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Effectiveness of eHealth interventions for diabetes management in public health surveillance: a systematic review

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Abstract. Diabetes poses a growing global public health challenge, creating a strong demand for management approaches that can support long-term monitoring and timely intervention. This study evaluates how eHealth interventions contribute to diabetes management within public health surveillance by reviewing recent evidence on their functions and impact. The analysis covers major digital tools currently applied in diabetes care—such as mobile health applications, remote glucose monitoring devices, telemedicine services, electronic health record systems, and decision-support technologies—and examines their performance using findings reported in recent empirical studies. Results across the literature show that eHealth interventions can improve treatment adherence, strengthen data continuity, and enable earlier identification of glycemic deterioration through continuous or near real-time data exchange. These tools also enhance communication between patients and providers, facilitating more responsive clinical adjustments and contributing to better surveillance at the population level. Despite these advantages, issues including system interoperability, uneven digital access, and unresolved data privacy concerns continue to limit broader implementation. Overall, the evidence indicates that eHealth technologies offer meaningful support for diabetes management and surveillance, while also highlighting the need to improve digital infrastructure and data standards to fully leverage their public health potential.

Keywords: eHealth, diabetes management, public health surveillance, digital interventions

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1. Introduction

1.1. Background & rationale

Diabetes Mellitus (DM) is rapidly increasing worldwide, posing major health challenges and placing a growing burden on healthcare systems.The global diabetes prevalence in 2019 is estimated to be 9.3% (463 million people), rising to 10.2% (578 million) by 2030 and 10.9% (700 million) by 2045 [1]. DM is recognized as a risk factor for cognitive decline and dementia [2]. It is frequently accompanied with multiple chronic diseases, such as cardiovascular disease, hypertension, and chronic kidney disease, which complicate treatment and worsen outcomes [3], these complications not only reduce quality of life but also bring heavy burden on healthcare systems, including increased medical expenditures [4], intensive resource consumption [5], long-term care demands [5].

Public health surveillance plays a role in chronic disease management, as it provides evidence to guide decision-making and optimize population health strategies. Specifically, it contributes data and information to assess and characterize the burden and distribution of adverse health events [6]; it helps prioritize public health actions based on identified needs [7]; it enables monitoring of the effectiveness and impact of control measures [8]; and it supports the identification of emerging health conditions that may significantly affect population health [8].In the context of scientific advances in public health surveillance, changing health care and public health environments, and rapidly evolving technologies, it is an efficient way to monitor and prevent the occurrence of diabetes.

1.1.1. Rise of eHealth

EHealth is an emerging field at the intersection of medical informatics, public health, and business, and refers to health services and information delivered or enhanced through the Internet [9,10].There are different types of eHealth tools,such as telemedicine [11], mobile applications [12], electronic health records (EHR) [13], short message service(SMS) interventions [14], wearable devices [15], and web-based platforms [16]. In the joint population of seven European counties, 44% of the total population reported using the Internet for health purposes in 2005 [17,18], increasing to 52.2% by 2007 [19]. EHealth has become highly popular worldwide, particularly in western countries.For instance, in Poland, which is consistent with European trends, 66.7% of the population reported using the Internet for health purposes in 2012 [20]. Among Internet users in the United States and Europe, approximately three quarters conduct health-related searches [17-19,21]. Most Norwegian households (97%) had Internet access in 2015, and 78% of the population 15 years and older have reported using the Internet for health purposes [22].

Digital health technologies are transforming diabetes management by empowering patients through enhanced self-management efficiency, enhancing connectivity, and improving clinical outcomes. Self-management refers to a patient's active participation in managing their health with the purpose of enhancing diagnosis and therapy as well as the maintenance of optimal levels of health [23]. Mobile health applications and SMS-based self-management programs increase patient engagement and adherence, resulting in higher self-efficacy and more consistent self-monitoring of blood glucose [24,25]. Moreover, by promoting patient self-management, digital interventions not only reduce direct and indirect healthcare costs, such as travel and productivity loss, but also lead to greater gains in Quality Adjusted Life Years (QALYs) with cost-savings [26]. Furtherfore, wearable devices and behavioral feedback tools foster patient resilience by encouraging lifestyle modification and preventive practices, which contributes to lower risk of complications [27]. Additionally, by overcoming geographical and logistical barriers, real-time monitoring has data sharing capabilities, enabling users to share data with family, carers and health care providers.It facilitates the formulation of personalized treatment plans and guides therapeutic changes [28]. In terms of clinical outcomes, the integration of digital data into clinical decision-making systems reduces medical errors and ensures patient health and safety while providing higher quality medical services [29].

1.1.2. Gaps in knowledge on how eHealth feeds into surveillance systems and impacts outcomes

Despite the growing integration of eHealth into healthcare systems, gaps remain in understanding comparative and effective evidence for different interventions in the management of chronic diseases.In this situation, bringing uncertainty for clinicians and policymakers in determining which modality is more aprrropriate for specific contexts and patient populations.It is necessary to establish modality-selection frameworks to recommend digital health intervention measures based on the characteristics of the disease, resource conditions, and patient needs, in order to achieve the optimal health outcome [30].To bridge these gaps, targeted research efforts are needed, such as evaluating clinical outcomes, complex interventions, cost-effectiveness, scalability, and fairness.

1.2. Gaps in previous review studies

Previous reviews mainly addressed personal-level impacts of eHealth, while research on broader system outcomes, long-term effects, and integration with public surveillance systems remains scarce.Many reviews concentrated on a single type of eHealth intervention, such as mobile health applications [12,31], telemedicine [11], or web-based platforms [30]. Such focused investigations are not a limitation in themselves; on the contrary, they provide the depth of understanding necessary for later synthesis. It is precisely because these specific studies have explored mobile health, telemedicine, or web-based platforms in detail that we are now able to compare across modalities and identify broader patterns. Building on this foundation, the present review aims to bridge these strands by offering a more comprehensive synthesis across technologies and highlighting system-level, long-term, and integrative perspectives.For example, studies on mobile health applications have primarily examined their role in supporting self-monitoring, lifestyle modification, and short-term glycemic control, but lack evidence on their long-term effectiveness [32], integration of educational information and participation of medical staff [31]. Telemedicine research focused on improving access to care, overcoming geographical barriers and improving HbA1c outcomes. But patient population, sample size, methods of glycemic monitoring, and insulin delivery restrict the clear interpretation of telemedicine's role in diabetes management [33]. Web-based platforms facilitate patient education, remote communication and self-management, though its application is mostly limited to countries with a high internet penetration rate [34]. Digital interventions require consideration of users' cognitive and technical skills, education level, and digital literacy level and of cultural appropriateness in addressing dietary preferences and religious customs [35]. While current studies provide valuable insights into specific interventions, future research should focus on clarifying the contextual suitability of different eHealth types and developing integrative models to optimize their combined impact.

1.3. Objectives

The primary objective of this review is to synthesize evidence on the use of eHealth interventions in diabetes care, with a focus on their applications in both clinical management and public health surveillance. Specific objectives are:

1. To assess the impact of eHealth interventions on therapeutic adjustments and continuity of care.
2. To examine the effectiveness of integrating digital health data into clinical decision-making systems in reducing medical errors, enhancing patient safety, and improving quality of care.
3. To analyze the cost-effectiveness of digital interventions.

2. Methods

2.1. Search strategy

To reach abundant and complementary evidence, two databases focusing on different aims are used in this review. Web of Science, with its coverage of broad topics, is particularly suitable for capturing research across diverse fields, while PubMed, with its strong focus on biomedical and health-related literature, provides more specialized and in-depth access to studies in medicine and public health.This review first conducted a broad search for articles that examine the effectiveness of diabetes management associated with eHealth interventions, using the search expression "eHealth(eHealth-related keywords, such as telehealth, electronic health, mobile health, digital health)" AND "diabetes (diabetes-related keywords, such as diabetes mellitus, type 1 diabetes, T1DM, gestational diabetes)" AND " public health surveillance(public health surveillance-related keywords, such as hospital, nursing home, population surveillance)" AND " effectiveness (and synonyms)." Specific keywords for each category can be found in Appendix A.

The search process was carried out in July 2025 by two reviewers working independently. To ensure the relevance of the retrieved literature, titles, abstracts, and keywords were initially screened against the review objectives. Studies that met these preliminary criteria were then subjected to a full-text assessment to determine their suitability for inclusion in the comprehensive review. Furthermore, the reference lists of the included articles were systematically examined using a snowballing method to capture additional relevant publications that might not have appeared in the initial database search.

2.2. Eligibility criteria

In this review, article selection was guided by three key considerations: ehealth interventions, DM-related outcomes, and document type. First, the intervention had to involve eHealth approaches, including mobile health applications, SMS-based programs, wearable-linked platforms, telehealth, or other digital tools integrated with diabetes care. Studies focusing on non-digital interventions or only traditional non-technology methods were excluded. Second, eligible outcomes were restricted to those directly relevant to diabetes management, such as clinical indicators (e.g., $HbA_{1}c$, fasting glucose), behavioral measures (e.g., adherence, self-monitoring), and surveillance-related metrics (e.g., data completeness, reporting latency). Studies addressing outcomes unrelated to diabetes were not included. Third, only peer-reviewed articles published in English within the past ten years were considered, while conference abstracts, dissertations, and unpublished manuscripts were excluded. Detailed reasons for exclusion are shown in Appendix A.

2.3. Data extraction and analysis

This review used the QualSyst assessment tool to evaluate article quality and the strength of evidence. The quality assessments for the selected articles are provided in Appendix B.

Data extracted from each article included: 1) basic information: article title,source title, conference title, authors, and publication year, 2) research process: research question, aims or objectives, study location (if applicable), study context, research methods, research design, data collection methods, data analysis methods, studied eHealth types, studied population (if applicable),use conditions, and 3) Outcomes: advantages and disadvantages of eHealth type, conclusions, limitations and future suggestions, and key takeaways relevant to this review. All data for the selected articles is shown in Appendix C.

3. Results

3.1. Study selection flow

The initial search across two databases identified 816 articles,with 626 from Web of Science and 190 from Pubmed. Figure 1 shows the procedure for article selection.After the removal of 318 duplicate records, 498 records were retained for title and abstract screening. 366 articles were excluded for irrelevance to the study focus, specifically those not addressing eHealth, diabetes, or public health surveillance. The full texts of 132 potentially relevant studies were assessed for eligibility. Of these, 82 studies were excluded for not meeting the inclusion criteria (not related to eHealth = 43; not related to diabetes = 28; not related to public health surveillance = 14). Ultimately, 47 studies met the eligibility requirements and were included in the systematic review. Additionally, 4 relevant studies were identified through a snowballing approach, resulting in a total of 51 articles included in the final analysis.

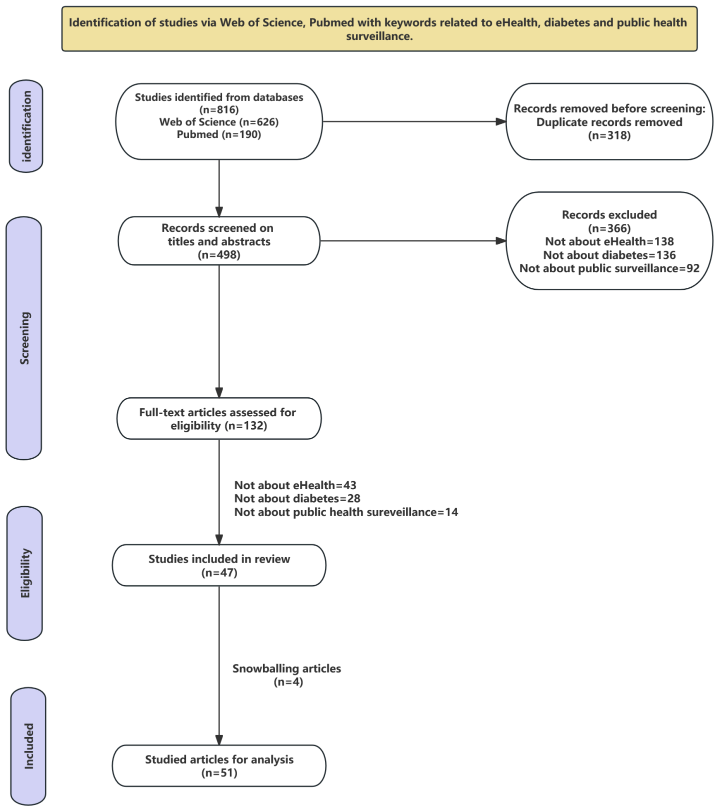

Figure 1. Flow diagram for selecting articles

3.2. EHealth interventions

EHealth utilization encompasses a broad range of digital health tools, including Electronic Health Record (EHR) [36], telemedicine [37], remote monitoring systems [38], smartphone applications [39], web-based platforms [40], Short Message Service (SMS) programs and machine learning–based prediction models [41, 42].These tools have been applied across diverse populations and contexts. Their usage conditions are influenced by a variety of factors,such as technical feasibility, patient characteristics, clinical needs, efficiency and cost-effectiveness considerations. To better distinguish the different application focuses, these interventions can be grouped into four functional types: messaging-based communication, educational interventions, monitoring systems, and predictive analytics (see Table 1). Figure 2 shows the proportion of 7 intervention methods in the selected articles.In the following parts for each ehealth type, we delineate: 1) the application context (care setting and delivery modality), 2) the target population (e.g., adults with type 2 diabetes and relevant comorbidities), and 3) the diabetes domain addressed (prevention, screening, self-management, glycemic control, or complications), and then appraise the intervention's impact, the effectiveness of integrating digital health data into clinical decision-making, and its cost-effectiveness.

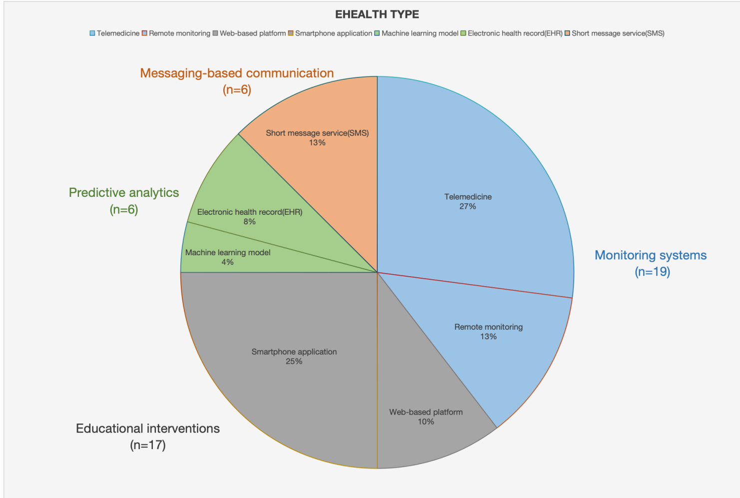

Figure 2. Proportion of 7 eHealth types

Table 1. Functional classification of eHealth interventions

Focus	Definition	Function	Included eHealth modalities	Examples of References
Messaging-based communication	Refers to the use of digital messaging technologies to facilitate direct, timely, and bidirectional communication between patients and healthcare providers, enhancing accessibility and continuity of care.	Facilitating communication between patients and providers through digital channels.	Short message service (SMS)	[36-37]
Educational interventions	Involve the delivery of tailored health information and behavioral guidance through digital platforms to enhance patients' knowledge, self-mangement and adherence to health-promoting behaviors.	Providing knowledge and behavioral support to improve self-management and adherence.	Smartphone applications, Web-based platforms	[43-45,52-53]
Monitoring systems	Encompass digital tools and platforms designed to collect, transmit, and analyze health-related data continuously or periodically, enabling remote assessment and proactive management of patient conditions.	Enabling continuous or periodic collection and transmission of health data.	Telemedicine, Remote monitoring	[57-60,64-66]
Predictive analytics	Utilizes advanced computational models and data-driven algorithms to identify patterns, predict disease trajectories, and support clinical decision-making aimed at improving personalized healthcare outcomes.	Using advanced analytics to forecast disease progression or treatment needs.	Machine learning model, Electronic health record (EHR)	[70,73-74]

3.2.1. Messaging-based communication

3.2.1.1. Short Message Service (SMS)

SMS is operated by using text messages on mobile phones to deliver information, reminders, or interactive support for patients [41]. Among the 51 studies examined, 6utilized this type, representing 11.76% of the total sample.The category of SMS involves the use of text messages, for delivering interventions such as medication reminders, lifestyle education (e.g., diet and physical activity), motivational support, and feedback [25].

The interventions frequently focused on medication adherence, dietary guidance, physical activity encouragement, and motivational reinforcement [25]. By providing continuous and personalized prompts [43], SMS systems effectively supported behavior change and improved treatment compliance, which subsequently contributed to enhanced glycemic control and reduced diabetes-related morbidity [43, 44]. Furthermore, patients reported higher satisfaction levels, emphasizing the acceptability and perceived usefulness of SMS as a convenient and empowering communication channel [43,45].

Furthermore, SMS approaches are characterized by their low cost, scalability, and feasibility, making them particularly suitable for large-scale public health surveillance and chronic disease management in resource-constrained settings [25, 46].

3.2.2. Educational interventions

3.2.2.1. Smartphone applications

Smartphone applications encompasses a diverse range of mobile software tools designed for chronic diseases management and education [39], with specific examples for diabetes including, mySugr [47], Walk with you [48], WhatsApp [49], Dnurse [50]. This modality was identified in 12 out of the 51 included studies,accounting for approximately 23.53% of all interventions.

In terms of diabetes management, these applications mainly support disease control by enabling the monitoring of blood glucose, dietary intake, knowledge about diabetes and physical activity [50], while also promoting medication adherence and the prevention of complications and incidence [51, 52].

Main outcome indicators commonly assessed include HbA1c and fasting blood glucose [51], additional measures such as blood pressure, lipids and body weight are also evaluated [53]. Continuous tracking of outcome indicators provides clinicians with reliable information to guide therapeutic decisions [51, 53]. This data-driven approach helps minimize medical errors, supports more individualized treatment, and promotes a higher standard of evidence-based diabetes management [54].

In J Li' study, app-based intervention has been proved to be more cost-effective than the conventional care model, saving 22.02 yuan per patient per year for healthcare services [55]. These results indicate that digital solutions are not only clinically beneficial but also cost-efficient and scalable for long-term diabetes management.

3.2.2.2. Web-based platforms

Web-based platforms commonly include online patient education systems and clinical decision support tools [40, 56]. Within the 51 studies reviewed, this type appeared in 5 instances, making up 9.8% of the dataset. The primary application context for these platforms was comprehensive disease management and prevention, particularly for complex chronic conditions like diabetes.In a case, the target populations included specific high-risk groups, such as high-risk pregnant women with Gestational Diabetes Mellitus (GDM) [57].

In some cases, the web-based platform serves as a diagnosis and treatment portal for clinicians. Its core functions include collecting patient baseline data, conducting intelligent assessments, aiding in diagnosis, and managing personalized prescriptions and lifestyle intervention plans [40,57]. In terms of effectiveness and surveillance-specific outcomes, research indicates that while web-based platforms can be useful tools, their impact on glycemic control (as measured by HbA1c) may be more limited compared to other digital interventions like smartphone apps or SMS [16].

3.2.3. Monitoring systems

3.2.3.1. Telemedicine

Telemedicine refers to the delivery of healthcare services and the exchange of medical information over distance through electronic communication technologies, with the aim of improving patients' clinical health outcomes [58]. Among the 51 articles included in this review , this type is represented by 13 articles, comprising roughly 25.41% of the total.

The application context predominantly emerged from the necessity to maintain diabetes care continuity during the COVID-19 pandemic, which accelerated the adoption of telehealth solutions to reduce in-person visits [59]. The population coverage of telemedicine applications is broad, for example, with focus on those facing barriers to traditional care, such as individuals in low-and-middle-income countries(LMIC) [60], and specific subgroups like pregnant women and older people with diabetes [37, 61, 62].

In clinical practice, telemedicine strengthens patient self-management and chronic disease control by extending professional nursing support and continuity of care beyond hospital settings, thereby improving both care quality and patient well-being [63].

From an economic perspective, telehealth can significantly reduce the number of diabetes-related visits and direct costs, without affecting pregnancy outcomes, nursing quality or patient satisfaction, although it increases the burden of nursing time [63,64].

3.2.3.2. Remote monitoring

Remote monitoring, which encompasses technologies such as continuous glucose monitors (CGM) [38], telemonitoring [65], smart pens for insulin monitoring [38] and web-based platforms [66], was utilized in 8 of the 51 included studies, accounting for 15.69% of all included research. Continuous glucose monitoring enables real-time tracking of blood glucose fluctuations over 24 hours and provides alert functions to notify patients when current or projected levels fall outside the target range [67].

This intervention is mainly targeted at patients with diabetes, for pregnant women with diabetes, blood sugar monitoring can adjust the insulin dosage based on dietary type, physical activity, and stress, optimizing the outcome for the fetus [67]. The monitoring indicators include HbA1c, total daily dose, the time spent above the range and the time spent below the range relative to the baseline. The exploratory indicators include health-related quality of life, diabetes-related quality of life [65]. These data are helpful for observing long-term trends and can detect cases of poor blood sugar control in advance, thereby providing a basis for clinical intervention [68].

To analyze the cost-effectiveness of digital interventions, CGM technology not only reduces the frequency of acute glycemic events and hospital visits but also lowers long-term complication-related costs by enabling early intervention [68]. Through continuous data feedback and improved treatment precision, CGM demonstrates potential economic benefits while maintaining or improving clinical outcomes [69].

3.2.4. Predictive analytics

3.2.4.1. Machine learning model

Machine learning, which encompasses predictive algorithms such as Extreme Gradient Boosting (XGBoost), Random Forest, and Logistic Regression designed to identify complex patterns from structured clinical data [42]. Out of 51 reviewed publications, 2 (representing about 3.92%) addressed this form of intervention.

Machine learning can assist clinicians in analyzing large-scale EHRs, enabling the construction of specialized models based on patterns in the data and handling multi-dimensional data [70]. The goal of machine learning (including deep learning) should be to predict, detect or facilitate the assessment of disease risks [70], it demonstrated high accuracy in predicting diabetes incidence [42]. The most influential predictors included HbA1c, fasting blood glucose, body weight, tetrahydrofuran, and triglycerides. These findings highlight the potential to assist clinicians in early diabetes detection and improve clinical decision-making [42].

From a system-level perspective, the use of machine learning–based prediction models shows potential for improving cost-effectiveness through earlier diagnosis and more precise intervention. These models may reduce both direct and indirect healthcare costs, optimize resource allocation, and ultimately support more efficient and sustainable healthcare delivery [42,70].

3.2.4.2. Electronic Health Record (EHR)

EHR generally contain diagnostic information, medication histories, and laboratory test results [36], enabling the identification of factors associated with the development of conditions of type 2 diabetes [71]. Out of 51 reviewed publications, 4 (constituting around 7.84%) addressed this form of intervention.

EHR serves as an important tool for influencing clinician behavior by providing evidence-based recommendations and intervention options through embedded clinical decision support (CDS) systems [72]. It will also combine the application of deep learning models to identify and predict individuals in the population who may develop type 2 diabetes [71] Its target populations include developing type 2 diabetes among relatively healthy populations and diagnosed patients [71,72]. In inpatient diabetes management, it also assists in establishing individualized glycemic goals, providing reminders for HbA1c testing, offering guidance on weight-adjusted dosing, and ensuring insulin plans correspond to nutritional needs [73]. In one case, implementation of the Behavioral Economics Electronic Health Record (BE-EHR) module utilizes the monitoring data of clinical assessment indicators to send feedback information to clinicians regarding their individual performance and its comparison with their respective clinics as well as the entire medical system [72].

EHR-based interventions can reduce healthcare costs by improving workflow efficiency and minimizing unnecessary tests and medication errors [72]. Streamlined documentation and decision-support functions help shorten hospital stays and optimize resource use, contributing to more cost-effective diabetes care [73].

4. Discussion

This systematic review synthesizes findings from 51 studies examining the role of eHealth interventions in diabetes management, with a dual focus on clinical effectiveness and public health surveillance utility. The findings demonstrate that eHealth tools consistently support glycemic control, enhance patient self-management, and improve care continuity, while also facilitating data integration for population-level monitoring and decision-making. This article delves deeply into how different ehealth interventions can be integrated into the public health surveillance systems. It not only explores the role of these modalities as clinical auxiliary tools, but also examines their role as an integral component of the public health surveillance systems. The evidence presented here enhances our understanding of the mechanisms through which digital health technologies contribute to both individual patient outcomes and system-wide health surveillance, offering valuable insights for designing integrated, scalable, and context-sensitive diabetes managment models.

4.1. Interpretation of effectiveness in clinical and surveillance terms: impact of eHealth interventions and integration of digital health data into decision-making

The clinical performance of eHealth interventions differed by function and care context rather than showing uniform effectiveness across modalities. SMS-based communication proved valuable in supporting medication adherence and lifestyle regulation, particularly through timely reminders and interactive feedback loops [25,43,44]. Smartphone applications were more effective in sustaining continuous self-management by supporting daily tracking of glucose, diet, and physical activity, which better facilitated long-term lifestyle adjustment and patient autonomy [50]. Web-based systems enabled online consultation, diagnostic assessment, and individualized intervention design for complex conditions such as gestational diabetes mellitus (GDM), which helped improve follow-up and continuity of treatment [40,56,57]. Remote monitoring solutions—including telemedicine and continuous glucose monitoring (CGM)—showed clinical value when in-person access was restricted, enabling timely therapy adjustment and stabilization of glycemic outcomes [37,59-61,65-68], particularly during the COVID-19 pandemic or when conventional health access was constrained. When digital health data were integrated into clinical decision systems, measurable improvements were observed in care quality and safety, including fewer treatment errors, standardized glycemic target setting, and more accurate treatment modification [36,71,72]. Furthermore, EHR-embedded decision support and predictive algorithms such as XGBoost enhanced clinical precision by supporting early risk identification and individualized care planning, strengthening clinicians' ability to intervene before complications progressed [42].

Beyond individual care, eHealth interventions contributed critical value to public health surveillance by generating continuous, high-granularity data that are largely scarce in conventional reporting systems. Self-tracking behaviors captured via smartphone apps and remote monitoring tools provided near real-time signals of glycemic patterns and lifestyle responses, strengthening the temporal sensitivity of diabetes monitoring [48-50,65-67]. Predictive models built on EHR enabled large-scale stratification of diabetes risk and early identification of high-risk populations, expanding surveillance capabilities from retrospective case reporting toward forward-looking risk detection [36,42,70-73]. These digital systems can reflect rapid health changes, support earlier recognition of population risk shifts, and contribute to a more adaptive, data-driven public health surveillance model for chronic disease management.

In conclusion, these findings indicate that eHealth effectiveness is relavent to contex: messaging-based systems excel in adherence support, smartphoneand web platforms in sustained self-management and clinical follow-up, remote monitoring in care continuity during access disruptions, and predictive analytics in early risk identification. When digital data are embedded into clinical workflows, they enhance decision accuracy, safety, and treatment quality, while at the population level, the same data streams extend surveillance capacity by enabling earlier risk detection and dynamic health trend monitoring. This dual clinical-surveillance utility highlights the importance of advancing system-level data integration to transform isolated digital tools into connected systems that support both individualized diabetes care and strengthened public health surveillance.

4.2. Dialogue with existing literature

While previous reviews have predominantly emphasized clinical outcomes such as HbA1c reduction and adherence improvement, the present analysis broadens the focus by examining how digital data integration contributes to both clinical decision-making and population health surveillance. Engaging with existing literature thus allows for a more nuanced understanding of where eHealth interventions have proven effective and where persistent gaps remain.

Consistent with previous studies, mobile health applications, telemedicine, and web-based platforms have demonstrated effectiveness in improving medication adherence, promoting self-management behaviors, and achieving short-term glycemic control [11,12,30-32]. The present results also reaffirm telemedicine's contribution to care accessibility and continuity, especially for patients in remote or resource-limited areas [33], and highlight the value of educational programs delivered via smartphone apps and web-based tools in strengthening patient knowledge and engagement [31,34]. These consistencies reinforce the evidence base supporting eHealth as a practical and scalable approach to improving patient-level outcomes and healthcare delivery efficiency.

Nevertheless, earlier reviews tended to emphasize individual-level outcomes rather than examining broader, system-oriented or long-term effects. Telemedicine studies often vary in population selection and clinical protocols, restricting comparability and generalization [33]. Research on mobile applications and web-based platforms tends to emphasize short-term behavior change rather than sustained engagement or integration with professional medical input [31,32,34]. Moreover, most published work originates from high-income countries, where contextual factors—such as digital literacy, socioeconomic conditions, and cultural considerations—may differ significantly from other settings [35]. By combining insights from multiple eHealth domains, the present analysis offers a more integrative perspective, suggesting the need for hybrid frameworks that interlink patient self-management, clinical operations, and public health monitoring to advance digital health over the long term.

4.3. Implications for integrating eHealth into routine surveillance systems

Integrating eHealth into routine public health surveillance is increasingly necessary, as traditional surveillance systems rely on delayed clinical reporting and population-level datasets that cannot capture day-to-day fluctuations in patient behavior or early signs of deterioration. The four functional categories of eHealth interventions identified in this review—messaging-based communication, educational interventions, monitoring systems, and predictive analytics—each contribute distinct capabilities to enhance surveillance. Messaging systems like SMS enable scalable patient engagement and adherence monitoring; educational platforms deliver tailored self-management support; monitoring technologies generate continuous clinical and behavioral data; while predictive tools improve risk stratification and forecasting accuracy.

The evidence synthesized in this review highlights several key potentials of integrating eHealth into surveillance systems. The integration of these complementary eHealth modalities creates a surveillance ecosystem with enhanced predictive capacity and operational efficiency. Messaging-based systems provide low-cost, scalable channels for maintaining patient contact and monitoring treatment adherence across diverse populations. Educational interventions empower patients through knowledge dissemination and self-management tools, fostering sustained engagement. Monitoring systems capture high-frequency physiological and behavioral data, enabling real-time assessment of disease control and treatment response. Predictive analytics leverage complex datasets to identify patterns and forecast individual and population-level risks. This multi-layered approach enables public health systems to move beyond retrospective reporting toward proactive management of diabetes and other chronic conditions.

However, the effective integration of these technologies faces significant challenges. The variable digital literacy among patients and healthcare providers, coupled with disparities in technology access, threatens the equity and representativeness of surveillance data. Furthermore, uncertainties regarding data governance, privacy protection, and ethical use create barriers to data sharing across clinical and public health systems. These constraints are particularly evident in the disconnect between patient-generated data from messaging and educational platforms and institutional health records, limiting the utility of digital information for comprehensive surveillance.

Addressing these challenges requires coordinated technical, organizational, and policy interventions. The development of standardized data architectures and interoperable interfaces is essential to integrate diverse eHealth modalities into unified surveillance infrastructures. Capacity-building initiatives and training program can improve data quality and ensure equitable participation across different population segments. Establishing clear governance frameworks that define data stewardship, consent mechanisms, and access rights is crucial to build trust and facilitate secure data exchange. By implementing these complementary strategies, eHealth integration can evolve from isolated technological applications into a coherent public health surveillance infrastructure—enabling more responsive, predictive, and equitable management of chronic diseases while maintaining ethical standards and operational sustainability.

4.4. Limitations and future directions

Reflecting on the synthesized findings, it becomes evident that certain limitations persist within the existing literature and should be systematically addressed in subsequent research.

First, the scope of this review was limited to two databases (Web of science and Pubmed) and English-language publications, which may introduce potential selection and geographical bias. Studies from non-English-speaking or low- and middle-income countries (LMICs)—where contextual challenges such as digital literacy barriers may affect implementation—were likely underrepresented. Future reviews should expand database coverage, include grey literature, and adopt multilingual search strategies to ensure greater inclusivity and minimize bias related to geography and publication language.

Second, substantial heterogeneity exists among studies in terms of intervention design and outcome definitions, which complicates comparability and limits the ability to perform synthesis and cross-study comparisons. Many studies reported short-term outcomes and small sample sizes, while intervention fidelity and engagement were often underreported. This aligns with prior literature identifying high variability in eHealth modalities, limited data on long-term sustainability, and methodological inconsistency. Economic analyses also vary substantially in scope, often neglecting indirect costs—such as those associated with system integration, maintenance, or workforce training. Future research should apply standardized frameworks for outcome reporting and cost assessment, such as adopting uniform metrics for HbA1c, engagement, and cost-effectiveness, to facilitate comparison and analysis.

Third, the dominance of single-site or pilot studies restricts validity and fails to account for technological evolution over time. As noted in previous reviews, small-scale pilot trials without control groups or adequate sample size calculations limit the strength and generalizability of findings and some digital interventions become outdated rapidly as new platforms emerge. Future studies should employ multicenter randomized controlled trials (RCTs) with larger, more diverse populations and longer follow-up durations to evaluate long-term efficacy, sustainability, and adaptability to new technological developments.

Finally, at the system level, the connection between clinical data from eHealth programs and population health surveillance remains weak. Most studies continue to evaluate patient-level effects without linking data streams to national or regional monitoring systems. This disconnect limits the translation of digital health evidence into broader surveillance insights. Strengthening integration between EHR, eHealth platforms, and public health databases—supported by unified data standards and governance structures—should therefore be a central priority for future research and policy development.

5. Conclusions

This review synthesized evidence from 51 studies covering diverse eHealth modalities—including SMS, smartphone applications, web-based platforms, telemedicine, remote monitoring, machine learning model and EHR. Collectively, these interventions have shown significant benefits in diabetes management by improving therapeutic adjustments, for example, care continuity, patient self-management, and clinical safety. eHealth integration enhanced data-driven clinical decision-making and reduced treatment errors, while predictive models and monitoring tools supported early detection of disease progression. Moreover, digital health solutions showed promising cost-effectiveness, reducing direct and indirect healthcare expenditures through improved efficiency and prevention of complications. These findings confirm that eHealth not only enhances clinical innovation but also prompts sustainable and equitable health system transformation.

To employ the full potential of eHealth, future policy efforts should prioritize system-level integration rather than isolated implementation. This includes developing standardized data architectures, ensuring integration between eHealth tools and public surveillance systems, and strengthening data governance frameworks that protect privacy while enabling real-time analytics. Governments and health organizations should invest in digital literacy training for both healthcare professionals and patients to improve participation and data quality. Meanwhile, research should move toward multicenter, longitudinal designs to evaluate the long-term effectiveness, scalability, and cost-effectiveness of these technologies across diverse populations and settings. Integrating remote monitoring, predictive analytics, and EHR data into surveillance networks can facilitate proactive disease forecasting and policy-driven public health interventions. A hybrid model—linking clinical care, patient self-management, and population-level surveillance—offers a promising path toward comprehensive digital health ecosystems.

This study contributes to the growing body of evidence by bridging fragmented insights across different eHealth modalities and emphasizing their collective role in both clinical and surveillance contexts. It advances understanding of how digital tools can be systematically embedded into routine healthcare workflows and public health monitoring frameworks. By examining how individual outcomes, system coordination, and economic factors interact, this review offers practical evidence to guide the development of connected, data-informed public health surveillance systems that improve diabetes management and long-term public health outcomes.

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