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THE IMPACT OF MOBILE APPLICATIONS ON HEALTHY LIFESTYLES AND CHRONIC DISEASE MANAGEMENT

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ABSTRACT

Introduction: Mobile applications (mHealth) are playing an increasingly important role in promoting healthy lifestyles and supporting patients with chronic diseases. Evidence from evidence-based medicine (EBM) studies indicates that they can support behavioral change, improve clinical parameter control and facilitate contact with the healthcare system.
Objective: The aim of this study was to present current scientific evidence on the effectiveness of mobile applications in the field of health, with particular emphasis on behavioral and social effects.
Methods: Systematic reviews, meta-analyses and randomized trials on the use of mobile applications for physical activity, weight loss, diabetes control, hypertension and other chronic diseases, as well as for improving adherence to pharmacotherapy recommendations, were included. Reports on data security, digital inequalities and WHO recommendations on mHealth were also analyzed.
Results: According to meta-analyses, diabetes management apps lead to a significant reduction in HbA1c (by ~0.5% on average), especially when they are part of integrated clinical care. Apps that remind users to take their medication improve health behaviors related to pharmacotherapy, while those that promote physical activity and diet promote moderate, short-term weight loss and increased physical activity. Interventions using behavior change techniques such as self-monitoring, feedback and reminders are most effective. Positive social effects include increased motivation through support networks and facilitation of telemonitoring, but there are challenges related to data security, digital inequalities and lack of standardization in app quality.
Conclusions: Mobile applications have potential as a tool to support the prevention and management of chronic diseases, but their effectiveness is moderate and variable. Further long-term randomized trials and the implementation of quality and safety standards are needed to fully exploit their clinical and social potential.

KEYWORDS

mHealth, Self-Monitoring, Healthy Lifestyle, Chronic Disease Management

1. Introduction

The development of mobile technologies, including smartphones and health applications, has revolutionized the approach to health promotion. Mobile health (mHealth) solutions are based on the use of mobile technologies in healthcare. Thanks to widespread access to mobile devices, health interventions have become easier and more common, making it possible to reach large groups of patients, including those in rural areas or with limited access to traditional healthcare [1].

In its 2019 guidelines, the World Health Organization (WHO) emphasizes the role of solid scientific evidence as the basis for the use of digital health interventions. The WHO recommends that the implementation of such interventions take into account the assessment of benefits, harms, acceptability, feasibility, resource use and equity. In addition, the organization points to the need for research that evaluates the effectiveness of interventions in real clinical and social settings [1].

Systematic reviews and meta-analyses indicate that mobile applications can be effective in improving health behaviors, which also has a significant impact on improving clinical trial outcomes. For example, a study published in *JMIR mHealth and uHealth* found that mobile applications can lead to small improvements in health outcomes, but the heterogeneity of the results was high, suggesting a need for further research with higher methodological quality [2].

Despite promising results, many mobile applications do not meet quality standards and are not based on scientific evidence. A systematic review of 52 randomized controlled trials indicates that mobile applications can promote healthy food choices, increase physical activity and reduce sedentary time. However, many commonly used apps are not evidence-based, are more disease-focused than patient-focused, have limited utility and raise serious concerns about user privacy [3].

The implementation of mobile applications in clinical practice involves a number of challenges, such as ensuring data security, integration with existing healthcare systems and ensuring equal access to technology. The WHO recommends that local conditions, technology availability and user needs be taken into account when implementing digital health interventions. In addition, it emphasizes the need to monitor the effectiveness of interventions in real-world settings and to continuously improve applications based on the data collected [1].

2. Application categories and evidence of their effectiveness
2.1 Applications supporting compliance with medication recommendations

Meta-analyses indicate that applications designed to support medication adherence are associated with higher levels of patient compliance and lead to moderate improvements in medication adherence. However, caution should be exercised when interpreting these results due to differences in effects across studies, small sample sizes from different patient populations and heterogeneity of the included studies [4].

Another systematic review (mHealth interventions for statin adherence) identified specific behavior change techniques (BCTs) that were more common in effective interventions. The most commonly used were: **goal setting (behavior), information about health consequences, behavioral feedback**, and **social support**. Studies that implemented a greater number of BCTs showed stronger effects of behavioral improvement [5].

A 12-month clinical trial using the **Perx** app evaluated the app's impact on medication adherence and clinical outcomes. Although the improvement did not differ significantly between groups, the proportion of people achieving ≥95% adherence was significantly higher in the intervention group [6].

It is also worth mentioning that apps targeting patients with chronic kidney disease (CKD) showed improvement in medication adherence, although the authors caution that the evidence is still weak due to the short duration of the intervention and the limited sample size [7].

Therefore, although the data suggest a moderate beneficial effect of using the app, further studies with greater statistical power, longer follow-up periods, and more homogeneous populations are needed.

Methodological limitations and considerations

- Many studies are based on self-reporting, which may result in bias.
- The heterogeneity of interventions (different app features, reminders, integration with other tools) makes it difficult to generalize the results.
- There is often a lack of data on clinically relevant outcomes (e.g., reduction in complications, hospitalizations).
- The effect may depend on user characteristics (age, technological proficiency, underlying disease).

2.2 Applications in diabetes (self-monitoring of blood glucose)

Studies show that self-monitoring apps (blood glucose reporting, reminders, education, contact with staff) bring about significant improvements in blood glucose, weight, and cholesterol control. Wearable devices are indicated to be more effective. However, further long-term studies are needed to maximize patient benefits from the daily use of such devices [8].

The review "Digital Health in Diabetes Care" (Maida et al., 2025) describes that digital technologies (mobile applications, telemedicine systems, connected insulin pens, continuous glucose monitoring devices) are associated with better glycemic control (including lower HbA1c, increased time in range), better patient engagement, and improved complication management [9].

A systematic review of mobile applications for diabetes intervention (Gomez-Garcia et al., 2025) focuses on functionalities related to glycemic control, analyzing randomized controlled trials. It was found that apps offering blood glucose reporting, medication reminders, education and contact with staff had a moderate but significant effect on reducing HbA1c, body weight and cholesterol levels [8].

In a pilot study using the **Mebix** app in patients with type 2 diabetes (3-month follow-up), a mean reduction in HbA1c of –1.0% (±0.8%) was noted compared to baseline, along with beneficial changes in body weight, well-being and diabetes-related stress. In another trial with the **Vitadio** app, in a group of 42 participants, there was a decrease in HbA1c of $-0.9 \pm 1.1\%$, weight loss (average -4.3 ± 4.5 kg), and favorable changes in waist circumference [10].

Despite growing evidence, many challenges remain: long-term adherence to app use, decline in engagement over time, technological barriers in older patients and the need for integration with the healthcare system. A review by Lee et al. (2024) emphasizes that the usability of apps must be comprehensively evaluated (e.g., according to ISO 9241-11 standards or the MARS scale), and future work should better describe the integration of apps into routine clinical care [11].

2.3 Apps promoting physical activity and weight loss

Meta-analyses show that apps featuring monitoring, goals and feedback increase physical activity and promote weight loss, but the effects are moderate and often short-lived—the sustainability of changes depends on the intervention design and external support. Further high-quality research in specific populations (e.g., overweight individuals, individuals with cardiovascular disease) is needed to confirm their effectiveness [12].

The review "Utilizing mHealth Apps for Lifestyle Interventions" (Spinean et al., 2025) indicates that app users reported improvements in glucose levels, weight loss and adherence to dietary recommendations, confirming the potential of these tools in the management of chronic metabolic diseases [13].

In a field study conducted in Asia (Ghrose et al., 2021), the use of an mHealth platform in 1,070 patients with diabetes led to improved glycemic control and reduced hospitalization costs [14].

An interesting methodology was used in an experiment using a reinforcement learning algorithm in patients with type 2 diabetes — the application generated personalized mobile messages, which resulted in increased physical activity and better glycemic control (decrease in HbA1c) compared to the control group [15].

In addition, the sustainability of the effects is a key challenge. Many studies have observed that the benefits decrease over time after the start of the intervention, which may be due to a decline in user activity, loss of motivation or lack of external support (e.g., coaching, reminders). Therefore, it is crucial to design interventions that take into account mechanisms for maintaining engagement, gamification, adaptive feedback and social integration.

2.4 Applications for other chronic diseases (e.g., hypertension, asthma)

For many chronic diseases, there is moderate-quality evidence on the impact of digital solutions on disease monitoring and control. Remote monitoring of parameters and educational applications can improve disease control and facilitate management, although the impact on aspects such as hospitalizations or cardiovascular events remains uncertain or limited by short observation periods and study heterogeneity [16].

2.4.1. Hypertension

For hypertension, digital interventions often include home blood pressure monitoring, medication reminders, education and communication with healthcare professionals. A meta-analysis published in the article "Artificial Intelligence and Advanced Digital Health for Hypertension" showed that culturally tailored digital interventions for hypertension were associated with a reduction in systolic blood pressure of approximately 4 mmHg at 6 months of follow-up in populations with limited access to healthcare, indicating an important factor in health equity [17].

2.4.2. Other chronic diseases (asthma, COPD, heart disease)

In the context of asthma, research focuses on applications that monitor symptoms, remind patients to use inhalers, educate patients and enable contact with medical care. In one project, the authors use a BCT technique selection approach when developing an application to improve asthma medication adherence, which indicates the direction of future research [4].

In the case of cardiovascular diseases, applications support patients, for example, in post-heart attack rehabilitation, risk factor monitoring, as well as education and psychological support. An example is the "Friends of Heart" application – in a study, it improved knowledge and health behaviors in patients with coronary artery disease [18].

Despite these results, there is a lack of large clinical trials with long follow-up periods that would assess the impact of such interventions on hard endpoints (e.g., hospitalizations, cardiovascular events, mortality).

Challenges and limitations

- A frequently observed limitation is the short duration of studies, which makes it difficult to assess the sustainability of intervention effects.
- The heterogeneity of populations (different diseases, severity) and interventions (different application functionalities) makes comparisons between studies difficult.
- The lack of standards for evaluating applications—different outcome measures (clinical, biochemical, application use)—makes it difficult to compare evidence.
- The integration of applications with healthcare systems remains limited, hindering scalability and sustainable implementation.
- Users with lower digital literacy, older age, or living in rural areas may have limited access or difficulty using the technology.

3. Mechanisms of action (behavioral) — what works best?

The effectiveness of digital interventions in modifying health behaviors does not depend solely on the type of disease or target population, but primarily on the psychological mechanisms and behavior change techniques (BCT) used. Scientific literature indicates that the effectiveness of mobile applications, telemedicine platforms and mHealth programs is closely related to how they engage the user, support the self-regulation process, and sustain internal motivation. Systematic reviews confirm that interventions that use a combination of several complementary BCT techniques—such as behavior monitoring, personalized feedback, action planning, external support and tailoring the intervention to the user—are more effective.

3.1 Behavior and data monitoring (self-monitoring)

Effectiveness: Interventions using self-monitoring techniques show potential in reducing sedentary behavior in adults. A review of 19 studies involving 2,800 participants showed a significant reduction in total sitting time (Hedges $g = 0.32$; $p = 0.001$), especially when objective monitoring tools were used [19].

Self-monitoring is one of the most commonly used and most effective BCT techniques. In their analysis of mHealth Apps Using Behavior Change Techniques to Self-Monitoring, Aguiar et al. (2022) conclude that the most commonly used techniques in health apps are **feedback and monitoring**, as well as goals and planning [20].

From a more detailed perspective, the study Effects of Mobile Health Prompts on Self-Monitoring and Self-Reported Behavior (MacPherson et al., 2019) shows that personalized reminders (prompts) increase the frequency of self-monitoring of physical activity or other health behaviors [21].

Furthermore, in the study Adults' Preferences for Behavior Change Techniques and Engagement With mHealth Apps, DeSmet et al. (2019) found that respondents preferred apps that offered **more self-monitoring options**, indicating that users also perceive this feature as useful [22].

Mechanism of action: Self-monitoring increases awareness of one's own habits, which can lead to their modification. Regular recording of physical activity, food intake, or health parameters allows the user to track progress and identify areas for improvement.

Self-monitoring also makes it easier to stay focused on progress and acts as a form of "external mirror" – the user sees graphs, trends, and alerts. mHealth applications often use data visualizations (graphs, lines, colors) as part of feedback, which increases motivation. In the Analysis of Personal Data Visualization Reviews On mHealth Apps, the authors show that users comment very positively on data visualizations in health applications (e.g., graphs, dashboards), suggesting that a well-designed visual element enhances self-monitoring [23].

However, monitoring alone without additional support (feedback, planning, reminders) is often not enough, as users may become discouraged if they do not see clearly how to interpret the data or how to translate it into action.

3.2 Feedback and personalization

Effectiveness: Personalized feedback in mobile applications can increase user engagement and intervention effectiveness. A review of studies indicates that personalized feedback, whether generated by algorithms or humans, can improve the effectiveness of health interventions [24].

The paper Personalizing mobile applications for health based on user preferences and behavior (Gosetto et al., 2025) discusses the use of BCT in mHealth applications, including monitoring, goals, feedback, reminders, and social support. The authors emphasize that personalization (customizing messages, interface, schedules) is increasingly used to increase the effectiveness of interventions [25].

Mechanism of action: Personalization involves tailoring content and recommendations to the individual needs of the user, which increases their relevance and motivation to change behavior. Feedback provides information about progress, which can reinforce positive habits.

Since people differ in terms of learning styles, motivations and living conditions, among other things, personalization allows for a better response to individual needs. For example, an app can deliver different messages to someone who exercises regularly and someone who rarely engages in any activity. Personalizing the notification schedule, intensity of information and communication style is also very important. Interventions that ignore personalization may provide information that is too general or inadequate, which reduces motivation and may lead to the rejection of notifications.

3.3 Reminders and action planning

Effectiveness: Reminders and planning techniques, in particular implementation intentions (i.e., "if-then plans"), are well-researched tools that support health-promoting efforts. In the experiment described in Implementation Intention and Reminder Effects on Daily Behavioral Goal Success, Pirolli et al. (2017) conducted a 28-day study with participants setting implementation intentions and receiving reminders. The result: reminders significantly improved the achievement of daily behavioral goals (OR = 7.52, p < .001) [26].

Mechanism of action: Reminders help overcome the barrier of forgetting and activate prospective memory. In addition, a reminder at the moment when the user has the opportunity to perform an action increases the likelihood of it being taken. A study by Pirolli et al. showed that the frequency and distribution of reminders (mass vs. distributed) affected their effectiveness, namely that reminders were more effective when spread out over time, which is consistent with the memory model (ACT-R) [26].

Action planning (if-then) creates a link between a specific stimulus (if) and behavior (then), which reduces the need to make decisions at a given moment—the response becomes more automated. This helps close the gap between intention and action (intention–behavior gap). In practice, applications can support planning by offering interactive forms such as "if condition X, then I will do Y," calendars, checklists, and reminders related to the plan.

3.4 Support from staff

Effectiveness: Interventions combining mobile applications with support from medical staff (blended care) can increase user engagement and the effectiveness of the intervention. Studies show that patients who used mobile applications supported by medical staff showed greater engagement and better health outcomes.

Mechanism of action: Combining technology with interaction with medical staff allows for individualization of interventions, monitoring of progress, and provision of support in problem solving, which can increase the effectiveness of interventions.

Support from staff works on several levels:

1. **Personalization** – a specialist can tailor recommendations to the patient's specific situation (health condition, barriers, preferences), which technology alone may not be able to capture.

2. **Emotional and motivational support** – human presence helps in moments of doubt or decreased motivation.

3. **Verification and correction of errors** – staff can interpret data (e.g., from the app) and suggest corrections, which reduces the risk of incorrect self-interpretation.

4. **Increased engagement** – regular contact keeps the user "on track" and counteracts a decline in app usage over time.

Hybrid interventions can therefore combine the advantages of automation (scalability, accessibility) with the power of interpersonal relationships, which can be particularly important in chronic diseases requiring long-term commitment.

3.5 Quality of intervention and user fit

Effectiveness: Adding many features to an app does not guarantee better results. The quality of the intervention, its fit to the user's needs, and the provision of ongoing support are key.

In the study A Multiple Health Behavior Change, Self-Monitoring Mobile Intervention (Thornton et al., 2021), the authors identify key BCTs for improving risk factors (including diet and activity) and emphasize that interventions that were tailored to each user had a greater chance of success [27].

The analysis of mHealth Apps Using Behavior Change Techniques also indicates that apps that use too many techniques without clear integration and consistency often lose their effect on the user due to excessive cognitive load or lack of clear guidance [20].

Mechanism of action: User-friendliness is key to maintaining engagement and usability. Applications that are intuitive, clear, flexible, and tailored to the user's level of digital competence (e.g., older patients) are more widely accepted and used.

From the perspective of the COM-B (Capability-Opportunity-Motivation-Behavior) model, an effective intervention should support capabilities, create opportunities, and strengthen motivation. If the interface or functions of the application are too complicated, the user may give up, even if the behavioral mechanisms are correct.

The literature on health application design increasingly points to user-centered design approaches, prototyping, and piloting to better tailor the intervention to the needs of the audience.

In addition, maintaining long-term support (or reminders, social interactions, new challenges) counteracts the effect of declining interest (the so-called freshness effect), when the user stops using the application after a few weeks.

3.6 Which mechanisms work best?

Reviews and studies show that **interventions combining multiple complementary BCT techniques are most effective**, rather than single mechanisms in isolation. For example, Aguiar et al. (2022) emphasize that combinations of monitoring + feedback + planning often appear in successful interventions [20].

Research on lifestyle interventions shows that effectiveness increases when the intervention includes at least three well-matched components: self-monitoring, feedback, and planning/reminder elements [28].

In the context of health apps, it has been observed that if an app offers monitoring but does not provide feedback or support planning, the user may not know what to do with the data — leading to abandonment. Conversely, feedback without monitoring has no basis. The combination of planning and reminders closes the cycle of change: you monitor → you get feedback → you plan the next step → you receive a reminder to take action.

The mHealth literature also often refers to persuasive computing/persuasive design models, where behavioral mechanisms are co-designed with the interface and engagement strategy — although research results, as in the Systematic Review and Meta-Analyses of Mental Health App RCTs (Lee et al., 2024), do not always show strong correlations between the number of persuasive principles and effectiveness – which emphasizes that it is not about quantity, but about their adequate matching and integration with BCT [29].

4. Social and systemic effects (evidence and interpretation)
4.1 Communities and support networks
Observational studies and systematic reviews indicate that support groups, competition, and sharing progress have a positive impact on motivation and maintaining healthy behaviors. mHealth interventions that integrate social elements, such as discussion forums or features that enable sharing results, can increase user engagement and improve health outcomes. However, most of the available evidence comes from short-term studies and self-reported user accounts, which limits the ability to draw definitive conclusions [13].

4.2 Facilitating access to care (telemonitoring)
Telemonitoring, or remote monitoring of health parameters such as blood glucose or blood pressure, can enable earlier intervention and optimization of treatment. Randomized controlled trials (RCTs) and systematic reviews suggest that telemonitoring can improve health outcomes, especially in chronic diseases such as heart failure [30].

However, the effects of telemonitoring on serious events such as hospitalizations are mixed and require further long-term studies. For example, a study of older adults found that telemonitoring did not reduce hospitalizations or emergency room visits and was even associated with higher mortality in the telemonitoring group [31].

The differences in results may be due to different study methodologies, patient populations, or intervention durations. Therefore, further research is needed to better understand the effectiveness of telemonitoring in different clinical contexts and to identify factors that influence its effectiveness.

4.3 Digital inequalities and accessibility
The risk of widening health inequalities related to access to digital technologies has been repeatedly highlighted. Health apps often benefit people with better access to technology, higher digital literacy, and greater motivation. Research indicates that older people, people with low levels of education, or people with limited internet access may have difficulty using health apps, which may exacerbate existing health inequalities [32].

World Health Organization (WHO) guidelines emphasize the need to consider barriers to access when implementing digital interventions to ensure equity in access to healthcare. The WHO recommends that digital interventions be designed in an inclusive manner, taking into account the diversity of users' needs and capabilities.

To minimize the risk of widening inequalities, it is necessary to take action at various levels, such as:
1. **Digital education** – providing training and support for users in the use of digital technologies.
2. **Technology accessibility** – ensuring access to devices and the internet for people with limited resources.
3. **Inclusive design** – creating applications and digital interventions tailored to different user groups, taking into account their needs and limitations.

Only through a comprehensive approach that takes these aspects into account will it be possible to ensure equal access to the benefits of digital health interventions.

5. Application security, privacy and quality — evidence and recommendations
Mobile health (mHealth) applications are becoming increasingly important in healthcare systems, enabling health monitoring, self-management of chronic diseases, patient education and patient-doctor communication. However, their widespread use poses serious challenges in terms of data security, user privacy and the reliability and quality of the applications themselves. If users do not trust that their data is protected, they may refrain from using such tools, which limits their effectiveness and scalability.

The digital health literature indicates that the gap between the technological potential and the actual adoption of mHealth applications often lies precisely in the aspect of privacy and security. Already in a scoping review published in JMIR mHealth and uHealth (Benjumea et al., 2020), the authors showed that methods for assessing privacy in mHealth applications vary, and that many applications have significant gaps in transparency and data protection [33].

5.1 Starting point — current state of research

In their review Privacy Assessment in Mobile Health Apps: Scoping Review, Benjumea et al. conducted a systematic analysis of how researchers assess the privacy of mHealth apps. A number of privacy assessment components were identified: privacy policy, user control over data, information about data collection and sharing, technical security measures, anonymization, data storage and data transmission [33].

At the same time, other studies analyzing security and privacy in mHealth emphasize that many applications do not use sufficient protective mechanisms, exposing users to the risk of data leakage or privacy violations [34], and that application designers often do not take legal and security requirements into account from the outset [35].

5.2 Key privacy and security gaps
5.2.1 Lack of transparent privacy policies

Many mHealth applications do not provide users with clear and understandable privacy policies. These documents are often too technical, too long, or difficult to find, making it difficult for users to understand what data is being collected, how it is being processed and with whom it is being shared. Lack of transparency in this area can lead to a loss of user trust and potential violations of data protection regulations [33].

A scoping review by Benjumea et al. indicates that these documents are often written in legal language, are long, difficult for the average user to understand, and their access is sometimes hidden (application menus, websites) [33].

5.2.2 Transferring data to third-party services

Many mHealth applications transfer user data to external analytics and marketing services without the users' explicit consent. Such practices can lead to the unauthorized sharing of sensitive health information, posing a serious threat to user privacy. An example of this is the analysis of telemedicine applications for people with addictions, in which the use of data tracking technologies by third parties, such as advertising and analytics tools, was detected.

In the study On the privacy of mental health apps (Empirical Software Engineering, 2022), the authors analyzed 27 mental health apps and found that many of them record and transmit data to external domains (including trackers) without clearly informing the user or without adequate anonymization [36].

Such practices pose the risk that health data, even if seemingly anonymous, can be linked to a specific person through cross-analysis (linkability). In addition, cooperation with multiple domains increases the attack surface: if one of the domains is compromised, the data of many applications is at risk.

5.2.3 Insufficient data encryption

Some mHealth applications do not use adequate data encryption methods, both during storage and transmission. The lack of encryption can lead to easy interception of data by third parties, which poses a serious threat to the security of users' health information. Studies have shown that mHealth applications often transmit sensitive medical information in unencrypted form and store it on third-party servers without ensuring adequate confidentiality [37].

It is emphasized that applications should use end-to-end encryption, secure protocols (e.g., TLS/SSL), as well as authentication and authorization mechanisms to restrict unauthorized access [38].

The study Security Analysis of Top-Ranked mHealth Fitness Apps identified specific errors: the use of AES in ECB mode (which does not provide semantic randomness), hard-coded API keys in the application code, and connectivity to multiple domains, which increases the risk of man-in-the-middle (MITM) attacks or network traffic eavesdropping [39].

Other technical vulnerabilities include:

Lack of multi-factor authentication (MFA) or session timeouts.

Storing data locally without security (e.g., in text files, SQLite without encryption).

No defense against application tampering (e.g., root/jailbreak detection).

Outdated software components vulnerable to known exploits.

Server configuration errors (e.g., incorrect SSL/TLS settings).

5.3 Recommendations for improving privacy and security

5.3.1 Implementation of privacy assessment standards

To improve user privacy, it is necessary to implement privacy assessment standards for mHealth applications. A review by Benjumea et al. proposes a set of privacy assessment criteria, including transparency of privacy policies, user control over data, and compliance with legal regulations. The implementation of such standards will allow for the systematic assessment and improvement of privacy practices in mHealth applications [33].

5.3.2 Ensuring compliance with legal regulations

mHealth applications should comply with applicable data protection regulations, such as the GDPR in the European Union or HIPAA in the United States. Compliance with these regulations ensures that users' personal data is adequately protected and minimizes the risk of legal violations. An example of this is an analysis of mHealth applications that found GDPR compliance violations, such as incomplete privacy policies and inconsistencies between declarations and actual data collection.

The article Patients' Perspectives on Data Confidentiality, Privacy, and Security emphasizes that users expect encryption, secure authentication methods and regulatory compliance (GDPR, HIPAA) in mHealth applications [40].

An analysis of GDPR Compliance Violations in Android mHealth Apps showed that many applications violate GDPR rules: lack of a complete privacy policy, inconsistency between declarations and actual application behavior, incorrect data transmission encryption [41].

5.3.3 Implementation of quality assessments and certification

Before widespread implementation of clinical applications, it is recommended that quality assessments and certification be carried out. These assessments should cover aspects such as data security, user interface quality, intervention effectiveness, and regulatory compliance. The implementation of such assessments will allow for the identification and elimination of low-quality or low-security applications, which will contribute to improving the overall quality of healthcare services provided using mobile technologies.

5.3.4 Education of users and professionals

A key element in improving privacy and security in mHealth applications is the education of users and healthcare professionals. Users should be aware of the risks associated with using mHealth applications and know the rules for using them safely. Healthcare professionals should be trained in assessing the quality and security of mHealth applications so that they can effectively advise patients on their selection and use.

In the study An Empirical Study on Secure Usage of Mobile Health Apps, the authors conducted attack simulations and tested how users respond: 73.3% of users rejected at least one permission request, and 36% preferred not to use any authentication method. Many users admitted that they agree to permissions without carefully reading the privacy policy, which indicates a need for education [42].

5.4 Conclusions

Data security, user privacy, and the quality of mHealth applications are key aspects influencing the effectiveness and acceptance of these technologies in healthcare. The implementation of privacy assessment standards, ensuring compliance with legal regulations, implementing quality assessments and certification, and educating users and healthcare professionals are essential steps toward improving these aspects. Only through a comprehensive approach to these issues will it be possible to ensure the safe, effective, and ethical use of mHealth applications in healthcare.

Recommendations include:

1. Implementation of privacy assessment standards, audit tools, and benchmarks.
2. Compliance with legal regulations (GDPR, HIPAA) through privacy by design and default concepts.
3. Quality assessments and certifications of applications, conducted by independent entities or healthcare institutions.
4. Education of users and healthcare professionals on application security and privacy rights.

6. Evidence limitations and research gaps (requiring further research)

6.1 Lack of sufficiently long-term RCT studies evaluating hard endpoints (e.g., mortality, hospitalizations)

Although mHealth interventions show promising results in short-term studies on improving health behaviors, there is a lack of robust evidence on their impact on hard endpoints such as mortality or hospitalizations. A systematic review of mHealth interventions in heart disease found that mobile applications do not reduce mortality or hospitalizations due to heart disease [43]. Similarly, other studies have not shown a significant impact of mHealth interventions on these hard endpoints. This is partly due to the short follow-up period and differences in study designs. Long-term studies with adequate statistical power are needed to assess the true impact of these interventions on public health.

6.2 Heterogeneity of interventions and lack of standardization in BCT reporting hinder synthesis of results

mHealth interventions are extremely diverse in terms of the behavior change techniques (BCTs) used, making it difficult to compare and synthesize study results. A systematic review of 21 studies found that techniques such as personalization, feedback, and monitoring are most commonly used in mHealth interventions, but their effectiveness depends on the context and target group [27]. The lack of uniform standards for reporting BCT makes it difficult to assess which techniques are most effective. To improve the quality of research, it is necessary to develop and implement standards for reporting BCT, which will enable better comparison and synthesis of research results.

6.3 Insufficient research in vulnerable populations (older adults, low-income individuals) and lack of cost-effectiveness data

Although mHealth interventions may offer benefits for older adults and those with limited access to resources, there are few studies evaluating their effectiveness in these groups. A review of studies on the cost-effectiveness of mHealth interventions for older adults found considerable methodological variation and a lack of clear evidence of their cost-effectiveness [44].

The lack of cost-effectiveness data makes it difficult to decide whether to implement these interventions in clinical practice. In addition, mHealth interventions often do not take into account the specific needs of older adults, such as technological limitations or vision problems, which may affect their effectiveness. In the future, it will be necessary to conduct studies that take these factors into account and to evaluate the cost-effectiveness of mHealth interventions in different social groups.

6.4 Conclusions

In summary, although mHealth interventions show promising results in short-term studies, there are many gaps in the scientific evidence regarding their long-term effectiveness, standardization of behavior change techniques, and cost-effectiveness. To fully realize the potential of mHealth in improving public health, high-quality research that takes these aspects into account is needed.

7. Practical recommendations (based on evidence)

For app developers, clinicians, and health policymakers, EBM recommendations include:

1. Evidence-based design — use behavior change techniques that have been shown to be effective (self-monitoring, feedback, reminders) and test them in RCTs.

2. Blended care — combine apps with clinical care (strongest evidence of improved outcomes).

3. Data transparency and regulatory compliance — implement privacy policies, encryption, and clear data flows.

4. Real-world monitoring and evaluation — maintain implementation registries/monitoring and analyze effects in practice.

5. Consider equal access — support programs for people with limited access to technology.

7.1 Evidence-based design

The design of mHealth applications should be based on behavior change techniques

(BCTs) that have been shown to be effective in research. Systematic reviews indicate that techniques such as behavior monitoring, feedback, reminders, and action planning are most commonly used in mHealth interventions and have a positive impact on health outcomes. For example, a review of studies found that mHealth applications that use techniques such as monitoring, feedback, and reminders are more effective in improving health outcomes than those that do not [20].

Additionally, it is important to test apps in randomized controlled trials (RCTs) to assess their effectiveness in different populations and contexts. RCTs are the gold standard for evaluating the effectiveness of interventions and should be an integral part of the mHealth app development process.

Practical recommendations

1. **Incorporate BCTs from the outset of design** - app developers should map app features to specific behavior change techniques. Example: step/glycemia/BMI self-monitoring module; feedback module; graphs; reminders; action plan (e.g., what the person will do if their glycemia is above/below the threshold).

2. **Randomized Controlled Trials (RCT)** - each application or intervention should be tested in at least one RCT, with a control group, preferably a placebo application or standard care, to test its effectiveness in real-world conditions. Such studies should take into account the heterogeneity of the population (age, gender, origin, digital competence).

3. **Iterative development and pilot studies -** before an application is widely implemented, conduct pilot studies, usability tests, and adapt functions based on user feedback. Test which functions are used most often and which cause users to abandon the application.

4. **Standardization of outcome measures -** health outcomes should be measurable, e.g., change in body weight (%), HbA1c (for diabetes), reduction in blood pressure, number of hospitalizations or episodes, or measures of quality of life. In addition, measures of app behavior and usage (e.g., logins, activity in the app) are important because the relationship between them and the outcomes is significant.

5. **Adaptation to the local context -** an application designed for the population in country X may require linguistic and cultural adaptation, as well as adaptation of the communication style and functions to the availability of devices and the internet.

7.2 Blended care

Combining mHealth applications with clinical care (blended care) shows strong evidence of improving health outcomes. Studies indicate that combining digital support with interactions with healthcare professionals leads to better health outcomes, such as weight loss, improved control of chronic diseases, and increased patient engagement [45].

An example is an analysis of data from 25,706 patients, which showed that elements such as coaching, monitoring, self-management, and education have varying effects on weight loss in the context of blended care [45].

The integration of mHealth applications with clinical care may include regular sessions

with healthcare professionals, monitoring of patient progress, and tailoring interventions to patient needs. Such a holistic model of care can increase the effectiveness of interventions and improve patient health outcomes.

The study Face-to-Face Versus Mobile Versus Blended Weight Loss Program: Randomized Clinical Trial (Belastroi et al., 2018) compared a traditional group, an app group, a blended group (app + face-to-face meetings), and a control group. The blended group achieved better weight loss than the app-only group BMI outcomes were significantly better [46].

A review of Blended mHealth Intervention for Health Behavior Change (Engagement and Use study, 2023) showed that people who participated in coaching sessions (part of the blended group) had greater engagement and better weight results than those who only used the app. The average weight loss in those who entered their weight in the first and last month of the intervention was approximately 4.0% (SD 3.6) in the Engagement and Use of a Blended mHealth Intervention study [47].

The study The Effectiveness of a Mobile Health Care App and Human Coaching Program in Primary Care Clinics: Pilot Multicenter Real-World Study (Korea) showed that combining a self-management health app with human coaching leads to better results than traditional primary care in terms of weight loss and sleep improvement [48].

Practical recommendations

1. **Designing blended care as standard -** where possible, mHealth apps should be part of a care system, with the option of coaching, online medical advice, or consultations. Developers and policymakers should plan a structure in which the user has contact with staff at specific times.

2. **Regular communication and support -** coaching, progress monitoring by staff, and follow-up sessions should be built into the intervention. This helps maintain motivation, engages the user, and increases adherence to recommendations.

3. **Scalability -** blended care requires resources (staff, time). Hybrid models should anticipate which elements can be automated and which require human intervention. E.g., automatic reminders + a coach for more difficult situations.

4. **Evaluations comparing different forms of blended care -** e.g., frequency of coaching sessions, type of interaction, cost-effectiveness, and what levels of support are necessary to achieve clinical endpoints.

5. **Integration with standard care -** blended care works better when the application is recommended by a doctor, monitored by a clinician, etc.

7.3 Data transparency and regulatory compliance

In the context of mHealth applications, it is essential to ensure data transparency and compliance with regulations such as the GDPR in the European Union. An analysis of mHealth application quality reviews has shown that many applications do not meet data privacy and security standards, such as a lack of transparent privacy policies, data transfer to third-party services, and insufficient encryption [49].

To ensure regulatory compliance, app developers should implement privacy policies, use appropriate data encryption mechanisms, and ensure clear data flow. In addition, it is important to conduct regular security audits and update apps to ensure compliance with applicable regulations.

The review Privacy, Data Sharing, and Data Security Policies of Women's mHealth Apps: Scoping Review and Content Analysis analyzed 23 apps in the area of women's health.

Results: all apps collected personal data. Only 70% (16/23) had a privacy policy, 52% requested informed consent, and 87% shared data with third parties [50].

The study Mobile Health and Privacy: Cross Sectional Study analyzed ~20,991 mHealth applications and found that most applications can collect and potentially share data with third parties; only half declare a privacy policy; data collection practices often go beyond what is declared [51]-

The review Enhancing privacy in mHealth Applications: A User-Centric model showed that transparent privacy policies, user control options over data sharing, and user-friendly interfaces increase trust and willingness to use the application [52].

Practical recommendations

1. **Privacy policies should be clear, understandable, and accessible -** no legal jargon, but accessible language, short sections; documents wherever the user may need them (before installation, within the application). Include shortcuts/demos of privacy options.

2. **Consent mechanisms that meet standards -** users must consciously consent to data collection; consent should be revocable; clear information about what data is collected and for what purpose.

3. **Data encryption -** both in transit (e.g., HTTPS, TLS) and at rest (on devices and servers). End-to-end encryption, key protection, authentication mechanisms, access control. Regular security tests and audits.

4. **Transparency of data flows -** explaining to the user whether data is transferred to third parties for analytics/marketing purposes, whether it is anonymous or pseudonymized.

5. **Regulatory compliance -** ensuring that the application complies with data law requirements: GDPR, HIPAA, local data protection regulations. Compliance with principles such as privacy by design and privacy by default.

6. **Content validation -** if the application contains medical or educational advice, the content should be verified by experts and based on current guidelines; avoiding misinformation.

7. **Independent audit and certification -** applications may be evaluated by external institutions and certified as safe/reliable; quality/safety labels visible to the user may be suggested.

7.4 Real-world monitoring and evaluation

Monitoring the effects of mHealth applications in real-world conditions (real-world evidence) is essential to assess their effectiveness and safety. Data collected in everyday clinical practice can provide valuable information on the effectiveness of applications in different populations and contexts [53].

Application developers should implement monitoring mechanisms such as patient registries, health outcome data collection, and real-time data analysis. In addition, it is important to conduct regular evaluations of application effectiveness and adjust their features based on monitoring results.

The study App Engagement as a Predictor of Weight Loss... (JMIR, 2024) showed that the level of engagement with the app in the early stages (e.g., the first month) can predict who will achieve greater weight loss. This is real-world observational data that confirms that monitoring user behavior is crucial [54].

Effectiveness of a Mobile Health Care App and Human Coaching Program in Primary Care Clinics (Korea) is a multicenter study in real-world clinic settings showing that the combination of an app + coaching yields better results than standard care [48].

Practical recommendations

1. **User and outcome registries -** creating databases that collect data on who uses the app, how often, and what the effects are (increased activity, weight change, biomarkers). These can be national registries or registries of care centers.

2. **Safety monitoring -** tracking incidents, privacy breaches, software errors, technical problems in real-world conditions.

3. **Long-term evaluations -** observations over 6-12 months to assess the sustainability of effects, whether engagement is declining, whether improved features are gaining acceptance.

4. **Analysis of differences in populations -** different age groups, geographical areas, economic groups, people with different levels of digital competence.

5. **Feedback from real users -** collecting opinions and observations on what users like, what is difficult, and what causes them to stop using the application.

6. **Publication of results -** including negative ones, to remember which applications fail and why.

7.5 Consideration of equal access

mHealth applications should be designed to ensure equal access to healthcare, especially for people with limited access to technology. Research shows that people with lower levels of education, older people, and people with lower incomes may have more difficult access to mHealth applications, which can lead to increased health inequalities [55].

To ensure equal access, app developers should consider user diversity, offer technical support, and adapt app interfaces to the needs of older people or those with technological limitations. In addition, it is important to conduct educational activities and training to increase users' digital literacy.

A systematic review, Patients' Perspectives... (JMIR, 2024), found that many people with lower incomes, lower levels of education, and older age express greater concerns about privacy, are less aware of security features, and are more likely to have limited access to mobile devices or the internet [40].

In the analysis Privacy, Data Sharing... Women's mHealth Apps, although applications

are available, many of them require location (GPS location) or geolocation data; they also require powerful devices or transmitted data, which can be a barrier for people with limited resources [50].

The study Enhancing privacy in mHealth Applications (User-Centric Model) found that user autonomy (e.g., control over data, choice of whether features are enabled) significantly increases trust and use of the application, suggesting that interfaces and features that help adapt to different needs are important [52].

Practical recommendations

1. **Inclusive design -** interfaces that are friendly to older people (larger font, simple navigation), offline mode or mode with lower data consumption, support for people with visual or motor impairments.

2. **Technical support and education** - help with use, tutorials, user support; training or instructions for groups less familiar with technology.

3. **Subsidization or financing models -** e.g., public programs, refunds, or subsidies for access to mHealth applications for low-income individuals or in regions with limited internet access.

4. **Local adaptations -** language, culture, local preferences; ability to operate offline or with minimal internet connection; compatibility with less expensive hardware.

5. **Inclusion of socioeconomic barriers in research -** recruiting diverse populations in RCTs and studies, including different groups, and analyzing disadvantaged groups separately to see if the intervention works well for them too.

8. Conclusions

EBM evidence indicates that mobile applications have the potential to improve health behaviors and, to some extent, improve the management of selected chronic diseases (e.g., diabetes, medication adherence), especially when used as part of integrated care and incorporating evidence-based behavior change techniques. However, the effects are heterogeneous, and effective, long-term implementation requires: high-quality research, data protection mechanisms, standardization of quality assessments, and policies to minimize digital inequalities [4].

Mobile applications (mHealth) show promising potential for supporting health behavior change. Research indicates that behavior change techniques (BCT), such as monitoring, feedback, reminders, and action planning, are effective in improving adherence to health recommendations. An example is the Medisafe app, which improved medication adherence in patients with chronic diseases [56].

mHealth applications can support the management of certain chronic diseases, such as type 2 diabetes and hypertension. However, results vary and the effects may be small. For example, a meta-analysis showed a small improvement in systolic blood pressure control compared to standard care.

Combining mHealth apps with traditional clinical care (blended care) may increase the effectiveness of interventions. Studies indicate that integrating apps with healthcare leads to better health outcomes, such as improved management of chronic diseases and increased patient engagement [57].

Many mHealth applications do not meet data privacy and security standards. The lack of transparent privacy policies, data transfer to third-party services, and insufficient encryption pose a serious threat to users [58]. It is recommended to implement assessment standards, data flow transparency, and compliance with regulations such as the GDPR in the EU.

The availability of mHealth applications may be limited for people with lower levels of education, older people, or people with lower incomes. Lack of access to technology, low digital literacy, and lack of motivation can lead to increased health inequalities [58]. WHO guidelines emphasize the need to consider barriers to access when implementing digital interventions.

There is a need for long-term randomized controlled trials (RCTs) evaluating hard endpoints such as mortality or hospitalizations. Current studies are often short-term and rely on self-reported user reports, which can lead to systematic errors. In addition, the heterogeneity of interventions and the lack of standardization in BCT reporting make it difficult to synthesize results.

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