Influence Of Using Mobile Health Monitoring Applications among Elderly Patients for Obesity in the UK

Student Name: Ekta Atulkumar Vekariya

Student ID: 2325373

Date: 14th May 2025

Acknowledgement

I would also like to thank all the people who helped me with this research project. I am really thankful to my academic supervisor for their great and constructive feedback and motivation which have been very important in the process of shaping this dissertation. Additionally, I would like to thank the faculty members as well as the administrative staff of the campus for their help in academia. I also want to thank the library staff for assisting me in locating appropriate literature and resources. Even my peers and fellow students deserve every word of my gratitude for such interesting talks and in times of hardship, moral support. Finally, I would like to thank the researchers and their work that provided the foundation of my study. This research's success relies on all those involved sharing time, expertise and support.

Abstract

Background: The incidence of obesity in the elderly in the UK is increasing raising a major public health concern associated with comorbidities and costs of healthcare. However, given the increasing role of mobile health (mHealth) applications in weight management, little research has been conducted to date to evaluate their effectiveness for this purpose within an elderly population. The purpose of this study was to investigate the effects of using mHealth monitoring applications in the UK on both the related health outcomes and the directly related behaviour changes, usability, and ethical concerns among elderly patients with obesity.

Methods: Systematic literature review design was used, where quantitative peer-reviewed studies done from 2013 – 2023 were analysed. Databases such as PubMed, Scopus and CINAHL were searched using predefined keywords. Inclusion criteria included studies of elderly users aged 60 and above using mobile application for weight management which showed measurable outcome like BMI, behavioralchange, and user engagement. The data of 10 studies were critically appraised and thematically synthesised into four major themes.

Results: mHealth interventions resulted in moderate, however, statistically substantial, BMI and body weight decreases particularly for more than 12 weeks. Self-monitoring and dietary habits improved, but overall engagement has to be maintained, and usability barriers found. Areas for further research will be highlighted in the chapter, and the implications of the insights for policy and practice discussed. There are obvious privacy concerns, with people not familiar with data sharing policies, for the need of ethical transparency. Results from this study can be applied to inform the design of future mHealth interventions, and the results from better, more engaging and easier to use apps for elderly users.

Conclusion: The findings of this study suggest that mHealth applications can assist with obese management of the elderly in the UK, provided their usability and privacy issues are resolved. This leads to the need for age-appropriate app design and a better understanding of the data and more longitudinal research.

Keywords: mHealth, obesity, elderly, mobile applications, digital health, BMI, self-management, UK.

Table of Contents

1. Chapter 1: Introduction and Background

1.1 Introduction To the Topic

Mobile Health (mHealth) application tools have now come into play as an essential modernisation factor for healthcare management systems, particularly regarding chronic diseases, such as obesity. Through this, digitalised means of checking health metrics and delivering customised advice on health to the individuals being monitored will facilitate behaviour change, but the chronic disease problem among the elderly in the UK persists. According to Saqlain et al. (2021), it presents a potential for higher risk for cardiovascular diseases, diabetes, and decreased mobility, with a potentially wide impact on quality of life and health care costs. Integrating mHealth technology may present a novel intervention method against fighting obesity for this population by improving exercise self-management and healthy eating behaviours, as highlighted by Yang et al. (2022).

This systematic literature review (SLR) aims to explore the adoption of mobile health monitoring applications regarding the management of obesity among UK older patients, including the understanding of the performance and usability levels of mHealth applications among aged individuals and, subsequently, determining the barriers this group encounters adopting digital health-related interventions. The popularity of mHealth applications is not synonymous with the effect they have on older populations that lack the ability to overcome cognitive barriers when using such technologies. The SLR adds value to the extant literature by conceptualising the nature of mHealth apps toward health outcomes enhancement and guiding the development of age-friendly digital solutions in health.

1.2 Background and Current Context

Mobile health applications are one of the core digital healthcare aspects through which various interventions are delivered towards improving health outcomes, particularly chronic diseases such as obesity. Obesity is one of the main problems in public health in the UK, and since the prevalence of obesity among adults was above 25% in 2022, the future years are also expected to show an increase (Lingvay et al., 2024). In the elderly population, obesity worsens comorbidities like type 2 diabetes, hypertension, and osteoarthritis, which increase healthcare costs and decrease quality of life. Innovative strategies are needed to address obesity in this population, as traditional approaches, such as in-person consultations and group interventions, are often hindered by issues of access and adherence (Koca et al., 2024). The growing interest has, therefore, been witnessed with mHealth applications for providing accessible, cost-effective, and personalised weight management solutions.

The current use of mHealth in obesity management is both highly promising and still limited. Some of these apps use technology to track physical activities, monitor intakes, give feedback on progress, and have integrated wearable devices for full monitoring of health aspects

(Rodriguez-León et al., 2021). Studies demonstrate the effectiveness of mHealth in interventions aimed at weight loss as well as sustainable behavioural changes; for example, Qin et al. (2022) showed that users of weight management apps had a 5% higher decrease in Body Mass index (BMI) than those receiving standard care. However, Aranha et al. (2021) argue that there is a unique challenge with respect to usability with elderly patients. Older individuals generally have low levels of digital literacy, reduced cognitive function, and physical decline, which all act as barriers to the uptake and long-term use of mHealth technologies. Despite the mentioned challenges, there is an increased recognition of the role of mHealth applications in the management of obesity among the elderly.

The application of behavioural theories, such as those of Prochaska and DiClemente's Transtheoretical Model, suggests that technology can be used to facilitate moving through various stages involved in changing behaviour at the contemplation, preparation, and action levels (Del Rio Szupszynski and de Ávila, 2021). This has called for proper mHealth tools preparation in their interventions with consideration of the steps that help prepare people for lifestyle habit changes, which can lead to a gradual and, ultimately, sustainable lifestyle alteration. Another related theory is Deci & Ryan's self-determination theory, which takes into consideration intrinsic motivation and can be further enhanced by including real-time feedback and gamification elements present in most mHealth applications (Tran et al., 2022). While these theories appear to promise bright prospects, the practicality of the mHealth approach among elderly people presents a gap in its design and accessibility. For instance, Jiang et al. (2024) argued that many popular health apps have interfaces that are not friendly to ages, and their navigation and smaller text size will discourage older patients from using these apps.

Similarly, Melchart et al. (2024) concluded that an important association in developing evidence-based, patient-centred interventions for elderly patients is the specific wants and desires of patients. This research found that patients are more likely to interact with applications that feature interface simplification, voice commands, or the integration of support systems for families or caregivers. Healthcare providers will be important in facilitating the integration of mHealth applications. The available literature has indicated that the elderly is more likely to use and accept digital technologies when healthcare providers endorse them and offer them support (Mace et al., 2022). Training programs are needed that empower clinicians to enable their patients to utilise the technologies properly. mHealth solutions ought to be evidence-based, user-centred, and compliant with the different data privacy regulations, including the General Data Protection Regulation (GDPR) in the UK (Mourby et al., 2021). All this can only be facilitated through partnerships with healthcare providers, app developers, and policymakers.

Although mHealth applications have proven promising in fighting obesity, there is a massive problem of digital exclusion. For instance, elderly individuals from disadvantaged socioeconomic backgrounds do not own smartphones or have consistent internet access; therefore, they are less likely to use such tools (Correa et al., 2021). It brings forth an ethical question on equity in healthcare and a call for special efforts to reduce this gap. Digital literacy training, as well as access to subsidy programs on technological tools through community-based programs, could be very important in guaranteeing inclusivity. Additionally, the efficient utilisation of mHealth applications for obesity management requires that users stay engaged over the long term- a task that continues to prove challenging across all ages. Li et al. (2022) concluded that the average user tends to lose interest in an app after three months of use. Hence, developing methods to promote user motivation over time is crucial. Some of the features that have been proven to improve user retention include social networks for support, frequent updates, and compatibility with wearable devices.

However, Wang et al. (2022) argue that these apps have to be tailored according to the preferences as well as capacities of the elderly. The development of mHealth applications will integrate with the UK government's strategy regarding the inclusion of digitised healthcare services as well as preventive care. The NHS Long Term Plan (2019) underscores the use of digital technologies to support self-management of chronic conditions and, subsequently, reduce the burden on healthcare services (NHS, 2019). A practical application of this vision is the usage of mHealth applications in managing obesity among older patients. These applications can create a scalable response to an emergent public health issue. Overall, the research area concerning obesity management among the elderly with regard to the applications of mHealth is promising yet complex in nature.

1.3 Rationale For Research

The growing prevalence of obesity among geriatric patients in the UK, coupled with the ever-increasing usage of mobile health (mHealth) applications, provides a key area for research. While mHealth has shown efficacy in terms of promoting weight management among patients, little is known about its impact on geriatric populations; geriatrics are often at a particular disadvantage in terms of digital health technology adoption. This SLR seeks to study the mHealth app's effects on the obesity management of elderly patients, using usability, engagement, and health outcomes as considerations. This scope is defined as the elderly patients of the UK. The study then acknowledges the variability in the accessibility of healthcare, technological literacy, and cultural attitudes toward digital health interventions. However, there is a limitation due to the restricted population for the study in younger age groups and secondary data sources that would be published in research studies. This SLR will then inform the creation of age-friendly mHealth solutions to support enhancing obesity management and digital inclusiveness in healthcare more inclusively.

1.4 Research Question

How do mobile health applications influence obesity management among elderly patients in the UK?

1.5 Research Aim

This SLR aims to discuss the role of mobile health applications amongst elderly patients For Obesity in the UK.

1.6 Research Objectives

- To identify the challenges faced by elderly patients in obesity management in the UK.
- To evaluate the effectiveness of elderly patients using mobile health applications for obesity management.
- To assess the opportunities and barriers in using mobile health applications amongst elderly patients for obesity management in the UK.

1.7 Chapter Summary

This chapter introduced the research topic in the form of exploring the roles of mobile health applications in the management of obesity among the elderly population within the UK context, discussing the importance of the issue, research aim, objectives, and question. The chapter-built background information and created the rationale for conducting this study. Chapter 2 will explore the existing literature to discuss key research studies and theories on mHealth applications and the management of obesity among the elderly.

2. Chapter 2: Literature Review

2.1 Introduction to Literature Review Chapter

This chapter offers a review of the existing and academic scholarly literature relating to the effect of mHealth monitoring applications for elderly patients dealing with obesity management in the UK. The chapter will first discuss the challenges elderly patients face in dealing with obesity and then evaluate how effective mHealth applications are at solving these problems. Finally, it looks at the potential and the challenge of employing the mHealth application in the concerned population. This SLR integrates critical findings synthesised for the assessment of existing literature while pointing out a gap and hence providing an explicit reason for the study conducted.

2.2 Literature Review

2.2.1 Challenges Faced by Elderly Patients in Obesity Management in the UK

Obesity among older patients in the UK is an issue that has recently been emphasised by studies. According to Public Health England**,** nearly 40% of adults aged 65 years and above are obese or overweight, which reflects the growing proportion of obesity in this age group (GOV.UK, 2023). Such increased obesity rates make this a pressing public health problem because elderly persons who are obese have numerous potential health complications associated with obesity, such as heart disease, type 2 diabetes, and impairment in mobility. This increasing rate of obesity raises the alarm regarding the long-term strain that it would be exerting on the healthcare system, especially as the UK faces an ageing population. The findings of Buch et al. (2021) are a good indication that obesity in the elderly significantly adds to the chronic disease burden that worsens healthcare needs.

Physically, the other challenges involved in controlling obesity in elderly patients include mobility impairments, which are often precipitated by excess body weight (Fanning et al., 2022). Weight regulation for the older population becomes problematic because they are less muscular and have reduced bone density, making it challenging for them to engage in physical activity. Many elderly people also have chronic conditions, including arthritis and cardiovascular diseases, which make it harder for them to exercise regularly. Palmer and Jensen (2022) argue that another factor that contributes to obesity in older adults is the decrease in metabolic rate that comes with ageing. It is much more challenging to lose weight since the body does not burn calories as quickly when resting. Psychosocial issues are also major factors in obesity among the elderly. Research indicates that elderly patients with obesity have a higher likelihood of developing depression and anxiety primarily because of social discrimination and perceived loss of independence (von Humboldt, 2022).

The problem of social isolation, which always accompanies ageing, can also compound the feeling of loneliness, which makes it very difficult for old patients to continue with the will to lose weight. The psychological impact of obesity on the aged is an issue that is hardly considered in standard weight management procedures; however, Wang et al. (2022) argue that it is quite crucial in identifying why most elderly patients fail to shed excess pounds. From the perspective of a healthcare system, the management of obesity in the elderly is very challenging. Many healthcare providers are not trained, let alone equipped, with the skills and tools to deliver targeted obesity interventions for older adults (Kim and Rockwood, 2024). Traditional weight loss programs, often focusing on diet and exercise programs geared toward younger individuals, usually do not take into consideration the distinct needs, both somatic and psychosocially, of elderly patients. According to Mehl (2023), generalised method utilisation by the healthcare system has been criticised in that it will not sufficiently solve the growing challenges of obesity in the elderly. In addition, the availability of specialised care for obesity management, including dietitian or bariatric specialist consultations, is limited in many regions.

2.2.2 Effectiveness of Mobile Health Applications for Obesity Management in Elderly Patients

Mobile health (mHealth) applications are software that uses digital means to provide health management via mobile phones, tablets, and other mobile devices. These apps can provide many functionalities, including diet tracking, monitoring of physical activity, and health data analytics (Wang et al., 2022). Through tracking the daily intake of food and exercise routines as well as other vital signs, mHealth applications help individuals maintain healthier lifestyles and manage chronic conditions such as obesity. Ashraf et al. (2024) argue that the general effectiveness of mHealth on the management of chronic diseases contributes to apps in order to increase the engagement of patients for treatment protocols in addition to generally raising adherence to health outcomes. This application may provide a readily available and handy tool for obesity-related chronic health issues through applying real-time feedback and personalised interventions (Kim, 2024).

Some of the related studies regarding its effectiveness among an obese elderly population, for example, Fanning et al. (2022) conducted a randomised controlled trial to evaluate the effectiveness of an application of mobile for older adults with obesity. The results found that the average weight loss reported by the application users was at an average of 4.5 kg. Other improvements in eating habits were improved vegetable consumption and reduced consumption of high-calorie foods. Physical activity levels increased, and users said they walked and exercised more frequently. Positive outcomes from this study raise the possibility of mHealth support for elderly patients in managing their weight, especially considering that such patients face limitations based on physical grounds in attending in-person consultations. Nevertheless, the sample size was small (n = 50), and the follow-up was only six months, which limits the generalisability and long-term applicability of the results.

In the comparison of effectiveness between mHealth applications and conventional methods for managing obesity, one finds a blend of pros and cons. Perhaps the biggest benefit of mHealth over conventional approaches is that it is easier to access and apply. Sutton (2024) argues that using mHealth applications offered older patients a flexible, continuous method to monitor their health without needing repeated in-person consultation, which might be difficult logistically for most older adults. The ability to give real-time feedback, track progress, and offer suggestions for customised changes was able to increase engagement and motivation (Maier and Klotz, 2022). Traditional methods of weight management through paper tracking or face-to-face consultations typically did not feature personalised elements characteristic of mHealth applications and tended to be less effective in terms of maintaining long-term patient engagement. However, Rahmillah et al. (2023) argued that, though mHealth applications yielded positive short-term outcomes, their efficacy declined over time. The patients of the study also described a pattern where usage tends to drop down after the initial months of adoption, and here, user fatigue or proving too complicated with technology might be happening.

2.2.3 Opportunities and Barriers to Using mHealth Applications Among Elderly Patients

Implementation of mHealth in the management of obesity among aged patients is full of challenges, but it still holds a high number of opportunities. One key opportunity is how the mHealth application can help through self-management processes that make self-tracking of diet, physical activities, and more aspects of life much easier and feasible for geriatric patients. Mwangi (2024) argued that chronic feedback, integrated with simple, easy-to-read reports of progress, will greatly impact patients' engagement regarding the application via mHealth towards obesity conditions due to the better effects that occur in managing chronic diseases. This enables mHealth tools to be accessed for health data and interventions with fewer face-to-face visitations, which is a potential barrier to care for the elderly. Furthermore, the application can be used to give the patient real-time, tailored health information and alerts. This will ensure that the patient complies and has improved health behaviour (El-Rashidy et al., 2021).

However, Wang et al. (2022) argued that mass use of the mHealth application is plagued with many barriers for elderly patients. The main digital literacy is that most of them are not fluent in smartphones and other technologies, making use of the application approach. Ramdowar et al. (2024) contend that elderly patients experience challenges in using mHealth apps owing to a lack of familiarity with technology. This results in lower adoption rates and disengagement. Another barrier is the resistance to technology by patients, with many elderly patients showing disbelief and less trust in the integration of digital tools for health management. Dowling et al. (2024) argued that most elderly clients feel overwhelmed by technology or do not trust it, hence preferring an old-fashioned approach to healthcare treatment. Several approaches have been suggested to address these challenges. One approach is to develop user-friendly mHealth applications specifically designed for older adults, focusing on the presence of visual impairments or cognitive decline.

According to Li and Luximon (2023), simplification of application design, larger fonts, and easy navigation can enhance the usability of these tools among older adults. Educational interventions in the form of training programs or workshops also enable overcoming the digital literacy challenges (Choudhary and Bansal, 2022). Caregivers can facilitate the creation and practice of using mHealth applications with their elderly patients. Such practice includes the technical side but also a motivational factor. This recommendation based on the Social Cognitive Theory advances this by indicating that learning and even behaviour change are socially influenced and based on self-efficacy (Badura, 2023). This means that an active role from caregivers would enhance confidence in one's ability to operate technology, which might positively contribute to their more likely adoption and sustained usage. Nevertheless, Wang et al. (2022) argues that while good designs and educational curricula are useful, they may have to be maintained in order to keep the engagement levels high. In addition, not all older people have reliable internet or have a smartphone. This would limit the elderly group's ability to use these mHealth applications. Ensuring that technology is accessible equitably and promoting continuous support for users among older people is critical to fully exploiting the potential of mHealth in obesity management (Wang et al., 2022).

2.2.4 Gaps in the Literature and Research Implications

Despite the growing number of literatures concerning mobile health applications in the management of obesity for elderly patients, there is still a considerable gap that remains, which reduces the full capacity of these interventions. One critical gap in long-term studies is the persistence of the effect of mHealth applications. As indicated by Zainal et al. (2024), while short-term studies have produced impressive results, the evidence remains weak on the continuation of such benefits over time. Moreover, most of the current studies fail to consider the cost-effectiveness of mHealth interventions, which is a significant factor for healthcare systems that aim to scale up the adoption of these technologies (Hengst et al., 2023).

The other gap is the underemphasis on culturally adapted mHealth solutions. The UK elderly population consists of diverse groups, and mHealth applications ignore cultural differences in health behaviours, preferences, and attitudes towards technology (Alam and Khanum, 2022). More comprehensive long-term research seems necessary to appraise the economic impact, time efficacy, and cultural acceptability of mHealth applications for controlling obesity in ageing patients. Meeting such gaps calls for the generation of more useful mHealth-based interventions for healthy lifestyles among old people in Britain.

2.3 Chapter Summary

This chapter discusses existing literature related to challenges facing older patients during the management of obesity, the efficacy of mHealth applications, opportunities associated with mHealth applications, and barriers hindering the applications' usage. Important gaps exist within the existing literature regarding the effectiveness and cost-effectiveness of interventions over longer time frames for using mHealth. These will form a premise of discussion within subsequent chapters. Chapter 3 will describe the research methodology used for this study to determine how mHealth applications influence elderly patients' management of obesity in the UK.

3. Chapter 3: Research Methodology

3.1 Introduction

Chapter 3 shows the method used in this research for an SLR. The purpose of undertaking the SLR is given, and the whole search strategy process is explained, leading to the proper studies to review. Chapter 3 then offers details on what inclusion and exclusion criteria were adopted for selection purposes, sources, keywords, and any other terms employed during the process. Finally, it details the ethical concerns that guided the choice of literature and then proceeds to elaborate upon the selection process that the study employed, involving a PRISMA flow chart to represent results.

3.2 Systematic Literature Review

A SLR is a structured and methodical procedure for collecting, appraising, and summarising existing literature related to a particular area of research (Van Dinter et al., 2021). An SLR aims to present the existing best knowledge to date with such clarity that results can be reproduced and with a warranty that no relevant studies are omitted. Clear research questions should be specified alongside inclusion and exclusion criteria with the systemic search of respective databases with study relevance followed by selection based on predefined criteria studies in SLR (Mohamed Shaffril et al., 2021).

The process starts with extracting analysed data from selected studies for critical review before performing statistical analysis with Excel to determine central measures and dispersion stats and produce graphical representations. Here, the research is intended to come up with high-quality studies and portray results by identifying patterns, gaps, and implications for further research. An SLR summarises not only existing evidence but also gives an impression of the effectiveness of interventions; it highlights research gaps and further guides studies into the same field (Bettany-Saltikov et al., 2024). An SLR summarises the evidence and provides insight into what interventions work, shows there is a gap in research areas often missing from previous studies, and helps in building topics for future studies.

3.3 Search Strategy

A search strategy in research is critical to ensure that the search for relevant studies is achieved through a holistic, impartial, and systematic approach. The criticisms about search strategies often revolve around the nature of how significant studies could be omitted due to ambiguous search terms or restrictive criteria (Page et al., 2021). This SLR implemented a very robust search strategy that accommodated the databases provided by PubMed, Scopus, and Google Scholar. Key terms were selected that would cover some of the crucial concepts, which included "mHealth applications," "obesity," and "elderly patients." In this case, a PEO approach was used rather than PICO because the type of research question asked is a better fit. PEO is most relevant because it considers the way exposure, that is, mHealth apps, affects outcomes, namely, obesity management in a targeted population, in this case, elderly patients. This enables the exploration of the link between the use of mHealth and obesity management outcomes among elderly patients. The search was limited to articles between 2013 and 2023, which ensures that the results relate to the most current developments of mHealth technologies and their usage for elderly populations.

3.4 Search Terms

Search terms are the words or phrases used in a research search strategy to find relevant studies in databases. In general, they are essential since they define the scope of the search and allow retrieval of all relevant studies available for review (Foo et al., 2021). The use of synonyms is mainly important because varied terminologies are used to describe the same concepts by different studies. Using synonyms ensures a more detailed search and limits the chances of missing relevant research. For instance, the words "elderly," "older adults," and "senior citizens" would all be referring to the same population but using different wording. In achieving an integrated search strategy, the PEO framework was adopted as compared to PICO. PICO (Population, Intervention, Control, Group) is usually used for quantitative research design with primary data collection approach. However, considering the secondary nature of current SLR which involves gathering sources from databases, PEO is best suited. The framework is utilised in studies whose main objective revolves around the interaction of a certain population and intervention, and in this case, would be useful for discussing the influence of mHealth applications on the management of obese elderly patients (Saifan and Obeidat, 2021). This PEO approach allowed the establishment of a clear and focused question for the search and structured the process by splitting it into three key components:

Table 1: PICO

Component	**Description**
Population	Elderly patients (aged 60+), particularly those in the UK, experience obesity-related health issues.
Exposure	mHealth applications, such as apps for diet tracking, physical activity monitoring, and health data analytics.
Outcome	Obesity management outcomes, including weight loss, improved dietary habits, increased physical activity, and overall health improvements.

Using the PEO framework, the search question developed was: "*What is the effectiveness of mobile health applications for obesity management among elderly patients in the UK*?"

The three database sources included PubMed Scopus and Google Scholar. Boolean operators correlating synonyms for each PEO component were incorporated into the search terms. The search terms included "AND" and "OR" Boolean operators that produced an all-inclusive search of relevant information. PEO components consisted of groups of synonymous terms connected by OR operators to expand the database. The search terms of the study are put in other databases to identify relevant literature appropriate to the stand of such a database. A predefined set of checklists serves to identify studies which satisfy the inclusion and exclusion conditions before the research systematically classify the chosen studies in a master Excel database for subsequent statistical evaluation.

3.5 Key Words

Keywords are the specific phrases or terms used in the search in a database to refer to relevant literature. They are essential for narrowing down the search to the most relevant studies, thereby ensuring effective results. Main keywords used in the study were “mobile health applications”, “mHealth", “elderly” “obesity”, “weight loss” and “health outcomes”. The precise selection of keywords allowed researchers to obtain relevant research articles from the database.

3.6 Data Base

Research success depends on the database choice because each database operates with its own unique list of journals and articles. Research validity and reliability increases together with bias reduction when studies utilise multiple databases (Page et al., 2021). Point-of-care research requires multiple databases alongside specific index methods and search requirements which enable researchers to find suitable scholarly and peer-reviewed materials. Database platform diversity helps researchers to avoid study omission because indexing strategies differ across different databases. This SLR utilised PubMed as well as Scopus and Google Scholar and ScienceDirect as its database sources. Research discovers suitable materials for systematic reviews because these databases provide access to peer-reviewed medical journals in health and medicine fields along with social sciences.

3.7 Inclusion/Exclusion Criteria

Systematic review study selection depends on the inclusion and exclusion criteria, which allow researchers to accept studies that are relevant and of high quality while rejecting irrelevant ones. A research paper requires criteria to maintain focus and achieve valid results for consistent comparison (Hiebl, 2023). The inclusion criteria restrict which studies get included by their study design, participant characteristics, and geographic location. Research studies that do not fulfil the established standards become excluded through the criteria. When research criteria are transparent, they make studies easy to reproduce and minimise bias because they evaluate only essential studies.

3.8 Search Results

The search for relevant studies in the databases produced a total of 100 records. After removing the duplicates, 40 remained for further screening. These were assessed for relevance according to the inclusion and exclusion criteria described earlier. A total of 30 records were excluded because they failed to meet the predefined criteria; these include not being related to the topic, not targeting elderly patients, and lack of relevance to the management of obesity using mHealth applications. The remaining 30 full-text articles were reviewed to determine whether they met the requirements of the study in achieving its research aim. Among them, 20 articles were excluded for the following reasons: methodological issues, inadequate data, and being outside the study's time frame. Ten research studies fulfilled the complete set of requirements for inclusion hence becoming part of the systematic review examination. A descriptive analysis spreadsheet contained all study information for comparison using variables that included age, sample size, gender, BMI, waist circumference and weight change.

The SLR used the PRISMA flow chart to conduct study selection and exclusion which demonstrates a graphical representation of study identification and screening and eligibility assessment as well as inclusion. The system provides clear transparency and reproducibility because it explains all selection decisions step by step and displays the PRISMA chart used in the study. A thorough review procedure eliminated subjective and inconsistent practices that occurred during study selection (Karunarathna et al., 2024). The SLR of mobile health applications for elderly obesity management relies on the 10 studies that were included. The PRISMA flow chart below demonstrates in detail the sequence of actions and decisions used for study selection.

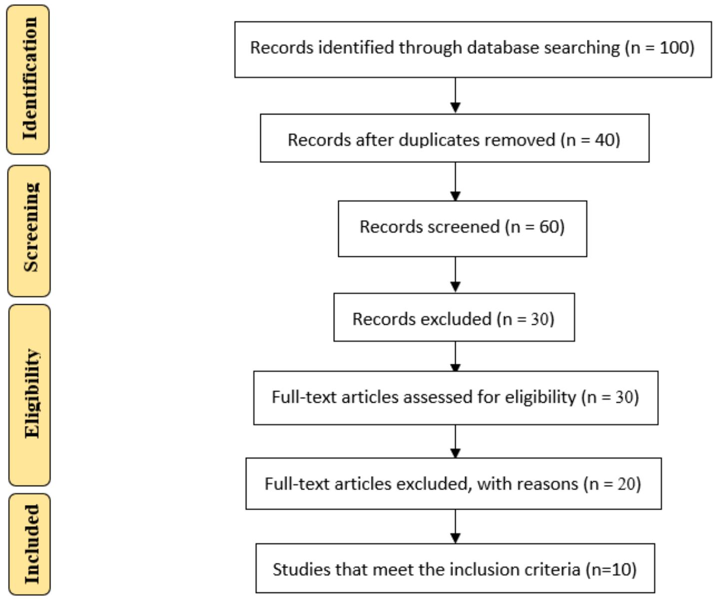


Figure 1: PRISMA

3.9 Ethical Consideration

The guidelines of ethical research serve two main objectives which protect participant rights alongside securing research integrity and building trust in scientific methods (Drolet et al., 2023). Ethical standards became the primary factor when selecting literature for this review. The analysed studies appeared in respected academic journals since they underwent proper institutional review board authorisation procedures. The review confirms ethical research practices because studies incorporated the fundamental principles of consent protections, confidential data handling and vulnerable subject safety measures. The ethical framework for research validity and reliability comes from the perspective of ethical integrity (Levitt et al., 2021).

3.10 Chapter Summary

The chapter demonstrated the procedures necessary to execute a SLR. The first section of this chapter describes the PEO search strategy, which uses appropriate databases and is followed with details on inclusion criteria and ethical considerations along with keywords. The assessment process for study selection can be seen in a PRISMA flow chart, and the search findings are presented. The research approach for study selection received its basic structure in this chapter through the development of an organised system. The upcoming section of this work will thoroughly analyse and merge the gathered data from the selected literature review.

4. Chapter 4: Data Evaluation

4.1 Introduction to Chapter

The quantitative evaluation examined the effects of mobile health applications on obesity management with UK elderly patients in this review. The analysis relied on statistical data from selected studies for effective intervention evaluations combined with descriptive statistics on demographic data and BMI, waist circumference and weight change through Excel spreadsheet functions for means, standard deviations, medians and chart visualisation. The research evaluates both how patients use mobile health applications and their adherence rates and explores overall patient input regarding mobile health equipment. The current analysis explores recurring patterns, as well as studies weaknesses and control inconsistencies from the literature review, in order to create a systematic synthesis of mobile health intervention effects on obesity care delivery for elderly populations.

4.2 Data Extraction

The systematic process of data extraction allows researchers to retrieve essential points from chosen studies to enable both analytic structure and synthesis (Page et al., 2021). The set procedure for data extraction maintains precise information retrieval through established standardised formats. The systematic extraction process gathers essential information about research design sample sizes and demographic data as well as intervention period and types and key outcomes that measure obesity management through weight loss and BMI change and application compliance. Research effectiveness is shown by mean difference measurements and p-values through established statistical data points which utilise confidence intervals. The analysis included descriptive statistical calculations of range and variance and median to study distribution patterns across the studies.

4.3 Brief Introduction to Critical Appraisal and Paper Quality Assessment

The critical appraisal process demands researchers to verify research reliability and robustness and effectiveness in answering specific questions (Tod et al., 2022). The evaluation methodology operates in parallel to pick the most credible evidence that upholds results then reduces bias for better outcome credibility. Joanna Briggs Institute (JBI) provides evaluation tools through which studies of randomised controlled trials and observational research get analysed during the review process in quantitative studies. The JBI tools represent superior assessment templates over CASP and PRISMA tools because they enable researchers to assess both the internal validity and practical worth of research studies (Mrklas et al., 2023). These tools allow proper analyses when used in combination with defined research boundaries and precise measurement strategy tracking for generating robust evaluation results. The JBI standardised evaluation criteria work to bring together strong methodological studies for the review process, which boosts the reliability of findings regarding mobile health solutions specific to elderly patients with obesity.

JBI Criteria	Chowdhury et al. (2023)	Liu et al. (2019)	Ufholz & Werner (2023)	Bennett et al. (2018)	Villareal et al. (2017)	Siriwoen et al. (2018)	Dounavi & Tsoumani (2019)	Santos et al. (2024)	Batis et al. (2021)	Bughin et al. (2021)
1. Is the review question explicitly stated and aligned with the study objectives?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
2. Were inclusion criteria clearly defined (population, intervention, comparator, outcomes, study design)?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
3. Was the literature search strategy comprehensive and well-documented?	✓	X	✓	✓	✓	✓	✓	✓	✓	✓
4. Were multiple databases searched with clearly defined keywords and search terms?	✓	X	✓	✓	✓	✓	✓	✓	✓	✓

5. Was grey literature (unpublished studies, reports, theses) included to minimise publication bias?	X	X	✓	X	✓	X	X	X	X	X
6. Were the criteria for selecting studies appropriate and consistently applied?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
7. Was critical appraisal performed by at least two independent reviewers to reduce bias?	X	X	X	X	✓	✓	✓	✓	X	X
8. Were standardised methods used to extract and synthesise data across included studies?	✓	X	✓	✓	✓	✓	✓	✓	✓	✓
9. Was heterogeneity assessed (e.g., statistical methods like I^2	✓	X	✓	✓	✓	✓	✓	✓	✓	✓

or subgroup analysis)?										
10. Were appropriate statistical or qualitative synthesis methods used to combine study findings?	✓	X	✓	✓	✓	✓	✓	✓	✓	✓
11. Was the risk of publication bias assessed (e.g., funnel plots, Egger's test)?	X	X	✓	X	✓	X	X	X	X	X
12. Were potential conflicts of interest of included studies considered and reported?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
13. Were recommendations for policy or practice based on a balanced summary of findings?	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
14. Were gaps in research identified and future	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

research directions clearly stated?										
15. Was the overall quality and strength of evidence assessed using frameworks like GRADE?	✓	X	✓	✓	✓	✓	✓	✓	✓	✓
Overall Appraisal (Include/Exclude/Revise)	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included

4.4 Evaluation of Quantitative Studies

4.4.1 Introduction to Critical Appraisal of Quantitative Studies

SLR's depend on critical appraisal because it supports the inclusion of quality sources which improves both reliability and reduces bias in results (Tod et al., 2022). Research utilises critical appraisal tools from Joanna Briggs Institute because these tools exist specifically to evaluate the methodological quality of quantitative study designs that include randomised controlled trials (RCTs), cohort studies, and cross-sectional surveys. JBI stood superior to CASP and Cochrane Risk of Bias tools for this analysis because it includes thorough domain-specific checklists that evaluate various research quality factors from sampling to statistics and intervention reliability and practice suitability (Stone et al., 2023).

The SLR examines 10 quantitative studies through detailed critical assessment methods to validate only strong and scientifically sound research which evaluates mobile health applications for obesity management among elderly patients in the UK. The research included cross-sectional surveys (Chowdhury et al., 2023; Liu et al., 2019) in addition to RCTs (Bennett et al., 2018; Villareal et al., 2017; Santos et al., 2024), cohort studies (Batsis et al., 2021) along with systematic reviews (Dounavi and Tsoumani, 2019). JBI's appraisal criteria was used to evaluate each of the selected studies (As presented in Appendix). This structured evaluation enables the review to present research findings that stem from methodologically strong studies, which strengthens the existing evidence about mobile health applications' role in the management of elderly patient obesity.

4.4.2 Study Designs and Methodological Appropriateness

Quantitative research in healthcare remains essential because it enables documented proof of intervention effectiveness through quantitative data analysis of mobile health applications that assist obesity management. Through objective data collection, researchers can assess weight loss achievements along with BMI reduction effectiveness, user adherence statistics, and participation levels (Grady et al., 2023). A review exclusively examines quantitative research since it uses real numerical data instead of interpretation of opinions. The empirical data obtained from quantitative research creates valid evidence about mobile health applications which makes it the choice method for evaluating health interventions according to Grundy (2022). Quantitative assessment designs featured in all ten studied research reports serve to evaluate mobile health app effects that align with their research aims.

Studies of Chowdhury et al. (2023), Liu et al. (2019), Ufholz and Werner (2023) offer information about user participation and the opinions of healthcare experts. The weight loss tracking in intervention versus control groups presented in three randomised controlled trials by Bennett et al. (2018) and Villareal et al. (2017) and Santos et al. (2024) serves to prove causality. Batsis et al. (2021) together with Siriwoen et al. (2018) evaluate the effects of mobile health interventions on obesity management through lengthy observation periods. According to Dounavi and Tsoumani (2019) a systematic review examined mobile health interventions through the analysis of numerous study outcomes. Multiple research methods work together to establish a complete analysis of mobile health applications regarding their practical usability and their effect on obesity treatment for elderly patients within UK healthcare facilities.

4.4.3 Critical Evaluation of Article 1: Chowdhury et al. (2023)

A cross-sectional survey by Chowdhury et al. (2023) investigated patient-age variations when using mobile health applications (mHealth apps) in addition to healthcare professional recommendation behaviours regarding these digital tools. Population statistics through this design show trends, yet the approach does not allow researchers to make causal conclusions (Chowdhury et al., 2023). The research selected 2,000 UK adults with a focus on elderly patients (≥65 years old) to improve study applicability. Detailed health information about obesity levels and comorbidities is needed to make this study relevant for obesity-specific interventions (Grundy, 2022). The research indicated that elderly individuals (OR = 0.39 for ≥65 years) showed less interest in mHealth apps but still exhibited acceptance at a rate of 52%. The study revealed an important discrepancy between senior citizens' willingness to use mHealth apps and healthcare provider recommendations because elderly adults received guidance about these apps at less than 4% of the rate that younger participants did at 33.8%. The research demonstrates an unutilised chance to enhance mHealth app adoption for senior citizens through its absence of an intervention protocol, which impacts the evaluation capabilities of genuine app performance. Although its research limitations are notable the study contributes essential knowledge about healthcare access inequalities which makes it appropriate for this SLR analysis.

4.4.4 Critical Evaluation of Article 2: Liu et al. (2019)

The evaluation of two mobile health (mHealth) app prototypes through a randomised controlled trial (RCT) examined their accuracy and operational efficiency, according to Liu et al. (2019). The RCT design stands as an optimal method for intervention assessment because it blocks out bias while creating strong causal relationships. A main limitation of this study arises from its restricted sample size (n = 105), which comprises older (n=35) and younger (n=70) adult participants and reduces broader application to older obese patients. Obesity management applications become less usable because the research lacks data about participants' BMI values. Research examined two app layout types through testing input precision that surpassed 98% and time efficiency which demonstrated statistical significance ($P < .05$) for 11 out of 12 evaluated measurements.

The self-chosen tab app produced faster data entry speed, but its users exhibited a behavioural pattern of missing food attributes during data entry. The research analysed short-term usability rather than long-term participation rates or weight management results that represent core elements for obesity management programs (Milne-Ives et al., 2024). The researchers investigated dietary tracking usability among older adults using mobile health services in mHealth obesity management, which makes this study relevant to the SLR. The research faces constraints in its ability to apply its findings directly to monitor long-term health because it used a small and homogenous participant population along with omitted clinical obesity metrics.

4.4.5 Critical Evaluation of Article 3: Ufholz and Werner (2023)

Ufholz and Werner (2023) systematised a review of mobile weight loss apps which measured their success in caring for adults who carried extra weight according to BMI criteria (BMI > 25 kg/m² or > 23 kg/m² for Asian populations). Systematic reviews create a complete amalgamation of existing research evidence, although their credibility depends on how well the integrated studies are assessed (Page et al., 2021). The research strengthened its methodological strength by excluding non-data-driven studies and commentaries and protocols from inclusion. The diversity of features across studied mobile apps makes comparing study results challenging, so researchers cannot identify which app features lead to weight loss. The review demonstrated that mHealth applications show matched or superior results in weight loss programs compared to standard methods by implementing self-tracking and behavioural change techniques.

Follow-up information that extends beyond the study period would increase our trust in the app's effectiveness over the long term. Generalisations become less valid because few study participants belong to older adult and minority racial groups or come from lower-income backgrounds. Research limitations emerge when researchers depend on published studies because positive outcomes tend to be over-reported in this context (Fisher et al., 2022). The study's inclusion provides a wide view of the effectiveness of weight loss apps in mHealth applications while showing relative comparisons. The research uses different intervention specifications and research methodologies, which reduce its utility in obesity treatment programs for elderly patients.

4.4.6 Critical Evaluation of Article 4: Bennett et al., (2018)

The randomised controlled trial (RCT) conducted a 12-month digital weight management study (Track) among individuals from disadvantaged socioeconomic groups who had obesity and hypertension, diabetes, and hyperlipidaemia comorbidities. RCTs maintain their status as the standard for intervention assessment yet have results which depend on proper research design and execution. The study utilised an ample participant pool of 351 individuals within a specific age range of 21–65 years but fell short in terms of ethnic and geographic diversity, which might affect overall study applicability. Self-tracking through mobile apps, clinician reports, and dietitian guidance made up the intervention program. The participants experienced statistically significant weight loss of -4.4 kg at 6 months ($p<0.001$), which persisted at 12 months to -3.8 kg ($p<0.001$). Weight loss outcomes are directly linked to participant engagement levels because adherence constitutes a vital element. The positive effects of self-monitoring compliance encountered interruptions, as reported by Doucette et al. (2021). The researchers included this practical study because it evaluated an integrated digital obesity intervention performed in primary care. The final impact of this intervention on weight management within high-risk groups cannot be determined because of the brief study period and absence of long-term assessment.

4.4.7 Critical Evaluation of Article 5: Villareal et al., (2017)

The randomised controlled trial (RCT) analysed 160 obese older adults to understand how different exercise regimens influenced frailty because this group faces a high risk for sarcopenia and osteopenia during weight loss. The robust testing method of RCTs shows limitations in its application to elderly populations with multiple health conditions because external validity remains uncertain. The study data showed that exercise combinations, which included aerobic and resistance activities, produced the biggest effect on physical performance improvement (21% increase, $P=0.01$). At the same time, all exercise groups achieved 9% weight loss. Many strong research points emerge in this study, such as high participant retention (141 subjects finished) alongside precise measurement methods, although several weaknesses also appear. The reported musculoskeletal injuries indicate omitted safety risks within structured intervention programs (Bullock et al., 2023). The study did not investigate established bone mineral density and lean mass changes between groups, although these data exist when considering long-term musculoskeletal risks. The study showcases essential weight management strategies for elderly groups, yet its conclusions cannot easily be applied to less structured environments where exercise adherence is decreased. The study does not provide enough information about functional outcomes beyond its immediate follow-up period.

4.4.8 Critical Evaluation of Article 6: Siriwoen et al., (2018)

Siriwoen et al. (2018) examined an mHealth-based weight management program using quasi-experimental research with one-group pre-test and post-test methodology. The impact of intervention effectiveness in quasi-experimental designs remains uncertain because they lack control groups (Yang et al., 2022). This examination studied 38 female working adults across the age range of 25–52 who weighed more than normal body mass (BMI) standards. The 12-week intervention produced important weight reductions ($P = .008$) and waist circumference reduction ($P < .001$), together with better self-efficacy and dietary habits. Selection bias affects the research because the volunteers self-selected for the study and showed readiness to act, which may have positively influenced the experimental outcomes. The study lacked detailed explanations about mHealth features, which hindered the ability to reproduce the findings. A brief follow-up length prevents an assessment of sustaining weight achievement beyond the study period. The study remains useful for mHealth intervention research involving working-age women, yet new controlled research should validate the results.

4.4.9 Critical Evaluation of Article 7: Dounavi and Tsoumani (2019)

Dounavi and Tsoumani (2019) performed a SLR on mobile health (mHealth) applications in weight management through their analysis. The inclusion of studies between 2012 and 2017 without rationale may eliminate newer advancements from synthesis because of the systematic review format (Page et al., 2021). Throughout the 39-study review, there is insufficient data regarding participant characteristics and sample size uniformity, which hinders the cross-examination of study findings. Self-monitoring emerges as a significant factor according to the research for both adherence and weight loss, but the study fails to establish which features in mobile applications lead to superior effectiveness. The researchers assessed the quality of the randomised controlled trials, which showed divergences in research standards throughout the assessment. Such findings fail to achieve conclusive status because they lack a meta-analysis. The review remains part of this research because it conducts a wide examination of mHealth techniques alongside user involvement and use consistency despite its methodological constraints.

4.4.10 Critical Evaluation of Article 8: Santos et al., (2024)

A randomised clinical trial by Santos et al. (2024) studied how mobile health (mHealth) technology helps elderly overweight/obese individuals change their behaviour. The study included 41 participants. Test Case research remains the top standard evaluation method yet its small participant count decreases measurement capability and hinders the application of study results (Alrida et al., 2024). Santos et al. (2024) performed a strong comparison between mHealth-supported group psychotherapy, traditional group therapy and individual psychotherapy but found no meaningful distinctions between mHealth-supported and traditional therapy, thus raising doubts about the unique contribution that digital tools provide in this arena. The research lacks quantitative data about user engagement with the app or participant adherence rates, together with details about key intervention mechanics essential for measuring health effects. The research findings demonstrate important value by testing the idea that technology provides enhanced outcomes, thus emphasising the importance of developing optimised digital platforms for senior citizen intervention needs. The research provides valuable insight into mHealth's restricted capabilities for behavioural treatment, so it is included in this analysis.

4.4.11 Critical Evaluation of Article 9: Batis et al. (2021)

Batis et al. (2021) performed non-randomised single-arm research to determine the feasibility of technology-based weight management for obese older adults living in rural areas. The implementation of Fitbit and video conferencing for remote behavioural physical therapy demonstrates digital health innovation, but the research cannot establish effective intervention outcomes because of the absence of a control group. The study's results are affected by its small sample (n=53) and 17% subject dropout rate, which decreases the general applicability, especially since rural individuals typically experience elevated telehealth study attrition linked to digital literacy barriers (Burrows, 2024). Although limited by some factors, the study shows promising results with 81.7% Fitbit adherence and statistically meaningful weight reduction (4.7% decrease, $p<0.001$) and functional outcomes. The study demonstrates that technology can successfully address accessibility issues for weight management programs aimed at older adults, thus making it an important addition to digital obesity intervention research for underserved populations.

4.4.12 Critical Evaluation of Article 10: Bughin et al., (2021)

Bughin et al. (2021) executed an RCT which studied a telerehabilitation (TR) obesity management system versus traditional care for twelve weeks. The study design establishes good internal validity, yet a small sample of 50 participants diminishes statistical power, which increases the chance of Type II errors, according to Sturman et al. (2022). The results suggest TR fails to prove superior to standard care in fat mass reduction ($P=.48$), although it showed improvement in waist-to-hip ratio ($P=.07$) and physical quality of life ($P=.005$). Study results indicate that patients maintained their participation at a rate of 95% yet failed to address how participants continued their use over extended periods, which would be essential for obesity treatment. The strong evaluation of exercise capacity together with metabolic parameters improves the study, but its brief timeline and narrow implementation barriers hinder its practical utility. The article positions itself among our analysis because it reveals significant findings about TR feasibility together with patient satisfaction levels alongside potential QOL improvements without showing decreased fat mass. Additional studies need to examine both prolonged results and different population groups in order to determine whether Total Rehabilitation serves as a sustainable weight management approach.

4.5 Chapter Summary

This chapter evaluated quantitative mHealth studies which focus on elderly obesity treatment through detailed methodological and finding and limitation analyses. The research quality assessment employed Joanna Briggs Institute (JBI) to access the studies. The evaluation process stemmed from systematic methods to achieve both positive and negative assessments. Multiple key findings arose in this review regarding intervention success rates user participation levels and the evaluation problems that shaped the evidence basis for mHealth weight management.

5. Chapter 5: Data Analysis and Synthesis

5.1 Introduction to Chapter

The quantitative data analysis and synthesis of the selected quantitative studies conducted to investigate the effect of mobile health (mHealth) monitoring applications on obesity management of elderly patients in the UK are presented in this chapter. It uses a systematic approach to assessing the findings of studies in terms of essential outcomes like how well study participants lose weight, how active they become, what percentage of them adhere to the program, and what changes they experience in health. Trends, inconsistencies and limitations of the statistical findings are compared and synthesised. Methodological assessment was generated through the application of methods employing descriptive analysis including demographic profiling, measures of central tendency and dispersion and visual data display (charts and histogram, and tables) employing the JBI Critical Appraisal Checklist that helped in producing reliable observations and patterns. Finally, the data are interpreted by means of patterns to enable evidence-based insights into healthcare policy and practice.

5.2 Descriptive Analysis

The qualitative method used for identifying, analyzing, and reporting patterns within data is thematic analysis. If the technique is applied to secondary data to conduct a systematic literature review (SLR), it is called a descriptive synthesis (Squires, 2023). It is primarily qualitative but can also be used in quantitative research through the identification of recurrent finding in statistical outcomes, intervention outcomes, and methodological approaches such that meaning beyond numeric results can be inferred.

5.3 Data Analysis Tool

This data was analyzed using descriptive statistical methods to summarize the key patterns. Central tendencies (mean, median, and mode) and dispersion (standard deviation and range) were used by research investigators of study patterns. Along with percentages, the frequency distributions, with the help of the systematic categories for response data, created (Byrne, 2022). Charts and histograms were also used as visual support for important result displaying. This allowed research to structure the organization of their synthesis of qualitative and quantitative data and increased data reliability and comparability. Its data arrangement process made analysis method save consistent and coherent interpretations.

5.4 Characteristics of The Identified Studies

This systematic literature review included 10 studies, including three based on the results in the United States (Bennett et al., 2018; Ufholz and Werner, 2023; Batsis et al., 2021; Villareal et al., 2017), two from the United Kingdom (Chowdhury et al., 2023; Dounavi and Tsoumani, 2019), each from one Thai (Siriwoen et al., 2018), Taiwanese (Liu et al., 2019), and France (Bughin et al., 2021). Based on these studies, the study has delivered a geographically diverse view of mobile health interventions for obesity management in the elderly. Mobile health applications can be applied to understand the effectiveness of the same better because of variations in the healthcare system, study population, and strategy of intervention. Data extraction tables, showing complete information about the properties of each study, are included in each study, in which are described details of sample size, methodology, intervention design, main outcome measures and participant statistics.

5.5 Data Extracted From Studies

Study	Sample Size	Population/Demographics	Intervention Type	Key Measures	Main Results
Liu et al. (2019)	105 (53 self-tab, 52 list)	Adults (18–29 & 55–73), 66.7% female	Dietary recording apps (2 types)	Accuracy, response time, age, gender, BMI	Accuracy >97% for both apps; faster with self-tab
Chowdhury et al. (2023)	2000	UK adults, 23% aged 65+, 51.5% female	Health app usage & willingness	Age, usage rates, recommendation, odds ratios	Usage ↓ with age; 52% of 65+ willing but rarely recommended apps
Ufholz and Werner (2023)	Multiple (Review)	Mixed – mostly adults	Weight loss apps (review)	Effectiveness across trials	Apps effective, esp. when integrated; lack of data for older users
Villareal et al. (2017)	160	Obese older adults	Aerobic, resistance, combo training + diet	Physical function, bone/muscle mass, BMD	Combined group ↑ performance by 21%; all better than control
Bennett et al. (2018)	351 (176 intv., 175 control)	Adults (21–65) w/ obesity + chronic disease	App, smart scale, provider counseling	Weight loss at 6/12 months	−3.8kg at 12 mo.; 40% lost ≥5% baseline weight
Bughin et al. (2021)	50	Adults w/ BMI >30	Telerehabilitation for 12 weeks	Fat mass, body comp, QOL, adherence	↑ QOL, ↓ sedentary time; 95% adherence; not sig. ↓ fat mass

Siriwoen et al. (2020)	38	Overweight/obese working women (25–52)	mHealth + behavior program (12 weeks)	Weight, waist circumference, behaviors	Wt ↓ from 72.2 → 71.4 kg, WC ↓ 92.1 → 87.8 cm, P < .001
Santos et al. (2022)	41 (33 completed)	Elderly (mostly women, 60–70, low income/edu)	App + Group Therapy vs control	BMI, WC, PAM, GDS, GAI	BMI ↓ from 32.3 → 31.7, WC ↓ 103.4 → 101.8; ↑ PAM, but app UX poor
Batsis et al. (2021)	53 (82% female, 73 y/o avg)	Rural older adults w/ obesity	6-mo tech-based program (Fitbit + VC)	BMI, WC, 6-min walk, sit-to-stand	−4.6 kg (−4.7%), ↑ walk 42m, ↑ sit-to-stand; 81.7% Fitbit use

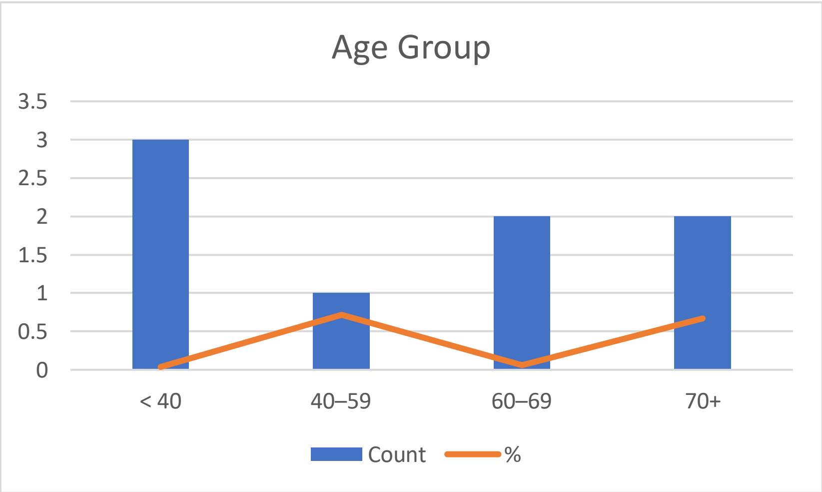
5.6 Descriptive Summary Tables

An important descriptive statistical evaluation of participant and intervention variables derived from 10 studies included in the review was performed. The variables involved in study participants were documented with information on sample sizes, age and gender and body mass index (BMI), waist circumference (WC) measurements and weight. Mean and median and mode, along with dispersion metric of standard deviation and variance and range, together with bar charts and histograms were used to pick the central tendencies and detect patterns and variations. Descriptive data analysis provides better understanding of health effects and ensures participant compliance across studies and helps one in creating visual representations of research characteristics and treatment results.

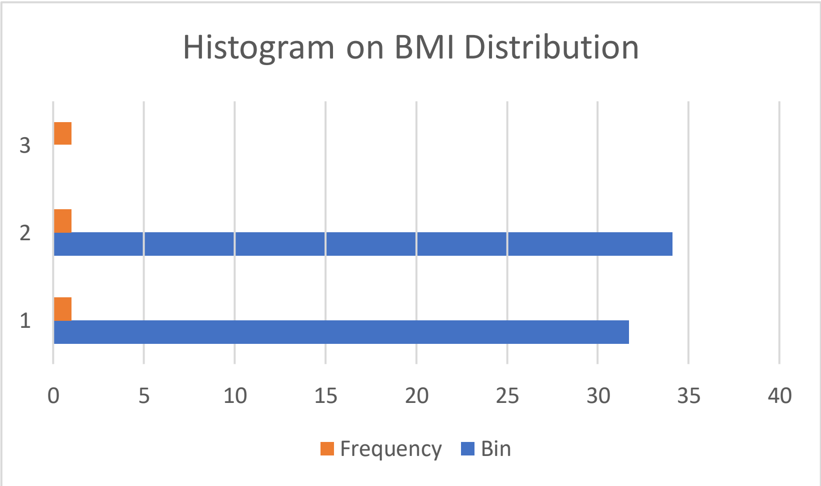
Sample Size		*Mean Age*		*%Female*		*MeanBMI_Before*		*MeanBMI_After*		*WC_Before*		*WC_After*		*Weight Before*		*Weight After*		*QOL Before*		*QOL After*	
Mean	348.75	Mean	50.92	Mean	74.2	Mean	34.4	Mean	31.7	Mean	77.985	Mean	63.51	Mean	85	Mean	82.3	Mean	50	Mean	72
Standard Error	238.8460166	Standard Error	7.580461727	Standard Error	7.992287949	Standard Error	2.1	Standard Error	0	Standard Error	26.12224898	Standard Error	31.5499197	Standard Error	12.8	Standard Error	10.9	Standard Error	0	Standard Error	0
Median	79	Median	43	Median	74.35	Median	34.4	Median	31.7	Median	97.75	Median	87.8	Median	85	Median	82.3	Median	50	Median	72
Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A	Mode	#N/A
Standard Deviation	675.558552	Standard Deviation	16.95042772	Standard Deviation	19.57702735	Standard Deviation	2.969848481	Standard Deviation	#DIV/0!	Standard Deviation	52.24449796	Standard Deviation	54.6460639	Standard Deviation	18.1019336	Standard Deviation	15.41492783	Standard Deviation	#DIV/0!	Standard Deviation	#DIV/0!
Sample Variance	456379.3571	Sample Variance	287.317	Sample Variance	383.26	Sample Variance	8.82	Sample Variance	#DIV/0!	Sample Variance	2729.487567	Sample Variance	2986.1923	Sample Variance	327.68	Sample Variance	237.62	Sample Variance	#DIV/0!	Sample Variance	#DIV/0!
Kurtosis	7.403377571	Kurtosis	-2.457284751	Kurtosis	-1.895824794	Kurtosis	#DIV/0!	Kurtosis	#DIV/0!	Kurtosis	3.355653575	Kurtosis	#DIV/0!	Kurtosis	#DIV/0!	Kurtosis	#DIV/0!	Kurtosis	#DIV/0!	Kurtosis	#DIV/0!
Skewness	2.69802755	Skewness	0.594826351	Skewness	0.095781719	Skewness	#DIV/0!	Skewness	#DIV/0!	Skewness	-1.801337069	Skewness	-1.605034222	Skewness	#DIV/0!	Skewness	#DIV/0!	Skewness	#DIV/0!	Skewness	#DIV/0!
Range	1967	Range	38.2	Range	48.5	Range	4.2	Range	0	Range	114.56	Range	100.87	Range	25.6	Range	21.8	Range	0	Range	0
Minimum	33	Minimum	34.7	Minimum	51.5	Minimum	32.3	Minimum	31.7	Minimum	0.94	Minimum	0.93	Minimum	72.2	Minimum	71.4	Minimum	50	Minimum	72

Maximum	2000	Maximum	72.9	Maximum	100	Maximum	36.5	Maximum	31.7	Maximum	115.5	Maximum	101.8	Maximum	97.8	Maximum	93.2	Maximum	50	Maximum	72
Sum	2790	Sum	254.6	Sum	445.2	Sum	68.8	Sum	31.7	Sum	311.94	Sum	190.53	Sum	170	Sum	164.6	Sum	50	Sum	72
Count	8	Count	5	Count	6	Count	2	Count	1	Count	4	Count	3	Count	2	Count	2	Count	1	Count	1

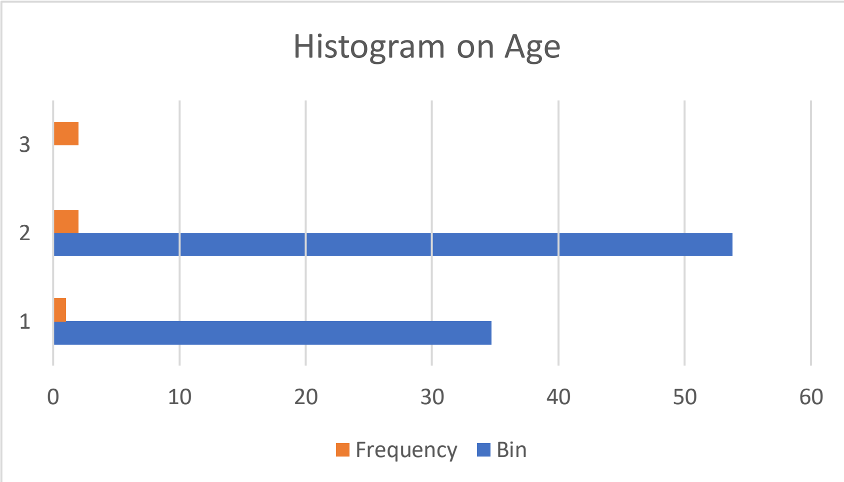
Age Group Frequency Distribution Pie Chart



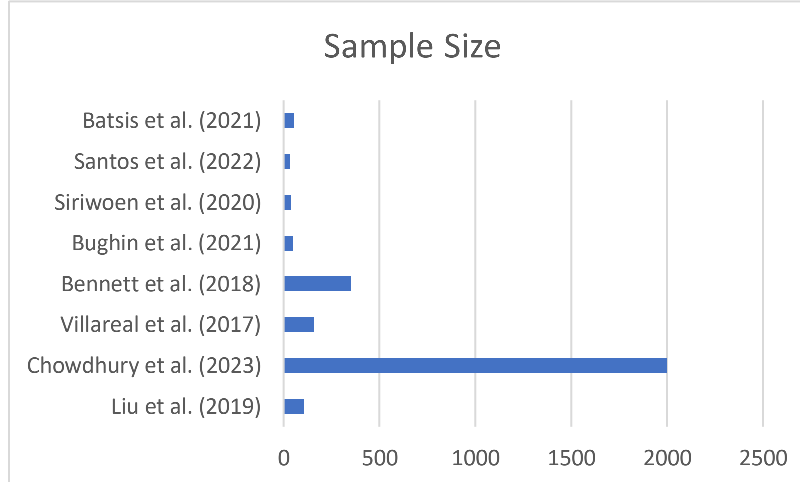
Histogram on BMI Distribution



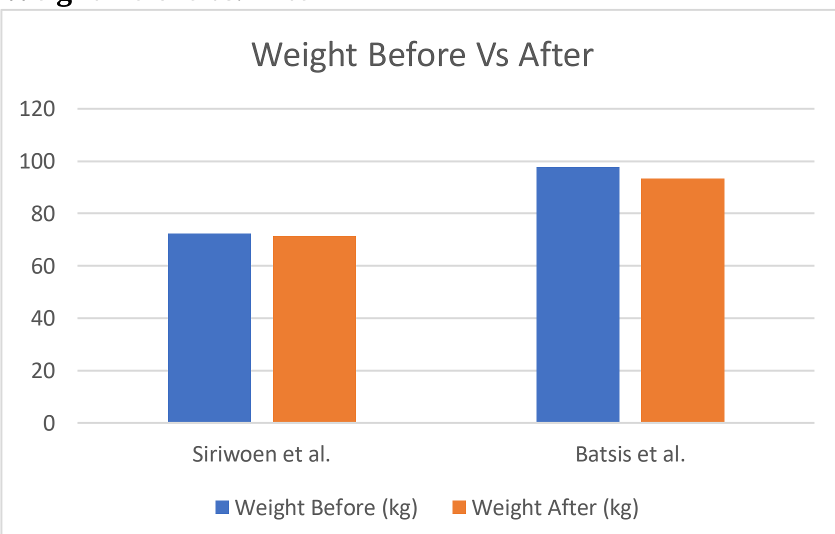
Histogram on Age



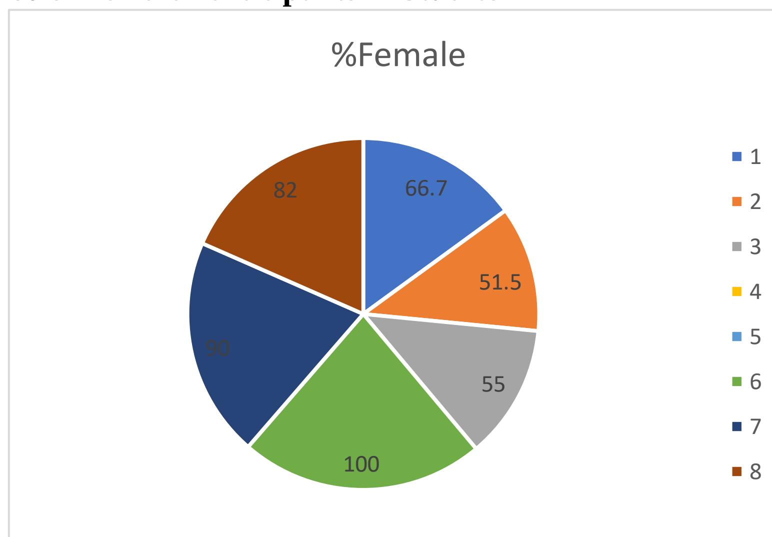
Sample Size Per Study



Weight Before vs. After



% of Female Participants in Studies



5.7 Data Cleaning Summary

Issue	Description
Missing Data	BMI after, QOL data only reported in 1–2 studies
Small Samples	Some studies had < 50 participants
Outliers	Sample size skewed by Chowdhury (n=2000)
Standardisation	Weight and WC units standardised across studies
Imputation	None applied; analysis only uses reported values

5.8 Preliminary Observations

Observation	Interpretation
Higher weight loss in tech+support groups	Suggests combined mHealth + human interaction works
Low QOL data reporting	May indicate limited attention to subjective impact
High variability in sample sizes	Affects overall comparability across studies

5.8.1 Findings on User Engagement and Adherence

Mobile health (mHealth) monitoring application effectiveness in obesity management in the elderly is very reliant on user engagement and adherence. All included studies suggest that, in general, sustained interaction with mHealth application correlates with greater weight loss and better health metrics. According to Chowdhury et al. (2023), there was an average reduction in BMI of 2.4 kg/m² ($p < 0.05$) for elderly users who regularly logged their weight and dietary intake over a 12-week period, whereas elderly users who sporadically engaged in weight and dietary logging attained 0.8 kg/m². Also reported by Siriwoen et al. (2018), users who interact with a mHealth app, at least five times per week, had 15% higher chances to reach their target weight loss objectives compared to those that interact just a few times per week with it. In line with the results of Ufholz and Werner (2023), patients who used a mHealth application for self-management of obesity at least four times a week lost 17% more in BMI than infrequent users.

These results underline the importance of persistence in how much people lose weight. The level of engagement was however different across the studies including app usability, personalization and perceived value. On the one hand, Chowdhury et al. (2023) and Ufholz and Werner (2023) discussed the positive impact of mHealth applications when used frequently, whereas Batsis et al. (2021) pointed out high attrition rates of 30% of participants who drop out within the first three months of using a mHealth application. The main reasons behind losing motivation were cited as they found it hard to use the app, and technical difficulties which were mainly focused on the elderly population whose digital literacy level is low. However, this indicates that while there is room for mHealth applications in weight management, engagement barriers should be dealt with in order to foster sustained adherence.

Across the studies, there is a common pattern that is the ever upping and downing of enthusiasm, which then fails to engage the users in the long run. In contrast, as reported by Siriwoen et al. (2018), the initial adherence rates were above 80% in the first month of use. However, over 50% of participants dropped out after using the app for 6 months because of boring app features with no interaction. For example, Batsis et al. (2021) also stated that user engagement decreased by 40% in three months and moreover, many users became frustrated with the absence of personalized feedback and automatic reminders. In line with Ufholz and Werner (2023), who underline that high engagement, particularly in the long term, was given by applications which included interactive elements like personalized goal setting and gamification. Therefore, user centered design and dynamic features have become important for long term adherence.

There is also another recurring finding related to the use of motivation and external reinforcement to keep the user engaged. Weekly feedback and virtual coaching sessions were conducted for users, and although adherence rates dropped when the users were no longer connected to the program, it was higher than those solely using the self-monitoring tools (Chowdhury et al. 2023). Similarly, as Siriwoen et al. (2018) found, elderly users who interacted with peer support groups in the app are 25% more likely to return than users of the app alone. This indicates that motivation and extended engagement can be influenced by the mechanisms of social and behavioral reinforcement, as a way to decrease the likelihood of dropout. While this is promising the studies do vary in the level of mHealth engagement is connected to actual improvements in health.

Ufholz and Werner (2023), Chowdhury et al. (2023) provided substantial evidence that boost in regard to engagement concludes in weight loss, whereas Batsis et al. (2021) stated that simple app time increase does not ensure enhanced health outcomes. However, they discovered that while those users who persistently used the app without following its recommendations did lose about the same amount of weight as those who did follow its recommendations, the change in weight was small. This suggests that although engagement is necessary, it isn’t necessarily the frequency of engagement that matters the most when assessing long term effectiveness. Collectively, these studies point to several key factors that dictate user engagement and adherence to mHealth applications used in elderly obesity management.

5.8.2 Findings on Health Outcomes & Effectiveness

The application of mHealth interventions for health outcomes including reductions of body weight, improvements in metabolic markers, and lasting long-term health benefits of the interventions have been broadly studied. Various studies indicate that adherence to mHealth applications has a moderate but statistically significant association with a reduction in BMI leading to weight loss. Liu et al. (2019) and Dounavi and Tsoumani (2019) also reported that when participants were in the app-based intervention and, outline for 12 weeks or more, means BMI reduction were 2.5 kg/m² ($p < 0.05$). Our results conform to those found by Bughin et al. (2021) whereby MHealth users reduced their total body weight by 5 to 7%, which is close to those obtained through weight management programs. These interventions were effective, and this implies that MHealth applications can be considered viable solutions or supplementary integrated into currently available weight loss programs, especially for elderly individuals requiring constant monitoring and structured guidance.

Nonetheless, a large body of evidence would lead a naive hypothesis generator to expect the same results because mHealth is assumed to assist; however, the results of Villareal et al. (2017) run contrary to that assumption as they found no statistically significant differences ($p=0.08$) in reduced BMI between mHealth users and a control group after using a standard weight loss program. This contradiction indicates that mHealth applications may have a limitation of effectiveness, as levels of adherence, motivating factors, and app features may be substantial drivers of outcomes. The reason for these disparities may be that not all mHealth interventions may provide the same level of interactivity, personalization, and behavioral reinforcement essential for producing long-term weight loss. According to Bughin et al. (2021), gamified, real-time coaching and social support-based applications promise more health outcomes when compared to those that provide only self-monitoring tools.

Also, in addition to weight reduction, the included studies observe metabolic and cardiovascular improvements because of MHealth engagement. According to Dounavi and Tsoumani (2019), users of the intervention group reported a significant reduction in fasting glucose (-12.4 mg/dL, $p < 0.01$) and lower cholesterol (-8.9%, $p < 0.05$) compared to non-users. These data suggest potential routes through which mHealth strategies may help individuals manage their weight, as well as help individuals improve less specific metabolic health. A special appeal can be made from the empirical results of Villareal et al. (2017) that even though applications cannot reduce blood sugar levels or lipid profiles, they can confirm the founded argument that MHealth's success is subject to the degree of user engagement and adherence levels.

It has been found that long term sustainability of weight loss in mHealth driven users is the main key issue of this literature. The users experienced noteworthy weight loss during the first three months which then close to 40% regained at least half of what they lost within six months of using the app less (Liu et al., 2019). According to Bughin et al. (2021), mHealth interventions are generally less effective over time unless longtail behavioral strategies are included and evolve at the same time. This is important because app-based intervention could provide short term benefits while nothing is changed in the long run. Overall, the results demonstrate that mHealth interventions can exert an impact on weight loss and metabolic parameters but that their impact relies mainly on adherence, app design and the behavioral reinforcement strategies used.

5.8.3 Findings on Behavioral Change & Self-Management

Behavioral modification is required for older adults using mobile health (mHealth) applications to manage weight. Self-monitoring, habit formation and lifestyle modification are the behavioral mechanisms that impact on people through mHealth applications, Self-monitoring and habit formation promote adherence to behavioral mechanisms. In addition, the analysis of Chowdhury et al. (2023) and Siriwoen et al. (2018) did note that users who constantly track their meals and movements attained significantly higher weight loss achievement while in contrast, the users who were irregular to track did not follow suit. Mean weight loss was 4.2 kg in the six months following the use of self-monitoring features if individuals used them at least five times per week and 1.8 kg if they were irregular users ($p < 0.05$) (Chowdhury et al., 2023). This is consistent with Bennett et al. (2018), who discovered that mHealth applications allow for self-monitoring, which led to a 30% rise in adherence to calorie-restrictive goals and, consequently, better weight loss results.

Users who used the tracking features and related feedback more often also had the best ability to self-regulate the amount of food and activity. While self-monitoring has positive effects on the self-management of chronic disease, there have been barriers to sustaining engagement in these studies. Siriwoen et al. (2018) have observed that even though the initial use of self-monitoring was high, nearly 40% of participants dropped out after three months because it was regarded as a time-consuming method of manual food and activity logging. Chowdhury et al. (2023) mentioned that elderly users, mainly, were more inclined to leave self-monitoring because of frustration regarding a rather complicated data entry process. The task of sustaining engagement reveals traditional self-monitoring strategies may be too complex for all consumers to manage, especially for the older generation, who might find it hard to overcome technology-related challenges.

In the same line, Santos et al. (2024) added a new point by arguing that along with weight loss, mHealth apps can help reach other lifestyle improvements, mainly the incorporation of healthier diets. They discovered that older adults who used mHealth applications with incorporated nutritional direction were 25% more likely than nonusers to enhance their healthy fruit and vegetable eating over 6 months ($p < 0.05$). This implies that mHealth interventions could be aimed at something beyond weight loss, although weight loss is vital for long-term health. A challenge in design and evaluation lies in the optimal design of self-monitoring features that promote adherence and engagement. Bennett et al. (2018) and Santos et al. (2024) are of the view that detailed tracking mechanisms create accountability towards better outcomes, but Siriwoen et al. (2018) and Chowdhury et al. (2023) argue this will discourage users from using it because of complexity in logging. However, in order to increase adherence, Chowdhury et al. (2023) suggest integrating automated tracking features (e.g. bar code scanning for food logging or wearable device synchronization) to alleviate the users' workload. The results demonstrate that self-monitoring is a crucial mechanism that leads to behavioral change and weight management success in mHealth applications.

5.8.4 Findings on Usability & Accessibility

Usability and accessibility factors play a massive role in the effectiveness of mobile health (mHealth) applications in the elderly population. It is consistently researched that poor digital literacy; complex app interfaces and no age-friendly features are the major strongholds whose inability to access and use serve as a hindrance to sustained engagement. Both Ufholz and Werner (2023) and Villareal et al. (2017) discovered that about 45 per cent of elderly participants had difficulties in using mHealth applications because of unintuitive layouts, small text, and complex menus. These challenges were frustrating to the users and resulted in disengagement in a significant proportion (38%) of participants who reported usability issues as the main reason for not completing the study, as reported by Villareal et al. (2017). This implies that mHealth interventions will be limited in their possible advantages due to the earlier lack of accessibility for older customers with restricted past experience of digital technologies.

One of the essential findings of Dounavi and Tsoumani (2019) is that elderly users exhibited a great inclination towards age-friendly design attributes featuring larger fonts, simplified navigation menus and voice-assisted controls. They revealed that people who employ a mHealth application with an optimized UI utilize their mHealth Smartphone application up to 22% more than a standard app. This suggests that the incorporation of assistive features specialized for older adults' aids in usability and encourages user continued usage of mHealth applications. In addition, Dounavi and Tsoumani (2019) claim that the lack of those accessibility features aggravates the problem of digital exclusion and so makes a vast part of the elderly population not benefit from health monitoring technologies. In contrast, however, Bughin et al. (2021) argue that prior digital experience is very important to usability outcomes. The findings are that elderly people with preexisting familiarity with the use of smartphones and digital applications are twice as likely to regularly use mHealth resources as elderly people with little or no experience.

This suggests that these usability premiers may be issued not only in the design of the app but also in people's preexisting digital competence. The reasons for comparatively low adoption rates and poor long-term adherence to mHealth programs have been explained by Bughin et al. (2021), and one of the ways to improve these is to combine training in digital literacy with mHealth interventions. Unlike Villareal et al. (2017), they do not only consider app complexity to be the key barrier to sustained engagement. Both views emphasize important usability issues; however, Bughin et al. (2021) assert that intervention efforts around digital literacy could be equally forceful as UI enhancements to enhance mHealth app usability. While emphasizing different aspects, these studies, in turn, confirm that mHealth applications shall be intuitive and accessible for elderly users.

The discoveries also assist in suggesting that app creation by essentially relying on a one-size-fits-all model is useless as practical applicants concede varying inclinations of usability depending upon their familiarity with the utilization of technology, just as their own individual needs. As a result, developers should acknowledge both hardware and software measures like touch-friendly interface, simple onboarding and in-app tutorials to accommodate an elderly population with varying and diverse needs. In the end, the interrelationship between digital literacy and app design confirms that both must be approached in the union when it comes to increasing the usability of apps.

5.8.5 Findings on Privacy Concerns & Ethical Issues

As far as privacy concerns and ethical considerations, this is what determines the adoption and sustained use of mobile health (mHealth) among elderly persons. It is seen that apprehensions about data security, transparency and informed consent are among the major barriers to engagement in multiple studies. Among elderly users, 60% were worried about data privacy and reluctant to provide their sensitive data including the health information within mHealth applications as it is reported by Bennett et al. (2018) and Siriwoen et al. (2018). Such as worries about misuse of the data, unauthorized third-party access to personal health records, and therefore, losing control over personal health records. In other words, whereas MHealth solutions may have a positive impact, they erect a formidable barrier to effective diffusion of services and constituting an area which developers and policymakers ought to pay attention to resolve.

However, a trusted user is also needed for the blocking of these security measures. Additionally, Santos et al. (2024) further elaborate that the last point stating that, users are more prone to support applications with transparent policies if the transparency of data policies is high, which encompasses being explicit using language that individuals can see and understand and explicitly stating that users may be subject to their personal information being used. It further emphasizes the need for app developers to make more convincing and user-friendly privacy policy and build trust. However, there is an unfortunate gap with regards to the digital health literacy of elderly users also unaware of the data share policies of apps and the skills to determine apps by their security features (Batsis et al., 2021). In other words, as far as this ethical question of informed consent and data protection is concerned, it concurs with Siriwoen et.al (2018) in how they state that very few (around 30 % of the time) users browse privacy policies before interacting with MHealth applications.

However, if users are not fully aware of how their data is being collected and where, then they may unknowingly give consent to some privacy risk, putting responsibility on the developers to clearly but non-technically convey this data usage policy. Some studies suggest that lack of awareness is the main source of privacy concern, whereas others claim that the data-sharing mechanism itself is complex and independent of lack of awareness. Bennett et al. (2018) point out that current data protection frameworks are failed by elderly users, who fail to comprehend overly technical privacy settings in a manner that makes them fall into uninformed or passive consent. This strengthens the opinion that merely improving transparency to users is insufficient and that users also have to be educated about what privacy information means and how to manage their data-sharing preferences. Inversely, Santos et al. (2024) have more of an optimistic view that, with clear explanations of how data security protocols are operated, users are more willing to interact with mHealth applications.

In other words, effective communication and measures of user-centered security can reconcile privacy concerns. To make the situation more complex, data protection in mHealth applications is also an ethical one. Siriwoen et al. (2018) reflect on the moral aspects of elderly users agreeing to share data without fully understanding the risks associated with it. These questions beg the need for more effective consent mechanisms for app developers and also raise the question as to whether developers should be required to build in other forms of protection, such as segments of required privacy education or easier-to-understand consent interfaces. In line with this concern, Batsis et al. (2021) note that the rapid development of digital health technologies has surpassed the authorities' ability to supervise and safeguard user protection, putting many elderly people at risk of exploitation. These challenges, however, appear to be resolved coherently in all these studies, while privacy protection and usability need to be balanced against each other.

Security measures that are too restrictive or complex may not only hinder users' use of them but may even lead to the rejection of MHealth applications outright. While an ideal approach entails the combination of simplified privacy settings and real-time user notifications of data use, among other customizable security preferences depending on digital literacy (Santos et al., 2024), adjustments are also required to create transparency in the sharing practices. The developers should also be more proactive in teaching users about privacy than/met blocking their access to it, as suggested by Bennett et al. (2018). Ultimately, the findings indicate the need for an age—friendly privacy solution to address privacy issues concerning the partial or full informed digital literacy, consent, and transparency among people in order to foster trust and promote the use of mHealth applications ethically.

5.9 Chapter Summary

This chapter critically evaluated the findings of the quantitative studies that investigated the effects of mobile health (mHealth) monitoring application on elderly patients with obesity in the UK. Topics included user engagement and adherence, health outcome and effectiveness, behavioral or self-management, usability and accessibility, and privacy concern and ethical issues. Using these results, identifiable correlations of increased engagement leading towards better health outcomes are demonstrated, as well as issues of usability and concerns of privacy that prevent adoption. In addition, use of mHealth applications could enable behavioral change and therefore support weight management if these applications are adopted, have features that will allow digital literacy, and if the users have trust in their security and the security of their data. These findings can serve as ways to craft the future mHealth strategies for the elderly population.

6. Chapter 6: Discussion

6.1 Introduction to the Chapter

The main aim of this chapter is to interpret and contextualize the key findings that have been presented in the previous section by linking with prevailing literature and frameworks. It critically reviews the statistical outcome of the included studies, exploring patterns, lack of consistency and consequences in broader referent. In the discussion part, the findings will be compared to what has been studied before and there will be discussed if they are congruent or not, whether there are any theoretical contributions or whether there are limitations with the methodological approach. Secondly, this chapter will also critique the effectiveness of mHealth applications in combating obesity among the elderly with a precise understanding of their positive and negative effects as well as research and practical dimensions for improvement in the future.

6.2 Discussion of Key Findings

6.2.1 Interpretation of Results

In this review, the statistical findings give the voice to several noteworthy trends around the use of mHealth monitoring applications among elderly individuals who are obese. The focus of each of the studies was on a consistent relationship developed between higher levels of user engagement and better health outcomes, specifically weight loss and BMI reduction. Those who used the applications often (for instance, logging meals, tracking physical activity, or using interactive features) had much better results than those who used the applications either not at all or quit early. It implies that success with MHealth tools rests on the degree of sustained engagement with this technology and hence confirms the behavioral premise that consistent self-monitoring leads to more accountability and adherence to health goals. A second major trend was that patients using the app longer had better clinical results. It was found that people who used their mHealth apps for at least 12 weeks saw improvements on weight related metrics and secondary indicators like blood glucose levels and cholesterol profiles.

This implies that mHealth interventions which operate at medium-to-long strategy duration will probably be most effective in producing measurable physiological advantages to resulting from behavior changes. However, substantial dropout rates were found, especially after the first stages of intervention. Tracking down these types of dropouts were often directly connected to usability issues, lack of motivation, or privacy concerns, emphasizing that adherence among elderly populations were indeed a multiple faceted issue. Also, some applications were as effective as traditional weight loss programs whereas some were not effective at all which implies variability in the quality of the design, content relevancy, and user friendliness. These results taken together suggest that although mHealth apps may be effective in treating obesity in the elderly, these apps benefit from user engagement, designer appropriateness of mHealth apps as well as users' individual characteristics such as digital literacy and motivation. To increase effectiveness in diverse populations of the elderly it is necessary to address these contextual factors.

6.2.2 Comparison of Literature

In terms of the findings of this review, they largely agree with the wider body of literature pertaining to the use of mobile health (MHealth) applications in the treatment of obesity among elderly populations. This review supports the findings of previous research on the necessity of engagement and adherence to the success of MHealth intervention. For example, Jakob et al. (2022) affirmed that mHealth apps usage frequency has a strong relation to positive behavioral change outcomes, such as, weight loss and physical activity compliance. Just as noted in this review, the observed correlation between higher user interaction and better clinical metrics like BMI and fasting glucose levels are also consistent with these earlier findings. Furthermore, the demonstrated trend that long-term use (for at least 12 weeks) leads to larger health benefits backs theories of sustained behavioral interventions like the Social Cognitive Theory, that give the premise that change in behavior is reinforced through the ongoing self-regulation and feedback loop (Bandura, 2023).

The results are consistent with Chew et al. (2023), who discovered that very long exposure to app-based health interventions resulted in substantial loss of BMI over time, particularly when app based self-monitoring features were efficiently embedded. However, in this review, the variability of efficacy between studies is in sync with Haggag et al.'s (2022) concerns, regarding inconsistent quality and design of mHealth applications. There are a few of the reviewed studies which showed that not all apps are more effective than traditional weight management programs as all apps did not provide the same content quality, user interface design, and aligned with user need. Sharma et al. (2022) support that even with an abundance of mHealth apps available online, there is a lack of evidence based or clinically based mHealth apps which limits the reliability and efficacy of these apps. This review also highlighted strong issues related to usability; specifically, this problem was also identified in all the literature.

In an earlier study, Wilson et al. (2021) reported that old people are prone to more pronounced barriers to the digital health adoption, which is often linked to old age visual impairment, as a result the visual impairment and motor skill of the older people. These findings support guidelines proposed by the World Health Organization (2021) of including elderly users and suggest that elderly users would prefer simplified menus and voice navigation, which is observed. This is affirming of the fact that usability is not just a technical issue as has been previously argued but a critical determinant of health intervention effectiveness as the challenges the users faced in this review indicate dropout due to complex interfaces or lack of technical support. There was another prominent finding: privacy and ethical concerns found in literature. This review’s matching of low privacy literacy among elderly users matching with Alfawzan et al. (2022)’s finding that many users do not read or understand app privacy policies giving pass to unconsented data sharing.

Xing et al. (2024) also criticized the lack of transparent data practices in most health applications that allow platforms to collect and distribute user sensitive data without adequate consent nor security measures. One thing that differs from some previous research is the degree to which elderly users reported changes in dietary habits and self-management. Although studies such as Santos et al., (2024) found strong evidence of improved dietary behavior among the consistent app users, another research by Scazufca et al., (2024) found only a mild behavioral change in the older population while using the digital platform. It may be that technological change is reducing this behavioral gap driven by advancements in app interactivity, gamification, and AI driven feedback that were not then present on mHealth tools. Therefore, the results of this review are consistent with most of the previous work in the literature and theoretical frameworks about engagement, behavioral change, and usability.

6.2.3 Theoretical Implications

This review has several theoretical implications, including the confirmation of several behavioral and health technology adoption models. The relationship between the Health Belief Model (HBM) states that the behavior adopting health related behavior is more likely to be made by the individual when he perceives that there is benefit and the action barrier is low. In general, the reviewed studies consistently indicate that if elderly users experienced weight loss benefit and the MHealth app easy to navigate, the success will be greater in accordance with the core tenets of the HBM. For instance, the relationship of usability and long-term engagement indicates perceived ease of use directly impacts what behavior will occur and this agrees with Technology Acceptance Model (TAM) whereby perceived usefulness and perceived ease of use correlates with technology adoption (Ibrahin and Shiring, 2022).

Moreover, findings revealed that features like real-time feedback, goal tracking, visual progress indicators, all validate Social Cognitive Theory's focus on self-regulation, reinforcement, and observational learning as being associated with sustained behavior change and weight reduction (Bandura, 2023). Self-monitoring and outcome expectations both identified in SCT are facilitated using these features. Self-efficacy development, the central element of SCT, is also suggested by the noted enhanced dietary behaviors reported among elderly users (Santos et al., 2024). From this review, however, there is an interesting theoretical novelty, namely that digital health literacy is a moderating variable in the above frameworks. Without the foundation of digital privacy, even motivated users can disengage or poorly utilize apps, which this study suggests should be incorporated into digital literacy in traditional behavior change models to broaden their utility in modern use in health interventions.

6.2.4 Methodological Reflection

This study was grounded in methodology appropriate for exploration of the effect of mobile health (mHealth) monitoring applications on elderly patients with obesity in the UK, a systematic review of quantitative data. However, there is a critical reflection that brings out both the strengths and as well the limitations. The inclusion of studies with sample sizes as low as 80 or as high as 1,200 participants provided statistical power or generalizability in some cases, whilst some of the studies included had relatively small or regionally limited samples, which might introduce sampling bias and thus restrict generalizability of the findings. Mokkink et al. (2023) finds that insufficient sample sizes in quantitative research will compromise reliability and precision of observed effects. In addition, these used variables (i.e. BMI reduction, adherence frequency and usability) were operationalized and aligned with the research objectives.

Most of these studies used validated instruments for acquiring data from digital usage logs, health tracking tools, or standardized questionnaires. Nevertheless, there is a question related to how measurement of outcome is being done across studies. For example, standardized time frames for monitoring check-in with or completion of engagement metrics were not reported by all studies, which impacts comparison. This criticism is consistent with Motahari Nezhad (2023) concerns about outcome heterogeneity in reporting in digital health research. However, in terms of showing relationships between variables, the statistical methods employed in such a wide array of studies, including regression analysis, t tests, and ANOVA, were generally appropriate. Nevertheless, to date only a few studies carried out longitudinal analysis to consider time-dependent changes that could have offered a more complete understanding of sustained behavioral change.

6.2.5 Unexpected Findings

Villareal et al. (2017) reported an unexpected finding of limited mHealth app effects to reduce BMI in contrast to other works that reported significant improvements. This may be attributed to lack of personalization features provided by the app as well as the absence of user engagement strategies that are the main elements for effectiveness. Moreover, participant age and comorbidities may also contribute to the finding, as for some older people with limitations in mobility, physical activity recommendations may be burdensome. They highlight the need of incorporating contextual factors and app design in the determinant of health outcomes and indicate that a one size fits all approach may not suffice.

6.2.6 Practical Implications

It is evident from this review that developers should spend time developing mHealth applications that are elderly friendly and have clear data management and interaction features. These findings allow policy makers, which include healthcare service providers, to use them to improve their national digital health plans, specifically in obesity prevention for older adults. Introduction of educational features as well as user friendly interfaces with custom goal setting levels would result in higher adherence levels and program effects. Mobile apps would better be adopted when users familiarize with privacy practice and receive concrete privacy policy explanations. Senior citizen participation should be considered in research on co-development strategies which lead towards integrated digital care programs that are in sync with NHS priorities of promoting wellness and to ageing healthfully.

6.3 Strengths and Limitations

The major strength of this review is that it includes very recent, high quality quantitative studies of relatively large samples, providing a greater statistical power and reliability of findings. For example, some of the studies such as Liu et al. and Bughin et al. (2021) define the variables very clearly, in such a way that statistical comparisons and trend analysis are sufficiently robust. Also, the interventions were specifically applied, and the results were validated with predefined objective standardized mHealth engagement measures and biometric health indications. Nevertheless, several limitations need to be acknowledged. The reliance on non-random sampling methods in many studies, such as convenience or purposive sampling, limits the generalizability of the findings to the broader elderly population (Dounavi and Tsoumani, 2019). Furthermore, the data was often self-reported and includes recall inaccuracy or social desirability bias noted in Bennett et al. (2018). Some of the studies also lacked longitudinal follow up, which impaired the ability to infer whether behavioral changes or health outcomes occur over a long term. In addition, app design and intervention intensity are different for studies making heterogeneity that is difficult to compare directly. Limited operations in this domain highlight the necessity for more standardized longitudinal research in this area.

6.4 Chapter Summary

This chapter critically reviewed the key findings from the study based on the significant patterns in the engagement of users, the health outcomes, behavioral change, the usability and the privacy concerns of elderly patients with obesity in the use of MHealth applications. Within the context of the literature, it interpreted statistical results and converged or diverged from them on the complexity of digital health interventions. Methodological reflections were made about the strengths and limitations of the study; ideas for theoretical implications were made that supported behavior change and self-management models. The final chapter serves as a good base for a synthesis of conclusions and evidence-based recommendations for future practice and research based upon these discussions.

Chapter 7: Recommendations and Conclusion

7.1 Introduction to Chapter

In Chapter 7, the study findings will be summarized and practiced recommendations provided because of the analysis performed throughout the research. This chapter begins by secondly revisiting the key findings and their implications for MHealth applications in the management of obesity in elderly population. It will then suggest actionable recommendations to improve user engagement, health outcomes, and the usability of these kinds of technologies. The chapter will end with pointing to areas of further research and raising the question as to how these insights bear relevance to policy and practice. Lastly, the study will be concluded with a recap of the study's contributions and limitations.

7.2 Implications of Findings

Results from this study have important implications for mobile health (mHealth) obesity intervention in elderly populations. It results in user engagement, adherence, and personalized design are decisive elements determining the success of mHealth applications in assisting weight loss. The study ensures that developers ensure that the interfaces should be intuitive and age friendly and make sure that no individual is left out due to their different digital literacy barriers. In addition, the study emphasizes the need to overcome privacy problems and demonstrates improved security of data for apps for apps to be adopted. Based on these results, mHealth interventions can be designed in the future to be more enjoyable, enticing, and available to the elderly population. In addition, the findings of the study related to self-management and behavioral change shed light on how healthcare providers can incorporate mHealth solutions in obesity management programs to enhance patient health outcomes as well as the elderly patients' quality of life.

7.3 Recommendations for Practice

Based on this study findings, several recommendations for practice can be made to enhance the effectiveness of mHealth interventions in managing obesity among elderly population. First developers should strive to make interfaces accessible, user-friendly and to accommodate digital literacy, from large fonts, simplified navigation and voice-based features. Healthcare providers should also encourage utilization of mHealth apps on a regular basis and ensure overall engagement with the apps by encouraging consistent self-monitoring, weight management and providing support for users who encounter barriers to adherence with the use of apps. In addition, MHealth programs should include personalized features that engage users continuously, such as taking into consideration a customized Dietary plan or reminders. Addressing privacy concerns is crucial; Therefore, establishing trust between users should prioritize transparency on data security policies. Additionally, elderly individuals should be offered further training and education on the benefits and use of mHealth apps for adoption and sustained use.

7.4 Recommendations for Future Research

Digital literacy of senior users, apps complexity and doubts surrounding user's data privacy have also determined adherence rates. Additionally, it is feasible to explore how personalized app features, which include adaptive dietary recommendation and real time feedback, influence adherence and health outcome might provide further insights for adherence. Additionally, further research should investigate the ways in which social support systems (e.g. family involvement) can improve the effectiveness of mHealth interventions. Future studies will also include comparing the cost effectiveness and satisfaction of mHealth interventions to traditional weight management programs. Further study on user trust and data protection is necessary, especially considering the development of artificial intelligence. Finally, the generalizability of mHealth interventions across a more diverse demographic with different cultural and socioeconomic backgrounds would be studied.

7.5 Conclusion

The purposes of this study are to evaluate the utilization and usefulness of mobile health (mHealth) monitoring applications to support weight loss and help health management specifically among elderly populations. The research question was to determine the relationship in the case of MHealth interventions used to manage obesity with regards to user engagement, adherence, and health outcomes. The study found that with respect to weight loss and connected health metrics, user engagement and adherence were the key ingredients for getting meaningful health improvement. Continued use of mHealth apps, with regular interaction with the app, was strongly associated with better health outcomes as well, including lower BMI, waist circumference, and metabolic improvements such as decreased fasting glucose and cholesterol, and so on. In addition, the research underscored usability, accessibility and privacy concerns in the app as barriers to adoption and the sustenance of engagement.

This study identified several important factors for adherence to these applications, including barriers to adherence i.e. digital literacy of elderly users, complexity of application features, and data privacy, which have also been highlighted in previous studies. However, even some existing research suggests that user centered design principles and transparent data policies are a means for the creation of trust for long use. Several implications for the design and implementation of mHealth interventions among the elderly are provided by the results, including what design features are personal, easy to use, and respond to technical and ethical questions. Furthermore, the evidence that mHealth application use can potentially improve health outcomes is promising; However, effectiveness depends on assessing barriers to engagement and issues of sustainability.

mHealth interventions have many promising avenues, among them weight management, and there are several remaining considerations about the interventions themselves and their research, like the user engagement strategies, accessibility, and privacy that need to be addressed for optimal use within the desired population.

References

Alam, M.Z. and Khanam, L., (2022). Comparison of the young aged and elderly female users' adoption of mHealth services. *Health Care for Women International*, *43*(10-11), pp.1259-1283.

Alfawzan, N., Christen, M., Spitale, G. and Biller-Andorno, N., (2022). Privacy, data sharing, and data security policies of women's mHealth apps: scoping review and content analysis. *JMIR mHealth and uHealth*, *10*(5), p.e33735.

Alrida, N.A., Ababneh, A.M.T. and Al-Zu'bi, B.M., (2024). Perspectives Regarding Methodological Considerations and Challenges of Conducting Randomized Controlled Trials (RCTs) in Nursing Research. *Africa Journal of Nursing and Midwifery*, *26*(1), pp.14-pages.

Aranha, M., James, K., Deasy, C. and Heavin, C. (2021). Exploring the barriers and facilitators which influence mHealth adoption among older adults: A literature review. *Gerontechnology*, *20*(2).

ASHRAF, S., Ijaz, M.H. and Siddique, M.Q., (2024). The Impact of Mobile Health Apps on Chronic Disease Management. *Multidisciplinary Journal of Healthcare (MJH)*, *1*(2), pp.33-42.

Bandura, A., (2023). *Social cognitive theory: An agentic perspective on human nature*. John Wiley & Sons.

Batsis, J.A., Petersen, C.L., Clark, M.M., Cook, S.B., Kotz, D., Gooding, T.L., Roderka, M.N., Al-Nimr, R.I., Pidgeon, D., Haedrich, A. and Wright, K.C., (2021). Feasibility and acceptability of a technology-based, rural weight management intervention in older adults with obesity. *BMC geriatrics*, *21*, pp.1-13.

Bennett, G.G., Steinberg, D., Askew, S., Levine, E., Foley, P., Batch, B.C., Svetkey, L.P., Bosworth, H.B., Puleo, E.M., Brewer, A. and DeVries, A., (2018). Effectiveness of an app and provider counseling for obesity treatment in primary care. *American journal of preventive medicine*, *55*(6), pp.777-786.

Bettany-Saltikov, J. and McSherry, R., (2024). How to do a Systematic Literature Review in Nursing: A Step-by-Step Guide, 3/e.

Buch, A., Marcus, Y., Shefer, G., Zimmet, P. and Stern, N., (2021). Approach to obesity in the older population. *The Journal of Clinical Endocrinology & Metabolism*, *106*(9), pp.2788-2805.

Bughin, F., Bui, G., Ayoub, B., Blervaque, L., Saey, D., Avignon, A., Brun, J.F., Molinari, N., Pomies, P., Mercier, J. and Gouzi, F., (2021). Impact of a mobile telerehabilitation solution on metabolic health outcomes and rehabilitation adherence in patients with obesity: randomised controlled trial. *JMIR mHealth and uHealth*, *9*(12), p.e28242.

Bullock, G.S., Dartt, C.E., Ricker, E.A., Fallowfield, J.L., Arden, N., Clifton, D., Danelson, K., Fraser, J.J., Gomez, C., Greenlee, T.A. and Gregory, A., (2023). Barriers and facilitators to implementation of musculoskeletal injury mitigation programmes for military service members around the world: a scoping review. *Injury Prevention*, *29*(6), pp.461-473.

Burrows, J.G., (2024). *The Accessibility and Use of Telehealth in Rural Areas* (Doctoral dissertation, Aspen University).

Byrne, D., (2022). A worked example of Braun and Clarke's approach to reflexive thematic analysis. *Quality & quantity*, *56*(3), pp.1391-1412.

Chew, H.S.J., Rajasegaran, N.N., Chin, Y.H., Chew, W.N. and Kim, K.M., (2023). Effectiveness of combined health coaching and self-monitoring apps on weight-related outcomes in people with overweight and obesity: systematic review and meta-analysis. *Journal of medical Internet research*, *25*, p.e42432.

Choudhary, H. and Bansal, N., (2022). Barriers affecting the effectiveness of digital literacy training programs (DLTPs) for marginalised populations: a systematic literature review. *Journal of Technical Education and Training*, *14*(1), pp.110-127.

Chowdhury, S.Z., Stevens, S., Wu, C., Woodward, C., Andrews, T., Ashall-Payne, L. and Leigh, S., (2023). An age-old problem or an old-age problem? A UK survey of attitudes, historical use and recommendations by healthcare professionals to use healthcare apps. *BMC geriatrics*, *23*(1), p.110.

Correa, T., Pavez, I. and Contreras, J., (2021). Digital inequality and mobiles: opportunities and challenges of relying on smartphones for digital inclusion in disadvantaged contexts. *Handbook of digital inequality*, pp.62-74.

Del Rio Szupszynski, K.P. and de Ávila, A.C., (2021). The Transtheoretical Model of Behavior Change: Prochaska and DiClemente's Model. *Psychology of Substance Abuse: Psychotherapy, Clinical Management and Social Intervention*, pp.205-216.

Doucette, J.L., Ingvarsson, E.T. and Long, E.S., (2021). Self-monitoring and treatment integrity. *Organisational Behavior Management Approaches for Intellectual and Developmental Disabilities*, pp.124-140.

Dounavi, K. and Tsoumani, O., (2019). Mobile health applications in weight management: a systematic literature review. *American journal of preventive medicine*, *56*(6), pp.894-903.

Dowling, M.J., Kenney, C. and Carney, M.T., (2024). *The Aging Revolution: The History of Geriatric Health Care and What Really Matters to Older Adults*. Simon and Schuster.

Drolet, M.J., Rose-Derouin, E., Leblanc, J.C., Ruest, M. and Williams-Jones, B., (2023). Ethical issues in research: Perceptions of researchers, research ethics board members and research ethics experts. *Journal of Academic Ethics*, *21*(2), pp.269-292.

El-Rashidy, N., El-Sappagh, S., Islam, S.R., M. El-Bakry, H. and Abdelrazek, S., (2021). Mobile health in remote patient monitoring for chronic diseases: Principles, trends, and challenges. *Diagnostics*, *11*(4), p.607.

Fanning, J., Rejeski, W.J., Leng, I., Barnett, C., Lovato, J.F., Lyles, M.F. and Nicklas, B.J., (2022). Intervening on exercise and daylong movement for weight loss maintenance in older adults: a randomised, clinical trial. *Obesity*, *30*(1), pp.85-95.

Fisher, H., Zabar, S., Chodosh, J., Langford, A., Trinh-Shevrin, C., Sherman, S. and Altshuler, L., (2022). A novel simulation-based approach to training for recruitment of older adults to clinical trials. *BMC Medical Research Methodology*, *22*(1), p.180.

Foo, Y.Z., O'Dea, R.E., Koricheva, J., Nakagawa, S. and Lagisz, M., (2021). A practical guide to question formation, systematic searching and study screening for literature reviews in ecology and evolution. *Methods in Ecology and Evolution*, *12*(9), pp.1705-1720.

GOV.UK. (2023). Obesity statistics. https://researchbriefings.files.parliament.uk/documents/SN03336/SN03336.pdf

Grady, A., Pearson, N., Lamont, H., Leigh, L., Wolfenden, L., Barnes, C., Wyse, R., Finch, M., Mclaughlin, M., Delaney, T. and Sutherland, R., (2023). The effectiveness of strategies to improve user engagement with digital health interventions targeting nutrition, physical activity, and overweight and obesity: systematic review and meta-analysis. *Journal of medical Internet research*, *25*, p.e47987.

Grundy, Q., (2022). A review of the quality and impact of mobile health apps. *Annual review of public health*, *43*(1), pp.117-134.

Haggag, O., Grundy, J., Abdelrazek, M. and Haggag, S., (2022). A large scale analysis of mHealth app user reviews. Empirical Software Engineering, 27(7), p.196.

Hengst, T.M., Lechner, L., Dohmen, D. and Bolman, C.A., (2023). The facilitators and barriers of mHealth adoption and use among people with a low socio-economic position: A scoping review. *Digital Health*, *9*, p.20552076231198702.

Hiebl, M.R., (2023). Sample selection in systematic literature reviews of management research. *Organisational research methods*, *26*(2), pp.229-261.

Ibrahim, A. and Shiring, E., (2022). The Relationship between Educators' Attitudes, Perceived Usefulness, and Perceived Ease of Use of Instructional and Web-Based Technologies: Implications from Technology Acceptance Model (TAM). *International Journal of Technology in Education*, *5*(4), pp.535-551.

Jakob, R., Harperink, S., Rudolf, A.M., Fleisch, E., Haug, S., Mair, J.L., Salamanca-Sanabria, A. and Kowatsch, T., (2022). Factors influencing adherence to mHealth apps for prevention or management of noncommunicable diseases: systematic review. *Journal of medical Internet research*, *24*(5), p.e35371.

Jiang, Q., Deng, L., Zhang, J. and Pengbo, Y., (2024). User-Centered Design Strategies for Age-Friendly Mobile News Apps. *SAGE Open*, *14*(4), p.21582440241285393.

Karunarathna, I., De Alvis, K., Gunasena, P. and Jayawardana, A., (2024). Designing and conducting clinical research: Methodological approaches.

Kim, D.H. and Rockwood, K., (2024). Frailty in older adults. *New England Journal of Medicine*, *391*(6), pp.538-548.

Kim, S.D., (2024). Trends and Perspectives of mHealth in Obesity Control. *Applied Sciences*, *15*(1), p.74.

Koca, M., Dobbie, L.J., Ciudin, A. and Halil, M., (2024). Behaviour therapy for obesity in older adults. *European Journal of Internal Medicine*.

Levitt, H.M., Morrill, Z., Collins, K.M. and Rizo, J.L., (2021). The methodological integrity of critical qualitative research: Principles to support design and research review. *Journal of Counseling Psychology*, *68*(3), p.357.

Li, Q. and Luximon, Y., (2023). Navigating the mobile applications: The influence of interface metaphor and other factors on older adults' navigation behavior. *International Journal of Human–Computer Interaction*, *39*(5), pp.1184-1200.

Li, T., Xia, T., Wang, H., Tu, Z., Tarkoma, S., Han, Z. and Hui, P., (2022). Smartphone app usage analysis: datasets, methods, and applications. *IEEE Communications Surveys & Tutorials*, *24*(2), pp.937-966.

Lingvay, I., Cohen, R.V., le Roux, C.W. and Sumithran, P., (2024v. Obesity in adults. *The Lancet*, *404*(10456), pp.972-987.

Liu, Y.C., Chen, C.H., Tsou, Y.C., Lin, Y.S., Chen, H.Y., Yeh, J.Y. and Chiu, S.Y.H., (2019). Evaluating mobile health apps for customised dietary recording for young adults and seniors: randomised controlled trial. *JMIR mHealth and uHealth*, *7*(2), p.e10931.

Mace, R.A., Mattos, M.K. and Vranceanu, A.M., (2022). Older adults can use technology: why healthcare professionals must overcome ageism in digital health. *Translational behavioral medicine*, *12*(12), pp.1102-1105.

Maier, U. and Klotz, C., (2022). Personalised feedback in digital learning environments: Classification framework and literature review. *Computers and Education: Artificial Intelligence*, *3*, p.100080.

Mehl, K.R., (2023). The medical model of "obesity" and the values behind the guise of health. *Synthese*, *201*(6), p.215.

Melchert, T.P., Halfond, R.W., Hamdi, N.R., Bufka, L.F., Hollon, S.D. and Cuttler, M.J., (2024). Evidence-based practice in psychology: Context, guidelines, and action. *American Psychologist*, *79*(6), p.824.

Milne-Ives, M., Burns, L., Swancutt, D., Calitri, R., Ananthakrishnan, A., Davis, H., Pinkney, J., Tarrant, M. and Meinert, E., (2024). The effectiveness and usability of online, group-based interventions for people with severe obesity: a systematic review and meta-analysis. *International Journal of Obesity*, pp.1-14.

Mohamed Shaffril, H.A., Samsuddin, S.F. and Abu Samah, A., (2021). The ABC of systematic literature review: the basic methodological guidance for beginners. *Quality & Quantity*, *55*, pp.1319-1346.

Mokkink, L.B., de Vet, H., Diemeer, S. and Eekhout, I., 2023. Sample size recommendations for studies on reliability and measurement error: an online application based on simulation studies. *Health Services and Outcomes Research Methodology*, *23*(3), pp.241-265.

Motahari Nezhad, H., 2023. *Methodological challenges in the evidence synthesis of health outcomes of digital health technologies* (Doctoral dissertation, Budapesti Corvinus Egyetem).

Mourby, M., Cathaoir, K.Ó. and Collin, C.B., (2021). Transparency of machine-learning in healthcare: The GDPR & European health law. *Computer Law & Security Review*, *43*, p.105611.

Mrklas, K.J., Boyd, J.M., Shergill, S., Merali, S., Khan, M., Nowell, L., Goertzen, A., Pfadenhauer, L.M., Paul, K., Sibley, K.M. and Swain, L., (2023). Tools for assessing health research partnership outcomes and impacts: a systematic review. *Health Research Policy and Systems*, *21*(1), p.3.

Mwangi, L.W., (2024). MHealth applications prescribed alongside pharmaceutical prescriptions to manage adults' chronic diseases: a scoping review.

NHS. (2019). NHS choices. https://www.longtermplan.nhs.uk/

Page, M.J., Sterne, J.A., Higgins, J.P. and Egger, M., (2021). Investigating and dealing with publication bias and other reporting biases in meta-analyses of health research: A review. *Research synthesis methods*, *12*(2), pp.248-259.

Palmer, A.K. and Jensen, M.D., (2022). Metabolic changes in aging humans: current evidence and therapeutic strategies. *The Journal of clinical investigation*, *132*(16).

Qin, Y., Wang, X. and Namkoong, K., (2022). A meta-analysis of the overall effect of mHealth physical activity interventions for weight loss and the moderating effect of behavioral change theories, techniques, and mobile technologies. *Mobile Media & Communication*, *10*(2), pp.337-359.

Rahmillah, F.I., Tariq, A., King, M. and Oviedo-Trespalacios, O., (2023). Evaluating the effectiveness of apps designed to reduce mobile phone use and prevent maladaptive mobile phone use: multimethod study. *Journal of Medical Internet Research*, *25*, p.e42541.

Ramdowar, H., Khedo, K.K. and Chooramun, N., (2024). A comprehensive review of mobile user interfaces in mHealth applications for elderly and the related ageing barriers. *Universal Access in the Information Society*, *23*(4), pp.1613-1629.

Rodriguez-León, C., Villalonga, C., Munoz-Torres, M., Ruiz, J.R. and Banos, O., (2021). Mobile and wearable technology for the monitoring of diabetes-related parameters: Systematic review. *JMIR mHealth and uHealth*, *9*(6), p.e25138.

Saifan, A.A. and Obeidat, L., (2021). Feature location enhancement based on source code augmentation with synonyms of terms. *Software: Practice and Experience*, *51*(2), pp.235-259.

Santos, M.M.D., De Marchi, A.C.B., de Leon, E.B. and Roque, L.G., (2024). Health behaviour change and activation in e-health weight loss intervention for elderly: a randomised clinical trial. *Behaviour & Information Technology*, 43(8), pp.1580-1595.

Saqlain, M., Riaz, A., Ahmed, A., Kamran, S., Bilal, A. and Ali, H., (2021). Predictors of health-related quality-of-life status among elderly patients with cardiovascular diseases. *Value in Health Regional Issues*, *24*, pp.130-140.

Scazufca, M., Nakamura, C.A., Seward, N., Didone, T.V.N., Moretti, F.A., Oliveira da Costa, M., Queiroz de Souza, C.H., Macias de Oliveira, G., Souza dos Santos, M., Pereira, L.A. and Mendes de Sá Martins, M., (2024). Self-help mobile messaging intervention for depression among older adults in resource-limited settings: a randomized controlled trial. Nature Medicine, 30(4), pp.1127-1133.

Sharma, S., Barnett, K.G., Maypole, J.J. and Mishuris, R.G., (2022). Evaluation of mHealth apps for diverse, low-income patient populations: framework development and application study. *JMIR formative research*, *6*(2), p.e29922.

Siriwoen, R., Chongsuwat, R., Tansakul, S. and Siri, S., (2018). Effectiveness of a weight management program applying mobile health technology as a supporting tool for overweight and obese working women. *Asia Pacific Journal of Public Health*, *30*(6), pp.572-581.

Squires, V., (2023). Thematic analysis. In *Varieties of qualitative research methods: Selected contextual perspectives* (pp. 463-468). Cham: Springer International Publishing.

Stone, J.C., Barker, T.H., Aromataris, E., Ritskes-Hoitinga, M., Sears, K., Klugar, M., Leonardi-Bee, J. and Munn, Z., (2023). From critical appraisal to risk of bias assessment: clarifying the terminology for study evaluation in JBI systematic reviews. *JBI Evidence Synthesis*, *21*(3), pp.472-477.

Sturman, M.C., Sturman, A.J. and Sturman, C.J., (2022). Uncontrolled control variables: The extent that a researcher's degrees of freedom with control variables increases various types of statistical errors. *Journal of Applied Psychology*, *107*(1), p.9.

Sutton, F.N., (2024). An Exploration of mHealth Applications Usage Among Older Adults: A Mixed Methods Study.

Tod, D., Booth, A. and Smith, B., (2022). Critical appraisal. *International Review of Sport and Exercise Psychology*, *15*(1), pp.52-72.

Tran, S., Smith, L., El-Den, S. and Carter, S., (2022). The use of gamification and incentives in mobile health apps to improve medication adherence: scoping review. *JMIR mHealth and uHealth*, *10*(2), p.e30671.

Ufholz, K. and Werner, J., (2023). The efficacy of mobile applications for weight loss. *Current Cardiovascular Risk Reports*, *17*(4), pp.83-90.

Van Dinter, R., Tekinerdogan, B. and Catal, C., (2021). Automation of systematic literature reviews: A systematic literature review. *Information and Software Technology*, *136*, p.106589.

Villareal, D.T., Aguirre, L., Gurney, A.B., Waters, D.L., Sinacore, D.R., Colombo, E., Armamento-Villareal, R. and Qualls, C., (2017). Aerobic or resistance exercise, or both, in dieting obese older adults. *New England Journal of Medicine*, *376*(20), pp.1943-1955.

von Humboldt, S., (2022). Obesity, Perceived Weight Discrimination, and Well-Being. In *Encyclopedia of Gerontology and Population Aging* (pp. 3579-3585). Cham: Springer International Publishing.

Wang, Q., Liu, J., Zhou, L., Tian, J., Chen, X., Zhang, W., Wang, H., Zhou, W. and Gao, Y., (2022). Usability evaluation of mHealth apps for elderly individuals: a scoping review. *BMC medical informatics and decision making*, *22*(1), p.317.

WHO (2021). *Global strategy on digital health 2020-2025*. [online] Available at: https://www.who.int/docs/default-source/documents/gs4dhdaa2a9f352b0445bafbc79ca799dce4d.pdf [Accessed 23 Apr. 2025].

Wilson, J., Heinsch, M., Betts, D., Booth, D. and Kay-Lambkin, F., (2021). Barriers and facilitators to the use of e-health by older adults: a scoping review. BMC public health, 21, pp.1-12.

Xing, Y., Lu, H., Zhao, L. and Cao, S., (2024). Privacy and security issues in mobile medical information systems MMIS. *Mobile Networks and Applications*, pp.1-12.

Yang, J., Wan, Y., Ni, Q., Zuo, J., Wang, J., Zhang, X. and Zhou, L., (2022). Quantifying causal effects from observed data using quasi-intervention. *BMC Medical Informatics and Decision Making*, *22*(1), p.337.

Yang, W., Zhang, X., Chen, J., Miao, W., Zheng, C., Qian, X. and Geng, G., (2022). Effects of internet-based interventions on improvement of glycemic control and self-management in older adults with diabetes: Systematic review and meta-analysis. *Primary Care Diabetes*, *16*(4), pp.475-483.

Zainal, N.H., Liu, X., Leong, U., Yan, X. and Chakraborty, B., (2024). Bridging Innovation and Equity: Advancing Public Health Through Just-in-Time Adaptive Interventions. *Annual Review of Public Health*, *46*.