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Review

Cesarean Section Surgical Site Infection Surveillance Using Mobile Health Technology: A Scoping Review

Ya-Ting Kuan[1,2,3], Hsiu-Ju Chang[1,4], Chi-Wen Chen[1], Hao-Chih Tai[5], Chi-Shan Tsai[6], Shu-Jing Guan[7], I-Ching Hou[1,4,*]

[1]College of Nursing, National Yang Ming Chiao Tung University, 112 Taipei, Taiwan
[2]College of Nursing, National Taipei University of Nursing and Health Sciences, 112 Taipei, Taiwan
[3]Department of Nursing, Taipei Veterans General Hospital, 112 Taipei, Taiwan
[4]Efficient Smart Care Research Center, College of Nursing, National Yang Ming Chiao Tung University, 112 Taipei, Taiwan
[5]Department of Surgery, National Taiwan University Hospital and College of Medicine, 112 Taipei, Taiwan
[6]School of Nursing, University of Washington, Seattle, WA 98195, USA
[7]Department of Nursing, Hsin Sheng College of Medical Care and Management, 325 Taoyuan, Taiwan
*Correspondence: evita@nycu.edu.tw (I-Ching Hou)
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Abstract

Background: With a global increase in cesarean section (CS) rates, timely surgical site infection (SSI) surveillance is increasingly challenging due to shorter postoperative hospital stays and limited access to follow-up care. Therefore, much of wound recovery has shifted to the home setting, creating new challenges for timely surveillance and early detection of complications. Mobile health (mHealth) technologies offer a promising approach to addressing these challenges by enabling remote monitoring, facilitating early infection detection, and supporting women's engagement in postoperative self-care. However, despite the rapid expansion of mHealth innovations, the extent to which these technologies have been applied to SSI surveillance following CS remains unclear. This study evaluated the current status and utilization of mHealth technologies for SSI surveillance among women after CS. **Methods:** This scoping review was conducted in accordance with the preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews (PRISMA-ScR) reporting guidelines and the Arksey and O'Malley methodological framework. A comprehensive literature search was conducted in PubMed/medical literature analysis and retrieval system online (MEDLINE), Ovid MEDLINE, the Cochrane Library, excerpta medica database (Embase), Web of Science Core Collection, Scopus, cumulative index to nursing and allied health literature (CINAHL), and institute of electrical and electronics engineers (IEEE) Xplore to identify publications published on or before August 20, 2026. Eligible sources included original empirical studies and study protocols that described, developed, implemented, or evaluated mHealth technologies for postcesarean wound or SSI surveillance. Eligible empirical study designs included observational, experimental, quasi-experimental, or mixed-methods studies. **Results:** Of the 65 records identified, 12 publications met the eligibility criteria. The mHealth technologies varied in functionality and were classified into 4 non-mutually exclusive functional domains supporting post-discharge surveillance following CS: communication-based systems, image-based wound surveillance, decision-support platforms, and emerging artificial intelligence applications. CS wound follow-up mainly occurred within the first 30 days, although some publications extended surveillance based on specific clinical objectives. Despite heterogeneity in study designs, populations, and outcomes, the included publications described diverse applications of mHealth technologies for CS wound surveillance. **Conclusions:** Current evidence suggests that mHealth technologies may be feasible and acceptable tools with considerable potential to support post-CS wound surveillance. However, the evidence base remains limited and heterogeneous in study design, technological approach, outcome measures, and follow-up duration, and several technologies remain in early development or validation stages. Robust comparative studies are therefore warranted before widespread clinical implementation can be recommended.

Keywords: mobile health; cesarean section; wound; surgical site infection; postpartum

Key Points

1. Current evidence describes the application of mobile health (mHealth) technologies for post-discharge surgical site infection surveillance following cesarean sections.

2. Cesarean section wound follow-up was mostly conducted within the first 30 days, with some publications extending surveillance according to specific clinical objectives.

3. The functional domains of mHealth technologies used for surgical site infection surveillance following cesarean sections included communication-based systems, image-based wound surveillance, decision-support platforms, and emerging artificial intelligence applications.

1. Introduction

Cesarean section (CS) is defined as fetal delivery through an open abdominal incision and an incision in the

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uterus [1]. CS wound surveillance using mobile health (mHealth) technology has become an emerging approach for postoperative monitoring. Despite the global increase in CS rates, research evaluating the use of mHealth technologies to address the unique needs of mothers following CS delivery remains limited. Generally, women are discharged from the hospital after approximately 1–5 days post-CS. However, surgical site infections (SSIs) can appear between postoperative days 4 and 7 [2], and the majority of cases occur after hospital discharge. The overall global incidence of SSIs after CSs is approximately 5.63% [3]. SSIs are classified by the depth and tissue layers involved, provided the infection occurs within 30 days of the procedure [4].

mHealth technology, which uses mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices to support health goals, has become one of the most innovative and empowering developments in digital healthcare [5,6]. The increasing availability of mHealth technologies has expanded opportunities for patients to access health information and healthcare resources. Additionally, 95.6% of patients perceived that mHealth technologies have potential utility for wound care outcomes, while 93.9% believed that wound management practices should be optimized for integration with mobile devices [7]. Moreover, mHealth technologies supported in-home wound care by facilitating postoperative monitoring as part of a broader intervention that included wound care education and the provision of care materials. This intervention was associated with a reduction in reported infection rates from 28.8% to 9.7% [8].

The use of mHealth technologies, particularly smartphones, may support maternal education, disease self-management, and remote wound monitoring [9]. Despite evidence showing the benefits of shared wound images, women undergoing CSs broadly welcome the use of digital imaging; however, few studies have investigated their involvement in mHealth technologies. In scoping reviews, rigorous and transparent methods are applied to map research areas that cover broader topics where multiple study designs may be applicable, making them a useful approach for synthesizing research evidence [10]. Thus, it is crucial to adapt these methodologies to specifically address the deployment of mHealth technologies in monitoring SSIs after CSs. In this scoping review, we aimed to comprehensively evaluate the status and implementation of mHealth interventions designed to support postoperative wound monitoring in women after CSs.

2. Methods

2.1 Scoping Review Framework

Scoping reviews serve to synthesize evidence and assess the scope of the literature on a topic. The decision to conduct a scoping review was related to the aim of exploring the phenomenon under study, which appeared to be based on preliminary research of recent interest in the context of CSs. According to the framework of Arksey and O'Malley [11], a scoping review is conducted in five phases: (1) identifying the research question; (2) identifying relevant studies; (3) study selection; (4) charting the data; and (5) collating, summarizing, and reporting the results (Table 1). The Joanna Briggs Institute (JBI) methodology was also applied to supplement the scoping review methodology [12]. The Arksey and O'Malley (2005) framework for scoping reviews was adapted using the preferred reporting items for systematic reviews and meta-analyses extension for scoping reviews (PRISMA-ScR) guidelines [13]. The checklist contains 20 essential reporting items and 2 optional items to include when conducting scoping reviews. As a scoping review, ethical approval was not required for the research. Rayyan (https://www.rayyan.ai/) was used to manage the references and facilitate the study screening process [14].

2.2 Stage 1: Identifying the Research Question

At the beginning of this scoping review, parameters were defined. It is crucial to maintain a broad approach to ensure comprehensive coverage. The first step was to establish a research question that needs to be addressed, thereby enabling the development of effective search strategies. The key facets of the research question were identified, such as the study population, interventions, or outcomes. The research question in this study was, "What mHealth technologies are used to monitor surgical site infections in women after cesarean sections?" The review considered the following Population, Concept, and Context (PCC) components: population (women who underwent CSs), concept (mHealth technologies), and context (discharge/home care).

The review protocol was developed in January 2025. Following peer review, the protocol was amended to expand the search from four to eight databases and extend the search through August 20, 2026. The amended protocol was registered and made publicly available on the Open Science Framework (https://doi.org/10.17605/OSF.IO/W6UF5).

2.3 Stage 2: Identifying Relevant Studies

At this stage, our goal was to comprehensively identify the eligible publications relevant to addressing the central research question. We implemented a systematic strategy involving searches across various sources. We searched the following 8 databases: PubMed/MEDLINE, Ovid MEDLINE, Cochrane Library, Embase, Web of Science Core Collection, Scopus, CINAHL, and IEEE Xplore.

The databases were searched using the "AND" and "OR" operators in the titles, abstracts, keywords, or as appropriate. The following search keywords and medical subject headings (MeSH) terms were used: ("mHealth" OR "m-Health" OR "mobile health" OR "mobile application") AND ("cesarean section" OR "caesarean section" OR "ce-

Table 1. The framework of Arksey and O'Malley.

Main phases	Concept of phases	Methods
1. Identifying the research question	This stage defines parameters and considers the implications of taking certain positions at the outset of a scoping review.	The research question in this study is: "What mHealth technologies are used to monitor surgical site infections in women after cesarean section?"
2. Identifying relevant studies	This stage aims to comprehensively identify eligible publications suitable for addressing the central research question.	Eight databases were searched for publications published on or before August 20, 2026.
3. Selecting studies	This stage involves a systematic review method used to develop inclusion and exclusion criteria, based on the research question, and ensure consistency in decision-making.	The eligibility criteria were determined by study design and target population.
4. Charting the data	The stage of the work involved 'charting' key information items obtained from the reviewed primary research reports. Charted data were entered into a 'data charting form' using the database program Excel.	Relevant studies were organized in a data extraction table (Table 2).
5. Collating, summarizing, and reporting the results	The objective of this phase was to provide an overview of all the materials reviewed.	The data were analyzed using qualitative content analysis based on the research question.

sarean delivery") AND ("surgical site infection" OR "surgical wound infection" OR "postoperative infection"). No lower publication-date limit was applied; publications published on or before August 20, 2026, were eligible. The date for the review was justified by significant advancements in mHealth technologies and the increasing CS delivery rates during this period, which together provide a comprehensive overview of recent developments and trends. This approach was used with the aim of identifying a robust set of studies to inform our research. The resulting evidence informed the subsequent analysis, interpretation of the findings, and development of the conceptual framework.

2.4 Stage 3: Study Selection

To ensure consistency in decision-making when selecting studies for systematic reviews, inclusion and exclusion criteria are developed based on the research question. The following criteria were used for study selection in this review.

Eligibility criteria: This review included original empirical studies and study protocols describing, developing, implementing, or evaluating mHealth technologies for post-cesarean wound or SSI surveillance. Eligible empirical studies employed one of the following designs: observational (e.g., cross-sectional or cohort), experimental (e.g., randomized controlled trial [RCT]), quasi-experimental, or mixed methods designs.

Exclusion criteria: This review excluded studies that investigated non-mHealth systems, literature reviews (systematic, narrative, or umbrella reviews), and qualitative studies.

Based on the abovementioned eligibility criteria, two independent reviewers (YT, CS) initially screened the titles and abstracts to identify potentially relevant articles. Articles that were deemed unclear or potentially relevant were subsequently assessed through a full-text review to determine their final eligibility. Disagreements between reviewers were resolved by a third reviewer (SC). All the studies included women as the target population. Owing to the comprehensive search for relevant literature, no restrictions were placed on patient age or region (Fig. 1).

2.5 Stage 4: Charting the Data

Key information from the included publications was charted using a data charting form in Microsoft Excel (https://www.microsoft.com/microsoft-365/excel). Data extraction included the authors and year of publication, country, study design, study aim, type of mHealth intervention, sample size, follow-up period, data collection methods, and key findings regarding the application of mHealth technologies for post-discharge surveillance of SSI following CSs.

2.6 Stage 5: Collating, Summarizing, and Reporting the Results

The objective of this stage was to provide an overview of all reviewed materials. Finally, the data classification enabled the preparation of a report on our scoping review results. The data elaborated in the framework were then analyzed based on the research question using qualitative analysis methods. The functional classification was developed inductively from the included publications. One reviewer (YT) initially coded the mHealth technologies reported in each publication, and a second reviewer (CS) reviewed the codes and domain assignments. Disagreements were resolved through discussion and consensus, with consultation with a third reviewer (SC) when necessary.

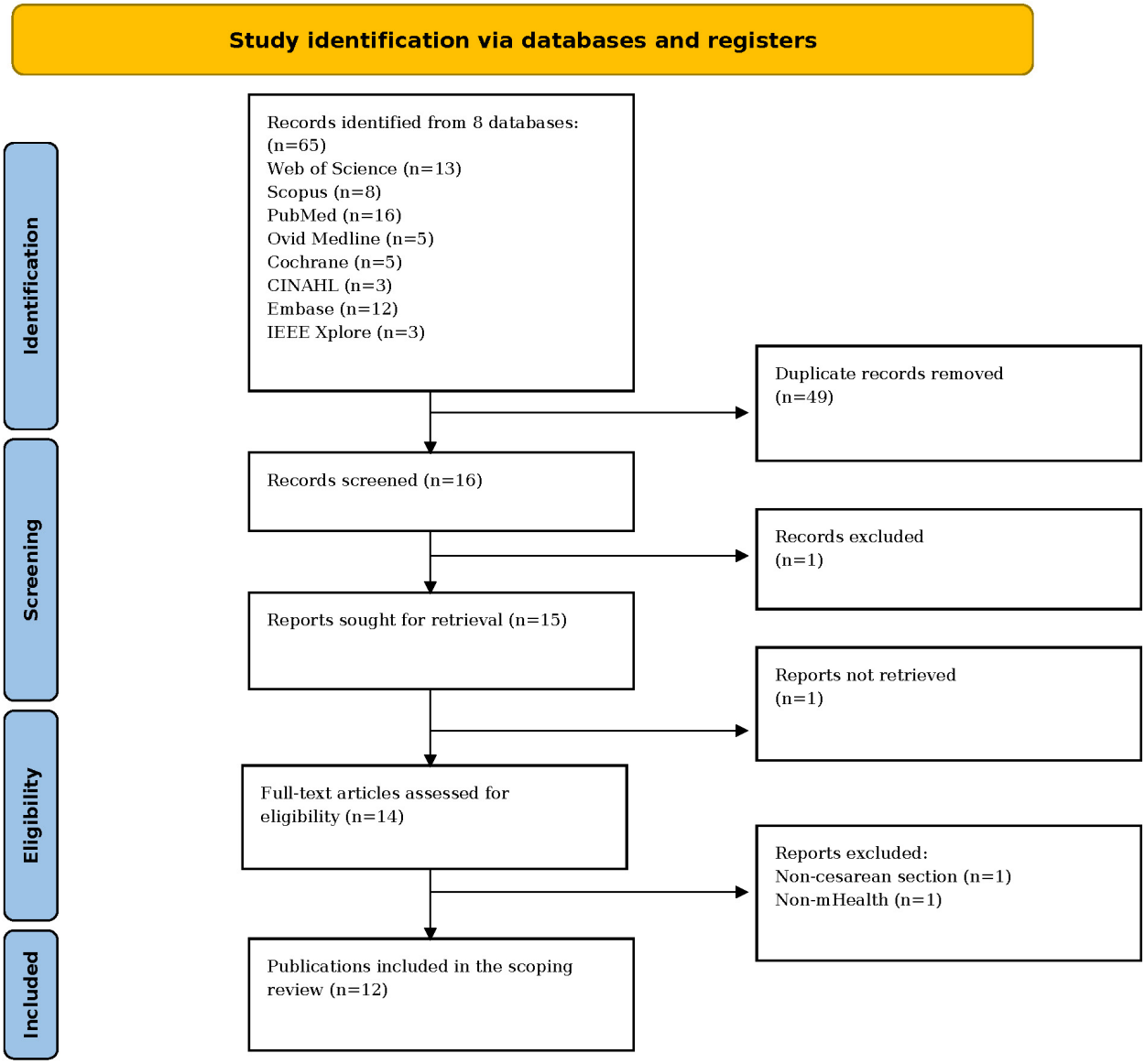


Fig. 1. Flowchart of publication identification and selection process.

3. Results

3.1 Identification of Publications

A total of 65 records were identified from the 8 databases. After 49 duplicate records were removed, 16 records remained for title and abstract screening. Of these, 1 record was excluded, and 15 reports were sought for retrieval. One report could not be retrieved, leaving 14 full-text articles for eligibility assessment. After full-text review, two reports were excluded, leaving 12 publications for inclusion in this scoping review (Fig. 1).

3.2 Characteristics of Included Publications

A total of 12 publications published between 2017 and 2024 met the eligibility criteria for this scoping review. These publications represented 10 independent research projects and study populations because two protocol publications [15,16] were linked to their subsequently completed studies (Fig. 2). The publications originated from four countries: Rwanda (n = 7), Australia (n = 2), Canada (n = 2), and Ireland (n = 1) (Fig. 3).

Considerable methodological heterogeneity was observed across the included publications with respect to study design, patient populations, outcome definitions, follow-up duration, and technological platforms. The included publications comprised reports of one randomized controlled trial, three prospective cohort studies, three prospective diagnostic studies, two interventional studies, one randomized controlled trial protocol, one interventional study protocol, and one feasibility study. One Australian protocol was linked to a completed interventional study, and one Rwandan protocol was linked to a completed randomized controlled trial. Three artificial intelligence pub-

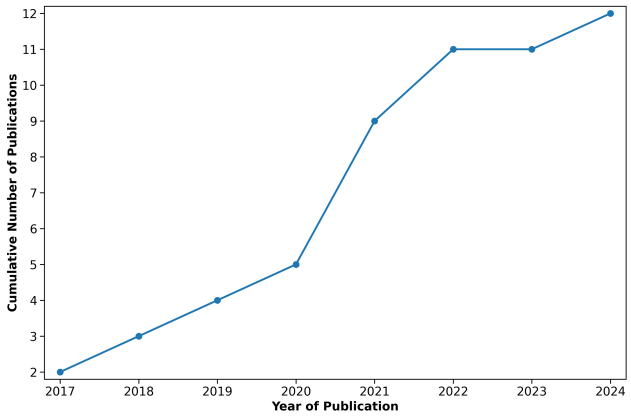


Fig. 2. Cumulative number of included publications reporting mobile health (mHealth) technology for post-cesarean wound surveillance, 2017–2024.

lications were produced by the same research team. References [17] and [18] reported different analyses of the same underlying cohort recruited between March and October 2017, whereas Reference [19] used a separate cohort recruited between September 2019 and February 2020. These three publications therefore represented two distinct participant cohorts. Although women undergoing CSs constituted the primary study population in all studies, several interventions additionally involved community health workers to facilitate home-based wound assessment, image acquisition, and referral, whereas clinician-confirmed diagnoses served as the reference standard in the prospective diagnostic studies. Eleven publications enrolled women aged ≥18 years, whereas one interventional study protocol did not report participant age because no participants had been recruited.

Reported outcome measures were heterogeneous and included patient engagement, self-monitoring, diagnosis, predictive performance, healthcare utilization, return to care, acceptability, and postoperative wound management outcomes. Follow-up schedules in completed studies ranged from daily application engagement during the first five postoperative days to assessments around postoperative day 10 and 30-day postoperative surveillance. One protocol additionally planned follow-up for up to 90 days among participants identified as having an SSI. No standardized follow-up schedule was identified across the included publications. A detailed summary of the characteristics of the included publications is presented in Table 2 (Ref. [15,16,17,18,19,20,21,22,23,24,25,26]).

3.3 Characteristics of mHealth Technologies

The included publications primarily focused on the use of mHealth technologies to support CS wound surveillance. Among mHealth technologies platforms, mobile applications were the most frequently used implementation platform (6/12) [15,20,22,23,25,26], followed by electronic tablets used for wound photography and community-based surveillance (2/12) [16,21]. Three publications (3/12) [17,18,19] used smartphone- or tablet-based imaging combined with machine learning or deep learning analysis, while one publication employed a telephone-based screening algorithm [24]. Across the included publications, reported outcomes associated with mHealth technology use included post-discharge surveillance, patient engagement and self-monitoring, return-to-care rates, timely healthcare-seeking behavior, feasibility and acceptability, diagnostic and predictive performance, support for preventive strategies, and reductions in unnecessary healthcare visits [15,16,17,18,19,20,21,22,23,24,25,26].

Conceptually, the identified technologies were classified into four non-mutually exclusive functional domains: communication-based systems, image-based wound surveillance, decision-support platforms, and emerging artificial intelligence applications. Communication-based systems primarily supported symptom reporting, patient self-monitoring, health education, and communication between women and healthcare professionals after hospital discharge [15,20,23,26]. Image-based wound surveillance enabled remote wound assessment through photographs captured using mobile devices and transmitted for clinical review, diagnosis, or referral [21,22,25]. One publication developed a telephone-based screening algorithm to support SSI identification and referral decisions [24]. The three artificial intelligence publications [17,18,19] evaluated machine learning or deep learning models using smartphone color images, thermal images, or combined questionnaire and wound image data to support automated SSI prediction.

4. Discussion

This scoping review examined the current landscape of mHealth technologies used to support post-discharge wound surveillance following CSs. The available evidence could be synthesized into four functional domains: communication-based systems, image-based wound surveillance, decision support platforms, and emerging artificial intelligence applications (Fig. 4). Technology platforms and outcome measures in Fig. 4 provide context. The domains were not mutually exclusive; a platform could be assigned to more than one functional domain if it supported multiple functions. These domains were mapped onto a surveillance pathway comprising data acquisition, transmission, interpretation, clinical action, and outcomes. These findings are consistent with the broader evolution of digital health technologies, which increasingly complement conventional postpartum follow-up while presenting new challenges for implementation and evaluation. By synthesizing the available evidence within this conceptual framework, this review highlights both the potential utility of mHealth technologies for post-CS SSI surveillance and the remaining evidence gaps that should be addressed in future research.

Table 2. Characteristics of the included publications.

Author (year)	Country	Study design	Aim of study	mHealth technology	Sample size (n)	Follow-up period	Data collection	Reported findings or planned outcomes
Ohr et al. (2024) [20]	Australia	Interventional study	Evaluated a surveillance system for monitoring surgical site infections following cesarean section	Post-discharge SSI surveillance system, mobile application	Screened 730; 382 responded	30-day postoperative follow-up	Questionnaire	The surveillance system was associated with post-discharge SSI surveillance and supported women's wound care self-management.
Kateera et al. (2022) [21]	Rwanda	Randomized controlled trial	Assessed the effect and feasibility of mHealth-supported community health worker interventions	Electronic tablet with CHW home visits and wound photo collection	Screened 1166, recruited 1025	30-day postoperative follow-up	Photographs	The intervention was associated with higher return-to-care rates and fewer unnecessary healthcare visits.
Nkurunziza et al. (2022) [22]	Rwanda	Prospective cohort study	Evaluated the feasibility and diagnostic accuracy of a telemedicine-based SSI diagnosis approach	Wound Screener application with WhatsApp image transfer	Screened 787, recruited 719	Postoperative day 10 (±3 days)	Photographs	The telemedicine approach demonstrated a high negative predictive value (96.4%) and high acceptability among women (100%).
Ke et al. (2021) [23]	Canada	Prospective cohort study	Explored patient engagement with a mobile application after cesarean section	Mobile application	Screened 92, recruited 36	Daily follow-up during days 1–5, day 14 survey, 30-day usage record	Questionnaire	The mobile application primarily supported monitoring of overall postoperative complications and was associated with self-monitoring and patient engagement.
Ohr et al. (2021) [15]	Australia	Interventional study protocol	Described the protocol for evaluating a post-cesarean SSI surveillance system	Mobile application	Planned sample: 700	30-day postoperative follow-up	Questionnaire	This protocol described the planned evaluation of a mobile application-based post-cesarean SSI surveillance system and specified postoperative outcome assessment procedures.

Table 2. Continued.

Author (year)	Country	Study design	Aim of study	mHealth technology	Sample size (n)	Follow-up period	Data collection	Reported findings or planned outcomes
Fletcher et al. (2021) [19]	Rwanda	Prospective diagnostic study	To develop and evaluate a deep learning model using smartphone-based thermal imaging for automated prediction of surgical site infection after cesarean section.	Smartphone-based thermal imaging using a low-cost thermal camera connected to a mobile phone	530 women after cesarean section (30 SSI, 500 non-SSI)	POD 11 ± 3 days	Thermal wound images captured using a smartphone-attached thermal camera; physician-confirmed SSI diagnosis served as the reference standard.	The transfer learning CNN achieved an AUC of 0.90 with 95% sensitivity and 84% specificity. Smartphone-based thermal imaging combined with deep learning showed strong diagnostic performance for automated SSI prediction, with reduced sensitivity to skin color variation.
Fletcher et al. (2021) [17]	Rwanda	Prospective diagnostic study	To develop and evaluate CNN and transfer learning models for predicting surgical site infection from smartphone color images after cesarean section.	Smartphone color imaging using an Android tablet/mobile device with AI-based image analysis	572 women after cesarean section (62 SSI; 510 non-SSI)	POD 10 ± 3 days	Color-wound images captured by community health workers using an Android tablet; physician examination served as the reference standard for SSI diagnosis. Images were uploaded to a central server for CNN model development.	The naïve CNN achieved AUC 0.655, 75% sensitivity, and 58% specificity. The transfer learning (ResNet50) model achieved 92% sensitivity but lower specificity (18%) and AUC (0.639). Smartphone color images combined with deep learning demonstrated potential as an SSI screening tool, although further optimization was required.
Cherian et al. (2020) [24]	Rwanda	Interventional study	Developed and validated a screening algorithm for identifying SSIs	Telephone-based screening algorithm	596 eligible, recruited 525	Postoperative day 10 (±3 days)	Questionnaire	The screening algorithm demonstrated adequate sensitivity and specificity for SSI detection.

Table 2. Continued.

Author (year)	Country	Study design	Aim of study	mHealth technology	Sample size (n)	Follow-up period	Data collection	Reported findings or planned outcomes
Fletcher et al. (2019) [18]	Rwanda	Prospective diagnostic study	To develop machine learning models using questionnaire and smartphone wound image data for predicting surgical site infection after cesarean section.	Smartphone-based wound imaging combined with questionnaire-based screening	Questionnaire analysis: 572 participants (61 SSI cases); image analysis: 568 participants (62 SSI cases)	POD 10 ± 3 days	Community health workers captured wound images using an Android tablet and administered a symptom questionnaire. SSI was confirmed by a physician's physical examination.	The image-based support vector machine (SVM) model achieved an AUC of 99.5%, 99% sensitivity, and 99% specificity, outperforming questionnaire-based models. Combined questionnaire and image data demonstrated the feasibility of AI-assisted SSI screening in this study.
Sonderman et al. (2018) [16]	Rwanda	Randomized controlled trial protocol	Investigated mHealth technology for identifying and referring SSIs	Tablet-based wound photography and referral system	Planned sample: 1166 participants	Planned 30-day follow-up; participants identified as having an SSI were to be followed for up to 90 days	Photographs	The protocol described the planned evaluation of a tablet-based wound-photography and referral system involving community health workers.
Castillo et al. (2017) [25]	Canada	Prospective cohort study	Assessed the feasibility of self-reported SSI surveillance	Mobile application	105	Postpartum days 3, 7, 10, and 30	Photographs Questionnaire	Self-reported SSI surveillance using a mobile application was found to be feasible following cesarean section.
Fawsitt et al. (2017) [26]	Ireland	Feasibility study	Compared the cost-effectiveness of integrated and standalone applications	Mobile application	244	First 30 days postpartum	Questionnaire	Cesarean mothers most preferred an integrated app (47.5%), followed by a telephone helpline (18.0%) and a stand-alone app (8.2%). Women preferred integrated applications; standalone applications were more cost-effective.

References [17] and [18] used the same underlying participant cohort. Abbreviations: AI, artificial intelligence; AUC, area under the curve; CHW, community health worker; CNN, convolutional neural network; POD, postoperative day; ResNet50, Residual Network 50; SSI, surgical site infection.



Fig. 3. Geographic distribution of the included publications by country, 2017–2024. Bubble size represents the number of included publications, not the cumulative participant sample.

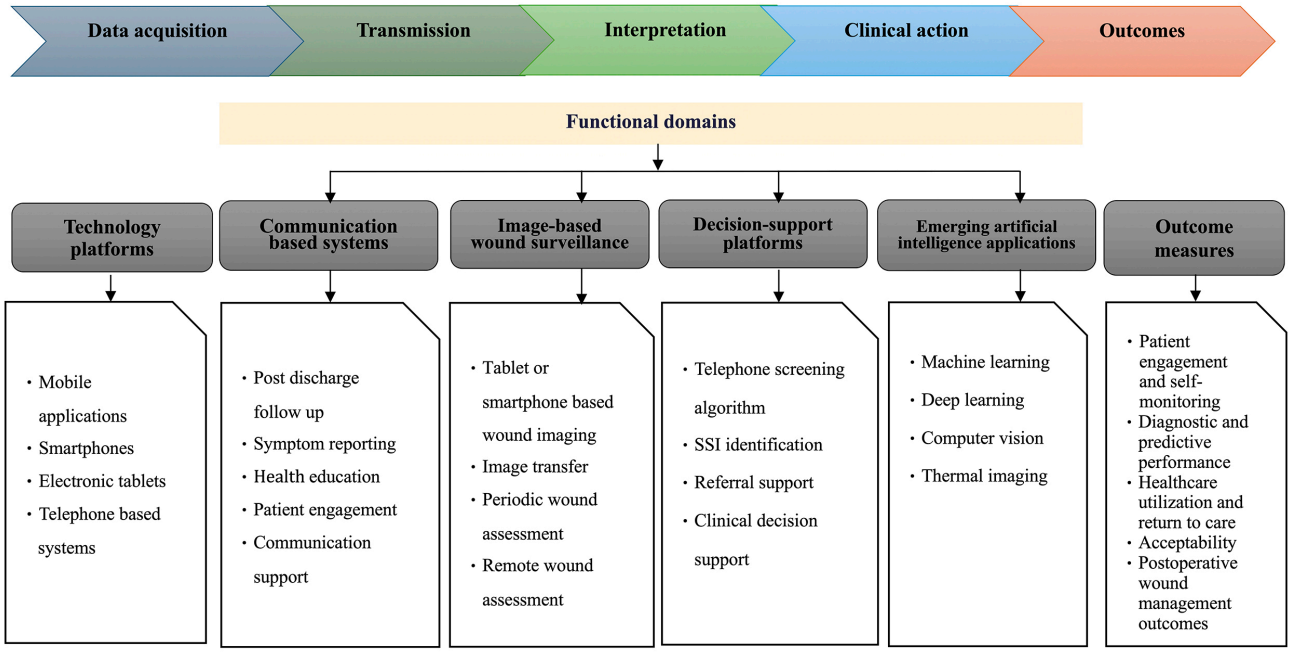


Fig. 4. Conceptual framework of mHealth technologies for cesarean section wound surveillance. Abbreviations: SSI, surgical site infection.

4.1 Communication-Based Systems

There is a rapid uptake of mHealth technologies that has expanded opportunities for remote communication and follow-up [27]. Compared with conventional outpatient follow-up, these systems may facilitate early symptom identification while potentially reducing unnecessary hospital visits, particularly in resource-limited settings [28]. The common applications for mHealth technologies include educational modules, staging tools, and caregiver-focused applications [23,29,30]. The use of mHealth technologies and smartphone-based self-monitoring may support post-CS care, primarily because they enable continuous follow-up throughout psychophysical recovery. mHealth technologies also allow users to record the wound-healing process, monitor signs of infection, consult with healthcare professionals, undergo hospital review, and receive antibiotic treatment [20]. Another study reported that these tools were used for documentation, wound monitoring, and postoperative follow-up in both clinical and home settings [30]. Care pathways following SSI detection varied across studies, with some women referred to hospital services and others managed by community healthcare providers, reflecting differences in healthcare systems and implementation strategies.

The World Health Organization recognizes the postnatal period as a critical phase requiring ongoing support for both women and newborns, underscoring the importance of effective post-discharge follow-up [31]. Engagement with mHealth technologies was highest during the early postoperative period and gradually declined over time, suggesting that their use may be influenced by symptom severity and recovery status. Response rates were 53%, 67%, and 61% on the first three postoperative days, respectively, falling to 42% and 44% on days four and five, respectively [23]. Higher levels of engagement have been reported in other surgical populations, where digital postoperative wound monitoring achieved an overall usage rate of 83.0% in routine clinical practice [32]. This difference may reflect variations in postpartum recovery, symptom severity, infant care demands, and time constraints. In addition, differences in health literacy may influence how women interact with mHealth technologies. Mothers with higher digital engagement have been shown to use smartphones and video-calling applications as important resources for postpartum support, whereas some continue to report limited confidence in making health-related decisions based on information obtained through digital platforms [33]. These findings suggest that both digital access and health literacy may influence engagement with mHealth technologies and should be considered when designing postpartum follow-up interventions. These findings may be interpreted using the Technology Acceptance Model (TAM), which proposes that continued use of technology is influenced by perceived usefulness and perceived ease of use [34]. Building on the TAM, the Unified Theory of Acceptance and Use of Technology (UTAUT) proposes a broader framework for understanding technology adoption by integrating multiple determinants of technology acceptance and use [35]. Although not applied in the included studies, these frameworks may offer a useful perspective for interpreting differences in user engagement across mHealth technologies.

4.2 Image-Based Wound Surveillance

The increasing availability of smartphones has expanded the use of image-based surveillance for postoperative wound monitoring. mHealth technology holds potential for remote postoperative wound monitoring [28]. According to another study, wound care patients can use mHealth technologies to assess their wounds by taking photographs daily, weekly, or every few weeks, after discharge from the hospital [28,32,36]. Women uploaded wound photographs and self-reported symptoms, including erythema, swelling, pain, fever, and healthcare utilization. Multiple studies have used mHealth technologies to monitor wound conditions in women following CSs for up to 30 days [15,16,21,23,25,26]. One study protocol planned follow-up for up to 90 days among participants identified as having an SSI [16]. These findings suggest that image-based wound surveillance is feasible over varying follow-up periods and may support continued postoperative monitoring beyond routine clinical care. Most image datasets used to develop and evaluate image-based surveillance systems have been collected in non-Western settings, and no publicly available datasets of CS wound infection images currently exist. In addition, limited reporting of image metadata and eligibility criteria may reduce reproducibility and hinder further development of image-based surveillance technologies [28].

4.3 Decision-Support Platforms

Decision support platforms combine patient-reported information with structured clinical algorithms to support postoperative assessment. Remote digital postoperative wound monitoring uses patient-reported symptoms and wound images to support clinician assessment [37]. In the included publication, a telephone-based screening algorithm was used to identify women with suspected SSI following CS. The combination of questions concerning fever, pain, and discolored drainage showed high sensitivity for both the general practitioners (GPs; sensitivity = 96.8%; specificity = 85.6%) and community health workers (CHWs; sensitivity = 87.1%; specificity = 73.8%) [24]. Decision support platforms use structured clinical algorithms to support postoperative assessment, clinical triage, and referral decisions while complementing, rather than replacing, clinical judgment, particularly for healthcare providers with limited training or experience in wound management [38]. Their implementation may be particularly relevant in rural and resource-limited settings, where access to specialist postoperative assessment may be limited. The decision-support application described in the included study focused

on telephone-based screening for suspected SSI [24]. Future research could explore user-centered designs that address a broader range of postpartum recovery needs.

4.4 Emerging Artificial Intelligence Applications

Integrating of mHealth technologies with artificial intelligence depends on effective data collection and may be challenging in outpatient and remote monitoring settings. Consequently, research in this area remains at an early stage [28]. Although artificial intelligence applications for post-CS wound surveillance are still emerging, studies have shown the potential of machine learning and deep learning models to support automated interpretation of wound images and prediction of SSI [17,18,19]. An Italian study applied artificial intelligence algorithms to predict the length of hospital stay after cesarean section, with the decision tree model achieving the highest classification accuracy (75%) [39]. Research has shown that recent advances in machine learning and computer vision have expanded the potential role of artificial intelligence in postoperative wound surveillance, including automated wound image interpretation, diagnosis, and disease treatment [40]. Other studies have used machine learning or thermal imaging to predict CS SSIs [18,19]. Nevertheless, several challenges remain before widespread clinical implementation [28,41,42], including infrastructure requirements, data privacy, limited external validation, algorithm performance across different skin tones, workforce training, and financial investment.

4.5 Implementation Challenges

The successful implementation of mHealth technologies depends on several key domains. First, human factors include digital literacy, patient acceptance, and socioeconomic and cultural factors [33,43,44]. The digital divide remains important, as women without an iPhone were excluded from participation [25]. In Ireland, women were also willing to pay between US $25.20 and US $29.61 for mHealth technologies providing postoperative support during the first 30 days after CS [26]. Evidence from rural Rwanda supported the feasibility of the mHealth intervention [21] and demonstrated high acceptance of mHealth technologies [22], suggesting that government policies and implementation strategies may need to be adapted to local healthcare systems and population needs. Second, organizational factors include regulatory issues, integration into routine clinical workflows, and socioeconomic and cultural considerations [30,45]. Third, technical considerations include network connectivity and interoperability with electronic health records (EHRs) [36], as well as data security and privacy [36].

Key evidence gaps include the lack of adequately powered randomized controlled trials, limited evidence regarding cost-effectiveness, poor integration of mHealth platforms with EHRs, the absence of standardized wound photography protocols, limited validation of artificial intelligence algorithms in real-world clinical settings, limited geographic diversity and uncertain transferability beyond the specific Rwandan programs studied, and limited data regarding long-term patient adherence and implementation barriers. Furthermore, none of the included publications were conducted in Asia. mHealth technologies hold promising potential to transform CS wound care, but realizing their full value will require ongoing innovation, robust evaluation, and responsiveness to the needs of both patients and healthcare providers.

4.6 Future Perspectives

The findings of this scoping review suggest that the future development of mHealth technologies for post-CS wound surveillance may depend on several key factors, including multidisciplinary collaboration, user-centered design, and consideration of women's healthcare needs. AI-based models have been investigated to support individualized prediction of delivery modes [46]. Their potential application to post-CS recovery and wound surveillance requires further investigation. Studies have explored machine learning and deep learning approaches using wound images and/or clinical symptom data to predict SSI following CS [17,18,19]. Obstetric and gynecologic healthcare professionals should consider individual symptoms and physical examination findings to identify high-risk individuals and provide personalized recommendations [47].

Future mHealth technologies may evolve beyond symptom reporting to integrate clinical data, wound images, and artificial intelligence models for risk prediction and clinical decision support. Although machine learning and deep learning approaches have been explored, the present review identified limited research on integrating large language models (LLMs) into mHealth technologies for post-CS wound care. Future integration should consider the safety and regulatory implications of LLM-based health applications [48]. Future research should evaluate the patient safety, usability, and implementation of mHealth technologies across diverse healthcare settings [45]. Such developments may contribute to more personalized, timely, and accessible postoperative wound surveillance following CSs.

4.7 Strengths and Limitations

This review summarized the current applications of mHealth technologies for CS wound surveillance and identified several limitations in the available evidence. First, although comprehensive search strategies were applied, only 12 publications met the eligibility criteria, reflecting the relatively limited evidence currently available. Additional search strategies, such as forward citation searching may have identified further relevant studies and reduced the potential for selection bias. Second, considerable heterogeneity was observed across intervention characteristics, technological platforms, follow-up duration, healthcare settings, outcome measures, and study designs. Similar find-

ings are reported in other literature [30,49]. The analysis revealed that there is neither a consensus on the methods for evaluating mHealth technologies nor a commonly agreed-upon definition or usage of the evaluated indicators, resulting in a wide variety of evaluation practices. Such variability limited direct comparison across studies and may reduce the generalizability of the review findings. Third, as a scoping review, it did not assess comparative effectiveness or undertake a formal risk-of-bias appraisal. Instead, it provided a broad overview of the knowledge and identified gaps in the research base. Even so, this review helps lay the groundwork for understanding how mHealth is being used in CS wound care today and points to clear directions for the future.

5. Conclusions

Current evidence suggests that mHealth technologies may be feasible and acceptable tools with considerable potential to support post-CS wound surveillance. The use of these technologies remains an evolving field, with available evidence suggesting that communication-based systems, image-based wound surveillance, decision-support platforms, and emerging artificial intelligence applications may support postoperative monitoring and follow-up. However, the evidence base remains limited and heterogeneous in terms of study design, technological approach, outcome measures, and follow-up duration, with several technologies still at an early stage of development or validation. Robust comparative studies are therefore needed before widespread clinical implementation can be recommended.

Author Contributions

Study conception and design: YTK, HJC, CWC, HCT, ICH. Data collection: YTK, CST, SJG. Data analysis and interpretation: YTK, CST, SJG. Drafting of the article: YTK. Critical revision of the article: HJC, CWC, HCT, ICH. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

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Conflicts of Interest

The authors declare no conflicts of interest.

Supplementary Material

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References

[1] American College of Obstetricians and Gynecologists. Cesarean birth (C-section). 2022. Available at: https://www.acog.org/womens-health/faqs/cesarean-birth (Accessed: 16 June 2026).

[2] Kawakita T, Landy HJ. Surgical site infections after cesarean delivery: epidemiology, prevention and treatment. Maternal Health, Neonatology and Perinatology. 2017; 3: 12. https://doi.org/10.1186/s40748-017-0051-3

[3] Farid Mojtahedi M, Sepidarkish M, Almukhtar M, Eslami Y, Mohammadianamiri F, Behzad Moghadam K, et al. Global incidence of surgical site infections following caesarean section: a systematic review and meta-analysis. The Journal of Hospital Infection. 2023; 139: 82–92. https://doi.org/10.1016/j.jhin.2023.05.019

[4] National Healthcare Safety Network. Surgical Site Infection Event (SSI). 2026. Available at: https://www.cdc.gov/nhsn/pdfs/pscmanual/9pscssicurrent.pdf (Accessed: 16 June 2026).

[5] World Health Organization. World Health Organization (WHO) Guideline: Recommendations on Digital Interventions for Health System Strengthening. 2019. Available at: https://iris.who.int/handle/10665/311941 (Accessed: 16 June 2026).

[6] Istepanian RSH. Mobile Health (m-Health) in Retrospect: The Known Unknowns. International Journal of Environmental Research and Public Health. 2022; 19: 3747. https://doi.org/10.3390/ijerph19073747

[7] Kuan YT, Wang TF, Guo CY, Tang FI, Hou IC. Wound Care Knowledge, Attitudes, and Practices and Mobile Health Technology Use in the Home Environment: Cross-Sectional Survey of Social Network Users. JMIR MHealth and UHealth. 2020; 8: e15678. https://doi.org/10.2196/15678

[8] Henarejos V, O'Connor K, Barrasa A, Villalonga A, Pastor C, Puyana JC, et al. Implementing a mHealth-Based Patient and Nurse Educational Program to Reduce Wound Infection in Rural Philippines. Annals of Global Health. 2022; 88: 76. https://doi.org/10.5334/aogh.3834

[9] Mosa ASM, Yoo I, Sheets L. A systematic review of healthcare applications for smartphones. BMC Medical Informatics and Decision Making. 2012; 12: 67. https://doi.org/10.1186/1472-6947-12-67

[10] Lockwood C, Dos Santos KB, Pap R. Practical Guidance for Knowledge Synthesis: Scoping Review Methods. Asian Nursing Research. 2019; 13: 287–294. https://doi.org/10.1016/j.anr.2019.11.002

[11] Arksey H, O'Malley L. Scoping studies: towards a methodological framework. International Journal of Social Research Methodology. 2005; 8: 19–32. https://doi.org/10.1080/1364557032000119616

[12] Peters MDJ, Marnie C, Tricco AC, Pollock D, Munn Z, Alexander L, et al. Updated methodological guidance for the conduct of scoping reviews. JBI Evidence Synthesis. 2020; 18: 2119–2126. https://doi.org/10.11124/JBIES-20-00167

[13] Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. Annals of Internal Medicine. 2018; 169: 467–473. https://doi.org/10.7326/M18-0850

[14] Ouzzani M, Hammady H, Fedorowicz Z, Elmagarmid A.

Rayyan-a web and mobile app for systematic reviews. Systematic Reviews. 2016; 5: 210. https://doi.org/10.1186/s13643-016-0384-4

[15] Ohr SO, Giles M, Munnoch S, Hunter M, Bolte M, Ferguson J, et al. What gets measured gets noticed. Tracking surgical site infection post caesarean section through community surveillance: A post intervention study protocol. Journal of Advanced Nursing. 2021; 77: 2530–2538. https://doi.org/10.1111/jan.14796

[16] Sonderman KA, Nkurunziza T, Kateera F, Gruendl M, Koch R, Gaju E, et al. Using mobile health technology and community health workers to identify and refer caesarean-related surgical site infections in rural Rwanda: a randomised controlled trial protocol. BMJ Open. 2018; 8: e022214. https://doi.org/10.1136/bmjopen-2018-022214

[17] Fletcher RR, Schneider G, Hedt-Gauthier B, Nkurunziza T, Alayande B, Riviello R, et al. Use of Convolutional Neural Nets and Transfer Learning for Prediction of Surgical Site Infection from Color Images. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference. 2021; 2021: 5047–5050. https://doi.org/10.1109/EMBC46164.2021.9630430

[18] Fletcher RR, Olubeko O, Sonthalia H, Kateera F, Nkurunziza T, Ashby JL, et al. Application of Machine Learning to Prediction of Surgical Site Infection. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference. 2019; 2019: 2234–2237. https://doi.org/10.1109/EMBC.2019.8857942

[19] Fletcher RR, Schneider G, Bikorimana L, Rukundo G, Niyigena A, Miranda E, et al. The Use of Mobile Thermal Imaging and Deep Learning for Prediction of Surgical Site Infection. Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual International Conference. 2021; 2021: 5059–5062. https://doi.org/10.1109/EMBC46164.2021.9630094

[20] Ohr SO, Ball J, Teber E, Ferguson JK, Petherbridge R, Giles M. Effectiveness of HealthTracker for post-caesarean section surgical site infection surveillance: An intervention study. Nursing & Health Sciences. 2024; 26: e13108. https://doi.org/10.1111/nhs.13108

[21] Kateera F, Riviello R, Goodman A, Nkurunziza T, Cherian T, Bikorimana L, et al. The Effect and Feasibility of mHealth-Supported Surgical Site Infection Diagnosis by Community Health Workers After Cesarean Section in Rural Rwanda: Randomized Controlled Trial. JMIR MHealth and UHealth. 2022; 10: e35155. https://doi.org/10.2196/35155

[22] Nkurunziza T, Williams W, Kateera F, Riviello R, Niyigena A, Miranda E, et al. mHealth-community health worker telemedicine intervention for surgical site infection diagnosis: a prospective study among women delivering via caesarean section in rural Rwanda. BMJ Global Health. 2022; 7: e009365. https://doi.org/10.1136/bmjgh-2022-009365

[23] Ke JXC, George RB, Wozney L, Munro A. Perioperative mobile application for mothers undergoing Cesarean delivery: a prospective cohort study on patient engagement. Canadian Journal of Anaesthesia = Journal Canadien D'anesthesie. 2021; 68: 505–513. https://doi.org/10.1007/s12630-020-01907-x

[24] Cherian T, Hedt-Gauthier B, Nkurunziza T, Sonderman K, Gruendl MA, Nihiwacu E, et al. Diagnosing Post-Cesarean Surgical Site Infections in Rural Rwanda: Development, Validation, and Field Testing of a Screening Algorithm for Use by Community Health Workers. Surgical Infections. 2020; 21: 613–620. https://doi.org/10.1089/sur.2020.062

[25] Castillo E, McIsaac C, MacDougall B, Wilson D, Kohr R. Post-Caesarean Section Surgical Site Infection Surveillance Using an Online Database and Mobile Phone Technology. Journal of Obstetrics and Gynaecology Canada: JOGC = Journal D'obstetrique et Gynecologie Du Canada: JOGC. 2017; 39: 645–651.e1. https://doi.org/10.1016/j.jogc.2016.12.037

[26] Fawsitt CG, Meaney S, Greene RA, Corcoran P. Surgical Site Infection after Caesarean Section? There Is an App for That: Results from a Feasibility Study On Costs and Benefits. Irish Medical Journal. 2017; 110: 635.

[27] Ogundaini OO, de la Harpe R, McLean N. Integration of mHealth Information and Communication Technologies Into the Clinical Settings of Hospitals in Sub-Saharan Africa: Qualitative Study. JMIR MHealth and UHealth. 2021; 9: e26358. https://doi.org/10.2196/26358

[28] Tabja Bortesi JP, Ranisau J, Di S, McGillion M, Rosella L, Johnson A, et al. Machine Learning Approaches for the Image-Based Identification of Surgical Wound Infections: Scoping Review. Journal of Medical Internet Research. 2024; 26: e52880. https://doi.org/10.2196/52880

[29] Lavender T, Smyth RM, Chimwaza AF, Mills TA, Dwan K. Mobile health (m-health) technological support for women during pregnancy or the first six weeks postpartum, or both. Cochrane Database of Systematic Reviews. 2023; 2023. https://doi.org/10.1002/14651858.cd015191

[30] Jogi S, Devi ES, Shanbhag V, Shenoy K B A. The utility of mHealth applications in pressure ulcer management: A scoping review. Digital Health. 2025; 11: 20552076251386656. https://doi.org/10.1177/20552076251386656

[31] World Health Organization. WHO recommendations on maternal and newborn care for a positive postnatal experience. World Health Organization: Geneva. 2022. Available at: https://www.who.int/publications/i/item/9789240045989 (Accessed: 16 June 2026).

[32] Rochon M, Cariaga K, Ingusan SD, Jawarchan A, Morais C, Rajakumar G, et al. Postoperative wound surveillance using patient smartphones: Learning from a large London maternity service. Wounds UK. 2024; 20: 34–39.

[33] Donelle L, Hiebert B, Hall J. An investigation of mHealth and digital health literacy among new parents during COVID-19. Frontiers in Digital Health. 2024; 5: 1212694. https://doi.org/10.3389/fdgth.2023.1212694

[34] Davis FD. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly. 1989; 13: 319–340. https://doi.org/10.2307/249008

[35] Venkatesh V, Morris MG, Davis GB, Davis FD. User Acceptance of Information Technology: Toward A Unified View1. MIS Quarterly. 2003; 27: 425–478. https://doi.org/10.2307/30036540

[36] Lin J, Bates SM, Allen LN, Wright M, Mao L, Kidd M. Integrating Mobile Health App Data Into Electronic Medical or Health Record Systems and Its Impact on Health Care Delivery and Patient Health Outcomes: Scoping Review. JMIR MHealth and UHealth. 2025; 13: e66650. https://doi.org/10.2196/66650

[37] McLean KA, Sgrò A, Brown LR, Buijs LF, Daines L, Potter MA, et al. Evaluation of remote digital postoperative wound monitoring in routine surgical practice. NPJ Digital Medicine. 2023; 6: 85. https://doi.org/10.1038/s41746-023-00824-9

[38] Jordan S, McSwiggan J, Parker J, Halas GA, Friesen M. An mHealth App for Decision-Making Support in Wound Dressing Selection (WounDS): Protocol for a User-Centered Feasibility Study. JMIR Research Protocols. 2018; 7: e108. https://doi.org/10.2196/resprot.9116

[39] Scala A, Bifulco G, Borrelli A, Egidio R, Triassi M, Improta G. Use of artificial intelligence to study the hospitalization of women undergoing caesarean section. BMC Public Health. 2025; 25: 238. https://doi.org/10.1186/s12889-025-21530-z

[40] Black J. Artificial intelligence in wound care: help or hinderance? Wounds International. 2025; 16: 5.
[41] Chadwick P. The role of artificial intelligence in wound care: applications, evidence and future directions. Wounds International. 2025; 16: 30–41.
[42] Wu G, Khair S, Yang F, Cheligeer C, Southern D, Zhang Z, et al. Performance of machine learning algorithms for surgical site infection case detection and prediction: A systematic review and meta-analysis. Annals of Medicine and Surgery (2012). 2022; 84: 104956. https://doi.org/10.1016/j.amsu.2022.104956
[43] Wittich L, Rödiger H, Rombey T, Brecher AL, Kraft L, Sgraja S, et al. Navigating the complexities of digital health technology implementation: a scoping review of barriers and facilitators. Implementation Science Communications. 2026; 7: 69. https://doi.org/10.1186/s43058-026-00892-4
[44] Dege T, Glatzel B, Borst V, Grän F, Goller S, Glatzel C, et al. Patient-Centered Chronic Wound Care Mobile Apps: Systematic Identification, Analysis, and Assessment. JMIR MHealth and UHealth. 2024; 12: e51592. https://doi.org/10.2196/51592
[45] Su JJ, Chan MHS, Ghisi GLDM, Kwan RYC, Wong AKC, Lin R, et al. Real-World Mobile Health Implementation and Patient Safety: Multicenter Qualitative Study. Journal of Medical Internet Research. 2025; 27: e71086. https://doi.org/10.2196/71086
[46] Zhou Y, Li J, Hou X, Li Z, Xu Y, Wang Y, et al. Artificial Intelligence for Predicting Delivery Modes: A Systematic Review of Applications, Challenges, and Future Directions. Clinical and Experimental Obstetrics & Gynecology. 2025; 52: 37807. https://doi.org/10.31083/ceog37807
[47] Xing X, Guo W. The Impact of Pregnancy and Mode of Delivery on Female Pelvic Floor Function: A Narrative Review. Clinical and Experimental Obstetrics & Gynecology. 2025; 52: 37358. https://doi.org/10.31083/ceog37358
[48] Freyer O, Wiest IC, Kather JN, Gilbert S. A future role for health applications of large language models depends on regulators enforcing safety standards. The Lancet. Digital Health. 2024; 6: e662–e672. https://doi.org/10.1016/S2589-7500(24)00124-9
[49] Weirauch V, Soehnchen C, Burmann A, Meister S. Methods, Indicators, and End-User Involvement in the Evaluation of Digital Health Interventions for the Public: Scoping Review. Journal of Medical Internet Research. 2024; 26: e55714. https://doi.org/10.2196/55714