module delivery at seven-day intervals over 12 weeks. This version included automated content notifications aligned with module releases, scheduled unlocking of home practice reviews for modules 2 to 11 at the end of each seven-day cycle, and the original generic illustrations. The remaining clusters received the unstructured design, which offered immediate access to all modules and activities after installation. This version incorporated several modifications: users could navigate the 12 modules at their own pace and in their preferred sequence; modules were subdivided into shorter tasks for easier navigation, with home practice review as the final task for modules 2 to 11; automated content notifications were disabled to accommodate flexible access; and generic cartoon images were replaced with culturally adapted illustrations featuring humanlike characters tailored to the Tanzanian context.

Factor C: Digital Support (Basic or Enhanced)

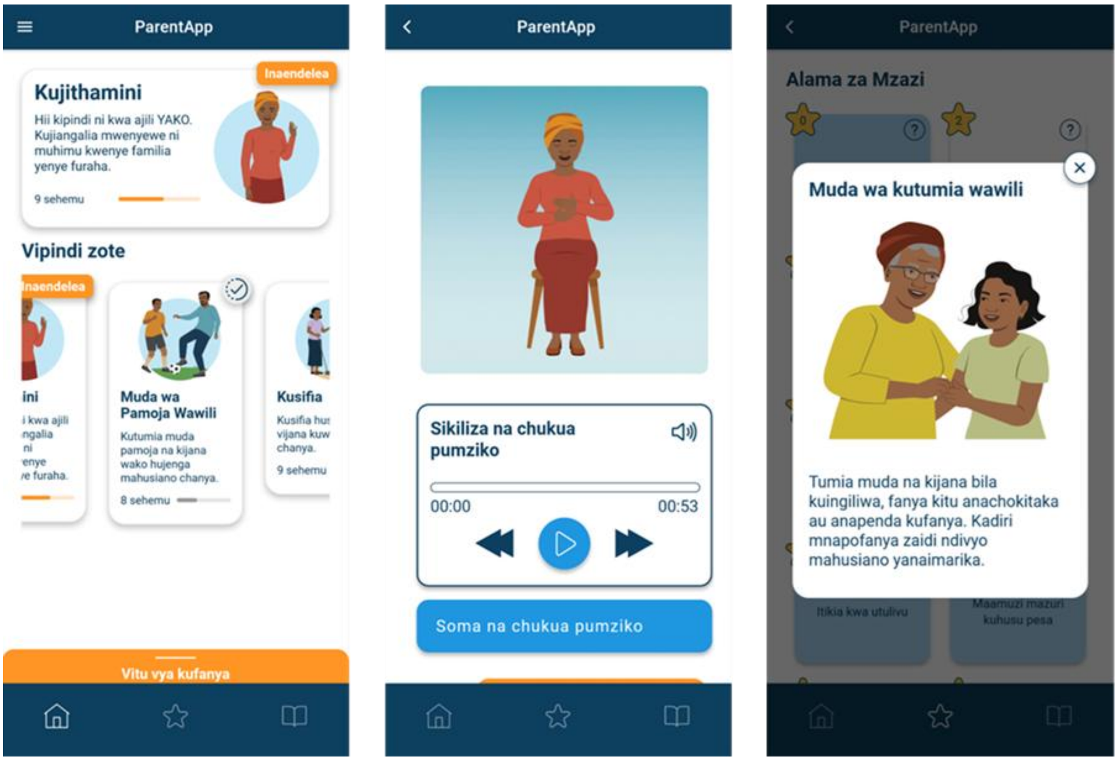
During formative testing, digital literacy challenges emerged as a critical consideration for app engagement. Consequently, this trial evaluated two levels of digital support during the onboarding session. Basic support, offered to all clusters, included an embedded ParentApp navigation tour followed by a group-based orientation of the app with demonstrations and practice opportunities. Half of the clusters received enhanced support, which included an additional 15- to 20-minute session focused on improving general smartphone literacy and user confidence. The training covered essential smartphone skills, including app installation, effective internet use, and web-based safety, and was delivered by research assistants at the end of the onboarding session. Both levels of digital support were optional.

Table 4. *Experimental factors, levels, and their core features*

Factor	Description	Core features
Guidance		
Self-guided	Participants accessed ParentApp's full content throughout the study.	• ParentApp without human support
Guided	Participants accessed ParentApp's full content throughout the study and received WhatsApp group guidance.	• ParentApp • WhatsApp groups moderated by 1 lead facilitator and 1 cofacilitator • Facilitators monitored discussions and shared tips and reminders • Facilitators led a weekly 1-hour live-chat session per group
App design		
Structured	ParentApp content followed a sequential, weekly format.	• 12 modules • First module available immediately, with 1 new module unlocked every 7 days • Sequential module order • Content-related notifications • Images featuring generic blue amorphous cartoon characters
Unstructured	ParentApp content followed an open, nonsequential format.	• 12 modules • All modules available immediately • Nonsequential module order • Modules divided into shorter tasks and activities • Content-related notifications disabled • Culturally adapted images featuring humanlike figures
Digital support		
Basic	Participants received an in-app navigation tour at first app launch, followed by a group-based orientation of the app.	• Brief built-in app navigation tour showing core app features • Group orientation on core features led by trained research assistants
Enhanced	Participants received an in-app navigation tour at first app launch, followed by a group-based orientation of the app and a supplementary training session focusing on broader smartphone skills.	• Brief built-in app navigation tour showing core app features • Group orientation on core features led by trained research assistants • Supplementary group training (15 to 20 min) on general smartphone skills led by trained research assistants

Figure 7. *Screenshot examples of the structured app design*

Figure 8. *Screenshot examples of the unstructured app design*



6.3.6 Measures and Assessment

Engagement data were collected through automated tracking each time a participant interacted with ParentApp. Use records, including module completion rates, content viewing patterns, and responses to in-app tasks and the baseline assessment, were uploaded to a Metabase cloud server (Metabase, Inc) whenever a device accessed the internet. Additional use data were automatically captured through Matomo Analytics (InnoCraft Ltd), including visit timestamps, session duration, and the frequency of actions or pages viewed. Data monitoring protocols were implemented to ensure accurate tracking and verify that participants received the correct app version based on their cluster allocation. The final dataset was extracted from Metabase and Matomo Analytics in March 2023, approximately four months after the last cluster of participants enrolled in the study. Research assistants and facilitators reported estimated attendance rates and session durations for the enhanced digital support training and WhatsApp live-chat sessions, respectively.

Primary Outcomes

Three primary engagement outcomes were evaluated: (1) the number of *app launches* throughout the intervention period, (2) the number of *modules completed* out of 12, and (3) the number of *home practice activities reviewed* out of 10. The home practice review outcome underwent a post hoc modification from the protocol, evaluating user initiation of post-activity reviews rather than access to the home practice tab for activity instructions.

Secondary Outcomes

Secondary engagement outcomes included (1) the number of *modules started* out of 12, (2) the total *time spent in the app* during the intervention period, and (3) the number of self-reported *positive parenting and mental health–promoting behaviors logged* throughout the intervention period.

Baseline Sociodemographic and Behavioral Measures

Baseline demographic and behavioral data were collected using a self-administered questionnaire embedded within the app's welcome survey in the first module. The questionnaire included multiple response formats: demographic questions primarily used binary choice buttons (e.g., gender: woman or man) or number entry fields (e.g., age), while behavioral measures used frequency scales. Participants could navigate between pages to review and modify their responses, with the assessments taking approximately 10 to 15 minutes to complete. All behavioral measures were non-proprietary, freely available, and recommended by the Global Parenting Initiative. Given the trial's focus on engagement rather than caregiver outcomes, abbreviated scales were used to minimize participant burden. All measures were translated into Kiswahili and back translated and were previously used in Tanzania (Lachman, Wamoyi, et al., 2024).

Demographic variables included caregiver age and gender, household structure, orphanhood status, and 2 items adapted from the Financial Self-Efficacy Scale on financial stress and food insecurity (1 item each) (Lown, 2011). Child maltreatment was assessed using 4 items from the International Society for the Prevention of Child Abuse and Neglect Screening Tool-Trial Version (Meinck et al., 2018). This included subscales for physical abuse (2 items; e.g., "How many times in the past month did you hit, spank or slap your child with a hand or object?") and emotional abuse (2 items; e.g., "How many times in the past month did you shout, scream or yell at your child?"), rated on a 0 to ≥8 frequency scale. Positive parenting was measured using 5 items from the Alabama Parenting Questionnaire (Essau et al., 2006), assessing involvement (2 items; e.g., "How many times in the past month did you praise your teen?") and supervision (3 items; e.g., "How many times in the past month did your teen stay out past their curfew?"), rated on a 0 to ≥8 frequency scale. Parental depression was measured using 3 items from the Centre for Epidemiologic Studies Depression Scale (Irwin et al., 1999). Items were rated on a 0- to 7-day frequency scale (e.g., "How often did you feel that everything you did was an effort?"). Parenting stress was assessed using 1 item adapted from the Parental Stress Scale (Berry & Jones, 1995), "How many times in the past month did caring for your children make you feel very stressed?" rated on a 0 to ≥8 frequency scale.

6.3.7 Power

An a priori simulation–based power analysis determined that 640 caregivers across 16 clusters (40 per cluster) were needed for adequate statistical power (Janowski et al., 2023). This cluster size was selected for future scalability, as larger WhatsApp groups offer greater reach and cost-effectiveness. Simulations accounted for clustering at the sub-ward level, participant-level covariates, and an α level of .05.

6.3.8 Randomization

The factorial experiment was conducted at the cluster level for logistical efficiency, streamlining screening, enrollment, and baseline data collection for participants receiving the same experimental conditions. Community representatives compiled lists of potentially eligible families within their designated sub-wards. Fieldwork coordinators then formed clusters by grouping geographically proximate sub-wards to minimize the risk of cross contamination. An off-site research team member performed single-stage randomization, assigning each eligible cluster to one of the eight experimental condition combinations using a randomization algorithm in R software (R Foundation for Statistical Computing). Final cluster sizes ranged from 32 to 49 caregivers (*M* 38.38, *SD* 6.20).

6.3.9 Blinding

Blinding was not feasible for the in-country research team and facilitators due to their involvement in implementation. Participants were only informed about the experimental conditions to which their cluster was assigned. The data analyst was blinded to cluster allocation but not to condition assignment due to effect coding (Kugler et al., 2018).

6.3.10 Statistical Analysis

Analyses used generalized linear mixed-effects models with a Poisson distribution to estimate the impact of experimental factors on engagement. Models included a random intercept term to account for the nesting of participants within clusters. Intention-to-treat analyses were conducted but included only participants who successfully installed ParentApp, as data collection was contingent upon app installation. Supplementary analyses found no significant effect of cluster randomization to experimental conditions on app installation status (Appendix 5, Supplementary File 5, Table S1). Missingness in engagement outcomes was minimal, affecting only two variables: app launches (6/614, 1%) and time spent on the app (11/614, 1.8%). Multiple imputation with fully conditional specification (van Buuren et al., 2006) was used to address missingness in caregiver baseline data (5% to 7.5% at item level). A total of 10 imputations were conducted using predictive mean matching. Clustering was accounted for by specifying –2 in the predictor matrix. Imputation at the item level was passive, summing behavioral items to generate total scores within the imputation process. Following imputation, caregiver baseline data were sample-mean centered within each of the 10 imputed datasets. Analyses were conducted in R software (version 4.3.1), using the glmer function from the *lme4* package for generalized linear mixed-effects models (Bates et al., 2015), and imputations were performed using the *mice* package (van Buuren & Groothuis-Oudshoorn, 2011).

In primary analyses, each factor's individual effect on primary and secondary outcomes was evaluated separately. Models were adjusted for the prespecified covariates: caregiver age, caregiver gender, financial stress, food insecurity, child maltreatment (physical and emotional abuse), positive parenting involvement and supervision, parental depression, and parenting stress. In exploratory analyses, all three factors were included as main effects alongside their 2-way interactions, while adjusting for baseline characteristics. The inclusion of interaction terms followed recent recommendations for factorial designs to account for potential interdependencies between factors (Muralidharan et al., 2023). All main and 2-way interaction effects were estimated using the full sample. Assuming similar effect sizes, this provided equally high power to detect all effects (Collins, 2018). Estimates for each model were pooled across the 10 imputed datasets using Rubin's rules (van Buuren & Groothuis-Oudshoorn, 2011).

Factors were effect-coded, assigning –1 to inactive or lower-dose levels and 1 to active or higher-dose levels (Appendix 5, Supplementary File 6). This coding scheme calculates the difference between levels as (+1 – [–1] = 2), whereas with dummy codes, it is simply (1 – 0 = 1) (Kugler et al., 2018). To ensure an accurate representation of the effect of a 1-unit change in the predictor variable within the effect coding scheme, unstandardized regression coefficients and their SEs were multiplied by a scaling constant of 2. Poisson regression coefficients (which represent the log of the expected change in the outcome per 1-unit increase in the predictor while holding other variables constant) and 95% CIs were exponentiated for easier interpretation. The main effects were interpreted as the ratio of mean event counts or mean ratio (MR), comparing participants in clusters randomized to the higher-dose factor level to those randomized to the contrasting factor level. Interaction terms were interpreted as the additional effect of one factor level in the presence of another.

6.3.11 Ethical Considerations

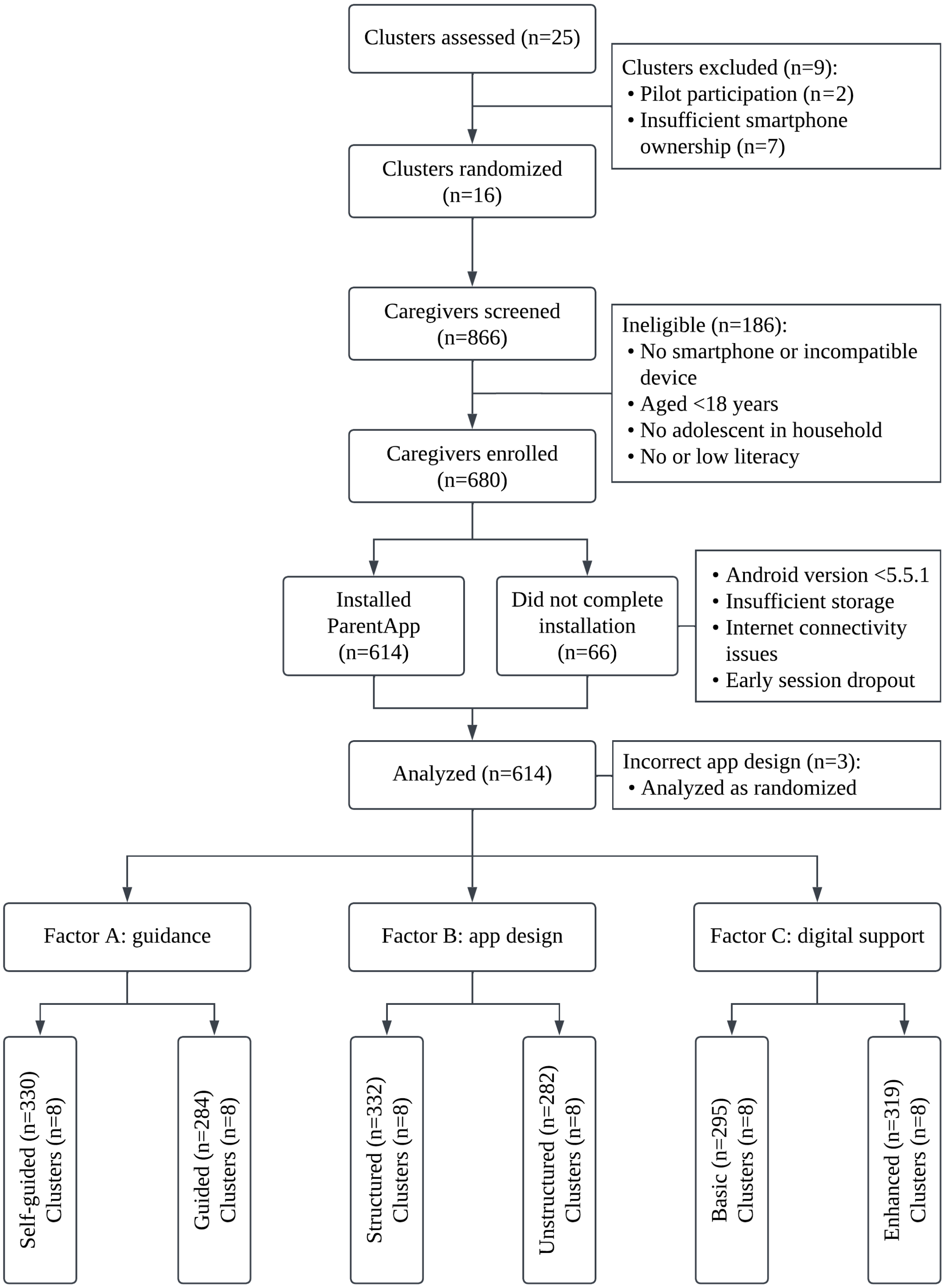
Ethics approval was granted by NIMR (NIMR/HQ/R.8s/Vol.IX/3856) and the University of Oxford Departmental Research Ethics Committee (R69744/RE001). Written informed consent was obtained from all study participants at the onboarding session. Participants also accepted the app's terms and conditions and privacy policy, which detailed how personal information from ParentApp would be collected, used, and shared. After completing the onboarding session, participants received a US $2 honorarium and monthly 1 GB internet bundles for four months to support data synchronization with study servers and WhatsApp group participation where applicable. No additional incentives or compensation were provided.

6.4 Results

6.4.1 Participant Flow

Participant recruitment and onboarding activities began on October 24, 2022, and concluded on December 1, 2022, coinciding with Tanzania's short rainy season. Of 866 caregivers screened for eligibility, 680 (78.5%) met the inclusion criteria and consented to participate. Among enrolled participants, 66 (9.7%) did not complete app installation due to technical difficulties, including phone-to-app incompatibility, insufficient storage capacity, and internet instability, while others left the onboarding session prematurely due to poor weather conditions and scheduling conflicts. The final sample included 614 participants (90.3% of those enrolled) who successfully installed the app, all of whom were included in intention-to-treat analyses. A CONSORT diagram illustrating participant flow through the study is presented in Figure 9.

Figure 9. *Consolidated Standards of Reporting Trials (CONSORT) diagram*



6.4.2 Participant Characteristics

Participant baseline characteristics, summarized in Table 5, showed a comparable distribution across the three factors' levels and the overall sample. Caregiver age ranged from 18 to 75 (*M* 35.94, *SD* 11.84) years. One-third (205/614, 33.4%) of the caregivers were men, which is notable given the challenges parenting programs typically face in engaging fathers (Panter-Brick et al., 2014). Households comprised an average of 3 (*SD* 1.80) adults and 3.61 (*SD* 2.12) children aged between 0 and 17 years. Most caregivers (485/576, 84.2%) reported experiencing food insecurity at least once in the past month, with 35.1% (202/576) reporting ≥7 instances during this period. Nearly half (276/576, 47.9%) of the sample reported that their adolescents had experienced the loss of a primary caregiver during their lifetime. Among these, 72.1% (199/276) reported that the death had occurred within the past three years, a trend likely influenced by the COVID-19 pandemic.

Table 5. *Baseline characteristics for the full sample and for each factor level*

Characteristic	Total[a]	Factor A: guidance		Factor B: app design		Factor C: digital support	
		Self-guided	Guided	Structured	Unstructured	Basic	Enhanced
Caregiver, n	n=577	n=307	n=270	n=307	n=268	n=281	n=296
Age (y), mean (SD)	35.94 (11.84)	35.83 (12.09)	36.07 (11.56)	37.16 (11.54)	34.54 (12.04)	36.35 (11.67)	35.55 (12.00)
Gender[b]	n=614	n=330	n=284	n=332	n=282	n=295	n=319
Women, n (%)	409 (66.6)	217 (65.8)	192 (67.6)	244 (73.5)	165 (58.5)	193 (65.4)	216 (67.7)
Men, n (%)	205 (33.4)	113 (34.2)	92 (32.4)	88 (26.5)	117 (41.5)	102 (34.6)	103 (32.3)
Household size[c]	n=580	n=310	n=270	n=313	n=267	n=281	n=299
Overall, mean (SD)	6.60 (3.23)	6.55 (3.53)	6.66 (2.85)	6.70 (3.46)	6.48 (2.95)	6.46 (3.16)	6.73 (3.30)
Adults, mean (SD)	2.99 (1.80)	3.04 (1.99)	2.94 (1.57)	3.06 (2.04)	2.91 (1.49)	2.9 (1.71)	3.05 (1.89)
Children (aged 0-17 y), mean (SD)	3.61 (2.12)	3.51 (2.29)	3.72 (1.90)	3.64 (2.16)	3.57 (2.07)	3.53 (2.16)	3.68 (2.08)
Food insecurity	n=576	n=310	n=266	n=308	n=268	n=277	n=299
≥1 day in the past month, n (%)	485 (84.2)	267 (86.1)	218 (82)	258 (83.8)	227 (84.7)	235 (84.8)	250 (83.6)
≥7 days in the past month, n (%)	202 (35.1)	113 (36.5)	89 (33.5)	108 (35.1)	94 (35.1)	103 (37.2)	99 (33.1)
Orphanhood[d]	n=576	n=308	n=268	n=306	n=270	n=277	n=299
Lifetime, n (%)	276 (47.9)	160 (51.9)	116 (43.3)	153 (50)	123 (45.6)	137 (49.5)	139 (46.5)
Past 3 years, n (%)	199 (72.1)	117 (73.1)	82 (70.7)	108 (70.6)	91 (74)	95 (69.3)	104 (74.8)

Note. [a]Sample sizes vary due to item nonresponse. [b]Missing caregiver gender data were supplemented with information from the screening questionnaires, resulting in 614 complete observations. [c]Cases missing all household size data were excluded from the analysis. [d]Past 3-year orphanhood percentages were calculated using lifetime orphanhood as the denominator.

6.4.3 Intervention Exposure and Engagement

Exposure

Among the 614 participants who successfully installed the app, 600 (97.7%) engaged with at least some of the module content throughout the study, while 14 (2.3%) did not access any content. On average, participants visited the app 3.69 (*SD* 4.73) times, where a visit was defined as either the initial app launch or visiting a page after a 30-minute interval since the last page view. Each visit involved approximately 20.75 (*SD* 17.10) actions or page views, totaling 63.81 (*SD* 85.54) actions on average throughout the study.

For the guidance factor, 53.7% (330/614) of the participants were in self-guided clusters, while 46.2% (284/614) were in clusters allocated to WhatsApp groups. WhatsApp groups averaged 35.5 (*SD* 6.03) caregivers per group. Half (4/8, 50%) of the WhatsApp groups experienced delayed initiation due to rolling recruitment and the December 2022 Christmas break, with two groups postponed until January 2023. These delays likely contributed to participant attrition from the groups. Facilitators reported moderate WhatsApp message participation, but live-chat engagement was low, with attendance ranging from 1 to 16 participants per session (*M* 2, *SD* 2.65).

For the app design factor, 54.1% (332/614) of the participants were in clusters allocated to the structured design and 45.9% (282/614) were in clusters allocated to the unstructured design. Research assistants activated the assigned design on participants' phones based on their respective cluster. In 4 cases, the structured design was mistakenly activated; 3 of these participants did not respond to follow-ups and were treated as randomized in the analyses.

For the digital support factor, clusters assigned to basic support included 48% (295/614) of the participants, and enhanced support 52% (319/614). Given that participation was optional, attendance was not systematically recorded. Research assistants and fieldwork coordinators estimated that 67.1% (214/319) of the participants in enhanced support clusters attended training sessions. Nonattendance was primarily attributed to scheduling conflicts. Session duration varied, lasting anywhere from 5 to 20 minutes, depending on the group size and the number of questions asked.

Engagement

Table 6 summarizes the raw mean comparison of engagement outcomes for the entire sample and each factor level. Module completion rates among the 614 participants who successfully installed ParentApp were as follows: 38.4% (n=236) completed at least 25% (3/12) of the modules, 21.5% (n = 132) completed at least 50% (6/12) of the modules, 13.8% (n = 85) completed at least 75% (9/12) of the modules, and 8% (n = 49) completed 100% (12/12) of the modules. Among the 600 participants who engaged with some module content, the average content completion rate across all 12 modules was 35.57% (*SD* 33.10%). This rate varied by factor levels: *guidance* (self-guided: *M* 32.8%, *SD* 31.34% vs guided: *M* 38.7%, *SD* 34.79%), *app design* (structured: *M* 34.6%, *SD* 31.73% vs unstructured: *M* 36.7%, *SD* 34.65%), and *digital support* (basic: *M* 34.3%, *SD* 32.48% vs enhanced: *M* 36.8%, *SD* 33.69%). For participants who started at least one module, survival analysis estimated a median retention time of 31 days (95% CI 25-36) from enrollment to last synchronization with the cloud server.

Table 6. *Mean comparison of outcomes for entire sample and for each factor level*

Outcome	Total	Factor A: guidance		Factor B: app design		Factor C: digital support	
		Self-guided (n=330)	Guided (n=284)	Structured (n=332)	Unstructured (n=282)	Basic (n=295)	Enhanced (n=319)
Primary engagement outcomes, mean (SD)							
App launches[a]	17.00 (22.59)	15.87 (20.93)	20.44 (24.18)	20.62 (26.81)	14.91 (15.86)	17.82 (23.67)	18.13 (21.56)
Modules completed[b]	3.40 (3.64)	3.09 (3.41)	3.77 (3.85)	2.91 (3.04)	3.99 (4.16)	3.26 (3.51)	3.54 (3.75)
Activity reviews[c]	1.62 (3.02)	1.39 (2.75)	1.88 (3.30)	0.49 (1.33)	2.95 (3.82)	1.48 (2.90)	1.74 (3.13)
Secondary engagement outcomes, mean (SD)							
Modules started[d]	4.57 (4.13)	4.22 (3.92)	4.99 (4.33)	4.34 (4.03)	4.84 (4.23)	4.43 (4.04)	4.71 (4.21)
Time spent in the app (min)[e]	54.99 (52.48)	48.79 (43.33)	62.22 (60.77)	51.46 (51.54)	59.19 (53.37)	53.39 (48.88)	56.49 (55.71)
Positive behavior logs[f]	38.96 (104.07)	30.70 (75.52)	48.56 (129.06)	32.35 (66.25)	46.74 (135.44)	32.67 (89.18)	44.78 (115.99)

Note. [a]Total app launches during the intervention period. [b]Number of completed modules (0 to 12). [c]Number of home practice activities reviewed (0 to 10). [d]Number of modules started (0 to 12). [e]Total minutes spent in the app. [f]Number of self-reported positive parenting and mental health–promoting behaviors logged.

6.4.4 Factor Effects on Primary and Secondary Outcomes

The main effect results for primary and secondary outcomes by factor are provided in Table 7. Following adjustments for baseline characteristics, caregivers who received WhatsApp group guidance in combination with ParentApp demonstrated significantly higher levels of engagement compared to those who were self-guided. Guided caregivers launched the app 2.93 times more (95% CI 1.84-4.68; $p < .001$), completed 1.29 times more modules (95% CI 1.05-1.58; $p = .02$), started 1.20 times more modules (95% CI 1.02-1.42; $p = .03$), spent 1.45 times more time in the app (95% CI 1.39-1.51; $p < .001$), and logged positive behaviors 2.73 times more frequently (95% CI 2.07-3.60; $p < .001$) than self-guided participants. Although guided caregivers initiated more home practice activity reviews compared to those who were self-guided, this difference was not statically significant (MR 2.17, 95% CI 0.84-5.63; $p = .11$).

The unstructured app design significantly outperformed the structured app design across all but one engagement outcome. App launch frequency did not differ significantly between designs (MR 0.88, 95% CI 0.70-1.11; $p = .28$). However, caregivers using the unstructured design completed 1.49 times more modules (95% CI 1.26-1.76; $p < .001$), initiated 7.49 times more home practice activity reviews (95% CI 5.19-10.82; $p < .001$), started 1.27 times more modules (95% CI 1.06-1.52; $p = .01$), and spent 1.84 times more time in the app (95% CI 1.70-1.99; $p < .001$) compared to those using the structured design. Notably, users of the unstructured design also logged 55.68 times more positive behaviors (95% CI 16.47-188.27; $p < .001$) compared to those using the structured design. A sensitivity analysis was conducted to address potential biases arising from extreme values in the positive behavior logs outcome (range 0-1342), where 10.4% (64/614) of the sample logged values exceeding 80 (deemed excessive in the study context). Models were rerun with positive behavior logs capped at 80. The results remained consistent with the original analyses (Appendix 5, Supplementary File 5, Table S2).

For the digital support factor, although enhanced support showed higher average engagement levels than basic support, these differences were not statistically significant (app launches: MR 1.01, 95% CI 0.79-1.27; p = .97; modules completed: MR 1.09, 95% CI 0.87-1.36; p = .45; home practice activity reviews: MR 1.15, 95% CI 0.39-3.34; p = .80; modules started: MR 1.06, 95% CI 0.88-1.27; p = .53; time spent in the app: MR 1.07, 95% CI 0.87-1.30; p = .53; and positive behavior logs: MR 1.44, 95% CI 0.82-2.54; p = .21).

Table 7. *Main effects of factors on engagement: Unadjusted and adjusted results*

Factor level and outcomes	Unadjusted		Adjusted[a]	
	MR[b] (95% CI)	*p*	MR (95% CI)	*p*
Guided versus self-guided				
App launches	2.90 (1.85-4.54)	<.001	2.93 (1.84-4.68)	<.001
Modules completed	1.29 (1.06-1.57)	.01	1.29 (1.05-1.58)	.02
Activity reviews	2.23 (0.89-5.59)	.09	2.17 (0.84-5.63)	.11
Modules started	1.23 (1.04-1.46)	.02	1.20 (1.02-1.42)	.03
Time spent in the app	1.48 (1.44-1.52)	<.001	1.45 (1.39-1.51)	<.001
Positive behavior logs	2.65 (2.03-3.45)	<.001	2.73 (2.07-3.60)	<.001
Unstructured versus structured				
App launches	0.87 (0.69-1.10)	.25	0.88 (0.70-1.11)	.28
Modules completed	1.45 (1.23-1.72)	<.001	1.49 (1.26-1.76)	<.001
Activity reviews	6.84 (4.73-9.73)	<.001	7.49 (5.19-10.82)	<.001
Modules started	1.24 (1.02-1.51)	.03	1.27 (1.06-1.52)	.01
Time spent in the app	1.72 (1.67-1.77)	<.001	1.84 (1.70-1.99)	<.001
Positive behavior logs	53.48 (17.44-164.03)	<.001	55.68 (16.47-188.27)	<.001
Enhanced versus basic				
App launches	1.02 (0.78-1.32)	.91	1.01 (0.79-1.27)	.97
Modules completed	1.09 (0.88-1.36)	.42	1.09 (0.87-1.36)	.45
Activity reviews	1.15 (0.41-3.24)	.79	1.15 (0.39-3.34)	.80
Modules started	1.07 (0.88-1.29)	.51	1.06 (0.88-1.27)	.53
Time spent in the app	1.07 (0.87-1.30)	.53	1.07 (0.87-1.30)	.53
Positive behavior logs	1.39 (0.78-2.48)	.27	1.44 (0.82-2.54)	.21

Note. [a]Adjusted models included the following covariates: caregiver age, gender, financial stress, food insecurity, parenting stress, caregiver depression, overall child maltreatment, and overall positive parenting. All covariates were sample-mean centered. [b]MR: mean ratio: estimated effects calculated as MR = exp (2β), where β is the unstandardized regression coefficient derived from the effect-coded experimental factors.

6.4.5 Factor Interaction Effects on Primary and Secondary Outcomes

Table 8 shows the 2-way interaction effects. Although none of the factors showed significant main effects on app launches, a significant interaction between guidance and enhanced digital support (MR 1.69, 95% CI 1.06-2.71; $p = .04$) indicated that their combined effect positively influenced each other's impact on the number of times a participant launched the app. For modules completed, all three factors showed significant main effects. In addition, guidance and enhanced digital support showed a significant interaction (MR 1.17, 95% CI 1.07-1.28; $p < .001$), suggesting a mutual positive influence on the number of modules completed. In the model analyzing home practice activity reviews, guided and app design factors had significant main effects, while digital support did not. A significant interaction between guidance and the unstructured app design (MR 0.77, 95% CI 0.63-0.92; $p = .004$) indicated a decrease in activity reviews, while a significant interaction between guidance and enhanced digital support (MR 1.38, 95% CI 1.21-1.58; $p < .001$) indicated an increase in activity reviews.

Among secondary outcomes, the joint influence of guidance and enhanced digital support on modules started was significant (MR 1.24, 95% CI 1.11-1.38; $p < .001$), despite the digital support factor showing no significant main effect. Similarly, the unstructured design and enhanced digital support showed significant interaction effects for time spent in the app, despite neither factor individually showing significance. However, their combined effects were attenuated (MR 0.36, 95% CI 0.31-0.42; $p < .001$), suggesting that their synergy led to a reduction in participants' app use time.

Table 8. *Interaction effects of experimental factors on engagement: Adjusted results*

Outcome	Main effect						Interaction effect					
	Factor A[a]		Factor B[b]		Factor C[c]		A×B		A×C		B×C	
	MR[d] (95% CI)	*p*	MR (95% CI)	*p*	MR (95% CI)	*p*	MR (95% CI)	*p*	MR (95% CI)	*p*	MR (95% CI)	*p*
App launches	1.53 (0.96-2.44)	.09	0.96 (0.54-1.71)	.89	1.01 (0.74-1.37)	.94	0.96 (0.72-1.26)	.75	1.69 (1.06-2.71)	.04	0.84 (0.47-1.50)	.56
Modules completed	1.22 (1.12-1.33)	<.001	1.42 (1.30-1.56)	<.001	1.09 (1.00-1.19)	.049	1.02 (0.94-1.12)	.59	1.17 (1.07-1.28)	<.001	1.09 (1.00-1.19)	.05
Activity reviews	1.63 (1.36-1.96)	<.001	7.06 (5.87-8.48)	<.001	1.15 (0.97-1.37)	.11	0.77 (0.64-0.92)	.004	1.38 (1.21-1.58)	<.001	1.07 (0.90-1.28)	.43
Modules started	1.17 (1.05-1.30)	.004	1.20 (1.07-1.34)	.001	1.07 (0.96-1.19)	.23	0.97 (0.88-1.08)	.63	1.24 (1.11-1.38)	<.001	1.10 (0.99-1.22)	.09
Time spent in the app	1.59 (0.97-2.62)	.07	2.08 (1.37-3.16)	.001	1.07 (0.56-2.03)	.85	1.48 (0.98-2.24)	.06	1.36 (0.82-2.23)	.23	0.36 (0.31-0.42)	<.001
Positive behavior logs	1.32 (0.58-2.99)	.51	2.37 (1.13-4.98)	.02	1.10 (0.41-2.96)	.85	1.10 (0.55-2.20)	.78	1.13 (0.50-2.58)	.77	1.24 (0.58-2.65)	.58

Note. [a]WhatsApp group guided versus self-guided. [b]Unstructured app design versus structured app design. [c]Enhanced digital support versus basic digital support. [d]MR: mean ratio: estimated effects calculated as MR = exp (2β), where β is the unstandardized regression coefficients derived from the effect-coded experimental factors.

6.5 Discussion

6.5.1 Principal Findings

This is the first known factorial trial of a digital parenting intervention for families with adolescents in an LMIC. It follows MOST principles (Collins, 2018) to optimize engagement with an app targeting socioeconomically disadvantaged families in Tanzania. Findings offer important insights into engagement-enhancing intervention design and delivery strategies for digital parenting interventions tailored to the unique contexts and needs of LMIC settings.

Receiving guidance through moderated WhatsApp groups significantly increased participant engagement across a wide range of engagement metrics. Compared to self-guided participants, those in WhatsApp groups launched the app more frequently, started and completed more program modules, spent more time in the app, and logged more positive parenting and mental health behaviors. These findings align with meta-analytic research on mental health apps and the broader digital health literature, which consistently shows that interventions incorporating some form of human guidance yield higher engagement rates compared to self-guided interventions (Baumeister et al., 2014; Borghouts et al., 2021; Jakob et al., 2022; Leung et al., 2022; Szinay et al., 2020). However, our study advances this literature in two distinct ways. First, we directly compared self-guided and guided conditions within the same trial, whereas previous research has largely relied on cross-study comparisons (Baumeister et al., 2014; Borghouts et al., 2021; Leung et al., 2022). Second, we implemented a group-based guidance model rather than individual approaches (e.g., one-on-one phone consultations, videoconferencing, or email) commonly used in previous studies (Corralejo & Domenech Rodríguez, 2018). This shift toward a less resource-intensive delivery model enhances potential for future scalability.

The mechanisms through which human guidance facilitates engagement with digital interventions are not fully understood. One possible explanation is the role of the relationship quality between facilitators and participants (Probst et al., 2019). Alternatively, guided participants may feel an increased sense of accountability in the presence of a facilitator (Mohr et al., 2011). The group-based format may also be important, as it enables interaction among caregivers. For instance, this setting allows participants with shared experiences to offer emotional and informational support (Dennis, 2003) potentially enhancing engagement through social connection and community building. Indeed, a recent systematic review on peer-based features in digital interventions highlighted the importance of asynchronous communication features in supporting program engagement (Elaheebocus et al., 2018). In addition to peer support benefits, findings from a systematic review of digital mental health interventions suggest that peer-to-peer groups are particularly effective in promoting engagement and retention when moderated by trained professionals (Biagianti et al., 2018). Nevertheless, contact with facilitators or fellow participants may not be universally desirable or beneficial, as evidenced by participants who left WhatsApp groups prematurely in this study. These findings align with a systematic review showing that synchronous communication features, such as web-based video calls or chat rooms, were associated with reduced engagement (Elaheebocus et al., 2018). Understanding which participants benefit from group-based support remains a critical direction for future research.

The unstructured app design, which featured flexible content access and culturally adapted, humanlike illustrations, significantly increased engagement compared to the structured design. Participants using the unstructured design completed more program modules, initiated more home practice reviews, started more modules, spent more time in the app, and logged more positive behaviors compared to those using the structured design. These findings align with research showing that user experience design, including app navigation and appearance, influences motivation and engagement with digital interventions (Oakley-Girvan et al., 2022; Yardley et al., 2016b). However, as this study evaluated two app design packages rather than distinct components, it remains unclear which specific aspect of the unstructured design contributed to enhanced engagement. Future research would benefit from more granular testing and analysis of these design components to determine their individual impact. Enhanced engagement might be attributed to the flexible content progression, which allowed participants to move through the program at their preferred pace. Alternatively, increased engagement could reflect the greater relatability of culturally adapted images, which may have improved app acceptability among caregivers (Corralejo & Domenech Rodríguez, 2018) and consequently boosted motivation to engage. While developing a universal app with content tailored for low-income contexts aimed to enhance scalability and reduce adaptation costs, our findings suggest that scalability alone does not ensure acceptability. Culturally adapted visual elements may therefore be crucial in fostering engagement with digital interventions.

A notable finding was the significant increase in home practice activity reviews among participants using the unstructured design. While the reason for this increase remains unclear, it could be attributed to the modular format of the design, which allowed participants to access home practice reviews without waiting for the seven-day cycle to be completed. Given that home practice of program skills is a key mechanism linking program implementation to behavioral outcomes in parenting interventions (Berkel et al., 2018), including home practice engagement as an outcome is a study strength. However, the study does not establish a direct link between engaging in home practice reviews within the app and the actual application of these skills at home. Furthermore, this study only measured when participants initiated home practice reviews in the app, without capturing related measures such as self-reports of activity completion.

A surprising finding was the limited effectiveness of the digital support factor on engagement, which tended to have MRs close to 1 across most engagement outcomes. This suggests that augmenting app-specific assistance with general smartphone support may not yield additional benefits for participants. Unlike recent systematic reviews which assessed baseline digital literacy and its association with engagement (Borghouts et al., 2021; Jakob et al., 2022), our study experimentally examined the provision of pre-program digital support. This was an important implementation consideration given our target population's relatively low exposure to digital technology. While systematic reviews indicate that app literacy, defined as technological competency in using a smartphone app, is important for both uptake and engagement (Szinay et al., 2020; van Kessel et al., 2023), it is plausible that the basic digital support module in our study adequately contributed to participants' competency and perceived digital skills. Another potential reason could be that the enhanced digital training may have inadvertently reduced ParentApp engagement by introducing participants to competing apps and features, particularly among those with limited previous digital experience.

The impact of digital support on engagement might also have been influenced by various individual factors. The relatively young age of the sample (*M* 35.94, *SD* 11.84 years) and their previous smartphone ownership may suggest sufficient baseline digital literacy. Moderator analyses could reveal whether factors such as caregiver age and other demographic characteristics influenced the results. If digital support proves effective only for specific participants, tailoring the type and intensity of support to individuals would be advantageous. Furthermore, it is essential to highlight that both digital support trainings were optional. The fieldwork team reported that while attendance was high for the basic training, some participants allocated to the enhanced training left the onboarding session early to resume economic and caregiving responsibilities. This reduced exposure could have attenuated the effects of the enhanced training and warrants consideration when interpreting the results.

Interaction analyses found evidence that combining enhanced digital support with guidance led to increased engagement across four of the six measured outcomes. These interaction effects suggest the importance of smartphone literacy in promoting engagement, although enhanced digital support training alone may not be sufficient to sustain engagement. The combination of enhanced digital support and the unstructured design appeared to reduce app use time, possibly because increased navigation confidence paired with a simplified design allowed more efficient use. Further research is needed to help explain these findings.

6.5.2 Limitations

Several limitations should be considered when interpreting the results. First, as this trial focused on engagement outcomes, we did not assess how the design and implementation factors influenced caregiver or adolescent outcomes. However, this trial serves as the optimization phase of the MOST framework within the broader ParentApp study, laying the groundwork for a comprehensive evaluation of the app's effectiveness in the forthcoming randomized controlled trial (Baerecke et al., 2024). Second, while the study's focus on broader implementation strategies provides valuable insights for implementers and researchers, the generalizability of results to different LMIC settings or populations remains unclear. Further investigation into the factors influencing uptake and engagement across diverse behavioral domains, digital platforms, and delivery contexts is needed.

Third, data collection via automated tracking required internet access for synchronization with the cloud servers. As a result, participant engagement data may have been incomplete for those whose 1 GB monthly internet bundles depleted before data synchronization occurred, potentially leading to an underestimation of engagement rates. Efforts to address this included sending participants an SMS text message reminder toward the end of the study, along with an additional data bundle. However, it remains unclear to what extent these measures resolved the issue. Fourth, technical challenges hindered app installation and use. Despite enrolling 680 caregivers, surpassing the desired sample size of 640, installation difficulties affected 66 (9.7%) participants, and 14 (2.1%) did not to access any core intervention content after installation. These challenges stemmed primarily from internet and phone-to-app compatibility issues. Forthcoming qualitative research conducted in parallel to this study highlighted additional barriers to uptake and retention, including the selling of phones due to financial needs, deleting the app due to storage constraints, and program dropout due to severely damaged screens. Despite these challenges, overall content completion rates for participants who started at least 1 module was 35.57% of the program. While only 8% (49/614) of participants completed all 12 modules, completion rates were consistent with other digital parenting intervention studies in HICs, such as the 7.5% completion rate reported in a large-scale study of the web-based ParentWorks program in Australia (Dadds et al., 2019). Nonetheless, investigating patterns of early dropout and identifying opportunities for keeping caregivers engaged throughout program delivery remain crucial areas for investigation.

6.5.3 Strengths

This study has several notable strengths. A key strength is the application of a randomized factorial experiment to identify the combination of candidate factor levels that, while remaining feasible and acceptable, most effectively promoted engagement with ParentApp. Findings from this experiment played a pivotal role in selecting which factor levels to include in the forthcoming randomized controlled trial in Tanzania (Baerecke et al., 2024). Following MOST framework decision-making guidelines (Collins, Trail, et al., 2014), significant main effects guided the selection of effective factor levels, while lower-dose factor levels were retained when effects were null. Cost-effectiveness analysis and qualitative feedback then helped assess feasibility and acceptability of retained factor levels for the optimized intervention package. In addition, the findings from this experiment have contributed to the development and refinement of other digital parenting interventions, including in South Africa (Ambrosio et al., 2024) and Malaysia (Cooper et al., 2024).

Another key strength is the study context. Recruitment through local gatekeepers and community leaders yielded a large community sample in an LMIC. This approach aligns with how the intervention could be disseminated in the future and enhances the sustainability of the program. The sample also included 33.4% (205/614) men, a demographic typically underrepresented in parenting interventions (Panter-Brick et al., 2014). This high proportion of male caregivers not only extends the generalizability of the results but also represents significant strides toward understanding how to engage underrepresented groups in digital parenting interventions in LMIC contexts. A forthcoming analysis of engagement predictors will provide further insights into this aspect of engagement.

Finally, unlike many digital intervention trials that provided participants with digital devices, this study's sample consisted of participants who used their own smartphones, including older and low-cost models. This approach demonstrates the feasibility of implementing digital interventions in real-world, low-income settings and highlights the potential for cost-effective scale-up. Furthermore, by including participants with varying levels of technological access and proficiency, this study establishes a model for inclusive digital intervention design, particularly relevant in regions such as Tanzania, where smartphone access is expanding but still limited (Takwa, 2022).

6.5.4 Conclusion

While digital interventions hold immense promise for addressing health and service needs in LMICs, their effectiveness critically depends on ensuring meaningful engagement. This trial is the first of its kind to use a randomized factorial experiment to optimize participant engagement with an app-based parenting intervention in an LMIC. Moreover, this study adds to the paucity of research addressing the need for effective and accessible violence prevention interventions for adolescents in LMICs. While further investigation is needed to understand the impact of experimental factors on parenting and adolescent outcomes, our findings demonstrate that facilitator-moderated WhatsApp group guidance; an unstructured, culturally adapted app design; and pre-program digital support can enhance engagement with app-based parenting interventions. Continued exploration and refinement of these approaches is needed for developing evidence-based, scalable digital interventions capable of addressing parenting challenges and fostering positive outcomes for families in resource-constrained contexts.

7. Paper 2 – Caregiver-Level Predictors of Engagement With a Digital Parenting Intervention: Evidence From a Factorial Randomized Trial in Tanzania

The following chapter will be submitted to the *Journal of Medical Internet Research: Pediatrics and Parenting* and has been written using US spelling, in accordance with the journal's submission guidelines. Tables and figures are embedded within the chapter, with supplementary materials provided in Appendix 6. Figure and table numbering continues sequentially from previous chapters of the thesis.

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Statement of Authorship: I confirm that I carried out the majority of this research study. I conceptualised the study, led the writing of the protocol and trial registration, and planned and conducted the analyses. I trained staff for data collection, led project administration, and oversaw the data collection and curation process. GJMT provided guidance on the analysis approach. I drafted the manuscript and received critical feedback from LDC, YS, GJMT, and LVN. Full authorship details are provided in Appendix 6 (Supplementary File 1).

7.1 Abstract

Introduction: Digital interventions offer a promising avenue for scalable parenting support in low- and middle-income countries (LMICs), where in-person coverage remains limited. However, engagement disparities may reduce their potential for population-level impact. This study examined caregiver-level predictors of engagement with ParentApp, a father-inclusive, smartphone-based adaptation of the Parenting for Lifelong Health Teens program for caregivers of adolescents aged 10–17 years.

Methods: This study was nested within a cluster-randomized factorial trial of ParentApp in Mwanza, Tanzania, implemented according to the optimization phase of the Multiphase Optimization Strategy (MOST). Sixteen clusters (N=614 caregivers, 33.4% men) were randomized to three components: guidance (guided vs. self-guided), app design (unstructured vs. structured), and digital support (enhanced vs. basic). Digitally tracked app engagement outcomes included number of modules completed, first module not started, and first module not completed. Baseline candidate predictors included demographic, socioeconomic, behavioral, and psychological factors assessed via an app-embedded questionnaire. Poisson generalized linear mixed-effects models with random effects for cluster assessed associations between predictors and each outcome. Interaction terms were specified to test whether associations differed by caregiver gender.

Results: Among 614 caregivers, 596 (97.1%) completed the first module; however, engagement declined rapidly thereafter, with only 281 (45.8%) completing module 2 and 49 (8.0%) completing all 12 modules. Overall, mean content completion was 35.6% (SD 33.1%) of the program. Women completed approximately 15% more modules than men (incidence rate ratio [IRR] 1.15, 95% CI [1.05, 1.27], p = .003), despite reporting higher levels of financial stress, food insecurity, child maltreatment, and depressive symptoms at baseline (all $p \leq .023$; Cohen's d=0.19–0.37). No other caregiver characteristics were significantly associated with engagement.

Conclusions: This is the first known study to investigate caregiver-level predictors of engagement with a digital parenting intervention in an LMIC. Engagement with ParentApp was broadly consistent across caregiver subgroups, with the exception that women completed significantly more modules than men. To equitably engage men and fathers, future studies should pair father-inclusive, identify-affirming content with implementation strategies that reduce social and economic barriers to participation.

Trial Registration: Pan-African Clinical Trial Registry PACTR202210657553944; https://pactr.samrc.ac.za/TrialDisplay.aspx?TrialID=24051

Keywords: digital health; engagement; parenting; mobile phone; violence prevention; low-and middle-income countries

7.2 Introduction

Parenting interventions are central to global efforts to prevent violence against children and promote family wellbeing (Little et al., 2026; World Health Organization, 2018). However, access to evidence-based parenting support remains limited in many low- and middle-income countries (LMICs). Workforce shortages and the high costs of in-person delivery restrict service availability, while travel, time, and competing work and caregiving responsibilities make it difficult for many families to participate (Mejia et al., 2017; Parra-Cardona et al., 2021). Promisingly, there is growing evidence that digital parenting interventions can improve parenting and child outcomes, including among hard-to-reach families in LMICs (Jäggi et al., 2025; Till et al., 2023). However, program effects are often small and user engagement is low (Aldridge et al., 2024), warranting investigation into how these interventions can be designed and implemented to sustain engagement and achieve population-level impact.

Engagement is a key mechanism for behavioral change (Ingoldsby, 2010). Research on engagement with digital interventions has largely been conducted within behavioral science, which typically defines engagement as the extent of program use (e.g., amount, frequency, duration, depth), although its operationalization varies widely across studies (Perski et al., 2017). While engagement challenges are not unique to digital delivery, they may be amplified by structural inequalities in digital access and use, particularly in LMICs.

Families living in poverty or rural areas often rely on lower-performing devices, have limited internet connectivity, and face digital literacy challenges (Biga et al., 2024). In Tanzania, for example, 82% of the population owns a basic mobile phone, compared with just 35% who own a smartphone (Tanzania Communications Regulatory Authority, 2025). Gender disparities in digital access further compound these barriers. Across LMICs, women are 17% less likely to own a mobile phone and 21% less likely to use the internet than men (Breen et al., 2025). These digital divides risk excluding already marginalized families and may deepen health and social inequities if unaddressed. Identifying which caregivers are most likely to engage—or disengage—is therefore essential for developing equitable and effective digital parenting interventions.

Existing evidence on caregiver engagement with digital parenting programs remains limited and inconsistent, with relatively few studies conducted in LMICs (Aldridge et al., 2024). Gender disparities are well documented in in-person programs, where fathers engage at markedly lower rates than mothers (Gonzalez et al., 2023; Panter-Brick et al., 2014). In a South African trial of the in-person Parenting for Lifelong Health (PLH) Teens program, fathers represented only 3% of participants and were significantly less likely to attend sessions than mothers (Shenderovich et al., 2018). Encouragingly, early evidence from HICs suggests mothers and fathers engage at similar rates in digitally delivered parenting programs (Dadds et al., 2019; Lin-Lewry et al., 2024). Whether these findings extend to LMICs remains unknown.

Beyond gender, evidence on caregiver-level predictors remains limited. Sociodemographic factors appear to be the most extensively studied, with lower education and income consistently linked to reduced engagement and increased attrition in HICs (Fletcher et al., 2023; Fossum et al., 2018; Horn et al., 2025; Lin-Lewry et al., 2024; Wähnke et al., 2024). Similar associations have been reported in in-person parenting programs in HICs (Chacko et al., 2016). By contrast, findings from a few in-person programs in LMICs suggest that socioeconomic disadvantage does not reliably predict lower engagement (Shenderovich et al., 2018). Evidence on behavioral and psychological predictors is comparatively limited and mixed, with positive parenting practices (Perrino et al., 2018; Wähnke et al., 2024) and caregiver mental health (Cai et al., 2024; Dadds et al., 2019; Horn et al., 2025; Wähnke et al., 2024) associated with both higher and lower engagement in digital parenting programs. To our knowledge, no studies of digital parenting interventions have examined these associations in LMICs.

The current study addresses this gap by examining caregiver-level predictors of engagement in an early version of ParentApp, a digital parenting intervention for caregivers of adolescents aged 10–17 years. Using data from a cluster-randomized factorial trial in Tanzania, implemented in accordance with the optimization phase of the Multiphase Optimization Strategy (MOST) (Collins, 2018), we test whether caregiver demographic, socioeconomic, behavioral, and psychological characteristics predict user engagement. We also explore whether these associations differ by caregiver gender. Findings are intended to inform targeted and inclusive strategies to enhance engagement in ParentApp and to support the equitable scale-up of digital parenting interventions in LMICs.

7.3 Methods

7.3.1 Study Design

This study was nested within a 2×2×2 cluster-randomized full factorial experiment implemented across 16 low-income urban and peri-urban communities in Mwanza, Tanzania (Janowski et al., 2025). Each community (cluster) was randomly assigned to one of eight experimental conditions, comprising all possible combinations of three components: guidance (guided vs. self-guided), app design (structured vs. unstructured), and digital support (enhanced vs. basic). The trial aimed to optimize user engagement in ParentApp, which was developed in partnership with the United Nations Children's Fund, the World Health Organization, and the Tanzanian national government. The trial was preregistered on the Pan-African Clinical Trial Registry (PACTR202210657553944) on October 11, 2022. Further information about the trial design can be found in the study protocol (Janowski et al., 2023) and the main trial results paper (Janowski et al., 2025).

7.3.2 Participants

Eligible participants were required to be at least 18 years old, be caring for an adolescent aged 10–17 years, reside in the same household as the adolescent for at least four nights per week in the previous month, and have regular access to an Android smartphone (operating system OS 5.1.1 or higher). To address the underrepresentation of fathers in parenting interventions, the study aimed to enroll at least 20% men. Participants were recruited on a rolling basis between October 24, 2022 and December 1, 2022, through local community leaders who were predominantly men. As respected members of the community, they introduced and endorsed the study during community meetings, an approach intended to build trust and acceptability among families.

7.3.3 ParentApp

ParentApp is designed to promote positive parenting, prevent violence against adolescents, and reduce risks of sexual violence victimization. It is a smartphone-based adaptation of the in-person PLH Teens program, originally evaluated in South Africa (Cluver et al., 2018), and subsequently implemented across multiple LMICs, including Tanzania (Lachman, Wamoyi, et al., 2024). ParentApp was developed to expand reach and reduce the costs and logistical barriers of in-person delivery. To support use in settings with limited or intermittent internet access, it operates offline after the initial download.

Development and testing followed a multi-phase process guided by the MOST framework (Collins, 2018). During the preparation phase, caregiver co-design, multi-country user testing (Awah et al., 2022), and pilot studies in South Africa and Tanzania demonstrated that the app was broadly acceptable. The preparation phase also identified opportunities to strengthen delivery through additional human support, greater flexibility in accessing content, culturally adapted imagery, and enhanced digital support for caregivers with lower smartphone literacy. These findings informed the selection of the three components evaluated in the optimization phase factorial trial: guidance, app design, and digital support (Janowski et al., 2025).

The intervention content tested in the optimization phase was organized into 12 modules, delivered via simple text, illustrations, and audio narration in Kiswahili. The introductory module focuses on parental self-care and stress reduction and includes a baseline questionnaire. Modules 2 to 11 introduce evidence-based strategies to support positive parenting and reduce harsh or abusive discipline, while also incorporating mindfulness-based excises throughout. The final module provides a summary of key concepts and includes a post-intervention assessment. Full details on module content, home practice activities, and user interface design are available in Janowski et al. (2025).

7.3.4 Experimental Components

Guidance

The guidance component compared self-guided use of ParentApp with facilitator-supported delivery. Following onboarding, participants in the self-guided condition used the app independently, whereas those in the guided condition were invited to join a facilitator-moderated WhatsApp group corresponding to their cluster allocation. Each group was co-facilitated by a mixed-gender facilitator pair to encourage engagement among both women and men. Following a standardized facilitation manual, facilitators posted weekly reminders and discussion prompts, responded to participants' questions, moderated discussions, and hosted weekly one-hour live chat sessions throughout the 12-week intervention period to support peer interaction and reflection.

App Design

The app design component compared a structured and an unstructured version of ParentApp. In the structured condition, modules were released sequentially over the 12-week intervention and retained the original abstract blue cartoon characters, which were non-gendered and developed for cross-cultural implementation during earlier pilot studies. In the unstructured condition, all modules were available immediately following installation, allowing participants to progress through the content at their own pace, and featured culturally adapted, human-like illustrations depicting both women and mean in caregiving roles.

Digital Support

All participants received basic digital support consisting of an embedded app tutorial and a group-based demonstration of key app features during onboarding. Clusters allocated to the enhanced digital support condition additionally received a 15–20-minute group-based training session designed to improve general smartphone literacy and confidence in smartphone use.

7.3.5 Procedures

Cluster-level onboarding sessions were conducted in local schools and community centers by staff from Tanzania's National Institute for Medical Research (NIMR) and trained facilitators from Investing in Children and Strengthening Their Societies, a local non-governmental organization. Sessions included study information, eligibility screening, and informed consent, followed by app onboarding and baseline data collection. After obtaining informed consent, participants were divided into small groups (5–10 caregivers) to facilitate hands-on support with downloading and installing ParentApp from Google Play (Google LLC). Following installation, NIMR research assistants moved between participants to configure each app according to its allocated intervention condition before guiding caregivers through the app's core features, including navigation, activity completion, and available resources. Participants then completed the introductory module, which included the embedded baseline assessment. Clusters allocated to the enhanced digital support condition also participated a brief group-based smartphone literacy session, while those allocated to the guided condition were added to facilitator-moderated WhatsApp groups.

7.3.6 Measures

Engagement Metrics

Engagement was assessed using automatically recorded in-app usage data. Use data, including app launches, content viewing patterns, and responses to in-app tasks were uploaded to a Metabase cloud server (Metabase, Inc.) when participants' devices connected to the internet. Retention was calculated as the number of days between first app launch and the final synchronization of app-use data with the cloud server. Additional usage data, including visit timestamps, session duration, and frequency of actions or pages viewed, were captured via Matomo Analytics (InnoCraft Ltd). These data were used to derive descriptive indicators and the primary and secondary outcomes.

The primary outcome was module completion, defined as the total number of modules completed (range 0–12). Secondary outcomes were first module not started and first module not completed, which identified the earliest point in the intervention sequence at which participants either failed to initiate or failed to complete a module, respectively. These outcomes were selected to capture cumulative content engagement and early disengagement.

Demographic and Socioeconomic Variables

Baseline data were collected via an in-app questionnaire embedded in the first module. Measures were translated and back-translated into Kiswahili. Candidate demographic predictors included caregiver gender (woman/man) and age (years). Additional demographics (e.g., household composition) were collected but not analyzed here. Candidate socioeconomic predictors were assessed using two items adapted from the Financial Self-Efficacy Scale (Lown, 2011). One item measured financial stress ("How many times in the past month have you felt worried or anxious about money?"), rated on a 0 to ≥8 frequency scale. The other item measured food insecurity ("How many days in the past month did you run out of money to pay for food?"), rated 0 to 30 days. These two items were analyzed separately due to differences in response formats.

Behavioral and Psychological Variables

Positive parenting was assessed using five items on parental involvement and supervision from the Alabama Parenting Questionnaire (Essau et al., 2006). Items were scored from 0 to ≥8 and summed to produce a total score, with higher scores indicating greater positive parenting. Harsh parenting was assessed using four items on physical and emotional abuse from the International Society for Prevention of Child Abuse and Neglect Screening Tools-Trial Version (Meinck et al., 2018). Items were scored from 0 to ≥8 and summed, with higher scores indicating greater maltreatment. Caregiver depression was measured using three items from the Centre for Epidemiologic Studies Depression Scale (Irwin et al., 1999). Each item was scored from 0 to 7 and summed, with higher scores indicating greater depressive symptoms. Internal consistency reliability for multi-item scales is reported in Appendix 6, Supplementary File 2.

7.3.7 Statistical Analysis

Analyses were conducted in R (version 4.5.0). Sample characteristics were summarized overall and by caregiver gender. Gender differences in age, financial stress, food insecurity, positive parenting, harsh parenting, and depressive symptoms were assessed using independent-samples *t*-tests, with Cohen's *d* calculated to estimate effect sizes. Engagement across the 12 modules was visualized using Kaplan-Meier survival curves stratified by caregiver gender.

Predictors of engagement were estimated using Poisson generalized linear mixed models with cluster-level random intercepts. Models were fit to multiply imputed datasets to address missing baseline data, and estimates were pooled across imputations (van Buuren et al., 2006). The primary outcome (number of modules completed) was modeled using an offset for exposure equal to the number of modules available. Secondary outcomes (first non-start and first non-completion) were analyzed as binary indicators (1 = event, 0 = none) with an offset for modules-at-risk, defined as the module at first disengagement for events and the total modules available for non-events.

Each predictor was tested in a separate model, with group-mean centering applied within clusters to isolate within-cluster effects. All models adjusted for experimental components (dummy-coded: guidance, app design, and digital support). Caregiver age and gender (grand-mean centered) were also included as control variables in all models except when either variable served as the predictor of interest. Moderation by caregiver gender was tested by including interaction terms between each predictor and caregiver gender. Gender was represented both as a group-mean centered variable and as a cluster-level mean to disaggregate individual- and cluster-level effects. Model estimates are reported as incidence rate ratios (IRR) with 95% confidence intervals (CIs) and corresponding *p*-values. The Benjamini–Hochberg procedure was applied to control for false discovery rate across models, with significance determined using adjusted critical *p*-value thresholds (Benjamini & Hochberg, 1995).

7.4 Results

7.4.1 Sample Characteristics

Baseline characteristics for the full sample and by caregiver gender are presented in Table 9. The trial included 614 caregivers (409/614 women, 205/614 men), with ages ranging from 18 to 75 years (*M* 35.94, *SD* 11.84). Independent samples *t*-tests indicated no significant gender difference in age or positive parenting practices. However, women reported significantly higher levels of several socioeconomic and psychosocial stressors compared to men, including financial stress (*M* 4.55 vs. 3.72; $p < .001$, $d = .30$), food insecurity (*M* 7.88 vs. 6.17; $p = .009$, $d = .22$), child maltreatment (*M* 7.40 vs. 5.07; $p < .001$, $d = .37$), and depressive symptoms (*M* 8.53 vs. 7.80; $p = .023$, $d = .19$). Although effect sizes were small, the findings suggest consistent gender disparities in exposure to adversity.

Table 9. *Gender differences in predictors: Means, standard deviations, and t-tests*

Measure	Total			Female			Male			Statistics	
	n	*M*	*SD*	*n*	*M*	*SD*	*n*	*M*	*SD*	*d*	*p*
Age (years)	577	35.94	11.84	386	35.70	11.15	191	36.43	13.13	0.06	.507
Financial stress	574	4.27	2.75	379	4.55	2.73	195	3.72	2.73	0.30	.001**
Food insecurity	576	7.30	7.78	3.81	7.88	8.09	195	6.17	7.01	0.22	.009**
Positive parenting	614	10.89	6.78	409	10.95	6.84	205	10.79	6.69	0.02	.777
Child maltreatment	614	6.62	6.42	409	7.40	6.42	205	5.07	6.14	0.30	.000**
Parental depression	614	8.29	3.95	409	8.53	4.12	205	7.80	3.56	0.19	.023*

Note. *M* = mean; *SD* = standard deviation. Cohen's *d* values represent the standardized mean difference between female and male caregivers, with positive values indicating higher scores for women. Effect sizes are interpreted as small ($d = 0.20$), medium ($d = 0.50$), and large ($d = 0.80$). * $p < .05$, ** $p < .01$

7.4.2 Program Engagement

Descriptives

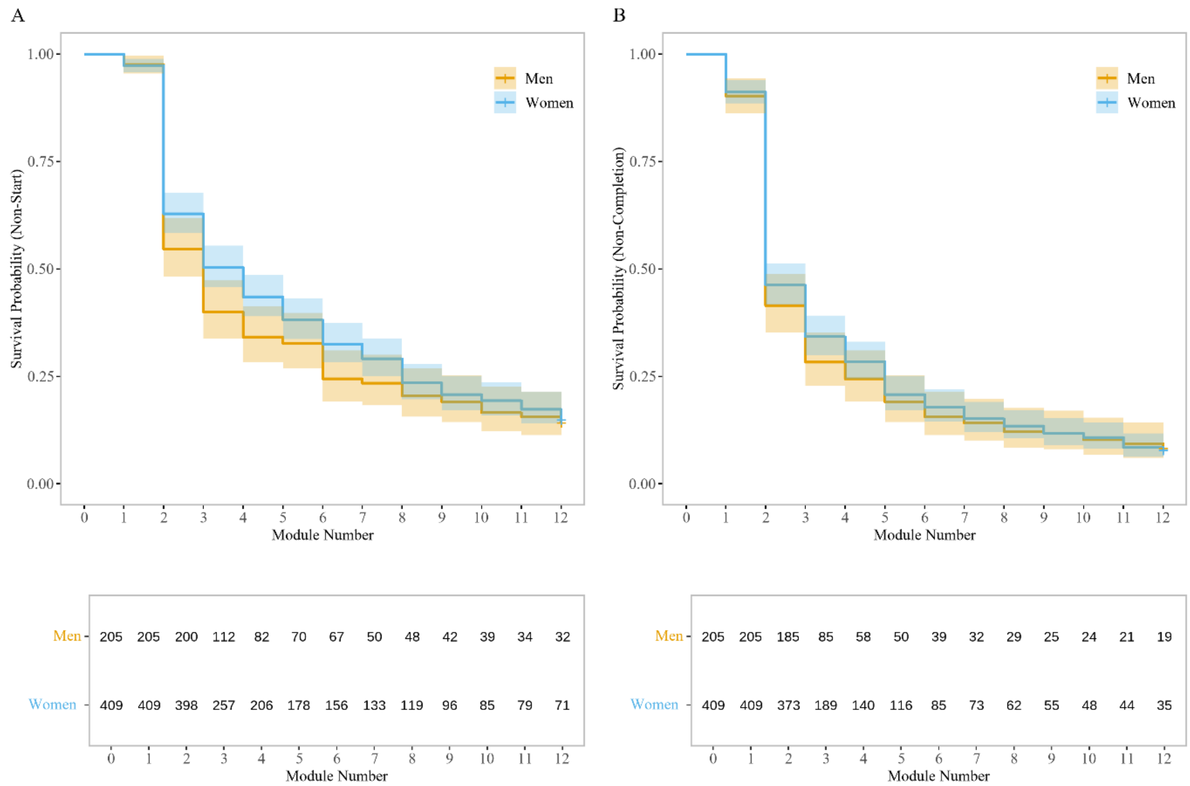
Of the 614 enrolled caregivers, 97.1% (*n* = 596) initiated the first module, and 90.2% (*n* = 554) completed it. This initial uptake was followed by a marked decline in engagement. By Module 2, only 59.8% (*n* = 367) had started the module, and 45.8% (*n* = 281) had completed it. On average, participants started 4.57 modules (*SD* 4.13) and completed 3.40 modules (*SD* 3.64) out of the 12 available (Table 10). The mean content completion rate across all 12 modules was 35.57% of the program (*SD* 33.10%). Completion rates were higher among participants assigned to the guided delivery, unstructured app design, and enhanced digital support conditions. Kaplan–Meier survival analyses indicated that the median retention time among content users was 31 days (95% CI: 25–36), measured from first app launch to final data synchronization with the Metabase cloud server. As shown in Figure 10, risk of disengagement was highest immediately after the first module. Although not statistically significant, women showed slightly lower risk of disengagement than men on both time-to-first non-start and time-to-first non-completion outcomes.

Table 10. *Mean modules started and completed, overall and by delivery component*

Variable	Overall	Guidance		App design		Digital support	
		Self-guided (n=330)	Guided (n=284)	Structured (n=332)	Unstructured (n=282)	Basic (n=295)	Enhanced (n=319)
Modules started	4.57 (4.13)	4.22 (3.92)	4.99 (4.33)	4.34 (4.03)	4.84 (4.23)	4.43 (4.04)	4.71 (4.21)
Modules completed	3.40 (3.64)	3.09 (3.41)	3.77 (3.85)	2.91 (3.04)	3.99 (4.16)	3.26 (3.51)	3.54 (3.75)

Note. Values represent mean scores, with standard deviations shown in parentheses. Variable range (0 to 12).

Figure 10. *Kaplan–Meier survival curves stratified by caregiver gender*



Note. Time to first non-start (A) and time to first non-completion (B), stratified by gender. Plots reflect survival probability (i.e., continued engagement) across modules. Risk tables indicate the number of participants still engaged at each module. Shaded areas indicate 95% confidence intervals.

Predictors of Engagement Outcomes

Each of the three engagement outcomes was regressed on seven baseline predictors, yielding 21 primary hypothesis tests. To control for the false discovery rate within each outcome, the Benjamini–Hochberg procedure was applied separately to each set of seven tests (Benjamini & Hochberg, 1995). The procedure compares each *p*-value to a ranked critical value, and only those below the adjusted threshold are interpreted as statistically significant. Statistically significant effects are highlighted in bold and marked with a † symbol in Table 11.

Caregiver gender was the only baseline characteristic significantly associated with the number of module completed. On average, women completed approximately 15% more modules than men (IRR 1.15, 95% CI [1.05-1.27], p = .003; Table 11). While associations between caregiver gender and the two disengagement outcomes followed a similar direction, they did not reach statistical significance. As a sensitivity check, Cox proportional hazards models were also fitted for the two disengagement outcomes; results were consistent with the primary analyses, indicating that the absence of significant effects was not sensitive to the modelling approach (Appendix 6, Supplementary File 2, Tables S2 and S3).

Table 11. *Baseline predictors of program engagement outcomes*

	Modules Completed		First Non-Start		First Non-Complete	
Predictor	IRR (95% CI)	p	IRR (95% CI)	p	IRR (95% CI)	p
Caregiver Gender	**1.15 (1.05-1.27)**	**.003**†	0.90 (0.74-1.08)	.251	0.92 (0.77-1.10)	.370
Caregiver age	1.02 (0.98-1.07)	.291	0.96 (0.90-1.04)	.325	0.99 (0.92-1.07)	.797
Financial stress	1.02 (1.00-1.04)	.060	0.98 (0.93-1.01)	.156	0.98 (0.95-1.01)	.308
Food insecurity	1.00 (1.00-1.01)	.667	1.00 (0.99-1.02)	.519	1.00 (0.98-1.02)	.413
Positive parenting	1.00 (0.99-1.02)	.566	1.00 (0.99-1.02)	.711	1.00 (0.99-1.02)	.711
Child maltreatment	1.00 (0.99-1.01)	.866	1.00 (0.98-1.01)	.698	1.00 (0.99-1.04)	.932
Parental depression	0.99 (0.98-1.01)	.219	1.00 (0.98-1.03)	.827	1.01 (0.99-1.04)	.316

Note. † = Effect significant below the Benjamini-Hochberg procedure's critical value. *IRR* = incidence rate ratio; *CI* = confidence interval. All predictors were group-mean centered within clusters. Caregiver gender was dummy-coded (0 = male, 1 = female); estimates represent effects for women relative to men (reference group). Each model includes dummy-coded delivery components (guidance, app design, digital support) as covariates. Caregiver age and gender (grand-mean centered) were included as covariates unless they were the predictor in a given model.

Gender as a Moderator of Engagement Predictors

To examine whether the associations between baseline characteristics and engagement outcomes differed by caregiver gender, moderation models were estimated for each of the seven predictors across all three outcomes (Table 12). As with the main effects models, the Benjamini–Hochberg procedure was applied separately for each outcome to control the false discovery rate. Two interaction effects between gender and the baseline variables food insecurity and caregiver depression were marginally significant for the module completion outcome, but neither meet the Benjamini–Hochberg threshold for statistical significance. No significant gender interactions were observed for the disengagement outcomes, indicating that the associations between baseline characteristics and disengagement did not vary meaningfully by caregiver gender.

Table 12. *Moderation of baseline predictors of engagement outcomes by gender*

		Main Effect		Interaction Effect	
Predictor	Outcome	IRR (95% CI)	*p*	IRR (95% CI)	*p*
Caregiver age	Modules completed	1.02 (0.98-1.06)	.412	0.92 (0.84-1.00)	.054
	First non-start	0.97 (0.90-1.05)	.493	1.09 (0.92-1.28)	.328
	First non-complete	0.99 (0.93-1.08)	.946	1.08 (0.92-1.27)	.327
Financial stress	Modules completed	1.02 (1.00-1.04)	.057	0.99 (0.96-1.03)	.758
	First non-start	0.98 (0.95-1.01)	.147	1.01 (0.94-1.09)	.755
	First non-complete	0.98 (0.95-1.02)	.305	1.00 (0.93-1.07)	.933
Food insecurity	Modules completed	1.00 (1.00-1.01)	.472	0.98 (0.97-1.00)	.029
	First non-start	1.00 (0.99-1.02)	.539	1.01 (0.98-1.04)	.533
	First non-complete	1.00 (0.98-1.01)	.381	1.02 (0.99-1.04)	.251
Positive parenting	Modules completed	1.00 (0.99-1.01)	.494	1.01 (0.99-1.03)	.371
	First non-start	1.00 (0.99-1.02)	.700	0.99 (0.96-1.03)	.689
	First non-complete	1.00 (0.99-1.02)	.680	0.99 (0.96-1.02)	.486
Child maltreatment	Modules completed	1.00 (0.99-1.01)	.947	1.01 (1.00-1.03)	.152
	First non-start	1.00 (0.98-1.01)	.683	0.99 (0.96-1.03)	.739
	First non-complete	1.00 (0.99-1.01)	.862	0.98 (0.95-1.02)	.325
Caregiver depression	Modules completed	0.99 (0.98-1.01)	.375	0.97 (0.94-1.00)	.041
	First non-start	1.00 (0.98-1.03)	.860	1.03 (0.97-1.09)	.383
	First non-complete	1.01 (0.99-1.04)	.322	1.02 (0.97-1.08)	.450

Note. IRR = incidence rate ratio; CI = confidence interval. All predictors were group-mean centered within clusters. Caregiver gender was dummy-coded (0 = male, 1 = female); interaction terms estimate differential effects for women compared to men (reference group). Gender was included as both a cluster-mean centered variable (within-cluster effect) and a cluster-level mean (between-cluster effect). Caregiver age (grand-mean centered) was included as a covariate in all models except when it was the predictor. All models also adjust for the three dummy-coded delivery components (guidance, app design, digital support).

7.5 Discussion

This study provides the first known analysis of caregiver-level predictors of engagement in a digital parenting program in an LMIC, with the notable strength of including a large proportion of men and fathers (33.4%). While nearly all participants initiated the program, engagement dropped substantially after onboarding, with the steepest decline occurring after the first module. This mirrors broader trends in digital health interventions, where attrition is typically concentrated in the early stages of program use (Pratap et al., 2020). These findings support prioritizing early-stage retention strategies that are responsive to both context and gender.

Of the baseline characteristics examined, caregiver gender was the only statistically significant predictor of engagement. Women completed approximately 15% more modules than men, a finding that contrasts with several digital parenting studies in HICs, where engagement is often similar across genders (Lin-Lewry et al., 2024). One possible explanation is that women's higher engagement may reflect greater exposure to socioeconomic and psychosocial adversity, including financial stress, food insecurity, depressive symptoms, and harsh disciplinary practices. Women reported significantly higher levels of each of these stressors, which may have increased the perceived relevance of the intervention and, in turn, their motivation to engage.

This interpretation aligns with the Health Belief Model, which posits that individuals are more likely to adopt health behaviors when they perceive the risks of inaction as high, and the benefits of action as tangible (Salari & Filus, 2017). From this perspective, socioeconomic and psychosocial adversity may have served as a cue to action, outweighing emotional or cognitive barriers that might otherwise prevent engagement (Hill et al., 2021). That women sustained engagement despite multiple, overlapping stressors is a notable finding. It suggests that digital parenting interventions may offer a feasible and acceptable modality for supporting high-risk caregivers in LMICs.

In contrast, the lower engagement observed among men may reflect a complex interplay of identity, norms, and structural constraints. In Tanzania and many other LMICs, caregiving is typically viewed as a maternal responsibility, while fatherhood is closely tied to provision, protection, and authority (Alsager et al., 2024; Okelo et al., 2022; Rabie et al., 2020). When program content is perceived as incongruent with these gendered expectations, or fails to affirm men's aspirations as fathers, it may appear irrelevant or incompatible with their roles. This is echoed in global fatherhood research showing that interventions which acknowledge and support men's caregiving identities and align with their aspirations tend to enhance perceived relevance and achieve higher engagement (Makusha & Richter, 2014; Panter-Brick et al., 2014).

Lower male engagement may also reflect deeper identity tensions under conditions of economic precarity. Qualitative research from Mwanza, Tanzania describes how many men aspire to be nurturing and involved fathers but face conflicting practical and social pressures from work demands, limited time, and community norms (Alsager et al., 2024). These experiences not only restrict men's capacity to participate in caregiving but may also lead to internal dissonance when they are unable to fulfil culturally sanctioned roles of fatherhood, a phenomenon that has been described as *moral injury* in fatherhood research (Madhavan et al., 2014; Ratele, 2015). Similar findings from Uganda indicate that even when men express egalitarian views, structural constraints and social stigma around caregiving can limit their involvement in parenting programs (Siu et al., 2017). These dynamics highlight the need for interventions that actively affirm men's caregiving identities and address the structural barriers that limit engagement. While women reported greater socioeconomic adversity in the present study, integrating digital parenting programs with broader economic and social protection initiatives may help reduce the opportunity costs of participation for both men and women (Jeong et al., 2023).

Although ParentApp was intentionally designed to support all caregivers rather than assuming mothers as the primary users, these findings suggest that additional strategies may be needed to improve engagement among men. Future iterations could benefit from further co-design with fathers to better understand how intervention content, tone, imagery, and delivery align with men's caregiving identities and everyday constraints. Emerging work on digital fatherhood interventions illustrates how user-centered design can be used to develop app-based support tailored to fathers' mental health, wellbeing, and parenting needs (Liverpool et al., 2023). However, improving engagement among men may require more than tailoring content or delivery; it may also require gender-transformative approaches that actively challenge inequitable norms and support identity shifts in caregiving. As highlighted in a recent systematic review of fatherhood programs in LMICs, gender-transformative interventions foster critical reflection, promote shared decision-making, and engage with normative change at individual and community levels (Jeong et al., 2023). Promising examples include in-person parenting programs such as REAL Fathers in Uganda (Ashburn et al., 2017), Bandebereho in Rwanda (Doyle et al., 2018), and Parenting for Respectability in Uganda (Siu et al., 2024), which have achieved shifts in father involvement, reductions in intimate partner violence (IPV), and improvements in household dynamics through facilitated dialogue, peer role-modelling, and local leadership.

Emerging evidence suggests that gender-transformative components can successfully be integrated into digital formats. One example is ParentText, a chatbot-based parenting intervention adapted from the PLH program suite and piloted in South Africa and Jamaica. ParentText incorporates content on gender-equitable behaviors and IPV prevention to support shared caregiving, challenge harmful gender norms, and reduce familial violence (Schafer et al., 2023). Qualitative findings suggest that men valued the anonymity, accessibility, and nonjudgmental tone of the chatbot, which facilitated engagement with sensitive topics such as relationships and caregiving (Schafer, Lachman, Zinser, Calderon, et al., 2025). A parallel pre-post pilot study reported modest reductions in women's experience of IPV and improvements in men's attitudes and gender-equitable behaviors. However, overall engagement with the program, and with the IPV-related content in particular, was limited, especially among men (Schafer, Lachman, Zinser, Calderón Alfaro, et al., 2025). Together with the findings of the present study, this emerging evidence suggests that moving beyond one-size-fits-all approaches may be key to improving engagement with digital parenting interventions.

7.5.1 Limitations

Several limitations should be acknowledged when interpreting these findings. First, engagement was operationalized through digital metrics (e.g., module completion), which offer behavioral indicators of app use but do not capture content comprehension or real-world application. This reflects a broader challenge in digital health research, where engagement is often equated with usage alone, without consideration of learning or behavior change outcomes (Finan et al., 2018). Moreover, these metrics do not capture users' subjective experiences, such as interest, attention, or emotional resonance, which may be equally important in understanding meaningful engagement (Perski et al., 2017). Future research should therefore incorporate multidimensional measures that capture both the quantity and quality of engagement, alongside users' subjective experiences.

Second, the range of caregiver characteristics assessed at baseline was limited by the brief, app-embedded format of the survey. Key variables such as perceived digital skills and prior experience with technology were not captured, although these factors have been shown to influence engagement with digital interventions (Jakob et al., 2022; van Kessel et al., 2023). The study also did not measure adolescent-level characteristics, such as child mental health symptoms, which have been positively associated with parental engagement in previous research (Finan et al., 2018). Accounting for these variables in future studies may improve the precision of engagement models and support more targeted intervention strategies.

Third, while the overall sample size was relatively large, the study may have been underpowered to detect gender interaction effects, especially given the smaller proportion of male caregivers relative to female caregivers. Future studies should consider adequately powered subgroup analyses to explore gender-specific patterns of engagement. Further, although the sample was drawn from low-income urban and peri-urban settings, all participants were required have regular access to a smartphone. As such, findings may not be generalizable to caregivers in rural areas or those with limited access to digital technology. Broader implementation research is needed to understand how structural barriers such as digital access, network reliability, and device sharing influence engagement, including in rural and more resource-constrained settings.

7.5.2 Conclusion

This study contributes new evidence on caregiver-level predictors of engagement in a digital parenting intervention in an LMIC. Across demographic, socioeconomic, behavioral, and psychological factors, only caregiver gender significantly predicted engagement, with women completing more modules than men. The absence of associations with other baseline characteristics suggests that ParentApp may be broadly accessible, even to caregivers facing high levels of adversity. However, the marked drop-off immediately after onboarding indicates a critical need to address retention. Early engagement may be strengthened by providing timely support, establishing immediate relevance, and affirming the caregiving identities of both women and men. Over the longer term, embedding gender-transformative content and linking digital programs to broader social protection systems may be necessary to improve engagement and achieve sustainable public health impact in LMICs.

8. Paper 3 – Moderators of Design and Delivery Component Effects on Engagement With a Digital Parenting Intervention: Evidence From a Factorial Randomized Trial in Tanzania

The following chapter has been submitted to *Annals of Behavioral Medicine* and has been written using US spelling, in accordance with the journal's submission guidelines. Tables and figures are embedded within the chapter, with supplementary materials provided in Appendix 7. Figure and table numbering continues sequentially from previous chapters of the thesis.

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Statement of Authorship: I confirm that I carried out the majority of this research study. I conceptualised the study, led the writing of the protocol and trial registration, and planned and conducted the analyses. I trained staff for data collection, led project administration, and oversaw the data collection and curation process. GJMT provided guidance on the analysis approach. I drafted the manuscript and received critical feedback from YS, LDC, JML, and GJMT. Full authorship details are provided in Appendix 7 (Supplementary File 1).

8.1 Abstract

Background: Digital health interventions are rapidly expanding in low- and middle-income countries (LMICs), yet little is known about how design and delivery components can be tailored to support engagement across diverse populations. Addressing this gap is critical for effective and equitable implementation. This study used a factorial experiment, embedded within the Optimization Phase of the Multiphase Optimization Strategy (MOST), to examine whether caregiver characteristics moderated the effects of design and delivery components on engagement with an app-based parenting intervention in Tanzania.

Methods: A 2×2×2 cluster-randomized factorial experiment was conducted in Mwanza, Tanzania (16 clusters; 614 caregivers of adolescents). Three components were tested: guidance (guided vs. self-guided), app design (unstructured vs. structured), and digital support (enhanced vs. basic). Engagement was operationalized as the number of intervention modules completed, tracked automatically via the app. Generalized linear mixed-effects models examined moderation by caregiver gender, age, financial stress, food insecurity, positive parenting, child maltreatment, and caregiver depression.

Results: Gender, age, positive parenting, and depressive symptoms moderated the effects of specific components on engagement. Women showed significantly higher engagement with the unstructured versus structured app design (incidence rate ratio [IRR] = 1.48, 95% CI [1.23–

1.80]), whereas no significant app design differences were observed among men. Older caregivers showed greater engagement under guided delivery (vs. self-guided; IRR = 1.15, 95% CI [1.06–1.25]) and enhanced digital support (vs. basic support; IRR = 1.15, 95% CI [1.06–1.26]). Greater engagement under guided versus self-guided delivery was also observed among caregivers reporting more positive parenting practices (IRR = 1.03, 95% CI [1.02–1.04]) and higher depressive symptoms (IRR = 1.06, 95% CI [1.03–1.09]). However, caregivers reporting more positive parenting practices showed lower engagement under enhanced digital support (vs. basic support; IRR = 0.96, 95% CI [0.95–0.98]). No moderation effects were observed for financial stress, food insecurity, or child maltreatment.

Conclusion: Tailoring design and delivery components to specific caregiver characteristics may enhance engagement and promote more equitable implementation of digital parenting interventions in LMICs.

Trail registration: Pan-African Clinical Trial Registry, PACTR202210657553944. Registered 11 October 2022, https://pactr.samrc.ac.za/TrialDisplay.aspx?TrialID=24051

Keywords: digital health; engagement; moderators; parenting; factorial experiment; Multiphase Optimization Strategy; Tanzania

8.2 Introduction

Violence against children is a major contributor to the global burden of disease, affecting over 1 billion children each year (Hillis et al., 2016). Parenting interventions are among the most effective strategies for preventing violence globally (World Health Organization, 2018). However, scaling these interventions remains constrained by high delivery costs and barriers to access, particularly among families experiencing adversity, marginalization, and socioeconomic stress (Berry et al., 2023; Finan et al., 2020; Finan & Yap, 2021). Digital delivery offers a promising solution to these challenges, with growing evidence indicating comparable effectiveness to in-person parenting programs (Florean et al., 2020; Flujas-Contreras et al., 2019; Hansen et al., 2019; Spencer et al., 2020).

Parenting for Lifelong Health for Parents and Teens (PLH Teens) is a group-based parenting intervention designed to reduce adolescents' exposure to violence by strengthening positive parenting, improving caregiver–child communication, and promoting caregiver wellbeing (Cluver et al., 2018). PLH Teens is one of the few low-cost parenting interventions for families with adolescents that has been rigorously tested and disseminated in low- and middle-income countries (LMICs) (Redfern et al., 2019). However, in-person delivery remains resource-intensive and logistically challenging to scale. To address these barriers, ParentApp was developed to deliver a remote, app-based version of PLH Teens.

Digital parenting interventions such as ParentApp frequently face challenges with engagement, broadly defined as the amount, frequency, duration, and depth of program use (Perski et al., 2017). These challenges may be particularly pronounced in LMICs, where digital infrastructure gaps and socioeconomic constraints can limit uptake and sustained use (Jäggi et al., 2025). Greater engagement in parenting interventions has consistently been associated with stronger outcomes (Becker et al., 2018; Chacko et al., 2016), making engagement optimization essential for achieving public health impact. However, little is known about which implementation strategies are most effective at engaging different caregiver subgroups. Identifying for whom specific strategies are most effective is therefore critical for reducing inequities in who engages with, benefits from, and is ultimately reached by digital parenting interventions.

In implementation science, implementation strategies are defined as “methods or techniques used to enhance the adoption, implementation, and sustainability of a clinical program or practice” (Powell et al., 2015, p. 2). In digital interventions, implementation strategies may include design components, which determine how content is organized and accessed within the platform, and delivery components, which determine how the intervention is delivered and supported in practice. The Multiphase Optimization Strategy (MOST) provides a framework for evaluating these design and delivery components (Collins, 2018; Szeszulski & Guastaferro, 2024). In the Optimization Phase of MOST, factorial randomized experiments are typically used to assess the individual and combined effects of selected components but can also be used to examine interactions between components and participant characteristics.

In Tanzania, Janowski and colleagues (2025) conducted a factorial experiment to optimize engagement with ParentApp by testing three design and delivery components while holding the core parenting content constant. The components included guidance (self-guided app use versus app use with facilitator-moderated WhatsApp groups), app design (sequential weekly module release with generic illustrations versus immediate unrestricted module access with culturally adapted illustrations), and digital support (basic onboarding versus enhanced smartphone literacy training). Main trial findings showed that guided delivery and an unstructured app design significantly increased engagement, whereas enhanced digital support offered no additional benefit (Janowski et al., 2025).

However, these findings reflect average effects and may mask important differences in how caregiver subgroups respond to specific components. Moderator analyses examine for whom or under what conditions particular components are most effective (Kraemer et al., 2002), helping to identify differential responses and inform more targeted and equitable implementation. Unlike predictors, which are associated with outcomes irrespective of intervention assignment, moderators interact with intervention components to alter the strength or direction of effects (Kraemer et al., 2002).

To date, few studies of digital parenting interventions have examined moderators, and those that have typically focused on overall program effects in randomized controlled trials (RCTs) (Creswell et al., 2024) or meta-analyses (Florean et al., 2020; Lin-Lewry et al., 2024; McAloon & Armstrong, 2024), rather than the effects of discrete intervention components. As a result, little is known about how specific components influence engagement across caregiver subgroups. The current study addresses this gap by examining whether baseline caregiver characteristics moderate the effects of specific design and delivery components on engagement with ParentApp.

Candidate moderators were selected based on contextual relevance and established person-level associations with engagement in digital interventions. Demographic characteristics such as gender and age were included because they are key determinants of digital engagement, influencing mobile phone ownership, internet access, and confidence in using technology (Borghouts et al., 2021; Jakob et al., 2022). These disparities are often more pronounced in LMICs, where women and older adults tend to have lower device access and connectivity (Breen et al., 2025), potentially shaping both overall engagement and responsiveness to strategies aimed at improving engagement.

Socioeconomic characteristics were included based on prior evidence linking economic strain to lower engagement in digital parenting programs (Fletcher et al., 2023; Fossum et al., 2018; Horn et al., 2025; Lin-Lewry et al., 2024; Wähnke et al., 2024). Financial stress and food insecurity were examined as complementary indicators of socioeconomic adversity, capturing both subjective economic pressure and material hardship. Economic constraints may limit caregivers' ability to engage with digital interventions, as well as shape how they respond to design and delivery components intended to support engagement.

Positive parenting and child maltreatment were examined as candidate moderators because both are primary behavioral targets of ParentApp, and engagement is a key mechanism through which parenting interventions produce change (Becker et al., 2018; Chacko et al., 2016). Baseline levels of these constructs may therefore influence how caregivers respond to specific design and delivery components. In the original PLH Teens RCT in South Africa, Shenderovich et al. (Shenderovich, Cluver, et al., 2020) examined positive parenting and child maltreatment as moderators of treatment outcomes but found no significant effects. However, to our knowledge, no study has examined whether these constructs moderate engagement with specific design and delivery components. Prior digital parenting research has nonetheless linked positive parenting practices to both higher (Wähnke et al., 2024) and lower (Perrino et al., 2018) engagement, while harsh and abusive parenting behaviors have been associated with lower engagement (Dadds et al., 2019). These findings suggest that the relationship between baseline parenting behaviors and engagement may depend on how interventions are designed and delivered.

Finally, caregiver depressive symptoms have been associated with lower engagement in digital interventions, potentially due to low mood, fatigue, and reduced motivation (Borghouts et al., 2021). However, more severe symptoms have also been associated with greater perceived need for support and willingness to engage [25], suggesting that the relationship between depressive symptoms and engagement may depend on delivery context. Consistent with these findings, prior research found that higher depressive symptoms in a digital parenting intervention were associated with lower enrollment in self-directed online delivery, but not in telehealth formats involving human support (Cai et al., 2024). To our knowledge, no study has examined whether depressive symptoms moderate engagement with specific design and delivery components, and given that caregiver wellbeing is also a key outcome of ParentApp, baseline depressive symptoms were included as a candidate moderator.

Accordingly, this study examines whether caregiver characteristics across demographic (gender, age), socioeconomic (financial stress, food insecurity), and psychosocial (positive parenting, child maltreatment, caregiver depression) domains moderate the effects of design and delivery components on engagement with ParentApp. Given the exploratory nature of this analysis in a novel LMIC context, we did not specify a priori hypotheses regarding individual moderators. By identifying for whom specific components are most effective, this study aims to inform more targeted and equitable implementation of digital parenting interventions in LMICs.

8.3 Methods

8.3.1 Experimental Design

This study uses data from the ParentApp optimization trial, a cluster-randomized full factorial experiment conducted across 16 low-income peri-urban and urban communities in Mwanza, Tanzania (Janowski et al., 2025). The trial tested three components: guidance (guided vs. self-guided), app design (unstructured vs. structured), and digital support (enhanced vs. basic). Component selection was informed by prior feasibility testing, which identified key barriers to engagement with ParentApp (Janowski et al., 2023). Full trial procedures and primary findings are detailed elsewhere (Janowski et al., 2025; Janowski et al., 2023). The current study presents a follow-up analysis examining whether caregiver characteristics moderated the effects of design and delivery components on engagement.

8.3.2 Participants

Participants were parents or primary caregivers of adolescents aged 10 to 17 years. Eligibility criteria included being 18 years or older, co-residing with their adolescent for at least four nights per week, and having access to an Android smartphone (operating system 5.1.1 or higher) to use ParentApp.

8.3.3 Intervention

All participants received ParentApp*,* a non-commercial smartphone app designed for offline use. The app was adapted from the PLH Teens program (Cluver et al., 2018) and consisted of 12 modules: an introductory module on caregiver self-care (which included the baseline assessment), 10 core modules focused on evidence-based parenting practices to promote positive parenting and reduce harsh discipline, and a final module that reviewed key concepts and included a post-intervention assessment. Full intervention details, including the TIDieR Checklist, are available in Janowski et al. (2025).

8.3.4 Experimental Components

Guidance (Self-guided vs. Guided)

Clusters were randomized to either self-guided delivery or guided delivery involving facilitator-moderated WhatsApp groups. Each cluster assigned to the guided condition was linked to a dedicated WhatsApp group overseen by a mixed-gender facilitator pair (eight groups total, four facilitator pairs). These groups were intended to promote social connection and sustain engagement with ParentApp throughout the 12-week intervention period.

Following a standardized manual, facilitators posted weekly reminders and discussion prompts, monitored discussions, and responded to participants' questions. Facilitators also conducted weekly 1-hour live chat sessions to encourage peer interaction and discussion.

App Design (Structured vs. Unstructured)

Clusters were randomized to either a structured or unstructured app design. ParentApp was originally designed with sequential weekly module release to align with PLH Teens' learning objectives and pacing and featured abstract, gender-neutral illustrations intended to support cross-cultural scalability. Although user testing and piloting indicated that this version was broadly acceptable, two potential areas for improvement were identified: some caregivers preferred greater flexibility in accessing content, while others raised concerns about the acceptability of the generic illustrations. In response, the trial evaluated two app designs. The structured version maintained sequential module delivery over 12 weeks and retained the original generic illustrations. In the unstructured version, all modules were available immediately upon installation, allowing caregivers to navigate content at their own pace, and the generic illustrations were replaced with culturally adapted imagery tailored to the Tanzanian context.

Digital Support (Basic vs. Enhanced)

All clusters received basic digital support consisting of an embedded app tutorial and a group-based demonstration of key app features during onboarding. Clusters assigned to the enhanced support condition received an additional 15–20-minute training session focused on improving general smartphone literacy and confidence in broader smartphone use.

8.3.5 Procedures

Onboarding sessions were conducted between October 24 and December 1, 2022, in schools and community centers. Following cluster-level randomization, community leaders within each cluster invited eligible caregivers to attend these sessions. One onboarding session was held per cluster (16 in total), with additional sessions conducted where recruitment targets were not met. Sessions were delivered by research staff from the National Institute for Medical Research (NIMR) and facilitators from Investing in Children and Strengthening Their Societies (ICS).

Each onboarding session included: (1) study information and eligibility screening, (2) informed consent, (3) app onboarding and digital support training, and (4) baseline data collection. Following consent, caregivers were divided into small groups of 5–10 participants to facilitate hands-on support with app installation and navigation. NIMR staff guided participants through downloading and installing ParentApp (available via Google Play), after which all participants received basic digital support training and completed the app's introductory module, which included the embedded baseline assessment. Sessions lasted approximately 90 minutes. In clusters assigned to enhanced digital support, caregivers received an additional 15–20-minute group-based smartphone literacy training.

To enable data synchronization, participants were provided with 1 GB of mobile data per month throughout the intervention period. Participants also received US $2 as compensation for attending the onboarding session. Additional procedural details, including the trial CONSORT diagram, are reported in the main trial publication (Janowski et al., 2025).

8.3.6 Measures

Engagement Outcome

Engagement was measured by the number of modules completed, a widely used indicator of sustained engagement in digital parenting interventions (Aldridge et al., 2024). Module completion was defined as navigating all pages within a module and selecting 'Finish' on the final page. Each completed module was scored as 1, yielding a total engagement score ranging from 0 to 12, with higher scores indicating greater exposure to intervention content. Other engagement metrics reported in the main trial paper (e.g., time spent using the app, home practice activity reviews, and behavior logs) were not examined due to data quality concerns (Janowski et al., 2025).

Candidate Moderators

All candidate moderators were drawn from open-access instruments recommended by the Global Parenting Initiative (GPI) and previously used in large-scale PLH program implementation in Tanzania and other LMICs (Lachman, Wamoyi, et al., 2024). Prior to the trial, measures underwent cultural adaptation, including co-development with Tanzanian experts in violence against children, forward–backward translation into Kiswahili, and pilot testing with 100 Tanzanian families. Abbreviated scales were intentionally selected to minimize participant burden during app-based onboarding, reflecting the study's pragmatic design and focus on engagement optimization rather than comprehensive caregiver outcome assessment.

Demographic moderators included caregiver gender (woman/man) and age (years). Additional demographic variables collected but not included in the present analyses were household composition and adolescent orphanhood status. Socioeconomic factors were assessed using two single items adapted from the Financial Self-Efficacy Scale (Lown, 2011). Financial stress was measured using the item, "How many times in the past month have you felt worried or anxious about money?", rated on a 0 to ≥8 frequency scale. Food insecurity was assessed as the number of days in the past month the household ran out of money for food (0–30 days). These items were analyzed separately because of differences in response formats.

Positive parenting was measured using five items from subscales of the Alabama Parenting Questionnaire (Elgar et al., 2007). Caregivers reported the frequency of specific parenting behaviors toward their adolescents on a nine-point count scale (0 to ≥8 times). The measure included items assessing positive parenting (e.g., "How many times in the past month have you praised your teen?"), involvement (e.g., "How many times in the past month did you get involved in activities that your teen likes?"), and supervision (e.g., "How many times in the past month did your teen stay out in the evening past the time they were supposed to be at home?"). Responses were summed to create a total positive parenting score, with higher scores indicating greater positive parenting.

Child maltreatment (physical and emotional abuse) was measured using four items from the International Society for Prevention of Child Abuse and Neglect Screening Tool-Trial Version (Meinck et al., 2018). Caregivers reported the frequency of behaviors in the past month on a nine-point count scale (0 to ≥8 times). The measure included items assessing physical abuse (e.g., "How many times in the past month did you physically discipline your teen by hitting, spanking, or slapping with your hand or an object like a stick or belt?") and emotional abuse (e.g., "How many times in the past month did you shout, scream, or yell at your teen?"). Responses were summed to create a total child maltreatment score, with higher scores indicating greater maltreatment.

Caregiver depression was measured using three items from the Centre for Epidemiological Studies Depression Scale (Irwin et al., 1999). Caregivers reported the number of days in the past week they had: (1) felt depressed, (2) felt that everything they did was an effort, and (3) felt hopeful about the future (reverse-coded). Responses were rated on a 0–7 day frequency scale and summed, with higher scores indicating greater depressive symptoms.

Internal consistency reliability statistics for multi-item scales are reported in Appendix 7, Supplementary File 2.

8.3.7 Statistical Analyses

Missing baseline data were addressed using multiple imputation (van Buuren & Groothuis-Oudshoorn, 2011). Analyses followed an intention-to-treat approach, with outcome models averaged across imputations. As shown in Figure 1, the distribution of the dependent variable (number of modules completed) was consistent with Poisson assumptions. Generalized linear mixed-effects Poisson models were used to account for the nested data structure.

Analyses proceeded in two stages for each candidate moderator. In step 1, separate models were estimated for each component and candidate moderator to assess their independent associations with engagement. In step 2, moderation was tested by adding an interaction term between the component and the candidate moderator (component*moderator) to the models from step 1. Likelihood ratio tests were conducted to assess the significance of the interaction. To avoid convolving individual and contextual effects, candidate moderators were cluster-mean centered. For each moderation model, the corresponding cluster-level mean of the tested moderator was included as a covariate to control for within- and between-cluster effects. All models also controlled for caregiver age and gender, which were sample-mean centered. To avoid model non-convergence, caregiver age was divided by a factor of 10. Component variables were effect coded (-1,1), and resulting unstandardized regression coefficients and standard errors were multiplied by a scaling constant of 2 (Kugler et al., 2018). Incidence rate ratios (IRRs) were derived from exponentiated coefficients, representing the relative change in module completion for each unit increase in the moderator. To control the false discovery rate (FDR) due to multiple comparisons, the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995) was applied to the *p*-values from likelihood ratio tests comparing models with and without the interaction terms. *P*-values are reported in the text and tables, but statistical significance was determined based on thresholds derived from the Benjamini-Hochberg procedure. All analyses were conducted in R (Version 4.3.1).

8.4 Results

8.4.1 Overview of Participants and Engagement

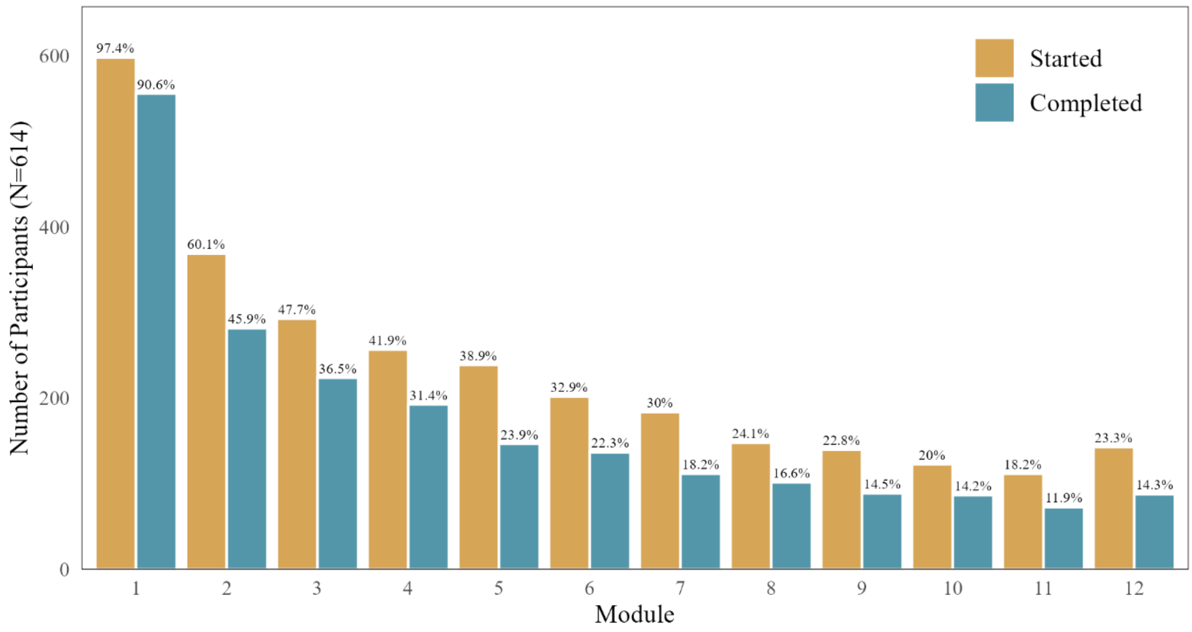
Table 13 summarizes caregiver baseline demographic, socioeconomic, and psychosocial characteristics. A total of 614 caregivers (33.4% men) were included in the analyses, ranging in age from 18 to 75 years (mean = 35.94, SD = 11.84). Caregivers reported high levels of socioeconomic adversity: 23% (132/574) reported feeling worried or anxious about money for seven or more days in the past month, and 84.2% (485/576) reported running out of money to pay for food at least once in the past month. Figure 11 shows the number of participants who started and completed each module. Engagement declined over time, with 38.4% of caregivers completing at least 25% of the modules, 21.5% completing at least 50%, 13.8% completing at least 75%, and 8% completing all 12 modules.

Table 13. *Baseline characteristics of study participants*

Continuous Measures	*n*	*M*	*SD*	Range
Age (y)	577	35.94	11.84	18-75
Financial Stress	574	4.27	2.75	0-8
Food Insecurity	576	7.30	7.78	0-30
Positive Parenting	614	10.89	6.78	0-40
Child Maltreatment	614	6.62	6.42	0-32
Caregiver Depression	614	8.29	3.95	0-21
Categorical Measure	*n*	%		
Gender (men)	205	33.4		

Note. Sample sizes vary due to missing data.

Figure 11. *Percentage of participants who started and completed each module*



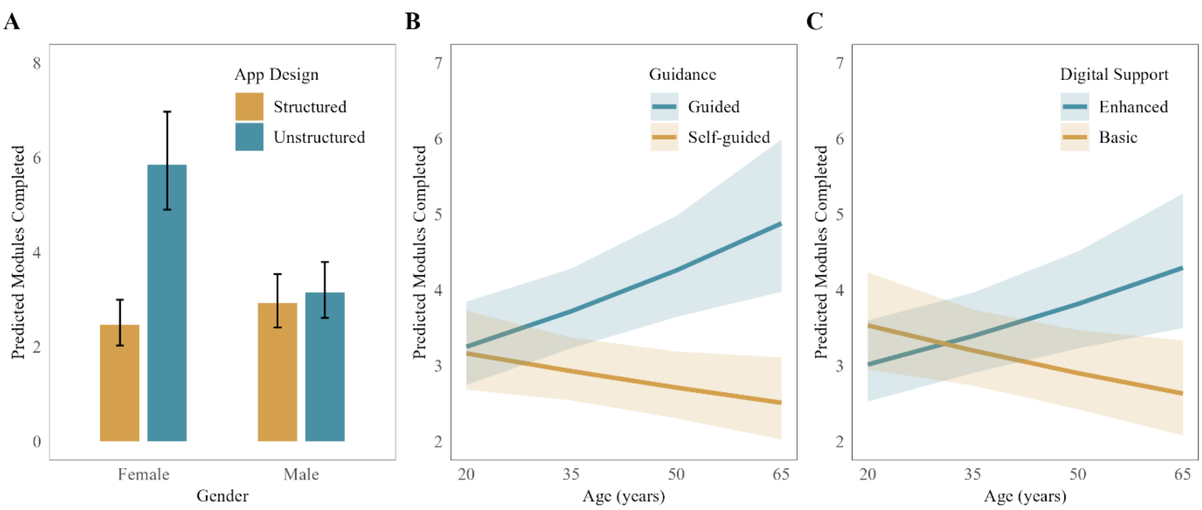
8.4.2 Moderators of Component Effects on Engagement

Six significant moderation effects were identified across demographic (Table 14; Figure 12) and psychosocial (Table 15; Figure 13) caregiver characteristics, with significance determined using the Benjamini-Hochberg procedure. No significant moderation effects were observed for socioeconomic characteristics (Table 16). Benjamini-Hochberg significance thresholds for all tested moderation effects are provided in Appendix 7, Supplementary File 3.

Gender showed a significant main effect on engagement, with women completing more modules than men overall. Gender also significantly moderated the effect of app design on engagement. Among women, those assigned to the unstructured app completed 48% more modules than those assigned to the structured app (IRR = 1.48, 95% CI [1.23–1.80], $p < .001$; significant at FDR < .05; Figure 12A), whereas engagement did not differ significantly by app design among men.

Caregiver age showed no significant main effect on engagement but significantly moderated the effects of both guidance and digital support. For every 10-year increase in age, the effect of WhatsApp-guided delivery (compared to self-guided use) was associated with a 15% increase in module completion (IRR = 1.15, 95% CI [1.06–1.25], $p = .001$; significant at FDR < .05; Figure 12B). The effect of enhanced digital support (compared to basic support) was similarly associated with a 15% increase in module completion for every 10-year increase in age (IRR = 1.15, 95% CI [1.06–1.26], $p = .002$; significant at FDR < .05; Figure 12C). These findings suggest that although older caregivers were not more engaged overall, they benefitted more from components that included additional support.

Figure 12. *Moderation effects of caregiver gender and age*



Note. Panel A shows the interaction between gender and app design, with error bars indicating 95% confidence intervals. Panels B and C show the interactions between caregiver age and (B) WhatsApp guidance and (C) digital support, respectively. Shaded ribbons represent 95% confidence intervals. Estimates are derived from pooled marginal means of multiply imputed generalized linear mixed models with Poisson distributions, adjusted for clustering, age, and gender.

Table 14. *Age and gender as moderators of component effects on engagement*

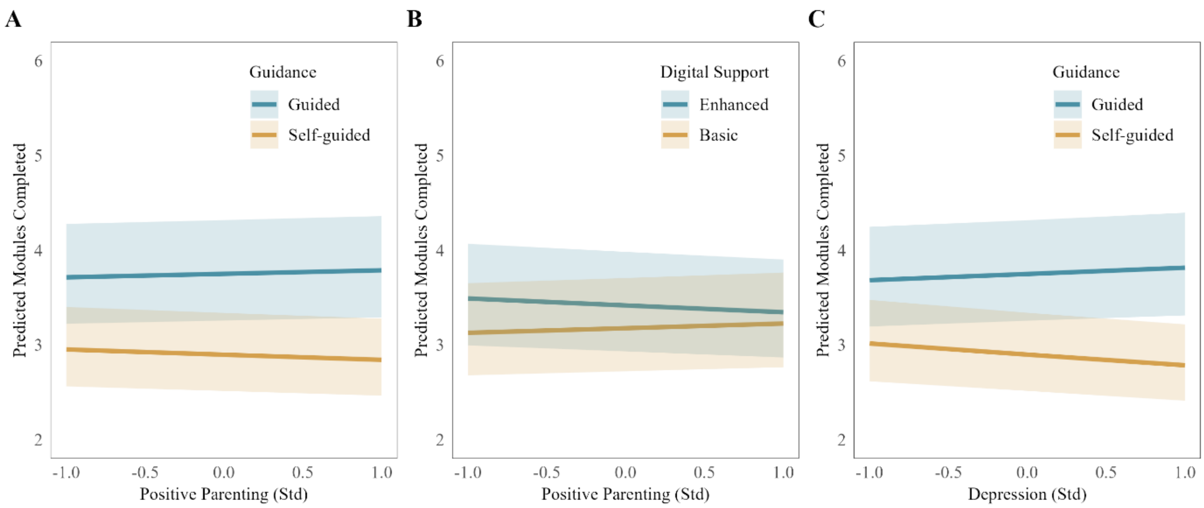
	Gender				Age			
Potential Moderator	*β*	IRR	95 %CI	*p*	*β*	IRR	95% CI	*p*
Guidance								
Step 1								
Guided vs. Self-guided	0.13	1.29	[1.07–1.56]	.007	0.13	1.29	[1.06–1.57]	.011
Potential Moderator	0.14	1.33	[1.10–1.61]	.004	0.02	1.04	[0.95–1.13]	.400
Step 2								
Guided vs. Self-guided	0.13	1.29	[1.07–1.55]	.009	0.13	1.29	[1.06–1.57]	.012
Potential Moderator	0.14	1.33	[1.10–1.62]	.003	0.02	1.04	[0.95–1.13]	.384
Interaction Term	0.10	1.21	[1.00–1.47]	.047	0.07	1.15	[1.06–1.25]	.001
Likelihood ratio test				.047				**.001**†
App Design								
Step 1								
Unstructured vs. Structured	0.24	1.61	[1.31–1.98]	<.001	0.20	1.50	[1.26–1.79]	<.001
Potential Moderator	0.15	1.34	[1.10–1.62]	.003	0.02	1.04	[0.96–1.13]	.362
Step 2								
Unstructured vs. Structured	0.23	1.60	[1.30–1.96]	<.001	0.20	1.50	[1.26–1.78]	<.001
Potential Moderator	0.11	1.25	[1.03–1.52]	.021	0.02	1.04	[0.95–1.13]	.410
Interaction Term	0.20	1.48	[1.23–1.80]	<.001	0.03	1.05	[0.96–1.15]	.252
Likelihood ratio test				**<.001**†				.255
Digital Support								
Step 1								
Enhanced vs. Basic	0.05	1.11	[0.90–1.37]	.309	0.04	1.08	[0.86–1.34]	.512
Potential Moderator	0.14	1.33	[1.10–1.61]	.003	0.02	1.04	[0.95–1.13]	.393
Step 2								
Enhanced vs. Basic	0.05	1.12	[0.91–1.38]	.302	0.04	1.07	[0.86–1.34]	.520
Potential Moderator	1.14	1.33	[1.10–1.62]	.003	0.01	1.01	[0.93–1.11]	.772
Interaction Term	-0.03	0.95	[0.79–1.15]	.601	0.07	1.15	[1.06–1.26]	.001
Likelihood ratio test				.602				**.002**†

Note. Dependent variable = number of modules completed. All models adjusted for age and gender. IRR = exp(2 * β), where β represents the unstandardized regression coefficient from effect-coded experimental factors. † indicates p-values that remain significant after Benjamini-Hochberg correction (gender × app design, *p* = .004; age × guidance, *p* = .004; age × digital support, *p* = .007).

Two psychosocial factors significantly moderated the effects of delivery components on engagement. While positive parenting was not associated with engagement in the main effects models, it moderated the effects of both guidance and digital support. For the guidance component, each unit increase in positive parenting was associated with a 3% increase in module completion in the WhatsApp-guided condition compared to self-guided use (IRR = 1.03, 95% CI [1.02–1.04], $p < .001$; significant at FDR < .05; Figure 13A). In contrast, for the digital support component, each unit increase in positive parenting was associated with a 4% decrease in module completion in the enhanced support condition compared to basic support (IRR = 0.96, 95% CI [0.95–0.98], $p < .001$; significant at FDR < .05; Figure 13B).

Similarly, caregiver depression moderated the effect of guidance. Although depression was not associated with engagement overall, each unit increase in depressive symptoms was associated with a 6% increase in module completion in the WhatsApp-guided condition compared to self-guided use (IRR = 1.06, 95% CI [1.03–1.09], $p < .001$; significant at FDR < .05; Figure 13C). No significant moderation effects were observed for child maltreatment.

Figure 13. *Moderation effects of positive parenting and caregiver depression*



Note. Panel A shows the interaction between positive parenting and WhatsApp guidance; Panel B shows the interaction between positive parenting and digital support; and Panel C shows the interaction between caregiver depression and WhatsApp guidance. Shaded ribbons represent 95% confidence intervals. Estimates are derived from pooled marginal means of multiply imputed generalized linear mixed models with Poisson distributions, adjusted for clustering, age, and gender.

Table 15. *Baseline psychosocial characteristics as moderators of component effects on engagement*

	Positive Parenting				Child Maltreatment				Parental Depression			
Potential Moderator	*β*	IRR	95 %CI	*p*	*β*	IRR	95% CI	*p*	*β*	IRR	95% CI	*p*
Guidance												
Step 1												
Guided vs. Self-guided	0.14	1.31	[1.08–1.60]	.007	0.06	1.13	[0.96–1.34]	.146	0.15	1.35	[1.07–1.70]	.010
Potential Moderator	-0.00	1.00	[0.98–1.01]	.560	-0.00	1.00	[0.98–1.01]	.976	-0.01	0.98	[0.95–1.01]	.238
Step 2												
Guided vs. Self-guided	0.14	1.31	[1.08–1.60]	.007	0.06	1.13	[0.95–1.33]	.159	0.15	1.35	[1.07–1.71]	.010
Potential Moderator	-0.00	0.99	[0.98–1.01]	.274	-0.00	1.00	[0.98–1.01]	.777	-0.01	0.98	[0.95–1.01]	.142
Interaction Term	0.01	1.03	[1.02–1.04]	<.001	0.01	1.02	[1.00–1.03]	.023	0.03	1.06	[1.03–1.09]	<.001
Likelihood ratio test				**<.001**†				.025				**<.001**†
App Design												
Step 1												
Unstructured vs. Structured	0.20	1.50	[1.26–1.79]	<.001	0.14	1.32	[1.12–1.55]	.001	0.20	1.49	[1.27–1.75]	<.001
Potential Moderator	-0.00	1.00	[0.98–1.01]	.545	-0.00	1.00	[0.98–1.01]	.945	-0.01	0.98	[0.95–1.01]	.219
Step 2												
Unstructured vs. Structured	0.20	1.50	[1.26–1.79]	<.001	0.14	1.32	[1.13–1.55]	.001	0.20	1.49	[1.27–1.75]	<.001
Potential Moderator	-0.00	0.99	[0.98–1.01]	.441	0.00	1.00	[0.99–1.02]	.945	-0.01	0.98	[0.95–1.01]	.183
Interaction Term	0.00	1.01	[0.99–1.02]	.338	-0.00	0.99	[0.98–1.01]	.495	-0.02	0.97	[0.94–1.00]	.026
Likelihood ratio test				.239				.501				.027
Digital Support												
Step 1												
Enhanced vs. Basic	0.05	1.11	[0.89–1.38]	.358	0.02	1.04	[0.89–1.22]	.616	0.05	1.10	[0.88–1.37]	.419
Potential Moderator	-0.00	1.00	[0.98–1.01]	.565	-0.00	1.00	[0.98–1.01]	.971	-0.01	0.98	[0.95–1.01]	.234
Step 2												
Enhanced vs. Basic	0.05	1.11	[0.89–1.37]	.361	0.02	1.04	[0.89–1.22]	.598	0.05	1.10	[0.88–1.37]	.424
Potential Moderator	-0.00	0.99	[0.98–1.01]	.497	0.00	1.00	[0.99–1.02]	.976	-0.01	0.98	[0.95–1.01]	.256
Interaction Term	-0.02	0.96	[0.95–0.98]	<.001	-0.01	0.99	[0.97–1.00]	.091	-0.01	0.98	[0.95–1.01]	.172
Likelihood ratio test				**<.001**†				.096				.173

Note. Dependent variable = number of modules completed. All models adjusted for age and gender. IRR = exp(2 * β), where β represents the unstandardized regression coefficient from effect-coded experimental factors. Likelihood ratio test *p*-values were adjusted for multiple comparisons using the Benjamini-Hochberg procedure. † indicates p-values that remain significant after Benjamini-Hochberg correction (positive parenting × guidance, $p = .004$; positive parenting × digital support, $p = .004$; parental depression × guidance, $p = .004$).

Table 16. *Socioeconomic factors as moderators of component effects on engagement*

	Financial Stress				Food Insecurity			
Potential Moderator	*β*	IRR	95 %CI	*p*	*β*	IRR	95% CI	*p*
Guidance								
Step 1								
Guided vs. Self-guided	0.13	1.31	[1.05–1.63]	.019	0.13	1.29	[1.05–1.58]	.015
Potential Moderator	0.02	1.03	[1.00–1.07]	.066	0.00	1.00	[0.99–1.02]	.696
Step 2								
Guided vs. Self-guided	0.13	1.30	[1.04–1.63]	.020	0.13	1.29	[1.05–1.58]	.016
Potential Moderator	0.01	1.03	[1.00–1.06]	.093	0.00	1.00	[0.99–1.01]	.824
Interaction Term	0.02	1.04	[1.00–1.07]	.048	0.01	1.01	[1.00–1.03]	.054
Likelihood ratio test				.050				.052
App Design								
Step 1								
Unstructured vs. Structured	0.20	1.48	[1.27–1.74]	<.001	0.20	1.49	[1.26–1.75]	<.001
Potential Moderator	0.02	1.03	[1.00–1.07]	.061	0.00	1.00	[0.99–1.02]	.715
Step 2								
Unstructured vs. Structured	0.20	1.48	[1.26–1.74]	<.001	0.20	1.48	[1.26–1.75]	<.001
Potential Moderator	0.01	1.03	[1.00–1.07]	.080	0.00	1.00	[0.99–1.02]	.731
Interaction Term	0.01	1.02	[0.99–1.06]	.252	0.01	1.01	[1.00–1.02]	.088
Likelihood ratio test				.254				.085
Digital Support								
Step 1								
Enhanced vs. Basic	0.05	1.10	[0.88–1.37]	.417	0.04	1.09	[0.87–1.36]	.456
Potential Moderator	0.02	1.03	[1.00–1.07]	.061	0.00	1.00	[0.99–1.02]	.717
Step 2								
Enhanced vs. Basic	0.05	1.10	[0.88–1.37]	.414	0.04	1.09	[0.87–1.37]	.445
Potential Moderator	0.02	1.03	[1.00–1.07]	.058	0.00	1.00	[0.99–1.02]	.730
Interaction Term	-0.00	1.00	[0.96–1.03]	.780	-0.00	1.00	[0.98–1.01]	.625
Likelihood ratio test				.780				.287

Note. Dependent variable = number of modules completed. All models adjusted for age and gender. IRR = exp(2 * β), where β represents the unstandardized regression coefficient from effect-coded experimental factors. No interaction effects were statistically significant before or after Benjamini-Hochberg correction.

8.5 Discussion

To our knowledge, this study is the first to examine how caregiver characteristics moderate the effects of discrete design and delivery components on engagement with a digital parenting intervention in an LMIC. It reports moderation analyses from a factorial experiment conducted in Tanzania as part of a MOST optimization trial, with main component effects reported elsewhere (Janowski et al., 2025). Building on findings that WhatsApp guidance and an unstructured app design significantly improved engagement, this study identifies for whom specific components were most effective.

8.5.1 Overall Findings

Gender, age, positive parenting, and depressive symptoms moderated the effects of specific design and delivery components on engagement with ParentApp. These findings suggest that tailoring app design and delivery to specific caregiver characteristics may further enhance engagement in digital parenting interventions. In contrast, financial stress, food insecurity, and child maltreatment did not significantly moderate the effects of any tested component, suggesting that some implementation strategies may operate similarly across families experiencing socioeconomic and parenting-related adversity. The following sections discuss each significant moderator in turn.

Gender moderated the effect of app design, with women showing significantly higher engagement when assigned to the unstructured version, whereas no significant differences in engagement by app design were observed among men. This version differed not only in navigation style but also in its visual design, featuring culturally adapted illustrations that predominantly depicted women. These features may have increased the perceived relevance or accessibility of the intervention for women. However, because visual content and navigation structure were bundled within the same component, the specific mechanisms underlying this effect cannot be isolated. Nevertheless, the findings highlight the importance of gender-transformative design.

Prior research, including a systematic review of father-inclusive interventions in LMICs, identified multiple barriers to male caregiver engagement, including time constraints, restrictive norms around caregiving, and lack of targeted design features (Jeong et al., 2023).

Programs such as Parenting for Respectability, an in-person intervention in Uganda, have demonstrated the feasibility of gender-transformative approaches such as men-only introductory sessions and content affirming fatherhood to engage male caregivers while challenging restrictive gender norms (Siu et al., 2017). In digital contexts, qualitative research on the chatbot-based ParentText program in South Africa and Jamaica found that anonymity, mobile delivery, and equitable messaging helped fathers feel more included and supported (Schafer, Lachman, Zinser, Calderon, et al., 2025). Together, these findings suggest that both content and delivery format play important roles in shaping the accessibility and relevance of parenting interventions for men.

Caregiver age moderated the effects of both guidance and digital support, with older caregivers showing higher engagement when assigned to either WhatsApp guidance or enhanced digital support. Although age was not associated with engagement overall, these findings suggest that older caregivers may benefit more from components that incorporate additional support. Field reports indicated that many older participants relied on borrowed smartphones and had limited digital experience. In such contexts, opportunities to ask questions and receive support may have improved engagement by addressing barriers related to digital competence and confidence. This interpretation aligns with a systematic review of attrition in digital health apps, which identified limited technical skills and lack of prior digital experience as key contributors to disengagement (Jakob et al., 2022). A further systematic review found that tailoring digital interventions to users' digital literacy needs can enhance engagement, particularly among older adults (Borghouts et al., 2021). Together, these findings highlight the value of integrating support strategies that address digital literacy, particularly for older caregivers. Programs may benefit from offering optional, low-intensity supports such as onboarding assistance or peer and facilitator support as part of standard delivery. As digital parenting interventions scale, automated approaches such as interactive onboarding tools may offer a more sustainable alternative. Research with older adults suggests that automated real-time, trial-and-error onboarding support can improve smartphone use, confidence, and motivation more effectively than static instructions (Jin et al., 2022), although the feasibility of such approaches within parenting interventions remains to be tested.

Positive parenting practices moderated engagement in opposite directions across two components. For the guidance component, higher baseline positive parenting was associated with greater module completion in the WhatsApp-guided condition. One possible explanation is that WhatsApp groups reinforced existing parenting strengths through structured reflection and peer exchange, thereby sustaining motivation to practice and refine skills over time. This interpretation aligns with evidence that guided digital delivery can enhance parenting-related self-efficacy (Lin-Lewry et al., 2024; McAloon & Armstrong, 2024).

In contrast, caregivers with higher baseline positive parenting showed lower engagement when assigned to enhanced digital support. These caregivers may have perceived less need for additional onboarding support, potentially contributing to lower engagement with this component (Perrino et al., 2018). From a self-determination theory (SDT) perspective, individuals with stronger perceived competence may disengage when support feels overly directive or undermines autonomy (Ng et al., 2012). Allowing caregivers to select their preferred level of digital support may therefore better align with individual motivation and perceived capacity. However, preference alone may not fully reflect actual digital literacy needs. Future research is needed to determine whether preference-based, assessment-based, or hybrid approaches most effectively balance autonomy, need, and engagement.

Caregiver depressive symptoms also moderated engagement, with caregivers reporting higher symptom levels completing more modules when assigned to the WhatsApp-guided condition. Prior research has linked parental psychological distress to lower engagement in self-directed digital parenting programs (Dadds et al., 2019). More broadly, depressive symptoms have been identified as barriers to participation in digital mental health interventions (Borghouts et al., 2021), potentially due to low mood, fatigue, or reduced motivation. In the context of this study, facilitator-moderated WhatsApp groups may have mitigated these challenges by fostering social support and peer connection, both of which have been identified as facilitators of engagement in digital interventions (Borghouts et al., 2021). These findings suggest that delivery approaches incorporating social connection may be particularly beneficial for caregivers experiencing elevated depressive symptoms.

8.5.2 Implications for Implementation

This study offers several implications for the adaptation and implementation of digital parenting interventions. First, the absence of moderation effects for financial stress, food insecurity, and child maltreatment suggests that the tested components functioned similarly across families experiencing socioeconomic and parenting-related adversity. Although null findings are often underreported, their consistency here is notable. In particular, the findings suggest that the design and delivery components examined here did not appear to disadvantage caregivers experiencing higher levels of adversity. This interpretation aligns with findings from the in-person PLH Teens RCT in South Africa, which similarly reported no significant moderation of outcomes by caregiver or household risk (Shenderovich, Cluver, et al., 2020).

Second, the identification of moderation by gender, age, positive parenting practices, and depressive symptoms suggests potential value in tailoring design and delivery features to enhance engagement. These findings align with precision health approaches, which emphasize adapting interventions to individual characteristics (Mauch et al., 2022). Although this study relied on static baseline characteristics to inform tailoring, future efforts may benefit from incorporating more dynamic data sources. Advances in smartphone-based monitoring, wearable sensors, and AI-enabled platforms offer opportunities to integrate real-time behavioral, contextual, and physiological data into adaptive delivery systems (Silvera-Tawil et al., 2020; Viana et al., 2021). Although such technologies are not yet widely implemented in LMIC settings, they represent a promising direction for developing more responsive and scalable parenting support.

Third, this study illustrates how the MOST framework, and specifically factorial experiments, can be used to examine both overall component effectiveness and subgroup differences within a pragmatic LMIC context. These findings contribute to growing evidence that optimization approaches can support more contextually responsive and scalable intervention delivery (Guastaferro & Collins, 2021; Szeszulski & Guastaferro, 2024). For intervention developers and implementers, the trial provides an applied example of how such methods can inform delivery refinement. More broadly, incorporating optimization approaches into intervention development may support more inclusive, targeted, and sustainable digital health delivery systems.

8.5.3 Limitations and Future Directions

Several limitations should be acknowledged when interpreting these findings. First, although the trial was adequately powered to detect main effects, moderation analyses typically require substantially larger sample sizes, particularly when moderators are unevenly distributed. As is common in moderation research, these findings should therefore be interpreted as exploratory (Shenderovich, Cluver, et al., 2020). Future optimization trials should conduct power calculations specifically for interaction effects.

Second, all moderation analyses were exploratory and included a broad set of candidate moderators, reflecting the limited prior evidence base in digital parenting research, particularly in LMIC contexts. Although corrections for multiple comparisons were applied to reduce the risk of false positives, future work should refine theoretical models of engagement to guide more targeted moderator selection. In addition, child characteristics such as age, gender, and behavior were not examined but may play an important role in shaping caregiver engagement.

Third, although measures were drawn from widely used open-access instruments and underwent cultural adaptation and pilot testing, several moderators were assessed using brief or single-item measures. Internal consistency was modest for some multi-item scales, introducing some degree of measurement error. More comprehensive assessments would strengthen confidence in these findings.

Fourth, engagement was operationalized solely as module completion. Although module completion is one of the most widely used and comparable indicators of engagement in digital parenting research (Aldridge et al., 2024), it does not capture dimensions of engagement quality such as depth of participation and skill enactment (Perski et al., 2017). Future studies should incorporate multidimensional engagement metrics to provide a more comprehensive understanding of engagement quality.

Fifth, the sample was drawn exclusively from low-income communities, which may have limited variability in socioeconomic indicators and reduced sensitivity to detect moderation by factors such as financial stress or food insecurity. Replication in more socioeconomically diverse samples would strengthen confidence in these findings. Finally, the study was conducted under pragmatic implementation conditions, including community-led recruitment, variable smartphone access, and variation in facilitation practices across clusters. While this enhances ecological validity and real-world relevance, it may also have introduced additional variability. Future implementation research should examine how differences in delivery context and fidelity influence both engagement and intervention outcomes.

8.5.4 Conclusion

This study provides novel evidence from an LMIC context that caregiver characteristics may moderate the effects of specific design and delivery components on engagement with a digital parenting intervention. Guided delivery and enhanced digital support appeared particularly beneficial for older caregivers, while guided delivery was also associated with higher engagement among caregivers with more positive parenting practices at baseline and those reporting higher depressive symptoms. The unstructured app design was more effective for women. At the same time, the absence of moderation by financial stress, food insecurity, and child maltreatment suggests that the tested components operated similarly across families experiencing socioeconomic and parenting-related adversity. By identifying for whom specific design and delivery components are most beneficial, this study contributes to emerging efforts to develop more person-centered and contextually responsive digital parenting interventions. As such programs continue to scale in LMIC settings, integrating optimization methods into intervention development may help ensure that implementation strategies are not only effective on average, but also responsive to the needs of diverse caregiver groups.

9. Overall Discussion

This chapter integrates the findings of the three empirical papers, situates them within the wider literature, and considers their implications. The chapter is organised as follows. Section 9.1 provides an overview of the thesis, and Section 9.2 summarises the findings of each empirical paper. Section 9.3 draws together insights across the three papers, while Section 9.4 discusses overarching limitations and challenges. Section 9.5 outlines the strengths of the research, Section 9.6 considers implications for future research and practice, and Section 9.7 makes recommendations for further research. Finally, Section 9.8 describes the strategies used to disseminate the findings.

9.1 Overview of Thesis

This thesis contributes to the understanding of how caregiver engagement with digital parenting interventions can be optimised in LMICs. It focused on a factorial optimisation trial of ParentApp, a smartphone-based parenting programme designed to prevent violence against adolescents in Tanzania. The central aim of the research was to generate evidence on whether, and for whom, different delivery strategies can enhance engagement, and to explore how caregiver characteristics shape engagement.

Three objectives guided the thesis. The first was to evaluate the effects of selected design and delivery components on caregiver engagement. The second was to identify which caregiver demographic, socioeconomic, and psychosocial characteristics were associated with greater or lower engagement, and whether these associations differed by gender. The third was to assess whether these characteristics moderated the effects of design and delivery components on engagement, with the aim of informing more targeted and equitable delivery. These objectives were addressed through three empirical papers, all of which drew on data from a

$2 \times 2 \times 2$ cluster-randomised factorial trial conducted in Mwanza, Tanzania. Each paper corresponded to one overarching research question:

1. What is the effect of design and delivery components (guidance, app design, and digital support) on caregiver engagement with ParentApp, and are there any interactions between these components? (Paper 1)

2. Which caregiver demographic, socioeconomic, and psychosocial characteristics predict engagement and disengagement with ParentApp, and do these predictors differ by gender? (Paper 2)

3. To what extent do caregiver demographic, socioeconomic, and psychosocial characteristics moderate the effects of design and delivery components on engagement with ParentApp? (Paper 3)

To answer research question 1, Paper 1 used mixed-effects models to test the main and interaction effects of the three delivery components on automatically tracked indicators of engagement. To answer research question 2, Paper 2 examined baseline predictors of engagement and disengagement and tested interactions with caregiver gender to assess whether these associations differed for women and men. To answer research question 3, Paper 3 used moderation analyses to test whether caregiver characteristics influenced the impact of the three design and delivery components on engagement. Collectively, these papers provide complementary evidence on the effects of design and delivery strategies, the role of caregiver characteristics, and the potential for tailoring digital parenting interventions to optimise engagement in LMIC contexts.

9.2 Summary of the Findings of Each Paper

9.2.1 Paper 1: Effects of Components on Engagement

Paper 1 reports findings from the first known factorial trial to experimentally evaluate how specific design and delivery strategies impact engagement with a digital parenting app in an LMIC. A 2×2×2 cluster-randomised factorial design was used to test the main and two-way interaction effects of three components: (1) guidance (self-guided vs. WhatsApp group-guided), (2) app design (structured vs. unstructured content release), and (3) digital support (basic vs. enhanced onboarding). Engagement was assessed using six automatically tracked indicators: app launches; modules started; modules completed; home practice activities reviewed; time spent in the app; and positive parenting behaviours logged. Generalised linear mixed-effects models were used to estimate component effects, with random intercepts included to account for clustering at the community level.

The findings indicate that, compared with self-guided delivery, WhatsApp group guidance significantly increased engagement across five of the six outcomes, including more frequent app use, greater time spent in the app, more modules started and completed, and increased logging of positive behaviours. Compared with the structured app design, the unstructured design also significantly improved engagement across all outcomes except app launches, including a sevenfold increase in home practice activity reviews. Enhanced digital support, compared with basic support, showed no significant main effects. However, exploratory analyses identified two significant interactions, where the combination of enhanced support and WhatsApp guidance was associated with higher levels of module completion and time spent in the app than either component alone. These results suggest that group-based guidance and a flexible, culturally adapted app design can improve engagement among caregivers living in conditions of socioeconomic vulnerability, such as those in

Mwanza, Tanzania. They also indicate that enhanced digital support, although ineffective on its own, may complement other supportive components such as WhatsApp groups.

9.2.2 Paper 2: Predictors of Engagement

In Paper 2, the predictive relationship between baseline caregiver characteristics and engagement with ParentApp was examined. Three engagement outcomes were investigated: (1) total number of modules completed, (2) first non-start (the first instance of not beginning a module), and (3) first non-completion (the first instance of starting but not completing a module). Predictors included caregiver gender, age, financial stress, food insecurity, positive parenting, child maltreatment, and depressive symptoms. Poisson generalised linear mixed models were used to test associations, with interaction terms included to assess gender differences and the Benjamini–Hochberg procedure applied to control the false discovery rate.

The analyses showed that gender was the only significant predictor of engagement, with women completing more modules than men. There was no evidence to suggest that the associations between baseline characteristics and engagement differed by gender. However, women reported significantly higher levels of financial stress, food insecurity, child maltreatment, and depressive symptoms at baseline. These findings suggest that higher adversity may increase the perceived relevance of the intervention and motivate greater engagement, at least among women. In contrast, lower engagement among men may reflect gendered barriers that require targeted, gender-responsive strategies. Overall, the absence of associations with other baseline characteristics suggests that ParentApp may be broadly accessible to caregivers facing a range of risk factors, provided that gender-related barriers are addressed.

9.2.3 Paper 3: Moderators of Component Effects on Engagement

In Paper 3, moderation effects were examined to determine whether the impact of the design and delivery components on engagement varied by caregiver characteristics. Moderation analyses tested seven potential moderators: caregiver gender, age, financial stress, food insecurity, positive parenting, child maltreatment, and depressive symptoms. Engagement was operationalised as the total number of modules completed, which had no missing data and was not affected by the zero-inflation observed in other engagement indicators used in Paper 1. Generalised linear mixed-effects Poisson models were used to estimate main and interaction effects, with random intercepts at the cluster level, cluster-mean centring of moderator variables, and the Benjamini–Hochberg procedure applied to control the false discovery rate.

Six significant moderation effects were identified. WhatsApp group guidance was more effective among older caregivers, caregivers with higher levels of positive parenting, and those reporting more depressive symptoms. Compared to the structured app design, the unstructured design was more effective for women. Enhanced digital support increased engagement among older caregivers but was significantly less effective among those with higher levels of positive parenting. No moderation effects were found for financial stress, food insecurity, or child maltreatment. These findings suggest that the effectiveness of certain design and delivery components may vary based on caregiver age, gender, parenting behaviour, and mental health. However, the absence of moderation by socioeconomic adversity or maltreatment risk suggests that the tested design and delivery strategies may promote engagement equitably across high-risk caregiver groups.

9.3 Discussion of Findings

Drawing together evidence from the three papers, this thesis makes three overarching contributions to understanding how caregiver engagement with digital parenting programmes can be optimised in LMICs. First, the findings demonstrate that relatively light-touch design and delivery strategies can increase engagement. Second, persistent gender disparities highlight the need for more inclusive, father-responsive design and delivery. Third, the results indicate that tailoring components to individual caregiver characteristics may offer additional opportunities to strengthen and sustain engagement. Each of these themes is discussed in turn below.

9.3.1 Engagement Gains May Still Fall Short

Paper 1 provides novel evidence that low-intensity, group-based support via WhatsApp can enhance engagement with a digital parenting intervention in an LMIC. This form of guidance offers an alternative to more intensive and costly formats typically used in HICs (Corralejo & Domenech Rodríguez, 2018) and has the potential to be a more scalable approach for supporting caregiver engagement in LMICs. The finding that an unstructured app design, featuring flexible navigation and culturally adapted illustrations, also increased engagement provides further support for the potential of simple, contextually sensitive design adaptations to strengthen caregiver engagement (Aldridge et al., 2024).

Despite these encouraging results, overall programme engagement rates remained modest, even among participants who received the most effective component levels. In the WhatsApp group guidance condition, participants completed an average of 38.7% of programme content, compared to 32.8% in the self-guided group. Similarly, those who received the unstructured app design completed 36.7% of content on average, compared to 34.6% using the structured version. Although these differences were statistically significant, the absolute completion rates raise questions about whether such strategies are sufficient to achieve the levels of engagement required for meaningful behavioural change. Paper 2 reinforces this concern by showing that most attrition occurred shortly after the initial in-person onboarding session, with only 8 % of caregivers completing all 12 modules. These patterns are consistent with evidence from the wider digital health literature, which documents steep reductions in participation following initial uptake. For example, a review of 11 real-world, self-guided digital mental health interventions found that while 21 % to 88 % of users engaged at least once, only 0.5 % to 28.6 % went on to complete all modules or sustain use over time (Fleming et al., 2018).

The current study did not collect sufficient post-intervention data on parenting or adolescent outcomes to establish whether the engagement levels achieved were adequate to translate into behavioural change. However, evidence from other digital parenting interventions shows that considerably greater engagement may be necessary. For example, Baggett et al. (2023), in a trial of a 15-session mobile parenting intervention with 184 predominantly black, socioeconomically disadvantaged mothers in the United States, found that participants who completed at least 10 sessions (approximately 66%) showed significantly greater reductions in child maltreatment risk compared to those with lower engagement (p < .001, Cohen's d = .83). These results suggest that, even with promising delivery strategies such as WhatsApp group guidance or an unstructured app design, the potential to achieve public health impact may be limited unless complementary strategies are developed that promote initial uptake and longer-term engagement.

In summary, although WhatsApp guidance and unstructured app design improved engagement, these strategies alone are unlikely to generate the level of sustained engagement needed to achieve public health impact. Future research should focus on clarifying the "minimum effective dose" of engagement required for behavioural change and on developing complementary strategies to maintain engagement throughout the full programme.

9.3.2 Engaging Men and Fathers Requires Attention

Paper 2 identified caregiver gender as the only predictor of engagement, with women completing significantly more modules than men. This finding aligns with a large body of evidence showing that father participation remains a persistent challenge in parenting interventions (Gonzalez et al., 2023; Panter-Brick et al., 2014). Although digital delivery has often been promoted as a way to reduce structural barriers for men, such as work schedules and stigma around help-seeking (Tully et al., 2017), the results of this trial indicate that universal digital parenting programmes that are not explicitly tailored to men and fathers may fall short of addressing the structural and social barriers that limit men's participation.

Notably, the trial achieved relatively high male enrolment (33.4%), similar to recent in-person parenting programmes in East Africa that also succeeded in engaging large numbers of men, including PLH Teens in Tanzania (34.4%; Lachman, Wamoyi, et al., 2024) and Parenting for Respectability in Uganda (44.4%; Siu et al., 2024). Community mobilisation, particularly outreach by male community leaders, appears to have been an effective strategy for generating initial interest among men. However, ParentApp content and delivery were not adapted to men's needs, motivations, and preferences, likely contributing to lower engagement over time. This reflects a broader challenge noted in the literature, in which programmes often include fathers but rarely adapt content or delivery to their needs (Jeong et al., 2023). Research highlights that seemingly neutral approaches, such as using the term "parent," may inadvertently discourage male participation, as these programmes are often perceived as primarily targeting mothers (McGirr et al., 2020). Explicit father-focused messaging and content, on the other hand, have been shown to be more effective for engaging men, with recent evidence demonstrating that father-targeted recruitment materials yield substantially higher participation than generic materials (Yaremych & Persky, 2023).

Gender differences in engagement were also evident in the moderation findings reported in Paper 3, which examined how the effects of different components varied by caregiver characteristics. These analyses showed that the unstructured app design, which incorporated flexible navigation and culturally adapted illustrations, increased overall engagement but was significantly more effective for women. Although it is not possible to determine which elements of the design drove these differences, the limited visual representation of fathers in caregiving roles may have reduced the app's relevance for men. In response, subsequent iterations of ParentApp have been refined to include more explicit visual depictions of men as caregivers.

However, evidence from in-person programmes such as Parenting for Respectability in Uganda (Siu et al., 2024) suggests that additional, gender-responsive strategies may be needed to strengthen men's engagement and parenting outcomes. These include father-focused content, male-only groups led by male facilitators, and safe peer spaces for men to reflect on masculinity and caregiving. Building on insights from such research, future iterations of ParentApp could be strengthened by moving beyond surface-level adaptations to incorporate these features in digital form, such as tailored pathways for fathers, facilitated male-only peer groups, and content that acknowledges and supports men's roles in caregiving. Such adaptations are essential not only for achieving equitable engagement but also for realising the broader benefits of father involvement for preventing violence, strengthening family relationships, and promoting gender-equitable caregiving (Bacchus et al., 2024; Doyle et al., 2018; Siu et al., 2024).

9.3.3 Component Effects Differ Across Caregiver Characteristics

Building on the findings reported in Paper 1, Paper 3 demonstrates that engagement with digital parenting interventions is influenced not only by the main effects of individual components but also by their interaction with caregiver characteristics. Gender, age, and psychosocial factors shaped how components affected engagement, sometimes enhancing and at other times diminishing their impact. These results underscore that optimisation decisions within the MOST framework need to account for subgroup differences when selecting, combining, or adapting components (Collins, 2018). To illustrate these implications for optimisation, the discussion first examines gender-related differences, then differences by age, and finally the role of psychosocial characteristics.

First, women benefitted more from the unstructured app design. When interpreted alongside results from Paper 2, which demonstrated that women engaged significantly more overall, this finding suggests that features such as flexible navigation and culturally adapted illustrations may amplify the higher levels of participation already observed among women. This result is noteworthy in LMIC contexts, where structural barriers frequently constrain women's access to and use of digital technologies (Breen et al., 2025). However, the gender-specific finding from Paper 3 needs to be considered alongside the persistent challenge of retaining men and fathers in parenting programmes, as discussed in 9.3.2. This raises a critical question for future optimisation: whether design and delivery strategies should focus on sustaining women's engagement, or on adapting components to address the heightened risk of disengagement among men. In the subsequent effectiveness trial of ParentApp, the unstructured app design was retained because it produced the strongest main effects (Paper 1). However, the moderation results from Paper 3 show that this approach comes at the cost of widening gender disparities. Further iterations of optimisation will therefore be needed to test alternative approaches that better support the engagement of men and fathers.

Second, component effects varied according to caregiver age. While Paper 2 found no overall association between age and engagement, Paper 3 showed that when older caregivers were offered enhanced digital support or WhatsApp group guidance, they engaged more with ParentApp than younger caregivers. These components may have been particularly helpful in addressing age-related barriers such as lower digital confidence and reduced familiarity with smartphone-based technologies (Borghouts et al., 2021; Jakob et al., 2022). Exploratory analyses in Paper 1 also identified a synergistic effect when these two components were combined, suggesting that older caregivers, who benefited from each component independently, may have contributed substantially to this combined effect. On the basis of these findings, both WhatsApp group guidance and enhanced onboarding support were carried forward into the subsequent evaluation trial of ParentApp. However, the moderation findings from Paper 3 suggest that these components may be especially beneficial for caregivers facing structural or skills-related barriers, raising the question of whether, in large-scale implementation, they should be provided universally or targeted to those most likely to benefit.

Third, component effects varied according to psychosocial characteristics. Although Paper 2 found no overall association between depressive symptoms and engagement, Paper 3 indicated that WhatsApp group guidance produced greater engagement among caregivers with higher levels of baseline depression. This result reinforces the importance of social connection and peer support for users with greater psychological needs (Borghouts et al., 2021) and highlights the potential value of tailoring higher-cost delivery components to those with greater perceived risk. At the same time, the same component also increased engagement among caregivers with more positive parenting skills, highlighting the risk that resource-intensive strategies can end up benefitting those who already have fewer barriers to participation (Day et al., 2021). Tailoring based on a single characteristic therefore carries the risk of unintentionally concentrating resources on those who need them least (Glasgow et al., 2019; Victora et al., 2003). Furthermore, caregivers with higher levels of positive parenting benefited less from enhanced digital support. Together, these findings indicate that decisions about tailoring need to consider how components operate in combination, rather than optimising each in isolation.

In summary, moderation findings from Paper 3 underscore that component selection involves complex trade-offs, particularly when the aim is to enhance engagement equitably rather than simply maximise average effects. Within the MOST framework, evidence on moderation is recognised as an important source of information for understanding for whom intervention components work best, and it has the potential to inform decisions about which components are retained in an optimised intervention package (Collins, 2018). To date, however, component selection in optimisation trials has rarely been guided by subgroup differences and is typically based on overall effects and feasibility considerations. The findings of Paper 3 suggest that such an approach risks overlooking opportunities to improve engagement among groups at greatest risk of disengagement. They point to the potential value of incorporating principles of precision prevention and adaptive intervention designs, which seek to improve intervention effectiveness by accounting for heterogeneity in user response and tailoring content and delivery accordingly (August & Gewirtz, 2019; Nahum-Shani et al., 2016). However, the promise of adaptive delivery must be weighed against the practical realities of resource-limited settings. The app evaluated in this thesis was intentionally designed to function offline, whereas most adaptive approaches require continuous internet connectivity, real-time data capture, and the infrastructure to analyse and act on these data.

9.4 Limitations

This thesis has several limitations that warrant discussion. Study-specific limitations are described in the discussion sections of each empirical paper. The discussion that follows focuses on overarching limitations that apply to the thesis as a whole. These include issues related to how engagement was measured, constraints in data collection, risks to internal validity, and factors that limit the generalisability of the findings.

9.4.1 Reliance on App Usage Metrics

The thesis relied on passively collected app usage data, which offered an objective and resource-efficient way to measure engagement and avoided the risk of social desirability bias inherent in self-reported measures. However, these data capture only one dimension of a complex construct and do not reflect users' subjective experiences (Perski et al., 2017; Yardley et al., 2016b). By focusing solely on objective behaviours, the study was unable to capture users' cognitive or emotional responses, such as perceived usefulness or satisfaction.

This limitation has important implications for interpreting the trial results. Usage data can indicate how often and how long a programme is accessed, but not whether the interaction was purposeful, meaningful, or sufficient to support behaviour change (Yardley et al., 2016b). In this study, for example, the "home practice review" metric was dominated by zero values, which may reflect genuine non-use, but could also suggest that the feature was difficult to find in the app, or that caregivers saw little value in recording their practice. In contrast, the "positive habits logged" metric sometimes contained implausibly high counts, likely encouraged by the gamified design, which rewarded repeated logging and may have promoted superficial use. These issues illustrate that low or high usage does not necessarily reflect whether caregivers engaged meaningfully with programme content. This is particularly concerning for metrics intended to capture participation in core programme activities, which are often considered the aspects of engagement most closely linked to behaviour change (Aldridge et al., 2024; Piotrowska et al., 2017). These limitations highlight the importance of combining app usage metrics with subjective measures to assess engagement quality and its relationship to programme outcomes.

9.4.2 Constraints in Baseline and Outcome Data Collected

The interpretation of findings was also constrained by the scope and quality of the baseline and post-assessment data collected during the trial. These constraints arose from three main issues discussed below.

Abbreviated and Single-Item Measures

Constructs such as socioeconomic vulnerability, parenting behaviours, and caregiver mental health were assessed using abbreviated or single-item measures. These adaptations were a deliberate, pragmatic decision to keep data collection brief, feasible, and acceptable within the operational capacity of the trial. They were based on items previously used in a local implementation of PLH Teens in Tanzania (Lachman, Wamoyi, et al., 2024) and enabled questionnaires to be delivered digitally with minimal burden on caregivers. However, short scales can fail to capture constructs with sufficient reliability and validity (DeVellis & Thorpe, 2021). To illustrate, analyses of scale reliability showed that the three-item caregiver depression scale had poor internal consistency (Cronbach's alpha = .50; McDonald's omega = .58) (see Appendix 6). Limited measurement precision of this kind introduces random error, which can attenuate true associations with engagement, contribute to null results, and obscure potential moderator effects.

Absence of Adolescent-Level Data

Apart from basic screening information on gender and confirmation that the adolescent fell within the target age range of 10 to 17 years, no additional details were gathered on adolescent demographic, behavioural, or mental health factors. These omissions were partly pragmatic, reflecting the trial's focus on caregivers and their engagement rather than on adolescent outcomes. However, the absence of these data meant it was not possible to explore how adolescent characteristics might have influenced caregiver engagement. Previous studies indicate that factors such as adolescent age, behavioural problems, and mental health difficulties can influence the extent to which caregivers engage with digital parenting interventions (Dadds et al., 2019; Finan et al., 2018; Perrino et al., 2018). Moreover, qualitative findings from the Tanzanian pre–post pilot of ParentApp suggest that adolescents sometimes helped caregivers navigate the app, highlighting that engagement may have been shaped by both caregivers and their adolescents. Without adolescent-level data and without separate profiles or logins for different users, it was not possible to determine whether app use reflected the caregiver alone or was shared with, or supported by, adolescents.

Mode of Data Collection

All baseline and post-assessment questionnaires were embedded within the app and completed independently by caregivers. This approach aligned with the intervention's digital delivery model and significantly reduced the resources required for data collection. However, it also introduced a range of validity risks. Self-administered digital assessments are vulnerable to a range of challenges, including low literacy, misinterpretation of items, and respondent fatigue or disengagement (Nielsen et al., 2020). Technical problems, including syncing failures and app crashes, further disrupted data capture and contributed to incomplete responses (discussed in more detail in 9.4.3). As discussed in Chapter 5.3.4, these issues led to substantial item-level missingness at baseline that had to be addressed using multiple imputation. In addition, attrition during the programme meant that many caregivers never reached the point in the app where the post-assessment survey was embedded, resulting in too few responses for meaningful outcome analyses. Unlike many trials, no additional incentives were offered to encourage completion of post-assessment measures, which may have further reduced the likelihood that caregivers who had disengaged from the app returned to complete the final module.

9.4.3 Challenges to Real-World Delivery and Internal Validity

Despite the use of a rigorous factorial design, several operational and implementation-related constraints may have affected the internal validity of the trial. These include limitations related to statistical power, delivery consistency, and technical fidelity in measuring engagement.

Statistical Power and Cluster Design

In a balanced factorial design, effect coding ensures that main effects and interactions can be estimated independently and with equal theoretical precision (Collins, 2018; Kugler et al., 2018). These conditions were maintained in this trial. However, two features of the design limited the precision of effect estimates. First, operational constraints, including the need to complete recruitment and onboarding within a shortened timeframe so that findings could inform the subsequent effectiveness RCT, meant that the trial proceeded with 16 rather than 24 clusters and a revised target of 640 participants instead of 960. A smaller number of clusters reduces degrees of freedom, limiting the precision of estimates and making interaction effects, which are often smaller than main effects, more difficult to detect. Methodological research shows that cluster-randomised trials with fewer than 20 clusters are particularly vulnerable to low power and inflated type I error rates unless small-sample corrections are applied, and even with these corrections, power remains low (Leyrat et al., 2018).

Second, recruitment success varied across sites, resulting in cluster sizes ranging from 32 to 49 caregivers (*M* 38.4, *SD* 6.2). While this degree of variation does not affect the factorial balance of the trial, unequal cluster sizes can reduce statistical efficiency because, in cluster randomised designs, the amount of information is determined primarily by the number of clusters rather than the number of participants within them. As a result, larger clusters do not contribute proportionally more information than smaller clusters, and uneven cluster sizes reduce the precision of effect estimates (Kerry & Martin Bland, 2001). Together, the small number of clusters and the variation in cluster sizes suggest that the effect estimates, especially for interaction effects, should be interpreted with caution.

Implementation Variability

Variation in the delivery of intervention components introduced uncontrolled heterogeneity across clusters that may have affected engagement outcomes. Onboarding and digital literacy training sessions, for example, differed in duration, group size, and staff composition. Some sessions involved more than 40 families, leaving little opportunity for individual support; others were smaller and allowed for more personalised assistance. Such differences may have shaped early impressions of the intervention and influenced subsequent engagement.

The roll-out sequence introduced additional variation between clusters. During the first half of recruitment, all onboarding sessions were conducted with clusters assigned to the structured app design because the unstructured version was still being developed. As a result, research assistants and facilitators gained their initial experience delivering onboarding with the structured version. This sequencing likely contributed to four app installation errors in the second half of recruitment, when staff accustomed to installing the structured version did not always switch to the unstructured version once it became available. These errors were identified retrospectively by matching screening information with unique app IDs. One case was corrected after successful follow-up, whereas the remaining three participants could not be reached and were therefore analysed according to their randomised allocation rather than the version they had actually received.

Variation was also evident in the delivery of the WhatsApp groups. Timing of group initiation varied, with about half of the groups beginning later than planned due to rolling recruitment and the December 2022 holiday period. In two clusters, groups did not commence until January 2023. These delays may have reduced early participation and contributed to attrition. Differences were also observed in facilitation style and responsiveness. Although all eight facilitators received the same training and standardised manuals, feedback from CWBSA trainers, who provided biweekly coaching, highlighted substantial variation in how facilitators managed the groups. Some actively initiated discussions, checked in regularly, and encouraged peer interaction, whereas others were less engaged. Evidence from the implementation of PLH Teens in Tanzania indicates that facilitator competencies such as empathy, confidence, and consistency are critical to programme delivery and caregiver participation (Martin et al., 2022). Such differences may therefore have introduced unmeasured variability that complicates the interpretation of the effectiveness of this delivery strategy.

Early Dropout

A further challenge was the substantial dropout that occurred immediately after onboarding. Several contextual and implementation-related factors may help explain these rates. Recruitment through respected community leaders likely encouraged initial uptake but may also have introduced social desirability bias, with some caregivers participating out of obligation rather than intrinsic motivation. While monetary incentives helped reduce participation barriers, field reports suggest they may also have drawn in individuals with limited intention to continue beyond onboarding. Technical and logistical difficulties during onboarding, including delays in SIM card distribution, internet connectivity problems, and device compatibility issues, created long waiting times and user frustration, potentially undermining trust in the programme. Language barriers may have further contributed to early dropout. The app was not available in Kisukuma, the primary local language that is mainly oral rather than written, and was instead developed in Kiswahili. While Kiswahili was more practical from a development perspective, it was less familiar to many caregivers.

Measurement Error Due to Technical Challenges

Although ParentApp was designed to function offline, periodic internet connectivity was required to synchronise usage data with the study server. To facilitate this, participants were provided with mobile data bundles, but synchronisation problems still appear to have been common. Evidence from post-trial focus groups suggested that some caregivers engaged with the app more than was reflected in the usage records. These discrepancies are likely to have been caused by a combination of factors, including poor network coverage, use of data for other applications or phone updates before opening ParentApp, and mobile data being switched off while the app was in use. Because the extent of this under-capture could not be systematically quantified, the accuracy of usage metrics as indicators of actual engagement remains uncertain.

9.4.4 External Validity Risks

Several contextual features of the trial may limit the generalisability of its findings to other settings and populations. First, although the trial was delivered under pragmatic community conditions, the inclusion of in-person onboarding, modest financial incentives, and the provision of mobile data helped to reduce barriers to participation and likely enhanced engagement; these supports, however, may not be feasible or sustainable during scale-up.

Second, while recruitment focused on caregivers living in low-income sub-wards, participants were required to own or have regular access to an Android smartphone. National data indicate that only 35 % of Tanzanians own a smartphone (Tanzania Communications Regulatory Authority, 2025), with ownership presumably lower in rural areas and among women and the poorest households. The trial sample therefore represents a relatively digitally connected subgroup of Tanzanians, and the components tested may be less effective in rural areas or other contexts where smartphone access and digital literacy are lower.

Third, although the trial recruited a higher proportion of male caregivers than anticipated (33.4% compared with 20% in the protocol; Janowski et al., 2023), drawing conclusions about men's engagement from these findings remains challenging. The recruitment approach relied heavily on community mobilisation through local leaders, which may not be feasible or equally effective elsewhere. The men who did participate may also represent a subgroup who were already more motivated, available, or socially supported to engage in a parenting programme delivered via a smartphone. These contextual factors suggest that strategies to engage fathers may need to be adapted and re-evaluated when implemented in different cultural and delivery settings. Finally, implementation coincided with the short rainy season and December holiday period, when many families travel to rural areas. Seasonal mobility and variable network coverage may have disrupted app use in ways that would not necessarily occur at other times.

Together, these factors indicate that findings from this trial cannot be assumed to transfer to other contexts. The ADAPT guidance (Moore et al., 2021) emphasises that when interventions are implemented in new settings, their effectiveness and implementation depend on systematic attention to context. This includes explicit assessment of similarities and differences between settings, early and ongoing engagement of local stakeholders, and transparent planning of adaptations to ensure that interventions remain aligned with local resources, delivery systems, and cultural norms. Without such processes, strategies that were effective in urban and peri-urban Mwanza may be less effective elsewhere. Replication accompanied by careful adaptation across settings is therefore essential to establish the generalisability and scalability of optimised delivery approaches.

9.5 Strengths

The overarching strengths of this thesis are presented below. These include the generation of timely and policy-relevant evidence to support the scale-up of digital parenting interventions, the use of an innovative experimental design to optimise engagement, and the integration of real-time monitoring to support responsive implementation. Study-specific strengths have been discussed in each empirical chapter.

9.5.1 Timely Evidence for Digital PLH Programmes

A central strength of the thesis is that it provides timely, policy-relevant evidence to inform the ongoing digital adaptation of PLH programmes. Since the COVID-19 pandemic, PLH, through the GPI, has rapidly expanded its suite of digital programmes in response to growing global demand for scalable, low-cost strategies to reduce VAC and promote positive parenting in LMICs (Lachman, Nurova, et al., 2024).

The factorial trial evaluated in this thesis is the first optimisation trial of a digital PLH intervention and has directly informed several subsequent PLH studies. Findings from the trial guided the development of the intervention package tested in the ParentApp effectiveness RCT in Tanzania (Baerecke et al., 2024). Preliminary results shared in early 2023 informed decisions about which components to retain, adapt, or remove, drawing on three sources of evidence: (i) quantitative engagement data from Paper 1 of this thesis, which identified the components most effective at engaging caregivers; (ii) qualitative interviews exploring the feasibility and acceptability of these components; and (iii) consultations with implementers, together with costing analyses, to assess scalability and sustainability. Based on this evidence, several implementation refinements were made, including reducing WhatsApp group sizes from 40 to 30 participants to encourage peer interaction, and restructuring the onboarding process into two shorter sessions (separating screening from app installation and digital support) to reduce participant burden and improve early user experience. Promisingly, engagement data from the subsequent effectiveness RCT indicated that participants completed an average of 76% of modules one month after enrolment, which is a substantial improvement compared to the optimisation trial.

Although costing analyses were not a primary focus of this thesis, the optimisation trial also contributed preliminary data on the potential cost-efficiency of digital delivery models. A retrospective analysis (Ornelas et al., in preparation) drawing on data from the ParentApp pilot, optimisation trial, and subsequent RCT estimated that delivering ParentApp with WhatsApp-based support could cost approximately US $5.39 per participant for a cohort of 10,000 users. This is considerably lower than the estimated US $24.10 per participant for in-person delivery of PLH Teens in Tanzania (Martin et al., in preparation).

Beyond Tanzania, the insights from this thesis have also informed the design of two further factorial studies within the PLH portfolio: one in South Africa evaluating a chatbot-led intervention for adolescent girls (Ambrosio et al., 2024) and another in Malaysia testing a hybrid digital programme targeting preschool children (Cooper et al., 2024). By generating experimental evidence on how design and delivery strategies influence engagement and demonstrating how these findings can be translated into programme adaptations, this thesis provides an important foundation for future implementation of digital parenting interventions in LMICs.

9.5.2 Novel Application of MOST in an LMIC Context

Another strength of this thesis is its novel application of a factorial experimental design, guided by the MOST framework, to optimise engagement with a digital parenting intervention in an LMIC. It makes a substantive contribution to the digital parenting intervention and implementation science literatures for three main reasons.

First, it extends the application of MOST beyond its predominant application in high-income settings. While a small number of studies have recently applied MOST to in-person parenting programmes in LMICs (Lachman et al., 2019; Piolanti et al., 2025), it has not previously been applied to optimise a digital parenting intervention in these contexts. By embedding a factorial optimisation trial within a community-based delivery model in Tanzania, this study shows that rigorous experimental methods can be implemented in ways that remain responsive to local priorities and delivery realities. In doing so, this thesis contributes both to methodological innovation in LMIC research and to the limited evidence base on digital parenting interventions in these contexts.

Second, it demonstrates the value of an implementation-oriented approach to intervention optimisation. MOST has traditionally been applied to optimise intervention components; however, there is growing recognition that it can, and should also be used to systematically select and refine implementation strategies (i.e., the ways in which interventions are delivered) to enhance feasibility, scalability and impact (Szeszulski & Guastaferro, 2024). By conducting a factorial experiment to compare alternative implementation strategies under pragmatic community conditions in an LMIC, this study provides one of the earliest empirical examples of extending MOST to the optimisation of implementation strategies.

Third, this thesis shifts the focus of experimental optimisation from intervention outcomes to engagement as a primary outcome. Although caregiver engagement is widely recognised as an essential determinant of programme impact, it is rarely prioritised as a primary outcome in experimental research targeting child and adolescent health (Georgeson et al., 2020). More broadly, research in LIMCs has tended to rely on descriptive approaches to understand how interventions work, with few studies using experimental methods to investigate the mechanisms through which interventions achieve their effects (Lazo-Porras et al., 2022). By testing whether and how specific delivery strategies influence engagement, and by examining for whom these strategies are most effective, this thesis provides causal evidence on how digital parenting interventions can be delivered in ways that better reach and retain socioeconomically vulnerable caregivers.

9.5.3 Using Real-Time Monitoring to Inform Responsive Implementation

A further strength of this thesis was the use of real-time monitoring systems to strengthen implementation. Automatically collected app usage data were used not only to evaluate engagement but also to identify and respond to implementation challenges as they arose. Specifically, an R Shiny dashboard developed by IDEMS International enabled the research team to monitor app usage, questionnaire completion rates, and cluster allocation. When problems were identified, such as low post-test response rates, responsive actions were taken, including sending data top-ups and reminder SMS messages to participants.

Although the scope for real-time adaptations was limited, and most adjustments were manual rather than automated, these efforts demonstrate how real-time monitoring can act as a practical tool to support implementation. Such monitoring contributes to the goals outlined in the broader implementation science literature, which emphasises the importance of understanding how interventions are delivered, the context in which they operate, and the mechanisms through which they produce effects (Moore et al., 2015). In LMICs, where constrained resources and rapidly changing conditions are common, recent reviews highlight the value of approaches that strengthen fidelity and identify modifiable barriers early (e.g., Lazo-Porras et al., 2022).

By treating engagement as a dynamic, modifiable target rather than a static outcome, this thesis demonstrates the potential of using app usage data to inform more adaptive, data-driven decision-making. While the systems implemented here were relatively simple and relied on manual responses, the experience points to the feasibility of integrating more automated feedback mechanisms as digital parenting interventions scale. Future implementation could extend this approach by using real-time data to trigger timely, tailored support, such as reminders, personalised guidance, or facilitator outreach, when early signs of disengagement emerge (Collins, Nahum-Shani, et al., 2014).

9.6 Implications for Research and Practice

The findings from this thesis have several implications for advancing the design, delivery, and evaluation of digital parenting interventions in LMICs. Across the three papers, the findings highlight the importance of embedding optimisation methods within early intervention development, designing scalable strategies that are responsive to caregiver needs, and clarifying the relationship between engagement and behavioural outcomes. Following this discussion, specific recommendations for future research and practice are outlined.

9.6.1 Early Optimisation to Inform Policy and Practice Needs in LMICs

Findings from this thesis have practical implications for how digital parenting interventions are developed and scaled in LMICs. The results demonstrate that embedding optimisation trials early in the intervention development cycle can generate timely, context-specific evidence that directly informs programme delivery. This approach challenges the traditional model of waiting for large effectiveness trials before considering questions of feasibility, scalability, and sustainability (Guastaferro & Collins, 2021; Skivington et al., 2021). Evidence from the factorial trial was used to make immediate refinements to ParentApp delivery in the subsequent effectiveness RCT (Baerecke et al., 2024) and contributed empirical data to national discussions on the scale-up of parenting interventions in Tanzania (van Tuyll van Serooskereken Rakotomalala et al., 2025; Wamoyi et al., 2025). The broader implication of this research is that early-stage optimisation provides a systematic way to ensure that interventions are designed for contextual relevance and scalability from the outset, rather than retrofitting adaptations after large effectiveness trials have already been completed.

9.6.2 Developing Scalable Tailoring Strategies Through Adaptive Design

Findings from this thesis have important implications for how digital parenting interventions can be designed to engage caregivers with different needs. The moderation analyses in Paper 3 show that a one-size-fits-all delivery model does not work equally well for all users: characteristics such as gender, age, and psychological wellbeing influenced which engagement strategies were most effective. For example, enhanced digital support, which had no significant main effect overall, was associated with increased engagement among older caregivers. These results suggest that tailoring delivery strategies to user characteristics can increase engagement among subgroups who might otherwise be underserved. However, they also reveal the practical challenge of tailoring in low-resource settings, where personalised in-person support is difficult to sustain at scale. As digital parenting interventions such as ParentApp move toward national delivery, there is a clear need for scalable approaches that do not depend on intensive human resources.

Recent innovations in automated, adaptive technologies offer one promising route forward. For example, interactive mobile guidance systems such as Synapse (Jin et al., 2022) have shown that automated support can increase digital confidence and motivation among older adults. Embedding similar adaptive features in digital parenting apps, or using adaptive intervention designs such as just-in-time adaptive interventions, could allow support to be dynamically adjusted in response to real-time engagement data (Kidwell & Almirall, 2023; Nahum-Shani et al., 2016). The broader implication of these findings is that scalable tailoring, using data-driven, adaptive strategies, represents an important next step for improving engagement and sustaining outcomes as digital parenting interventions are brought to scale.

9.6.3 Strengthening the Evidence Linking Engagement to Outcomes

The findings of this thesis underline the importance of clarifying whether strategies that increased engagement also contribute to improvements in caregiver and adolescent outcomes. While Paper 1 showed that several delivery strategies successfully increased engagement with ParentApp, the study was not able to establish whether these gains translated into meaningful changes in parenting or adolescent outcomes due to limited outcome data (see 9.4.2).

This limitation reflects broader concerns in the digital health literature about the common but often untested assumption that greater engagement implies greater effectiveness (Perski et al., 2017; Yardley et al., 2016b). Reviews of digital parenting interventions (Aldridge et al., 2024) similarly highlight that while specific intervention components can increase engagement, there is less evidence linking these strategies to improvements in parenting and child outcomes. To advance the field, optimisation efforts should investigate whether the same or different design and delivery components are needed to improve both engagement and behavioural outcomes. Future trials should also test whether specific engagement metrics mediate improvements in parenting and adolescent outcomes, and seek to define what constitutes a “minimum effective dose” of engagement. Greater conceptual and empirical clarity in this area is essential for guiding the design, optimisation, and scale-up of digital parenting interventions.

9.7 Recommendations for Future Research and Practice

Building on the implications outlined above, this thesis identifies six priority areas to guide future digital parenting intervention research in LMICs. These priorities concern broadening the optimisation criteria, linking engagement to outcomes, refining the operationalisation of engagement, addressing gender disparities, and advancing tailored implementation strategies.

9.7.1 Integrating Multi-Criteria Decision-Making

Future optimisation trials should expand decision-making criteria beyond engagement to include factors such as feasibility, cost-effectiveness, scalability, and sustainability. In this thesis, while engagement was the primary focus, decisions about which components to carry forward into the effectiveness RCT also drew on qualitative feedback and preliminary costing and implementation data. These additional considerations were incorporated in an informal manner rather than through a structured multi-criteria process, and are not reported in detail here as they lay outside the scope of this thesis. Future optimisation efforts would benefit from the use of formal frameworks such as DAIVE (Designing for Accelerated Impact, Value, and Equity; Strayhorn et al., 2023) to systematically integrate multiple criteria into decision-making. Complementary approaches such as ADAPT (Moore et al., 2021) should also be considered to guide how optimised intervention components are adapted to different cultural and implementation contexts while maintaining fidelity to their core functions.

9.7.2 Link Engagement to Caregiver and Adolescent Outcomes

To ensure that engagement optimisation strategies translate into meaningful impact, future research should explicitly examine whether the tested components lead to improvements in parenting and adolescent outcomes. This thesis was unable to do this due to low response rates on the embedded post-test questionnaire. Future studies should consider alternative data collection strategies that are not dependent on continued app use. Survey platforms such as REDCap (Research Electronic Data Capture) or ODK (Open Data Kit) offer secure and flexible options for capturing outcome data via offline mobile forms or external survey links, which may help improve follow-up rates.

Future optimisation trials should also incorporate mediation analyses to assess whether specific engagement behaviours function as mechanisms of change. For example, such analyses could examine whether completing home practice activities mediates improvements in parenting outcomes. Clarifying these pathways is essential to ensure that engagement optimisation efforts are linked to meaningful behavioural impact rather than superficial app usage. Such evidence would also strengthen how engagement is operationalised, by identifying which aspects of engagement are most strongly associated with impact and therefore most important to monitor and optimise.

9.7.3 Reflect on How to Operationalise Engagement

Researchers and implementers should critically reflect on how engagement is conceptualised and measured in digital parenting interventions. This thesis used objective usage metrics such as module completion and home practice reviews, which were feasible to collect in a pragmatic trial but may not capture the depth or quality of user interaction (Yardley et al., 2016b). Future studies should therefore adopt mixed-methods approaches that combine objective usage data with self-reported measures of user experience. Low-burden methods such as in-app micro-surveys, periodic SMS prompts, or short qualitative feedback can capture perceptions of usefulness, motivation, and emotional connection (Aldridge et al., 2024). These data may offer richer insights into how users experience digital interventions and inform more responsive engagement strategies.

Researchers should also consider whether engagement is best operationalised through single indicators, multidimensional metrics, or composite scores. Composite indices, as used in programmes like ezPARENT (Breitenstein et al., 2017), can simplify analysis and enable comparison, but may obscure meaningful variation across behaviours. As Pham et al. (2019) note, engagement in digital health interventions is context-dependent, and similar usage patterns can reflect different levels of user investment depending on delivery model and user characteristics. Future research should carefully weigh the trade-offs between analytic simplicity and conceptual precision, and prioritise identifying which dimensions of engagement are most predictive of behavioural change.

9.7.4 Explore Mechanisms Underlying Male Engagement

Future research should prioritise identifying and addressing the mechanisms that influence men's and fathers' engagement in digital parenting interventions. Promising strategies include the involvement of male facilitators or peer supporters during recruitment and delivery (Jeong et al., 2023) and the explicit use of the term "father" or culturally relevant equivalents in programme materials (McGirr et al., 2020; Yaremych & Persky, 2023). Recommendations also include the integration of gender-transformative content that challenges inequitable norms and promotes shared caregiving responsibilities (Schafer, Lachman, Zinser, Calderon, et al., 2025; Siu et al., 2024). Digital delivery also offers opportunities to tailor engagement strategies dynamically. Feedback mechanisms and adaptive intervention designs (see 9.7.5) could be used to deliver gender-responsive content based on men's usage patterns and preferences. Further research is needed to evaluate the effectiveness and feasibility of these adaptations in resource-constrained settings.

9.7.5 Explore Feasible Approaches to Adaptive Intervention Design

Building on the finding that caregiver characteristics moderated the effectiveness of engagement strategies, future research efforts should explore adaptive intervention designs that enable more responsive and person-centred delivery of digital parenting programmes. Adaptive interventions, including just-in-time approaches, offer a promising way to tailor digital support in response to user needs and behaviours (Kidwell & Almirall, 2023). Applying such approaches in LMICs requires careful consideration of feasibility and infrastructure constraints. ParentApp was deliberately developed as an offline-first intervention to maximise access in settings with limited or unreliable connectivity. While this approach increased reach, it also limited the capacity for real-time adaptations during delivery. Future work should therefore investigate hybrid models that retain offline accessibility while incorporating simplified rule-based tailoring or delayed feedback mechanisms that can respond to user characteristics or usage patterns without requiring continuous connectivity. Where infrastructure allows, designs such as SMARTs can be used to evaluate the effectiveness of different sequences or intensities of tailoring over time (Collins, Nahum-Shani, et al., 2014; NeCamp et al., 2019). These approaches, which have been successfully applied in community-based child behaviour research (Kidwell & Hyde, 2016), could help identify scalable, adaptive strategies that improve engagement even further.

9.8 Dissemination Strategies

A range of dissemination strategies were used to ensure that findings from this thesis informed the design, implementation, and scale-up of ParentApp and other digital parenting interventions in LMICs. As trial manager, I collaborated closely with GPI research teams, implementation partners, and multilateral stakeholders, including the WHO's Behavioural Insights Team. This collaboration involved stakeholder engagement throughout the Preparation and Optimisation Phases of ParentApp to ensure contextual relevance and delivery feasibility. In March 2023, I presented preliminary findings to key partners (CWBSA, IDEMS International, INNODEMS Kenya, NIMR, and ICS) to inform joint decision-making on components for the subsequent RCT in Tanzania. I also led a GPI-hosted webinar in the same month, where I shared early optimisation trial results with an international audience of implementing partners, policy-makers, and researchers.

In academic settings, I presented the optimisation trial plans at the University of Oxford's Department of Social Policy and Intervention (CEBI seminar, 2022). That same year, I shared early piloting results and the factorial trial design at the ESRC Early Career Conference (St Anne's College, Oxford) and the Symposium for Early Researchers in Social Policy and Intervention (SERSPI, Nuffield College, Oxford). These forums provided valuable feedback that shaped subsequent adaptations to both the intervention and the analytical approach. In 2024, I returned to CEBI to present the main optimisation trial findings, and in 2025, I delivered a seminar at the Department of Experimental Psychology, University of Oxford, as part of the Oxford Psychological Interventions for Children and Adolescents Research Group seminar series.

Findings from the optimisation trial were also presented at international digital health and implementation science conferences. In 2023, I gave oral presentations at the European Society for Research on Internet Interventions (Amsterdam) and the Implementation and Evidence Summit (online), sharing results from Paper 1. In 2024, I presented Papers 2 and 3 at the International Society for Research on Internet Interventions (Limerick), the Karolinska Institute–UNICEF Joint Conference on Global Child and Adolescent Mental Health (Stockholm), and the Sexual Violence Research Initiative Forum (Cape Town).

Dissemination is ongoing through peer-reviewed publications and policy briefs co-developed with implementing partners. To date, the study protocol has been published in *BMC Public Health*; Paper 1 has been published in the *Journal of Medical Internet Research*; Paper 2 is due for submission to the *JMIR Pediatrics and Parenting*; and Paper 3 is under review in *Annals of Behavioral Medicine*.

Conclusion

Across LMICs, families face persistent structural and social challenges that heighten the risk of VAC. Digital parenting interventions offer a promising approach to supporting families at scale. However, their effectiveness depends on user engagement, and there is limited evidence on how such engagement can best be promoted and sustained. Through a cluster-randomised factorial trial of ParentApp in Tanzania, this thesis examined whether discrete design and delivery strategies enhanced caregiver engagement, identified caregiver characteristics that predicted engagement, and assessed how these characteristics influenced the effectiveness of the tested strategies.

The findings provide important early evidence on how digital parenting interventions can be optimised under real-world conditions in LMICs. WhatsApp group support and a flexible, culturally adapted app design improved several indicators of engagement, although overall levels remained modest. A key finding was that men and fathers, despite enrolling in large numbers, were less likely than women to complete programme modules. An equally important finding was that the effects of design and delivery strategies differed across caregiver subgroups, with greater benefits observed among women, older caregivers, and those experiencing higher levels of depression and positive parenting practices. Collectively, these results highlight the need for adaptive digital delivery models that respond to diverse caregiver needs and provide stronger support for groups at higher risk of disengagement, particularly fathers and other underserved populations.

As digital parenting interventions continue to expand, the challenge ahead is to ensure that these innovations translate into meaningful and equitable improvements in family wellbeing. Meeting this challenge will require evidence that links engagement strategies to outcomes for caregivers and adolescents, and delivery systems that can adapt to the diverse realities of families. The research presented in this thesis demonstrates how systematic optimisation can generate such evidence and offers a foundation for designing digital parenting interventions that are more inclusive, responsive, and sustainable. Building on these foundations will be critical if digital technologies are to fulfil their promise of helping families create safer, more supportive environments for children and young people.

Appendices

Appendix 1: Study Protocol

Please see the following published protocol outlining the plans for the ParentApp optimisation trial:

Janowski, R., Green, O., Shenderovich, Y., Stern, D., Clements, L., Wamoyi, J., Wambura, M., Lachman, J. M., Melendez-Torres, G. J., Gardner, F., Baerecke, L., Te Winkel, E., Booij, A., Setton, O., Tsoanyane, S., Mjwara, S., Christine, L., Ornellas, A., Chetty, N., . . . Cluver, L. D. (2023). Optimising engagement in a digital parenting intervention to prevent violence against adolescents in Tanzania: Protocol for a cluster randomised factorial trial. *BMC Public Health*, *23*(1), 1224. https://doi.org/10.1186/s12889-023-15989-x

Appendix 2: Submission of Thesis Requirements Checklist

Component Required	Included	Location
Thesis Title	X	Thesis Document: Title Page
Thesis Abstract	X	Thesis Document: Pages 15-17
Thesis Outline	X	Thesis Document: Chapter 1
Introduction and background to the research topic	X	Thesis Document: Chapter 2 and 3
Three empirical papers with substantive findings	X	Thesis Document: Chapters 6-8
Conclusions	X	Thesis Document: Chapter 9
Statements of authorship certifying that the papers represent the work of the candidate	X	Appendix 5-7
Research ethics forms	X	Appendix 3

Appendix 3: Ethics Forms and Approvals

Name	Roselinde Janowski
Student status	PRS
Supervisor	Professor Lucie Cluver
Project start and end dates	2022-2023
Title	Optimising caregiver engagement in an app-based parenting intervention prevention of violence against children in Tanzania
Brief description	This doctoral research is undertaken in the context of a 2x2x2 cluster-rand factorial trial of the ParentApp for Teens intervention, conducted in Tanzania b October 2022 and March 2023. The objectives of this dissertation are operati in three research papers. The first paper is a protocol paper outlining the ra aims, research questions, and methods proposed for the factorial trial. The p was pre-registered on the Pan African Clinical Trials registry and publishe Open Access journal *BMC Public Health*. The second paper presents the results from the factorial trial (*N* = 614), identifying factor levels with the engagement impact. The third paper will investigate whether p sociodemographic and behavioural characteristics moderate factor level effec effectiveness. The data collection and analyses proposed for these papers have been appr CUREC 2a (reference number R69744/RE001) and Tanzania's National Ins Medical Research (reference number NIMR/HQ/R.8s/Vol.IX/3856).
Methods [please tick **all** that apply] 1. ☐ Literature review 2. ☐ Systematic review 3. ☐ Theoretical papers 4. ☐ Documentary analysis 5. ☐ Secondary analysis 6. ☒ Survey 7. ☒ Qualitative I confirm that I am using data that was collected before the project was formulated, is fully anonymised and is publicly available. ☐ (Checking this box means you will not need to complete a	If you have ticked boxes 1, 2, 3 or 4 only; please sign below and send Supervisor in the first instance. **Date.........2023-10-03...** **Signed by student.....** R Janowski **...** **Signed by supervisor.....** Lucie Cluver **.................................** If you have ticked boxes 5, 6 or 7 you may need to fill in a **CUREC 1a** c [available from http://www.admin.ox.ac.uk/curec/apply/ssh-idrec-process/] a an electronic copy to ethics@spi.ox.ac.uk. Please read the FAQ http://www.admin.ox.ac.uk/curec/faqs-glossary/faqs/ to determin whethe project requires a CUREC before filling one out. Please make sure you download the CUREC checklist from the above webs time you fill it in, in order to make sure you are using the most up-to-date ver Please note that CUREC 1a will request further information and give guidan whether a CUREC 2 should also be submitted. **You MUST allow enough time for your research to be ethically approve CUREC/2 application is required this can take up to sixty days.**

Department of Social Policy & Intervention
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Professor Lucie Cluver
Department of Social Policy and Intervention
University of Oxford

Reference: R69744/RE001 Amendment dated 20th May 2022

9th June 2022

Dear Lucie,

Parenting for Lifelong Health Digital (PLH Digital): Development and feasibility study of an open access parenting app

The new proposed title of the study is "ParentApp for Teens Feasibility and Optimisation Study: An App-Based Intervention to Promote Positive Parenting and Prevent Violence Against Children"

Your application for research ethics approval in connection with your research project amendment has been considered by the Departmental Research Ethics Committee (DREC) in accordance with the procedures laid down by the University for Ethical Approval.

I am pleased to inform you that, on the basis of the information provided, the proposed research has been judged as meeting appropriate ethical standards and DREC approval has been granted.

If any revisions to your research methodology are made subsequent to this approval, these must be detailed in writing and submitted to DREC immediately.

Yours sincerely,

Dr Jamie Lachman
Chair of DREC

Point of contact: ethics@spi.ox.ac.uk | +44 (0) 1865 280734
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NIMR/HQ/R.8a/Vol. IX/3856

03rd December 2021

Dr. Joyce Wamoyi
Principal Research Scientist
NIMR – Mwanza Research Centre
P.O. Box 1462
Mwanza

RE: ETHICAL CLEARANCE CERTIFICATE FOR CONDUCTING MEDICAL RESEARCH IN TANZANIA

This is to certify that the research entitled: **ParentApp for teens feasibility and optimisation study: An app-based intervention to promote positive parenting and prevent violence against children (Wamoyi J. et al.)** has been granted ethical clearance to be conducted in Tanzania.

The Principal Investigator and supervisor of the study must ensure that the following conditions are fulfilled:

1. Progress report is submitted to the Ministry of Health, Community Development, Gender, Elderly & Children and the National Institute for Medical Research, Regional and District Medical Officers after every six months.
2. Permission to publish the results is obtained from National Institute for Medical Research.
3. Copies of final publications are made available to the Ministry of Health, Community Development, Gender, Elderly & Children and the National Institute for Medical Research.
4. Any researcher, who contravenes or fails to comply with these conditions, shall be guilty of an offence and shall be liable on conviction to a fine as per NIMR Act No. 23 of 1979, PART III Section 10(2).
5. Sites: Mwanza and Shinyanga regions.

Approval is valid for one year: 03rd December 2021 to 02nd December 2022.

Name: Prof. Yunus Daud Mgaya

Signature
CHAIRPERSON
MEDICAL RESEARCH
COORDINATING COMMITTEE

Name: Dr. Aifello Wedson Sichalwe

Signature
CHIEF MEDICAL OFFICER
MINISTRY OF HEALTH, COMMUNITY DEVELOPMENT, GENDER, ELDERLY & CHILDREN

CC: Director, Health Services-TAMISEMI, Dodoma.
RMO of Mwanza and Shinyanga regions.
DMO/DED of respective districts.

Appendix 4: Missing Data Analysis Supplementary Figures

Figure S1. *Proportion of missingness by variable*

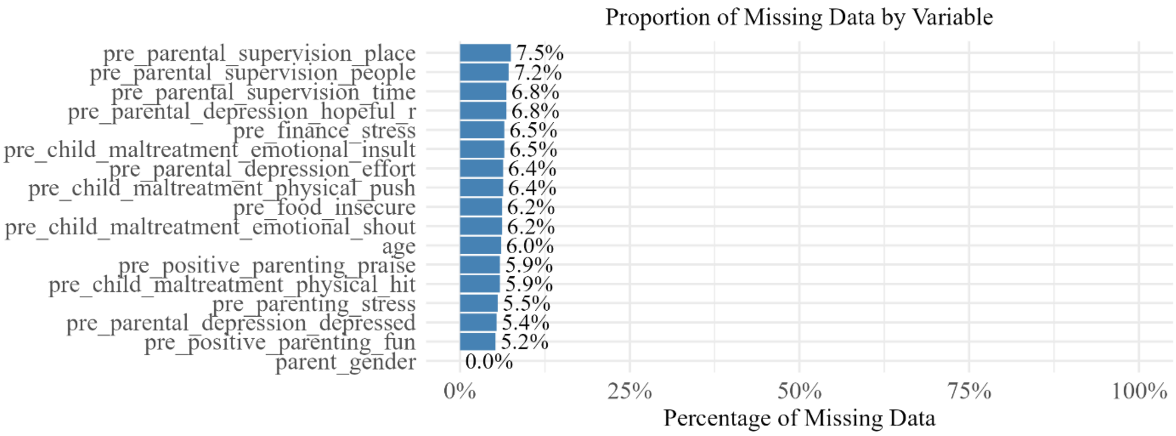


Figure S2. *Pattern of missingness*

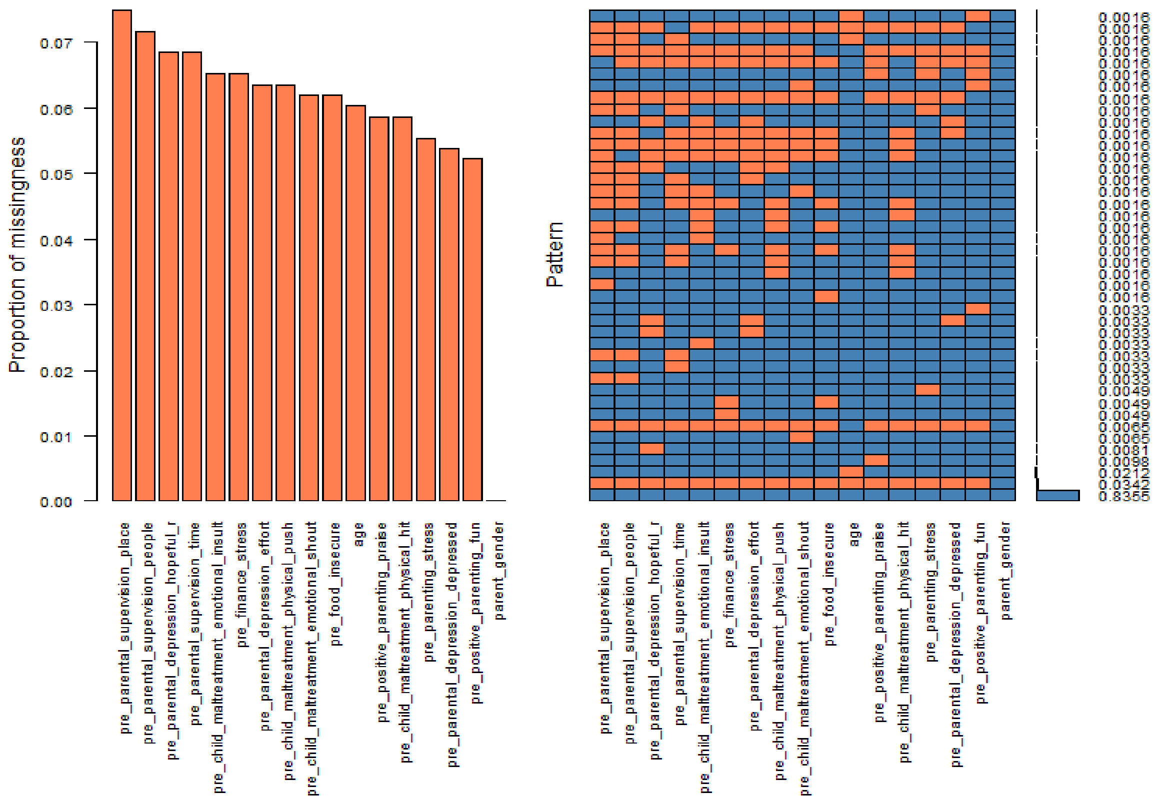
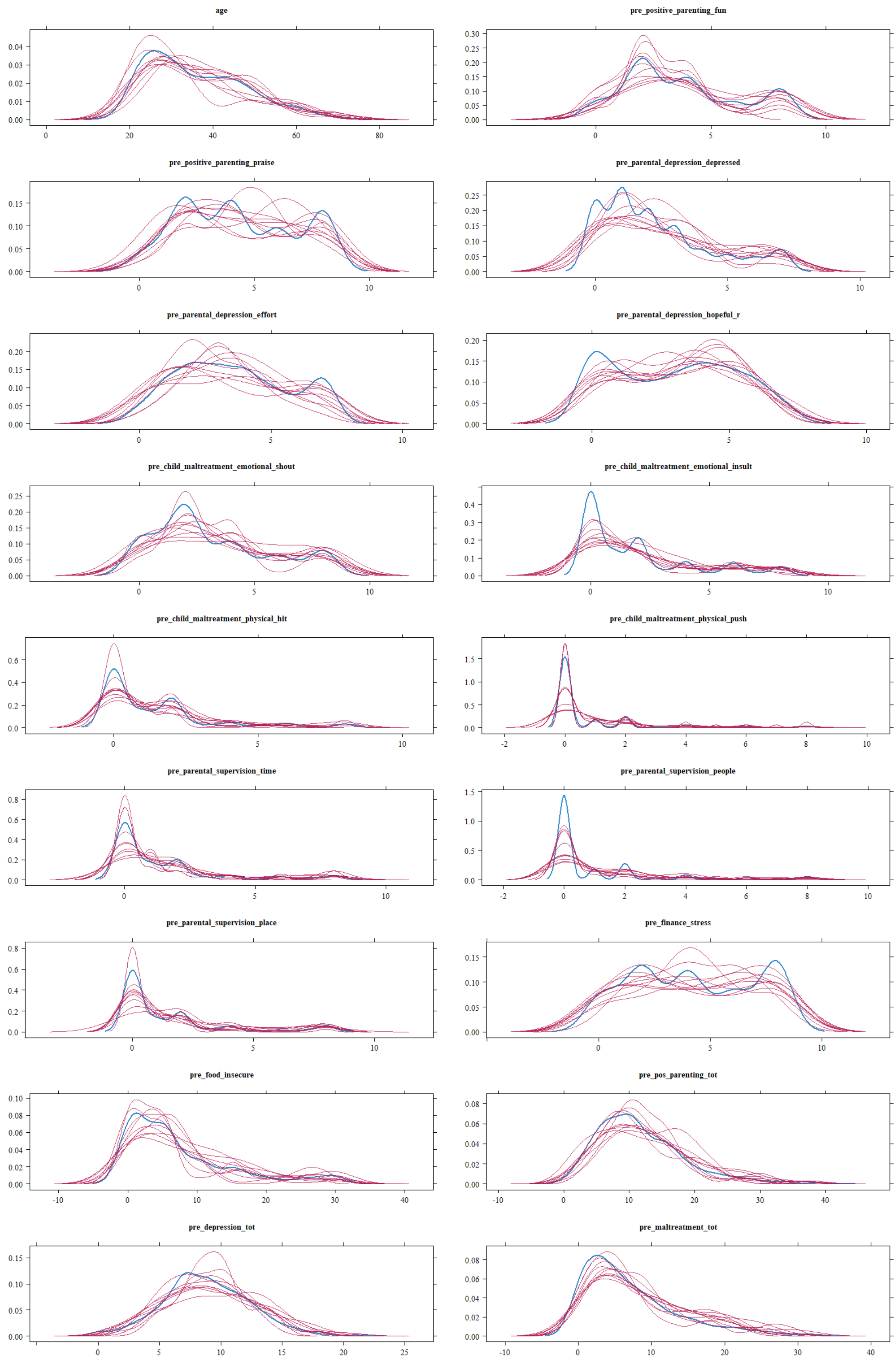


Figure S3. *Density plots*



Appendix 5: Paper 1 Supplementary Files

Supplementary File 1: Paper 1 Statement of Authorship

Paper Title: *Optimizing Engagement With a Smartphone App to Prevent Violence Against Adolescents: Results From a Cluster Randomized Factorial Trial in Tanzania*

Full Reference: Janowski, R., Cluver, L. D., Shenderovich, Y., Wamoyi, J., Wambura, M., Stern, D., Clements, L., Melendez-Torres, G. J., Baerecke, L., Ornellas, A., Chetty, A. N., Klapwijk, J., Christine, L., Mukabana, A., Te Winkel, E., Booij, A., Mbosoli, G., & Lachman, J. M. (2025). Optimizing Engagement With a Smartphone App to Prevent Violence Against Adolescents: Results From a Cluster Randomized Factorial Trial in Tanzania [Original Paper]. *J Med Internet Res*, *27*, e60102. https://doi.org/10.2196/60102

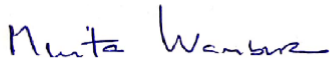
Authors' Contributions: RJ led the study conceptualization and design, with contributions from LDC, JW, DS, L Clements, LB, ETW, AB, and JML. Trial implementation and data collection were managed by RJ, with project administration support from JW, MW, AO, ANC, L Christine, AM, and GM. DS, L Clements, and ETW led app development and app-generated data management. RJ conducted statistical analyses with guidance from GJM-T and L Clements. RJ drafted the manuscript, which was reviewed and edited by LDC, YS, L Clements, GJM-T, LB, ANC, JK, ETW, and JML. All authors approved the submitted manuscript.

We the co-authors certify that the majority – at least 70 per cent – of this work represents the work of the candidate.

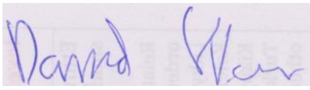
Lucie Cluver: Lucie Cluver
____

Yulia Shenderovich:
____

Joyce Wamoyi: ______________________________



Mwita Wambura: ______________________________



David Stern: ______________________________

Lily Clements: ______________________________

G.J. Melendez-Torres: ______________________________

Lauren Baerecke: ______________________________

Abigail Ornellas: ______________________________

Angelique Chetty:

Jonathan Klapwijk:

Laetitia Christine:

Ateamate Mukabana:

Esmee Te Winkel:

Anna Booij:

Gervas Mbosoli:

Jamie Lachman:

Supplementary File 2: CONSORT-EHEALTH checklist

For access to the completed CONSORT-EHEALTH checklist, please refer to the published article. The checklist is available as a downloadable PDF under Multimedia Appendix 5 at the following link: https://www.jmir.org/2025/1/e60102.

Janowski, R., Cluver, L. D., Shenderovich, Y., Wamoyi, J., Wambura, M., Stern, D., Clements, L., Melendez-Torres, G. J., Baerecke, L., Ornellas, A., Chetty, A. N., Klapwijk, J., Christine, L., Mukabana, A., Te Winkel, E., Booij, A., Mbosoli, G., & Lachman, J. M. (2025). Optimizing Engagement With a Smartphone App to Prevent Violence Against Adolescents: Results From a Cluster Randomized Factorial Trial in Tanzania [Original Paper]. *J Med Internet Res*, *27*, e60102. https://doi.org/10.2196/60102

CONSORT-EHEALTH checklist (V.1.6.1): Information to include when reporting ehealth/mhealth trials (web-based/Internet-based intervention and decision aids, but also social media, serious games, DVDs, mobile applications, certain telehealth applications)

Do you feel items are missing/unclear/unnecessary? Please comment at http://tinyurl.com/consort-ehealth-v1-5

If you are working on a manuscript submission, please fill in this checklist electronically at http://tinyurl.com/consort-ehealth-v1-6

Section/Topic	Item No.	CONSORT* Checklist Item	EHEALTH Extensions (additions to, or clarification of the CONSORT item)	*Importance*
TITLE & ABSTRACT	1a	Identification as a randomized trial in the title	i) **Identify the mode of delivery in the title**. Preferably use "web-based" and/or "mobile" and/or "electronic game" in the title. Avoid ambiguous terms like "online", "virtual", "interactive". Use "Internet-based" only if Intervention includes non-web-based Internet components (e.g., email), use "computer-based" or "electronic" only if offline products are used. Use "virtual" only in the context of "virtual reality" (3-D worlds). Use "online" only in the context of "online support groups". Complement or substitute product names with broader terms for the class of products (such as "mobile" or "smart phone" instead of "iphone"), especially if the application runs on different platforms.	*Essential*
			ii) Mention **non-web-based components or important co-interventions in the title**, if any (e.g., "with telephone support").	*Highly Recommended*
			iii) Mention **primary condition or target group in the title**, if any (e.g., "for children with Type I Diabetes") Example: *A Web-based and Mobile Intervention with Telephone Support for Children with Type I Diabetes: Randomized Controlled Trial*	*Essential*
	1b	Structured summary of trial design, methods, results, and conclusions NPT** extension: Description of experimental treatment,	Methods (in Abstract): i) Mention **key features/functionalities/components of the intervention and comparator in the abstract**. If possible, also mention theories and principles used for designing the site. Keep in mind the needs of systematic reviewers and indexers by including important synonyms.	*Essential*

CONSORT EHEALTH 2011 checklist *Page 1*

Supplementary File 3: TIDieR (Template for Intervention Description and Replication) checklist

TIDieR
Template for Intervention Description and Replication

The TIDieR (Template for Intervention Description and Replication) Checklist*:
Information to include when describing an intervention and the location of the information

Item number	Item	Where located **	
		Primary paper (page or appendix number)	Other † (details)
	BRIEF NAME		
1.	Provide the name or a phrase that describes the intervention.	_____3-4_____	_______________
	WHY		
2.	Describe any rationale, theory, or goal of the elements essential to the intervention.	______4______	______________
	WHAT		
3.	Materials: Describe any physical or informational materials used in the intervention, including those provided to participants or used in intervention delivery or in training of intervention providers. Provide information on where the materials can be accessed (e.g. online appendix, URL).	_____5-6_____	___Multimedia Appendix 2____
4.	Procedures: Describe each of the procedures, activities, and/or processes used in the intervention, including any enabling or support activities.	_____4-6_____	______________
	WHO PROVIDED		
5.	For each category of intervention provider (e.g. psychologist, nursing assistant), describe their expertise, background and any specific training given.	_____4-6_____	______________
	HOW		
6.	Describe the modes of delivery (e.g. face-to-face or by some other mechanism, such as internet or telephone) of the intervention and whether it was provided individually or in a group.	_____5-6_____	______________
	WHERE		
7.	Describe the type(s) of location(s) where the intervention occurred, including any necessary infrastructure or relevant features.	___3-4 and 6__	______________
	WHEN and HOW MUCH		

8.	Describe the number of times the intervention was delivered and over what period of time including the number of sessions, their schedule, and their duration, intensity or dose.	_____5-6_____	_____________
	TAILORING		
9.	If the intervention was planned to be personalised, titrated or adapted, then describe what, why, when, and how.	______5______	_____________
	MODIFICATIONS		
10.‡	If the intervention was modified during the course of the study, describe the changes (what, why, when, and how).	______NA____	_____________
	HOW WELL		
11.	Planned: If intervention adherence or fidelity was assessed, describe how and by whom, and if any strategies were used to maintain or improve fidelity, describe them.	__9 and 11-14_	_____________
12.‡	Actual: If intervention adherence or fidelity was assessed, describe the extent to which the intervention was delivered as planned.	___11-14_____	_____________

Supplementary File 4: TIDieR (Template for Intervention Description and Replication) Description

Table S1. *TIDieR description of ParentApp*

Item		Description
1.	Brief name	ParentApp
2.	Why	ParentApp is a smartphone app adapted from the in-person, group-based PLH Teens program, which was originally developed in South Africa to address the need for cost-effective, culturally appropriate violence prevention (Cluver et al., 2018). Initial evaluations of PLH Teens in South Africa demonstrated significant effects, including reduced child maltreatment, improved positive parenting practices, and decreased parental depression, stress, substance use, and financial stress (Cluver et al., 2018). PLH Teens has since been adapted and widely implemented across more than 18 LMICs (Shenderovich, Ward, et al., 2020), including a large-scale delivery in Tanzania to over 75,000 caregivers and adolescents (Lachman, Wamoyi, et al., 2024). Despite strong, emerging evidence for the effectiveness of the in-person program, the app-based delivery was adapted to address access and scalability challenges, including logistic barriers, human resource constraints, and economic costs associated with in-person delivery.
3.	What (materials)	The content material mirrors the content of in-person program in a condensed format and draws on existing evidence-based violence prevention interventions. In response to piloting and requests from families, adaptations were made to the program content to include (1) content to support caregiver mental health through mindfulness techniques, (2) content for families experiencing bereavement, (3) enhanced evidence-based content to prevent and respond to risks of sexual and online violence including No Means No Worldwide program content.
4.	What (procedures)	Eligible caregivers attended an in-person orientation and onboarding session where locally recruited trained research assistants and facilitators guided enrolled participants in downloading the app from Google Play and installing it on their smartphones. Once installed, caregivers participated in an optional

app orientation training provided by facilitators and research assistants. ParentApp content focuses on relationship-building between caregivers and adolescents, stress management and problem-solving skills, non-violent approaches to discipline, and adolescent safety. This material is provided through text, images, and audio in 12 modules. A range of recurring activities are used in each module to reinforce learning and practical skills-building. These include:

Mindfulness-based stress reduction activities: Modules start with a “How are you?” emotional check-in, prompting users to assess their current state, followed by tailored feedback and relaxation exercises from a library of over 30 mindfulness activities. These promote presence, body awareness, and emotional regulation.

Comics and scenario exploration: Modules present parent-child scenarios through ‘negative comics’ and their positive alternatives. Users explore these through interactive segments such as “Question Time,” which includes tapping on emotions and selecting multiple-choice answers to understand different perspectives. This helps parents recognize potential challenges and learn how new skills can lead to positive outcomes.

Reflection on benefits: Short introductory messages and audio testimonials from other parents (translated into Kiswahili) underscore the benefits of each new skill, encouraging users to see their relevance and effectiveness.

Essential Tools: Modules include clear, concise overviews of key messages titled “Essential Tools.” These summaries facilitate the application of skills through simple headings, real-life examples, and links to module activities.

Home practice activities: Each module concludes with a “Ready to Practise?” activity, inviting users to plan how to apply the skill in their home environment. This section includes a testimonial from a local teenager to highlight the practical impact of the skill in a familiar context. **Home activity reflection**: After completing home practice activities, a prompt (“How did your practice go?”) appears in the module overview. Users reflect on their experiences through multiple-choice questions and receive tailored solutions for overcoming any challenges they report. Positive feedback prompts reinforcement, while challenges trigger empathetic responses that acknowledge difficulties and provide practical guidance.

		ParentPoints: Users can track their progress over time by collecting ParentPoints through self-reported use of positive parenting and mental health promoting practices which are aligned with module content: self-care practices ("relax," "treat yourself well," "praise yourself"), relationship-building behaviors ("one-on-one time," "praise your teen"), effective communication ("positive instructions"), emotion regulation ("respond calmly"), family management ("good money choices," "calm consequences"), and safety promotion ("keep your teen safe").
5.	Who (provides)	The intervention is delivered remotely as a smartphone app compatible with Android devices running version 5.5.1 or later. As part of the factorial design of the ParentApp optimisation study, local trained facilitators provided moderated WhatsApp groups support to half of the participants. Facilitators were paraprofessionals with prior experience supporting caregivers remotely during the Tanzanian pilot and were trained by CWBSA, an NGO with experience leading PLH training globally.
6.	How	The intervention was delivered remotely via an app. Half of the participants additionally received facilitator-moderated WhatsApp group guidance.
7.	When and how much (mode of delivery)	ParentApp material is delivered through text, images, and audio in 12 sessions. To encourage continued usage, three sets of push notifications are sent to participants: one scheduled within the first day of the user's initial app launch, another scheduled 6 days after the user's last app launch, and a third scheduled 30 days after the user's last app launch. For the WhatsApp groups, facilitators monitored caregiver discussions, shared helpful tips and reminders, addressed questions raised by participants, and led weekly 1-hour live chat sessions to encourage discussion and reflection.
8.	Where	The intervention was delivered via app to caregivers of adolescents aged 10-17 years in urban and peri-urban communities in the Mwanza region of Tanzania.
9.	Tailoring	Content is tailored according to whether participants selected using ParentApp alone or in a group setting with family or friends. Push notifications to encourage continued usage were tailored according to participant engagement.

10.	Modifications	Revisions and modifications for future iterations of delivery will be based on the findings of the current paper and from findings from qualitative focus group discussions covered in a subsequent publication.
11.	How well (planned)	Fidelity to the program was assessed based on engagement data (see results section of the paper) and via qualitative focus group (the results of which will be covered in a subsequent publication).
12.	How well (actual)	Automatically tracked engagement data assessing the actual adherence is reported in the present paper, and further information on adherence based on findings from qualitative focus group discussions with users will be covered in a subsequent publication.

Note. TIDieR: Template for Intervention Description and Replication

Supplementary File 5: Supplementary Analyses

Table S1. *App installation status as a function of randomization to experimental factors*

Outcome	Factor level[a]	MR[b]	95% CI	*p*
App installed vs. app not installed	Guided vs. Self-guided	0.65	(0.38–1.12)	.125
	Unstructured vs. Structured	1.45	(0.82–2.56)	.206
	Enhanced vs. Basic	077	(0.45–1.33)	.345
Random Effects				
σ^2	3.29			
τ_{00} cluster	0.02			
ICC	0.01			
N	16			

[a]Guided=WhatsApp group guided versus self-guided, Unstructured=Unstructured app design versus structured app design, Enhanced=Enhanced digital support versus basic digital support. [b]MR denotes estimated effects, where MR = exp(2 * β), with β representing the unstandardized regression coefficient. Observations = 680. Marginal R^2 / Conditional R^2 = 0.030 / 0.035

Table S2. *Positive parenting and mental health habits logged: Sensitivity analysis*

		Unadjusted			Adjusted[c]		
Outcome	Factor level[b]	MR	95% CI	*P* value	MR	95% CI	*p*
	Guided vs. Self-guided	1.86	(1.46–2.36)	<.001	1.77	(1.39–2.24)	<.001
Positive habits logged[a]	Unstructured vs. Structured	16.22	(5.87–44.82)	<.001	16.92	(5.89–48.59)	<.001
	Enhanced vs. Basic	1.19	(0.83–1.72)	.345	1.20	(0.84–1.71)	.309

[a]Positive habits logged capped at 80. where MR = exp(2 * β), with β representing the unstandardized regression coefficient. [b]Guided=WhatsApp group guided versus self-guided, Unstructured=Unstructured app design versus structured app design, Enhanced=Enhanced digital support versus basic digital support. [c]Adjusted for caregiver age, gender, and baseline scores: financial stress, food insecurity, parenting stress, caregiver depression, overall child maltreatment, overall positive parenting. All covariates were sample-mean centered.

Supplementary File 6: Table of Experimental Conditions With Effect Coding

Table S1. *Eight experimental conditions with effect coding*

Condition	Factor A: Guidance	Value	Factor B: App Design	Value	Factor C: Digital Support	Value
1	Self-guided	-1	Unstructured	1	Enhanced	1
2	Self-guided	-1	Unstructured	1	Basic	-1
3	Self-guided	-1	Structured	-1	Enhanced	1
4	Self-guided	-1	Structured	-1	Basic	-1
5	Guided	1	Unstructured	1	Enhanced	1
6	Guided	1	Unstructured	1	Basic	-1
7	Guided	1	Structured	-1	Enhanced	1
8	Guided	1	Structured	-1	Basic	-1

Appendix 6: Paper 2 Supplementary Files

Supplementary File 1: Paper 2 Statement of Authorship

Paper Title: *Caregiver-Level Predictors of Engagement With a Digital Parenting Intervention: Evidence From a Factorial Randomized Trial in Tanzania*

Full Reference: Janowski, R., Cluver, L. D., Wamoyi, J., Lachman, J. M., Melendez-Torres, G.J., Stern, D., van Niekerk, L., Shenderovich, Y., (2025). Caregiver-Level Predictors of Engagement With a Digital Parenting Intervention: Evidence From a Factorial Randomized Trial in Tanzania

We the co-authors certify that the majority – at least 70 per cent – of this work represents the work of the candidate.

Lucie Cluver: ____________________________

Joyce Wamoyi: ____________________________

Jamie Lachman: ____________________________

G.J. Melendez-Torres: ____________________________

David Stern: ________________________________

Lauren-Jayne van Niekerk: ________________________________

Yulia Shenderovich: ________________________________

Supplementary File 2: Supplementary Analyses

Table S1. *Internal consistency reliability for baseline measures (≥2 items)*

Measure	Scale	Items	Cronbach's α	Omega (ωt)	Omega (ωh)
Child maltreatment	International Society for Prevention of Child Abuse and Neglect Screening Tools-Trial Version	4	0.76	0.77	0.77
Positive parenting	Alabama Parenting Questionnaire	5	0.54	0.57	0.54
Caregiver depression	Centre for Epidemiologic Studies Depression Scale	3	0.50	0.58	0.58

Note. Cronbach's alpha, Omega Total (ωt), and Omega Hierarchical (ωh) were computed using the psych package in R. Reliability analyses were conducted on scales with two or more items. Reverse-coded items were automatically detected and adjusted using the check.keys = TRUE option. Missing data were handled via pairwise deletion (the default in psych), meaning correlations were computed using all available pairs of observations without removing entire cases. Unidimensional reliability estimates were obtained by specifying one factor (nfactors = 1) in the omega analyses.

Internal consistency for scales with two or more items was assessed using Cronbach's alpha, McDonald's Omega Total (ωt), and Omega Hierarchical (ωh), calculated with the psych package in R (version 4.5.0). The child maltreatment items (4 items; International Society for Prevention of Child Abuse and Neglect Screening Tools-Trial Version) demonstrated good reliability, with $\alpha = 0.76$, $\omega t = 0.77$, and $\omega h = 0.77$. The positive parenting items (5 items; Alabama Parenting Questionnaire) showed modest internal consistency, with $\alpha = 0.54$, $\omega t = 0.57$, and $\omega h = 0.54$. The caregiver depression items (3 items; Centre for Epidemiologic Studies Depression Scale) exhibited lower reliability estimates ($\alpha = 0.50$, $\omega t = 0.58$, and $\omega h = 0.58$), indicating limited internal consistency for this brief measure.

Table S2. *Cox proportional hazards models for time to first non-start*

Predictor	HR	95% CI	*p*	Adjusted *p*
Caregiver gender (female)	0.872	0.727-1.047	0.143	0.264
Adolescent gender (female)	0.959	0.806-1.14	0.634	0.713
Caregiver age	0.995	0.987-1.003	0.195	0.351
Financial stress	0.975	0.944-0.944	0.123	0.239
Food insecurity	1.004	0.992-1.015	0.526	0.713
Positive parenting	1.003	0.99-1.017	0.637	0.713
Child maltreatment	0.997	0.983-1.011	0.665	0.726
Parental depression	1.00	0.975-1.027	0.974	0.974
Parenting stress	1.009	0.976-1.042	0.598	0.713

Note. Models control for intervention conditions (support, skin, digital literacy effects). Random effects included for trial clusters. Hazard ratios < 1 indicate lower risk of non-start. *P*-values adjusted using Benjamini-Hochberg procedure.

Table S3. *Cox proportional hazards models for time to first non-completion*

Predictor	HR	95% CI	*p*	Adjusted *p*
Caregiver gender (female)	0.903	0.757-1.077	0.257	0.451
Adolescent gender (female)	0.991	0.838-1.172	0.918	0.944
Caregiver age	0.998	0.991-1.006	0.679	0.728
Financial stress	0.977	0.947-1.008	0.141	0.264
Food insecurity	0.995	0.984-1.007	0.427	0.591
Positive parenting	1.003	0.99-1.016	0.688	0.728
Child maltreatment	0.999	0.986-1.012	0.873	0.911
Parental depression	1.012	0.986-1.038	0.362	0.539
Parenting stress	1.001	0.97-1.033	0.947	0.960

Note. Models control for intervention conditions (support, skin, digital literacy effects). Random effects included for trial clusters. Hazard ratios < 1 indicate lower risk of non-start. *P*-values adjusted using Benjamini-Hochberg procedure.

Appendix 7: Paper 3 Supplementary Files

Supplementary File 1: Paper 3 Statement of Authorship

Paper Title: *Moderators of Design and Delivery Component Effects on Engagement With a Digital Parenting Intervention: Evidence From a Factorial Randomized Trial in Tanzania*

Full Reference: Janowski, R., Shenderovich, Y., Wamoyi, J., Stern, D., Lachman, J. M., Melendez-Torres, G.J., Cluver, L. D., (2025). Moderators of Design and Delivery Component Effects on Engagement With a Digital Parenting Intervention: Evidence From a Factorial Randomized Trial in Tanzania. Submitted to *Annals of Behavioral Medicine*

We the co-authors certify that the majority – at least 70 per cent – of this work represents the work of the candidate.

Yulia Shenderovich: ______________________________

Joyce Wamoyi: ______________________________

David Stern: ______________________________

Jamie Lachman: ______________________________

G.J. Melendez-Torres: ______________________________

Lucie Cluver: Lucie Cluver

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Supplementary File 2: Table of Internal Consistency Reliability Results

Table S1. *Internal consistency reliability for baseline measures (≥2 items)*

Measure	Scale	Items	Cronbach's α	Omega (ωt)	Omega (ωh)
Child maltreatment	International Society for Prevention of Child Abuse and Neglect Screening Tools-Trial Version	4	0.76	0.77	0.77
Positive parenting	Alabama Parenting Questionnaire	5	0.54	0.57	0.54
Caregiver depression	Centre for Epidemiologic Studies Depression Scale	3	0.50	0.58	0.58

Note. Cronbach's alpha, Omega Total (ωt), and Omega Hierarchical (ωh) were computed using the psych package in R. Reliability analyses were conducted on scales with two or more items. Reverse-coded items were automatically detected and adjusted using the check.keys = TRUE option. Missing data were handled via pairwise deletion (the default in psych), meaning correlations were computed using all available pairs of observations without removing entire cases. Unidimensional reliability estimates were obtained by specifying one factor (nfactors = 1) in the omega analyses.

Supplementary File 2: Table of Benjamini-Hochberg Correction

Table S2. *Benjamini-Hochberg corrections*

Component	Moderator	*p*	Adjusted *p*	Significant after correction (Y/N)
Guidance	Gender	.047	.099	No
Guidance	Age	.001	.004	**Yes**
Guidance	Financial stress	.050	.099	No
Guidance	Food insecurity	.052	.099	No
Guidance	Positive parenting	.001	.004	**Yes**
Guidance	Child maltreatment	.025	.071	No
Guidance	Parental depression	.001	.004	**Yes**
App Design	Gender	.001	.004	**Yes**
App Design	Age	.255	.315	No
App Design	Financial stress	.254	.315	No
App Design	Food insecurity	.085	.149	No
App Design	Positive parenting	.239	.315	No
App Design	Child maltreatment	.501	.554	No
App Design	Parental depression	.027	.071	No
Digital Support	Gender	.602	.632	No
Digital Support	Age	.002	.007	**Yes**
Digital Support	Financial stress	.780	.780	No
Digital Support	Food insecurity	.287	.335	No
Digital Support	Positive parenting	.001	.004	**Yes**
Digital Support	Child maltreatment	.096	.155	No
Digital Support	Parental depression	.173	.260	No

Note. P-values adjusted using the Benjamini-Hochberg correction for multiple testing comparisons. Results considered significant if adjusted $p < .05$.

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