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Digital Technologies in Maternal Healthcare: A Thematic Review of mHealth, Telehealth and Artificial Intelligence

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ABSTRACT

Digital health has evolved through multiple technological generations from machine learning prediction, but these technologies have never been synthesized as a single trajectory. Thus, this paper provides a thematic review of the evolutionary progression of digital health interventions in maternal care, with a focus on continuity and emergence of themes. Searches were conducted using structured search protocols for mHealth, telehealth, data infrastructure, artificial intelligence predictions, decision support systems, cosnversational agents, remote monitoring, equitable delivery of care and governance. Records were screened for relevance to digital maternal care, and thematic synthesis was performed on 67 sources that met the criteria for the study. The synthesis was organized by generation and coded for continuity vs. emergence. Ten themes were identified across all 67 sources. While mHealth improved attendance at antenatal appointments and service linkage, most studies had poor methodological quality and did not assess mortality effects directly. Telehealth demonstrated safety at scale, with 45.94% of antenatal consultations provided via video, without significant change in preeclampsia, fetal growth restriction, preterm birth or stillbirth. Artificial intelligence-based prediction studies reported strong discrimination (AUROC = 0.7–0.9; median = 0.8); however, only 11 of 28 studies (39%) provided external validation, and data completeness in one national maternal electronic record reached 28%. Themes such as equity, infrastructure, data quality and clinician trust were consistent throughout all three generations. Calibration, explainability, algorithmic bias, federated learning and large-language-model governance were identified as emerging themes during the transition from mHealth to AI. Thus, instead of resolving the field's core problems, each successive technology generation amplified those same issues rather than replacing them. The field's current constraints remain workflow integration and data quality.

INTRODUCTION

Maternal mortality is a major global health problem. Each year globally, there are approximately 303,000 maternal deaths and 5.4 million child deaths. The burden of maternal mortality falls disproportionately on low- and middle-income countries (LMICs) (Kanayan, 2025; Modi *et al.*, 2019). Even when looking at individual country levels, there are also significant disparities; for example, India's maternal mortality ratio, which varies by reporting period and source hides large regional discrepancies (Mohit *et al.*, 2026). As long-term trends show, maternal mortality decreased by forty-five percent, while under-five mortality fell dramatically, declining from an average of 90 per 1,000 live births in 1990 to 43 in 2015 (Lee *et al.*, 2015). While progress has been made, that progress is limited. That progress has largely resulted from increased access to services as well as improved service quality, rather than from any specific technological advancements. The use of digital technologies has been proposed as a means to improve access to services in order to increase coverage. The premise is simple enough: mobile-cellular penetration of developing countries reached nearly all people by the mid-2010s, providing a method to deliver technology without having to build new physical infrastructure (Sondaal *et al.*, 2016). Following this, twenty years of interventions were developed. Those interventions can be grouped together into distinct generations. For this review, the generations are operational categories rather than mutually exclusive chronological periods: mHealth refers to SMS, voice and phone-based services; telehealth to remote consultations and monitoring; and data-driven AI to algorithmic prediction and decision support. The first generation, mHealth, relied on voice, SMS and phone-based decision support and addressed behavior modification, appointment reminders and the linking of patients to needed medical services. The second, telehealth, went beyond just communications; it began substituting face-to-face consultations with remote consultations and in-clinic exams with home monitoring. The third and most current generation is data-driven: artificial intelligence (AI) and machine learning models that assess patient risk, analyze images and predict outcomes from patient data that is commonly collected.

Each generation has had its reviews. What is lacking is a comprehensive review that views the three generations collectively and asks what problems each generation helped solve, what problems it failed to address and what new problems it may have created. This thematic review compares reported functions, implementation constraints, and strength of evidence across mHealth, telehealth and AI, with particular attention to persistent versus emerging

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challenges. It does not estimate comparative effectiveness across technologies.

MATERIALS AND METHODS

Search Strategy

Sixteen structured searches were run across the academic literature, covering eight thematic angles: (i) mHealth interventions and maternal, newborn and child health outcomes in LMICs; (ii) AI and machine learning for maternal mortality risk prediction in low-resource settings; (iii) digital health equity and access barriers; (iv) machine-learning prediction of adverse pregnancy outcomes from electronic records; (v) mobile device–enabled decision support for community health workers; (vi) SMS and mobile messaging for antenatal care attendance; (vii) telehealth and remote antenatal care; and (viii) maternal health data quality in electronic health record systems. Additional searches covered AI in perinatal imaging, digital health scale-up and sustainability, federated learning, conversational agents, qualitative work on technology acceptance, AI governance in LMICs, remote blood-pressure monitoring, and explainable clinical decision support.

Eligibility and selection

Records were retained if they addressed a digital technology applied to maternal and health; reported empirical, trial, review, or synthesis findings; and were relevant to either high-income or low-resource implementation contexts. Records were removed as duplicates where the same work was returned by more than one search, and duplicate reports of the same study (for example, preprint and published versions) were counted once. Figure 1 presents the reported selection counts. Because the search was not exhaustive and a reproducible database-level strategy is not documented, this diagram should not be interpreted as evidence of a fully PRISMA-compliant systematic review.

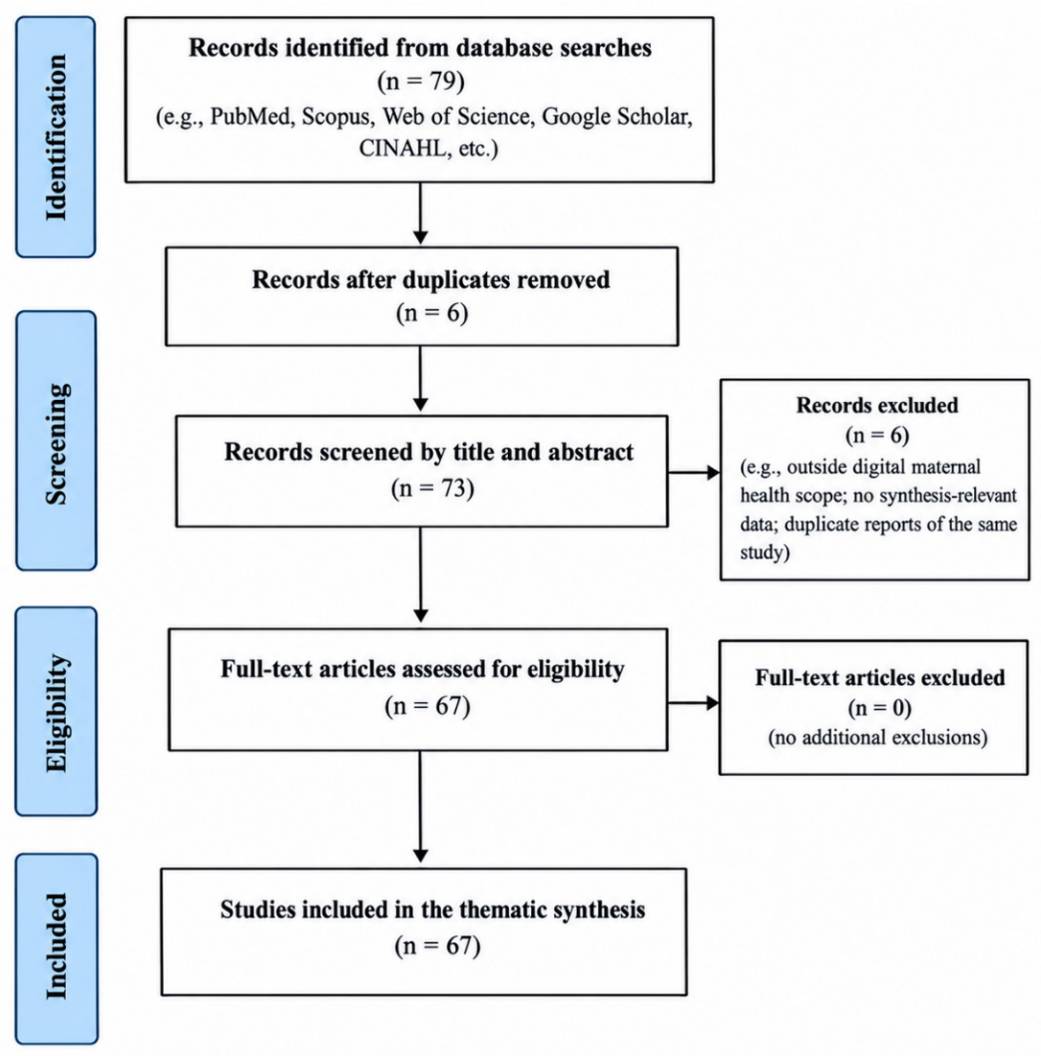


Figure 1: PRISMA Flowchart

Note: The counts in Figure 1 reflect the retrieval and screening yields of the searches conducted for this synthesis rather than an exhaustive systematic database harvest, and they are reported so the inclusion base can be audited. All 67 included reports passed eligibility assessment, as shown in Table 1.

Table 1: Study Characteristics of the Included Sources

No.	Study	Generation	Design	Setting	Key findings
1	Till *et al.* (2023)	mHealth	Cross-disciplinary scoping review	Africa & other LMICs	Codebook thematic analysis; barriers include overreliance on text-based communication; opportunities in cheaper mobile data, smartphones/wearables, culturally appropriate low-literacy apps
2	Samaran (2024)	mHealth	Review	—	Integration of digital health technologies in maternal and child health management: opportunities and challenges
3	Kabongo *et al.* (2021)	mHealth	Realist synthesis	LMICs	Models the mechanisms and contextual conditions that explain mHealth impact on MCH care
4	Atkinson *et al.* (2023)	Telehealth	Review	High-resource settings	Historical ANC = 12–14 face-to-face visits; telehealth appeared not to increase adverse outcomes; acceptable to women and providers
5	Ames *et al.* (2019)	mHealth	Qualitative evidence synthesis	RMNCAH	Targeted digital communication via mobile devices; thematic analysis as analytic method
6	Lee *et al.* (2023)	mHealth	Qualitative	Women pre- to post-pregnancy	Personalization and localization as key expectations; 5 themes and 9 subthemes
7	Susilowati *et al.* (2025)	mHealth	Scoping review	Maternal care	Effect of digital health use for maternal care
8	Sondaal *et al.* (2016)	mHealth	Systematic review	LMICs	Effect of mHealth interventions on maternal and neonatal care
9	Amoakoh-Coleman *et al.* (2016)	mHealth	Systematic review	LMICs	19 studies (10 intervention, 9 descriptive) targeting health care workers; none directly assessed maternal/neonatal mortality
10	Zenitasari *et al.* (2026)	mHealth	Scoping review	—	E-health interventions and maternal outcomes
11	Asamoah (2025)	mHealth	Systematic review	Global	Digital health innovations and reduction of maternal and infant mortality: successes, challenges, best practices
12	Turkmani *et al.* (2023)	Telehealth	Programme evaluation	Bangladesh & Lao PDR	Introduction of telehealth for remote antenatal and postnatal contacts during COVID-19
13	Konnyu *et al.* (2023)	Telehealth	Review	—	Changes to prenatal care visit frequency and telehealth
14	Bossman *et al.* (2022)	mHealth	Systematic literature review	Sub-Saharan Africa & Southern Asia	mHealth interventions to reduce maternal and child mortality

15	Kanayan (2025)	Data-driven/ AI	Systematic narrative review	LMICs	42 studies from 436 screened; AUROC 0.75–0.93; deployments in Kenya, India, Ethiopia, Guatemala
16	Sylvain *et al.* (2025)	Data-driven/ AI	ML analysis of EMR data	Rwanda	117,069 women delivered; only 32,783 analysable (28% completeness) vs 85% in a prior HIV-care EMR study
17	Aifuobhokhan *et al.* (2025)	Data-driven/ AI	Systematic review	Rural settings	28 studies; sub-Saharan Africa n = 12, South Asia n = 8; datasets 402 to >31 million records; Random Forest n = 14, ensemble n = 11, neural networks n = 11; AUROC 0.70–0.95 (median 0.84); sensitivity 70–92%; specificity 65–85%; external validation in 11 studies (39%)
18	Umar *et al.* (2026)	Data-driven/ AI	Narrative review	Resource-limited settings	AI in MCH through digital health initiatives
19	Bhagya *et al.* (2026)	Data-driven/ AI	Scoping review	LMICs	AI for predicting and managing high-risk pregnancies
20	Modi *et al.* (2019)	mHealth	Cluster RCT	Tribal Gujarat, India	ImTeCHO mHealth job aids delivered via frontline health workers in the public system
21	Mohit *et al.* (2026)	Data-driven/ AI	ML framework	Indian Himalayan region	UttaraRisk-Next multi-task ensemble; 22.4% of pregnancies identified high risk; 2.1 ms inference; 45 MB footprint
22	Lee *et al.* (2015)	mHealth	Systematic review & meta-analysis	LMICs	Effectiveness of mHealth for maternal, newborn and child health
23	Knop *et al.* (2024)	mHealth	Systematic review	LMICs	mHealth from conception to 24 months postpartum; searched PubMed, Cochrane, Embase, CINAHL, Web of Science, Scopus, PsycINFO, Trip Pro (2000–2022)
24	Lund *et al.* (2014)	mHealth	Cluster RCT	Zanzibar	"Wired mothers" SMS: 2 messages/month before week 36, intensifying to 2/week from week 36 to 6 weeks postpartum
25	Gitonga *et al.* (2021)	mHealth	RCT	Rural Kenya	118 per arm; 75% of intervention group completed four targeted ANC visits vs 10% of controls; SMS reminders raised odds of attendance 27-fold ($P < 0.001$)
26	Masoi *et al.* (2023)	mHealth	Quasi-experimental	Dodoma, Tanzania	Interactive mobile health technologies; SMS module auto-generated from previous visit date and gestational age
27	Oliveira-Ciabati *et al.* (2017)	mHealth	Cluster RCT	Brazil	PRENACEL: 20 units (10 intervention, 10 control); bi-directional SMS with weekly education messages and text queries
28	Dzabeng *et al.* (2016)	mHealth	Qualitative synthesis	Developing countries	Community health workers' experiences of mobile device–enabled CDSS for MNCH
29	McNabb *et al.* (2015)	mHealth	Pre/post-intervention	Northern Nigeria	Mobile phone decision support (CommCare: 50+ organisations, 30 countries); 33% fewer decision errors, 30% higher protocol compliance

30	Amoakoh *et al.* (2019)	mHealth	Cluster RCT (18 months)	Eastern Region, Ghana	mHealth CDSS delivering emergency maternal/neonatal protocols by SMS/USSD
31	Nigussie *et al.* (2021)	mHealth	Programme evaluation	Ethiopia	mHealth for timeliness/quality of MNH in primary care; infrastructure mitigation (data, electricity, devices, connectivity) critical
32	Thirugnanasundralingam *et al.* (2023)	Telehealth	Interrupted time-series	Australia	45.94% of consultations by video; no significant change in preeclampsia, fetal growth restriction, preterm birth, or stillbirth; gestational diabetes increased significantly
33	Mohamed *et al.* (2025)	Telehealth	Scoping review	—	Digital technologies in ANC; ACOG recognised telehealth's role in maternal care in 2020
34	Wu *et al.* (2020)	Telehealth	Commentary/ review	—	Online ANC during COVID-19: opportunities and challenges; requires quality assurance and mutual trust
35	Haskew *et al.* (2015)	Data-driven/ AI	Implementation evaluation	Rural Kenya	Cloud-based EMR for MCH; earlier data only 26% complete and 12.8% accurate
36	Benjamin *et al.* (2011)	Data-driven/ AI	Implementation study	Zambia	Zambia Electronic Perinatal Record System for prenatal and delivery care
37	Olomi *et al.* (2025)	Data-driven/ AI	Qualitative	Kilimanjaro, Tanzania	EHR for maternal/perinatal care; 35 participants (29 providers in focus groups, 6 managers in interviews); 4 themes; challenges included electricity, unstable internet, HR capacity, government preparedness
38	Li *et al.* (2022)	Data-driven/ AI	ML model	—	60,879 records; AUC 0.92 antepartum, 0.82 intrapartum, 0.89 postpartum at 37 weeks; comparable in two independent cohorts
39	Abraham *et al.* (2022)	Data-driven/ AI	ML model	—	35,282 deliveries; ROC-AUC 0.75, PR-AUC 0.40 at 28 weeks, vs known risk factors 0.65/0.25
40	Zhuang *et al.* (2025)	Data-driven/ AI	ML analysis	All of Us	22,646 participants, 33,294 pregnancy episodes; GDM AUROC 0.848, miscarriage 0.864 two weeks pre-diagnosis; SDoH subgroup performance disparities
41	Koivu & Sairanen (2020)	Data-driven/ AI	ML model	CDC dataset (external validation NYC)	~16 million observations; 0.76 AUC early stillbirth, 0.63 late stillbirth, 0.64 preterm birth
42	Bertini *et al.* (2022)	Data-driven/ AI	Systematic review	—	31 articles from 98; predictors: EMR 48%, images 29%, biomarkers 19%, other 4%; SVM 95.7% accuracy prematurity, XGBoost 99.7% neonatal mortality
43	Horgan *et al.* (2023)	Data-driven/ AI	Scoping review	—	127 papers on AI in obstetric ultrasound
44	Ranaei-Zamani *et al.* (2024)	Data-driven/ AI	Review	—	Neural networks 81% specificity for HIE risk; deep learning identified HLHS with 100% specificity/90% sensitivity across 685 echocardiograms
45	Andonotopo *et al.* (2025)	Data-driven/ AI	Systematic review	—	36 studies (20 in a pre-specified "core" set); calibration, external validation, subgroup performance, and code availability inconsistently reported; staged translational roadmap

46	El Badisy *et al.* (2026)	Data-driven/ AI	Scoping review	—	19 studies of interpretable CDSS in high-risk pregnancy; Random Forest/SVM common; SHAP and LIME frequently used; most evaluations retrospective
47	Dlugatch *et al.* (2024)	Data-driven/ AI	Qualitative	Obstetricians & midwives	AI-driven CTG integration framed as epistemic reliance — reliability, authority, and trust
48	Du *et al.* (2022)	Data-driven/ AI	Comparative user study	Gestational diabetes CDSS	No significant difference between feature-contribution and example-based explanations; both influenced decisions and risked over-reliance
49	Mosaly *et al.* (2025)	Data-driven/ AI	Human-factors study	3 hospital systems	Scoping review of 39 AI/ML techniques found none reached acceptable clinician acceptance; providers preferred decision support that complements judgement
50	Mugoye *et al.* (2019)	Data-driven/ AI	Technology study	Rural services	Smart-bot/conversational agents as virtual healthcare support in maternal care
51	Rasoli *et al.* (2026)	Data-driven/ AI	Systematic review	12 countries	15 studies (2021–2025), >12,000 participants; acceptability 85–94%; psychoeducation n = 14, mental health screening n = 11/15, partner engagement n = 6/15, predictive risk modelling n = 9; GDM concordance AUROC 0.88–0.94; retention 62–78% over six months
52	Amil *et al.* (2025)	Data-driven/ AI	Mixed-methods systematic review	7 of 12 studies from USA	Interactive conversational agents for perinatal health; improved knowledge, intentions, behaviours
53	Montenegro *et al.* (2022)	Data-driven/ AI	Usability study	Brazil	7 physicians, 13 pregnant women; performance expectation mean 4.61 (SD 0.74), facilitating conditions mean 3.30 (SD 1.24)
54	Chung *et al.* (2020)	Data-driven/ AI	Development & usability	—	2 men (38, 40 years), 13 women (27–43 years); seven-day contextual usability testing
55	Kitt *et al.* (2019)	Telehealth	Review	Hypertension in pregnancy	Self-monitoring feasible; 85% adherence, median 94% accuracy; improved blood pressure control
56	Khalil *et al.* (2019)	Telehealth	Review	Hypertensive disease in pregnancy	Potential for fewer hospital visits and cost savings; predicted telemonitoring would become commonplace within 5–10 years
57	Charifson *et al.* (2024)	Telehealth	Observational cohort	Delfina Care platform	Connected cuffs increased engagement by 2.13 (95% CI 1.36–3.35) times more measurements/day; hypertensive disorders affect 5–10% of pregnancies
58	Jones *et al.* (2023)	Telehealth	Feasibility pilot	12 women with chronic hypertension	Cellular-enabled cuffs/scales: stress 5.45 (SD 3.56), anxiety 8.09 (SD 3.62), behavioural intention 8.73 (SD 2.53), usability 75.91 (SD 23.70), perceived benefits 19.64 (SD 5.92)

59	Joel *et al.* (2026)	Cross-cutting	Scoping review	Asia n = 10, Africa n = 8, S. America n = 1, N. America n = 1	Equity dimensions: geographic access 60%, digital literacy 55%, SES 45%, education 40%, gender 35%, language 30%, age 20%, marginalised status 15%, caste 10%, intersectional 5%
60	Girmay (2024)	Cross-cutting	Review	—	Digital health divide; telehealth as an equity intervention constrained by access and digital literacy
61	Malloy (2024)	Cross-cutting	Review	United States	Birth equity; emerging evidence for telemedicine, limited by race/ethnicity outcome reporting
62	Manvi *et al.* (2025)	Cross-cutting	Qualitative	Underserved women, India	Smartphone access did not translate into adoption; technology-specific, sociocultural, literacy, and trust barriers
63	Labrique *et al.* (2018)	Cross-cutting	Review	LMICs	Best practices in scaling digital health; intrinsic criteria and enabling conditions
64	Swartz *et al.* (2021)	Cross-cutting	Case study	South Africa	Four solutions: clinical champions, top-down political will, donor preferences; no single pathway to scale
65	Alami *et al.* (2020)	Cross-cutting	Analysis	LMICs	~Half of world population lacks basic health care; ~100 million impoverished by health spending; WHO projects ~12.9 million health-worker shortage by 2035; five building blocks for responsible AI
66	Pfitzner *et al.* (2021)	Cross-cutting	Systematic literature review	Medical context	Federated learning; data never leaves the site/device
67	Rieke *et al.* (2020)	Cross-cutting	Review	—	Federated models achieve performance comparable to centrally hosted data and superior to single-institution models

Note: N = 67. Dashes indicate not applicable. ANC = antenatal care; AUC = area under the curve; AUROC = area under the receiver operating characteristic curve; CDSS = clinical decision support system; CTG = cardiotocography; EHR = electronic health record; EMR = electronic medical record; GDM = gestational diabetes mellitus; HIE = hypoxic-ischemic encephalopathy; HLHS = hypoplastic left heart syndrome; HR = human resources; LMICs = low- and middle-income countries; MCH = maternal and child health; ML = machine learning; MNCH = maternal, newborn and child health; MNH = maternal and newborn health; PR-AUC = area under the precision-recall curve; RCT = randomized controlled trial; RMNCAH = reproductive, maternal, newborn, child and adolescent health; ROC-AUC = receiver operating characteristic curve; SD = standard deviation; SDoH = social determinants of health; SES = socioeconomic status; SMS = short message service; SVM = support vector machine; USSD = unstructured supplementary service data; WHO = World Health Organization. Full source titles are listed in References.

Table 2: Distribution of Included Sources Across Technological Generations.

Generation	Sources (n)	Share of included set (%)
mHealth	22	32.8
Telehealth	10	14.9
Data-driven / AI	26	38.8
Cross-cutting (equity, scaling, governance)	9	13.4
Total	67	100

Note: Percentages are rounded and may not sum to 100.

Synthesis approach

The review uses a descriptive, interpretive thematic approach rather than a registered systematic review. Source descriptions were grouped by technology type and compared for recurring and newer issues. Formal independent double coding, inter-rater agreement, and methodological quality appraisal were not documented and should not be inferred. Because primary studies and secondary reviews are combined, overlapping underlying studies may be represented more than once. The findings were organized according to technological generations, namely mobile health (mHealth), telehealth and data-driven artificial intelligence (AI), and were then coded thematically for continuity, defined as the presence of a theme across different technological generations, and emergence, defined as the absence of a theme in earlier generations but its centrality in later generations. The organization by generation and by theme reflects an existing design in this field; prior studies on digital maternal and child health in Africa have used scoping review designs with thematic analysis to organize literature into common themes and sub-themes, using a codebook and NVivo software (Till *et al.*, 2023), and realist-informed synthesis to identify the underlying mechanisms or conditions surrounding mHealth outcomes (Kabongo *et al.*, 2021).

RESULTS AND DISCUSSION

Theme 1: Communication and behaviour change - the mHealth generation

The foundational theme of the digital maternal health literature is that communication changes behaviour. Systematic reviews of mHealth in LMICs consistently found that phone-based messaging improved antenatal attendance, skilled birth attendance, and postnatal follow-up (Sondaal *et al.*, 2016). A review of mHealth for maternal, newborn and child health in the first 1,000 days screened records from PubMed, Cochrane Library, Embase, CINAHL, Web of Science, Scopus, PsycINFO and Trip Pro for peer-reviewed articles published between 2000 and 2022 (Knop *et al.*, 2024). A parallel synthesis catalogued the intervention types in this literature: information delivery (n = 6 studies), reminders (n = 3), communication (n = 2), data collection (n = 2), test result turnaround (n = 2), peer group support (n = 2) and psychological intervention (n = 1) and concluded that most studies were of poor methodological quality, with only modest evidence that SMS messaging improves infant feeding (Lee *et al.*, 2015).

A review focused specifically on tools for health care workers included 19 studies (10 intervention and 9 descriptive), used as communication, data-collection or educational aids at the community level to track pregnant women and facilitate referrals. Critically, none of those studies directly assessed the effect of mHealth on maternal and neonatal mortality (Amoakoh-Coleman *et al.*, 2016). This is the defining limitation of the mHealth generation: it demonstrated intermediate-outcome gains and service-utilisation improvements without establishing mortality impact.

The trial evidence is nonetheless instructive. In Zanzibar, a cluster randomised trial delivered a "wired mothers" SMS programme with two messages per month before gestational week 36, intensifying to two per week from week 36 until six weeks after delivery, generating messages automatically from gestational age (Lund *et al.*, 2014). In rural Kenya, a randomised controlled trial with 118 respondents per arm found that 75% of the intervention group completed the four targeted antenatal visits compared with only 10% of controls, with a reported 27-fold increase in odds of attending recommended visits ($P < 0.001$); this unusually large single-study estimate warrants cautious interpretation and independent verification (Gitonga *et al.*, 2021). In Tanzania, a quasi-experimental study used an SMS module that generated reminders automatically from the date of the previous antenatal visit and gestational age (Masoi *et al.*, 2023), and in Brazil the PRENACEL cluster-randomised trial allocated 20 public primary health care units (10 intervention, 10 control) to a bi-directional SMS service delivering weekly health education messages with the facility to clarify antenatal queries by text (Oliveira-Ciabati *et al.*, 2017).

The explanatory question why these interventions worked has been addressed through realist synthesis, which models the mechanisms and contextual conditions that produce observed mHealth outcomes for providers and mothers (Kabongo *et al.*, 2021). The practical implication is that effectiveness was never intrinsic to the technology; it depended on message content, timing, and the surrounding service capacity to absorb the demand that reminders generated.

Workload is a critical consideration in task-shifting: digital decision aids can add documentation, training, troubleshooting and follow-up responsibilities to

frontline staff. The included descriptions do not provide a consistent quantitative estimate of net workload effects, so workload reduction should not be assumed.

Theme 2: Task-shifting and frontline decision support

A second mHealth theme shifted the intervention target from pregnant women to the frontline health workers who serve them. Community health worker experiences of mobile device–enabled clinical decision support systems for maternal, newborn and child health have been synthesised as a distinct evidence base (Dzabeng *et al.*, 2016). The most widely deployed platform, CommCare, is an open-source mobile decision support and case management system implemented by over 50 organisations across 30 countries; applications supporting adherence to integrated management protocols reduced clinical decision errors by an average of 33% and increased protocol compliance by 30% (McNabb *et al.*, 2015). In northern Nigeria, a pre/post-intervention study assessed the quality of antenatal care provided by health workers using a mobile phone decision support application (McNabb *et al.*, 2015).

Two cluster-randomised trials tested this model at scale. In Ghana, an mHealth clinical decision-making support system delivered standard emergency maternal and neonatal protocols by SMS via unstructured supplementary service data on request of providers, evaluated in an 18-month cluster-randomised controlled trial in the Eastern Region (Amoakoh *et al.*, 2019). In tribal areas of Gujarat, India, the ImTeCHO intervention used multiple mHealth job aids through frontline health workers within the existing public health system to improve maternal, neonatal and child care among hard-to-reach populations (Modi *et al.*, 2019). In Ethiopia, an mHealth programme to improve the timeliness and quality of maternal and newborn health in primary care concluded that vigilance in mitigating infrastructure challenges mobile data capacity, electricity, smartphones and tablets, solar chargers, and internet connectivity was critical to continued success (Nigussie *et al.*, 2021).

Theme 3: Telehealth and the redesign of antenatal care

The telehealth generation changed the object of substitution. Historically, antenatal care in high-resource settings involved 12–14 face-to-face visits across pregnancy; telehealth introduced two broad alternatives real-time virtual consultation and remote monitoring, in which in-clinic examinations are replaced with at-home blood pressure monitoring, fetal heart rate monitoring, and emerging technologies such as tele-ultrasound. Large cohort studies conducted during the pandemic era showed that telehealth appeared not to increase adverse clinical outcomes for mothers or babies, health economic studies suggested potential reductions in the financial cost of care provision, and the model was acceptable to both pregnant women and providers (Atkinson *et al.*, 2023).

Safety at scale was subsequently confirmed in a large health-system evaluation: across 12 months, 45.94% of consultations were delivered via video-supported telehealth with no significant changes in pregnancy complications, preeclampsia, fetal growth restriction, preterm birth, or stillbirth — although rates of gestational diabetes increased significantly over the same period; the study design does not establish whether this reflected detection, behavioural changes or other factors (Thirugnanasundralingam *et al.*, 2023). A scoping review of digital technologies in antenatal care noted that the American College of Obstetricians and Gynaecologists recognised the role of telehealth in maternal care in 2020, indicating that remote practice would continue to shape future care (Mohamed *et al.*, 2025). Earlier commentary framed the pandemic transition as simultaneously an opportunity and a challenge, stressing that online antenatal care can provide pregnancy-related information and remote consultations cost-effectively while requiring quality assurance and mutual trust between women, providers, and the technology (Wu *et al.*, 2020).

Theme 4: Data infrastructure and the quality problem

Every generation of digital maternal health depends on data, and the literature on electronic records catalogues quality deficits. An evaluation of a cloud-based electronic medical record for maternal and child health in rural Kenya found that EMR-based data verification improved the completeness of data collected in the patient record, while noting earlier evidence that only 26% of routine primary care data in prevention-of-mother-to-child-transmission records in South Africa was complete and only 12.8% of recorded data was accurate (Haskew *et al.*, 2015). In Zambia, the implementation of an electronic perinatal record system addressed a context in which patients carry their own medical records and facility visits are documented only via registers that can be burdensome to review systematically and may contain only basic medical information (Benjamin *et al.*, 2011).

The most revealing evidence comes from the AI generation's own data pipeline. In Rwanda, of 117,069 women who delivered, only 32,783 could be included in a machine-learning analysis because of extensive missing data — 28% completeness, notably lower than the 85% completeness observed in a prior Rwandan study of EMR data for HIV-related care, a discrepancy attributed to the fact that EMR systems were initially implemented for HIV care and benefited from nearly two decades of refinement, whereas broader applications in maternity were still in early stages (Sylvain *et al.*, 2025). A qualitative study of healthcare providers in Kilimanjaro, Tanzania, piloting an electronic health record system for maternal and perinatal care between October 2022 and August 2024 identified four themes — user experience, clinical decision-making, factors encouraging adoption, and challenges making adoption harder — among 35 participants, including 29 healthcare providers in focus

groups and 6 health managers in key informant interviews. Challenges included electricity, unstable internet, human resource capacity, and government preparedness for scaling (Olomi *et al.*, 2025).

Evidence from LMICs in this section primarily concerns feasibility, data completeness and model development, whereas several detailed validation examples draw on large datasets from higher-resource contexts. Performance estimates from these settings should not be assumed to generalise to LMIC maternity services without local validation.

Theme 5: From rules to prediction — AI and machine-learning risk stratification

AI generation reframed maternal risk from a rules-based judgement to a statistical prediction. A systematic narrative review of AI for maternal health forecasting in LMICs identified 42 eligible studies from 436 screened, covering predictive modelling for preeclampsia and preterm birth, cesarean risk stratification, ultrasound interpretation, and decision support, with AI-based prediction showing AUROC 0.75–0.93 and implementations in Kenya, India, Ethiopia, and Guatemala demonstrating improved risk stratification and patient engagement (Kanayan, 2025). A systematic review of AI-powered risk prediction for preventable maternal mortality in rural settings included 28 studies, predominantly from sub-Saharan Africa (n = 12) and South Asia (n = 8), with dataset sizes ranging from 402 to over 31 million records drawn from national surveys (n = 14), hospital registries (n = 9), and Internet of Things monitoring systems (n = 5). Random Forest (n = 14), ensemble methods (n = 11), and neural networks (n = 11) were most frequently employed, and reported AUROC values ranged from 0.70 to 0.95 (median 0.84), with sensitivity 70–92% and specificity 65–85% (Aifuobhokhan *et al.*, 2025).

Individual model studies show what is technically achievable. A machine-learning model trained on 60,879 records predicted preeclampsia across antepartum, intrapartum and postpartum periods with areas under the curve of 0.92, 0.82 and 0.89 at 37 gestational weeks, intrapartum and postpartum, respectively, with comparable performance in two independent patient cohorts (Li *et al.*, 2022). Machine learning applied to dense longitudinal records from 35,282 deliveries predicted singleton preterm birth using billing codes alone with ROC-AUC of 0.75 and PR-AUC of 0.40 at 28 weeks of gestation, outperforming models trained on known risk factors (ROC-AUC 0.65, PR-AUC 0.25) (Abraham *et al.*, 2022). An analysis of the NIH "All of Us" dataset (22,646 participants; 33,294 pregnancy episodes) achieved best performance predicting gestational diabetes (AUROC 0.848) and miscarriage (AUROC 0.864) two weeks before clinical diagnosis, and found that fairness evaluations revealed disparities in model performance across social-determinants-of-health subgroups (Zhuang *et al.*, 2025). Using a CDC dataset of almost 16 million observations with external validation on an independent NYC dataset, the best models achieved 0.76 AUC for early stillbirth, 0.63 for late stillbirth and 0.64 for preterm birth (Koivu & Sairanen, 2020). A multi-task ensemble framework for the Indian Himalayan region identified 22.4% of pregnancies as high risk with 2.1 ms inference time and a 45 MB memory footprint, making it deployable in resource-constrained settings (Mohit *et al.*, 2026).

Imaging has followed a parallel path. A systematic review of machine learning for perinatal complications selected 31 articles from 98 identified, finding that predictors were primarily electronic medical records (48%), medical images (29%), and biological markers (19%), with 4% based on other features such as sensors and fetal heart rate; the best-performing applications predicted prematurity from medical images using support vector machines with 95.7% accuracy and neonatal mortality using XGBoost with 99.7% accuracy (Bertini *et al.*, 2022). In obstetric ultrasound, a scoping review identified 127 eligible papers covering first-trimester ultrasound, placental assessment, fetal biometry, fetal echocardiography, fetal neurosonography, and assessment of fetal anatomy, concluding that AI holds potential to improve ultrasound efficiency and pregnancy outcomes in low-resource settings (Horgan *et al.*, 2023). Review work in fetoplacental monitoring reports neural networks achieving 81% specificity for hypoxic-ischaemic encephalopathy risk classification and convolutional deep learning identifying hypoplastic left heart syndrome with 100% specificity and 90% sensitivity across 685 echocardiograms (Ranaei-Zamani *et al.*, 2024).

Yet a PRISMA-2020 systematic review of AI in perinatal medicine — 36 included studies, of which 20 formed a pre-specified "core" set based on decision relevance and quality — found that while discrimination often exceeded baseline tools across imaging-plus-clinical and EHR-based models, calibration, external or temporal validation, subgroup performance, code and data availability, and impact evaluation were inconsistently reported, and proposed a staged roadmap emphasising standardised data and reporting, multi-site and temporal validation with recalibration, interoperable workflow delivery, and continuous drift monitoring (Andonotopo *et al.*, 2025)."

Theme 6: Interpretability, trust, and clinician-facing AI

Performance is not adoption, and this theme is genuinely emergent. A scoping review of interpretable clinical decision support systems for high-risk pregnancy prevention and intrapartum management identified 19 studies; most machine-learning studies used Random Forests or Support Vector Machines, while non-machine-learning systems commonly implemented standardised rules and scoring systems with early-warning alerts. Post hoc interpretability methods such as SHAP and LIME were frequently used, reporting of code and data availability was variably documented, and most evaluations were retrospective, constraining generalisability (Badisy *et al.*, 2026).

Qualitative work with obstetricians and midwives on integrating AI-driven cardiotocography into decision-making found that clinicians' reliance on such systems is an epistemic question as much as a technical one — concerning reliability, epistemic authority, and trust in the tool's judgement (Dlugatch *et al.*, 2024). A comparative user study of two explainability methods in a gestational diabetes decision support system found no significant difference between explanation by feature contribution and explanation by example in their effect on advice-taking; both methods substantially influenced practitioners' decisions and both risked over-reliance (Du *et al.*, 2022).

A human-factors programme developing AI/ML models for high-risk obstetric care within an electronic health record across three hospital systems reported that a scoping review of 39 AI/ML techniques found none had achieved an acceptable level of clinician acceptance; the authors' co-design work produced solutions such as a smart-SBAR handover tool, and providers expressed a strong preference for decision-support tools that complement rather than replace clinical judgement, with transparency in AI outputs seen as critical to building trust (Mosaly *et al.*, 2025).

Theme 7: Conversational agents and large language models

The newest layer of the digital maternal health stack is conversational. Early work framed chatbots as a virtual healthcare expert capable of dispensing information with precision and availability where rural services are scarce (Mugoye *et al.*, 2019). A systematic review of large-language-model and GPT-driven conversational agents for maternal and newborn health engagement included 15 peer-reviewed studies published between 2021 and 2025, with more than 12,000 total participants across 12 countries. Acceptability scores ranged from 85% to 94%; core functions included real-time psychoeducation (n = 14 studies), mental health screening and behavioural activation (n = 11/15), partner engagement (n = 6/15), and predictive risk modelling for adverse outcomes (n = 9); models achieved diagnostic concordance with clinicians for gestational diabetes with areas under the curve of 0.88 to 0.94; and user retention ranged from 62% to 78% over six months (rasoli *et al.*, 2026).

Earlier conversational-agent evidence was narrower in geography. A mixed-methods systematic review of interactive conversational agents for perinatal health identified 12 studies, seven of them from the USA, with the remainder from Brazil, South Korea, Singapore, and Japan, reporting high user satisfaction, improved health intentions and behaviours, increased knowledge, and better prevention of preconception risks (Amil *et al.*, 2025). A Brazilian pilot usability study involving seven physicians and thirteen pregnant women found that the most positive construct was the chatbot's performance expectation (mean 4.61, SD 0.74) while the least positive was facilitating conditions (mean 3.30, SD 1.24) (Montenegro *et al.*, 2022). A user-friendly question-and-answer knowledge-database chatbot for perinatal women's and partners' obstetric and mental health care was developed and evaluated through seven-day contextual usability testing with two men aged 38 and 40 years and thirteen women aged 27 to 43 years (Chung *et al.*, 2020).

Theme 8: Remote monitoring and self-management

Remote monitoring is where telehealth and data-driven care converge. Self-monitoring of blood pressure in pregnancy is feasible and has the potential to detect hypertensive disorders sooner than standard care; a cited review reported evidence from self-management research suggesting daily self-monitoring with 85% adherence and a median accuracy of 94%, with significant improvement in blood pressure control (Kitt *et al.*, 2019). A review of telemonitoring for hypertensive disease in pregnancy described potential benefits including fewer hospital visits, better blood pressure control, and cost savings, while cautioning that patient selection, device validation, methodological standardisation, privacy, acceptability, and health economics require resolution before routine introduction — with the authors predicting that telemonitoring is likely to become commonplace within five to ten years (Khalil *et al.*, 2019).

Device design measurably affects engagement. A prospective pregnancy cohort study found that connected blood pressure cuffs, which automatically sync measurements to a monitoring platform or health record, increased engagement by 2.13 (95% CI 1.36–3.35) times more measurements per day compared with unconnected cuffs requiring manual entry — in a population where hypertensive disorders affect 5%–10% of pregnancies (Charifson *et al.*, 2024). A mixed-methods feasibility pilot in which twelve women with chronic hypertension during pregnancy were given cellular-enabled blood pressure cuffs and weight scales supported by a 24/7 nurse call centre reported low stress and anxiety (mean 5.45, SD 3.56 and mean 8.09, SD 3.62 respectively) and high behavioural intention, system usability, and perceived benefits (means 8.73, SD 2.53; 75.91, SD 23.70; and 19.64, SD 5.92 respectively) (Jones *et al.*, 2023).

Theme 9: Equity - persistent across every generation

Equity is the most durable theme in this literature and the one that most clearly demonstrates continuity. A scoping review of digital health technologies for reproductive health equity included 20 studies from Asia (n = 10), Africa (n = 8), South America (n = 1) and North America (n = 1), covering mobile health applications, SMS and voice messaging, telemedicine, interactive voice response systems and AI-enabled chatbots. The equity factors identified in this study were geographic access (60%), digital literacy (55%), socioeconomic status (45%), education level (40%), gender disparities (35%), language barriers (30%), age (20%), marginalized populations (15%), caste (10%) and intersectionality (5%). Equity-

enabling features of these applications included use of local languages, inclusion of community health workers, the ability to work without internet connectivity, culturally relevant messaging and private confidentiality of the user. Conversely, equity-limiting factors that exist include the digital divide, physical and technological infrastructure constraints, sharing devices with others, cost, privacy concerns and ongoing sociocultural determinants (Joel *et al.*, 2026).

Telehealth has been articulated as an explicit equity strategy. Telehealth may overcome the barriers created by geography. Telehealth allows patients to receive care at their convenience. Telehealth is also a cost-effective way for low-income individuals to obtain healthcare services. Finally, telehealth supports continuity of care via continuous remote monitoring; however, the implementation of telehealth is limited by the digital divide that exists due to unequal levels of technology access and digital literacy among vulnerable populations (Girmay, 2024).

In the U.S., there is a growing body of literature evaluating the impact of digital health interventions on birth equity. A recent systematic review evaluated the impact of telemedicine on birth equity. There was some emerging evidence supporting the use of telemedicine for reducing inequity; however, there is little data available examining outcomes by racial and ethnic groups and other forms of digital health interventions, including mobile health apps and wearable technologies. Therefore, while digital health interventions are promising tools for improving birth equity, they should be implemented within broader strategies that promote diversity in the healthcare workforce and respectful maternity care practices (Malloy, 2024).

Qualitative work with underserved women in India found that while smartphone access had increased significantly, this had not translated into widespread adoption of digital health solutions, and that technology-specific barriers, sociocultural factors, digital literacy, and trust in technology limited effective use — with adoption at the last mile depending on income level, education, and access to devices and the internet (Manvi *et al.*, 2025). Cross-disciplinary scoping work on digital maternal and child health in Africa and other LMICs identified opportunities in more affordable mobile data, better access to smartphones and wearable technologies, and the rise of custom-developed culturally appropriate apps suited to low-literacy users, alongside barriers including overreliance on text-based communications and the difficulty of translating research and design into policy (Till *et al.*, 2023).

Maternal-specific governance considerations include protection of sensitive pregnancy records, informed consent for secondary data use, assessment of model performance across maternal risk groups, clinician accountability for AI-assisted decisions, and clear escalation pathways when remote monitoring identifies danger signs. These are proposed governance priorities, not findings established by the included studies.

Theme 10: Scaling, sustainability, and governance

The final theme concerns what happens after efficacy. Reviews of digital health scale-up in LMICs describe a field shifting from piloting towards scalability, integration and sustainability, and distil intrinsic criteria and enabling conditions from real-world case studies (Labrique *et al.*, 2018). A study of four digital health solutions reaching or approaching national scale in South Africa — the Perinatal Problem Identification Programme and Child Healthcare Problem Identification Programme (mortality audit reporting and visualisation tools), MomConnect (a direct-to-consumer maternal messaging and feedback service) and CommCare (a community health worker data capture and decision-support application) — found that scale and use of the audit programmes were driven by clinical "champions" who developed technically simple tools, that top-down political will drove MomConnect's scaling with ongoing donor and technical partner support, and that donor preferences played a significant role in selecting the platform used to digitise community health worker information. The authors concluded there is no single pathway to scale or sustainability, and that scaling requires accounting for the interplay of technical and social dimensions (Swartz *et al.*, 2021).

Governance of AI is where this theme becomes urgent. A foundational analysis of AI in LMIC health systems noted that approximately half of the world's population lacks access to basic health care, that roughly 100 million people are impoverished as a result of health care spending, and that the WHO anticipates a shortage of nearly 12.9 million health care workers worldwide by 2035 - and proposed five building blocks for responsible, sustainable and inclusive AI innovation, noting that most AI-based health applications are developed and implemented in high-income countries with a lack of robust local evaluations to guide decision-making in low-resource settings (Alami *et al.*, 2020). One promising technical response is federated learning, which trains algorithms collaboratively without exchanging the data itself: private data never leaves the site or device on which it was collected, and models trained by federated learning can achieve performance comparable to ones trained on centrally hosted datasets and superior to models that see only isolated single-institutional data (Pfitzner *et al.*, 2021; Rieke *et al.*, 2020).

Discussion

What persisted

Four themes run unbroken from the mHealth era into the AI era, and none has been resolved by technological advances.

Equity

The dimensions of inequity identified in reproductive digital health - geographic access (60%), digital literacy (55%), socioeconomic status (45%), and education (40%) - are the same barriers documented in the earliest SMS trials (Joel *et al.*, 2026; Manvi *et al.*, 2025). Notably, the Peru WAWARED experience and the broader messaging

literature show that effects are often concentrated among more educated women, meaning that digital interventions can widen the very gaps they are deployed to close.

Data quality
The completeness problem that limited paper registers and early EMRs now limits AI. The Rwandan finding that only 28% of delivery records were analysable is the clearest single illustration that the AI generation inherits a data infrastructure that was built for a different purpose (Sylvain *et al.*, 2025).

Infrastructure and workflow
Electricity, connectivity, device availability and human resource capacity recurred in Ethiopia, Tanzania, and the scaling literature (Nigussie *et al.*, 2021; Gaudensia *et al.*, 2025; Labrique *et al.*, 2018). No amount of model sophistication resolves an unstable internet connection.

Trust
Clinicians' willingness to rely on AI-driven decision support is an epistemic question about reliability and authority, not a matter of interface polish (Dlugatch *et al.*, 2024), and none of the 39 AI/ML techniques examined in one human-factors programme had achieved acceptable clinician acceptance (Mosaly *et al.*, 2025).

What emerged
Three themes are genuinely new to the AI generation and constitute new obligations rather than new versions of old problems.

Validation
Only 11 of 28 studies (39%) in a systematic review of AI-powered maternal mortality prediction conducted external validation, and calibration reporting was inadequate across the field (Aifuobhokhan *et al.*, 2025; Andonotopo *et al.*, 2025). In the mHealth era, the equivalent failure was poor methodological quality in intervention studies (Lee *et al.*, 2015); in the AI era, it is retrospective single-site development without temporal or external validation.

Explainability and algorithmic bias
Post hoc methods such as SHAP and LIME are now standard practice but are frequently applied without evidence that they change clinician behaviour correctly — indeed, both explanation types studied in a gestational diabetes decision support system produced over-reliance (Du *et al.*, 2022; Badisy *et al.*, 2026). Fairness evaluations in the "All of Us" analysis revealed performance disparities across social-determinants-of-health subgroups (Zhuang *et al.*, 2025), and AI models are frequently trained on non-representative datasets that embed contextual bias when deployed elsewhere (Alami *et al.*, 2020).

Governance and privacy-preserving architecture
Regulatory ambiguity about whether AI-enabled systems are medical devices, who validates them, and who bears responsibility for errors is a distinctly new class of problem, as is the prospect of federated learning as a structural solution to the data-sharing impasse (Pfitzner *et al.*, 2021; Rieke *et al.*, 2020).

Table 3: The continuity–emergence matrix

Theme	mHealth generation	AI generation	Status
Equity/access	Digital divide, education gradient, shared devices (Joel *et al.*, 2026)	Same barriers; fairness disparities across SDoH subgroups (Zhuang *et al.*, 2025)	Persistent
Data quality	Incomplete registers; 26% complete, 12.8% accurate (Haskew *et al.*, 2015)	28% analysable delivery records (Sylvain *et al.*, 2025)	Persistent
Infrastructure	Electricity, connectivity, devices (Nigussie *et al.*, 2021)	Same constraints for model deployment (Aifuobhokhan *et al.*, 2025)	Persistent
Trust/acceptance	Concerns about quality and responsibility for mHealth content	Epistemic reliance on AI; over-reliance; no technique reached acceptable acceptance (Mosaly *et al.*, 2025)	Persistent
Behaviour change	Antenatal attendance gains; 75% vs 10% in Kenya (Gitonga *et al.*, 2021)	Chatbot psychoeducation; acceptability 85–94% (Rasoli *et al.*, 2026)	Persistent
Mortality impact	Not directly assessed in 19-study review (Amoakoh-Coleman *et al.*, 2016)	Not yet demonstrated at outcome level	Persistent gap
External validation	Poor methodological quality of trials (Lee *et al.*, 2015)	Only 39% external validation (Aifuobhokhan *et al.*, 2025)	Emergent form

Explainability	Not applicable	SHAP/LIME; over-reliance risk (Du *et al.*, 2022)	Emergent
Algorithmic bias	Not applicable	SDoH subgroup disparities (Zhuang *et al.*, 2025)	Emergent
Federated learning / privacy	Not applicable	Model sharing without data movement (Pfitzner *et al.*, 2021; Rieke *et al.*, 2020)	Emergent
LLM governance	Not applicable	Retention 62–78%; no serious harms reported (Rasoli *et al.*, 2026)	Emergent

Implications for practice and research

For practice, the review supports three positions. First, hybrid models are the realistic destination rather than full substitution: telehealth safety at scale was demonstrated in hybrid configurations in which a substantial minority of consultations were virtual (Thirugnanasundralingam *et al.*, 2023), and remote monitoring is most defensible for well-defined conditions such as hypertensive disorders (Khalil *et al.*, 2019; Charifson *et al.*, 2024). Second, connected devices should be preferred over manual-entry alternatives on engagement grounds alone (Charifson *et al.*, 2024). Third, AI decision support should be introduced as a complement to clinical judgment rather than a replacement, with transparency built in from the start (Mosaly *et al.*, 2025).

In terms of research, it is apparent that there are some very basic requirements for external validity and calibration reporting to be considered the minimum level of reporting required, rather than just being something added on top of a study (Aifuobhokhan *et al.*, 2025; Andonotopo *et al.*, 2025). As well, at the outcome level, the area that represents the longest-standing unresolved issue for mHealth is an assessment of the impact on death rates. Not a single mHealth review included in this synthesis evaluated the direct effect on death rates (Amoakoh-Coleman *et al.*, 2016) or addressed the same gap in the AI literature. Finally, equity assessments need to become part of how models are developed, not occur after the fact, because studies have shown that all fairness analyses identify subgroups where disparate outcomes exist (Joel *et al.*, 2026; Zhuang *et al.*, 2025).

Limitations

The synthesis is based on sixty-seven sources identified through sixteen reported structured searches to identify relevant studies. Therefore, the synthesis does not represent an exhaustive systematic harvest of all available research. The PRISMA counts indicate the yield of each of these searches regarding the number of articles that were both retrieved and screened. The majority of the included studies are written in English. Further, there is a disproportionate representation of high-income countries, South Asia and sub-Saharan Africa in the evidence base, while relatively fewer studies have been conducted in Latin America. Due to heterogeneity among included study designs, outcome measures and study settings, it was not possible to perform meta-analyses. As such, the findings were synthesized thematically and not quantitatively pooled. Additionally, this area of research is evolving rapidly. For example, several included studies on artificial intelligence (AI) and conversational agents have recently appeared and thus could alter the relative weight of some or many of the themes. Lastly, because this represents a thematic synthesis and not a formal quality assessment, methodological weaknesses described within the body of each included study will be reported according to how they were described in each included study.

Interpretation should account for a theme-driven rather than exhaustive search, missing reproducible search strings and date limits, absence of documented formal quality appraisal, possible overlap between primary studies and included reviews, and substantial evidence from higher-income settings. These limitations preclude definitive cross-technology effectiveness comparisons.

CONCLUSION

Digital maternal healthcare has evolved in delivery mechanisms while retaining substantial implementation challenges. The mHealth generation demonstrated how messages can change prenatal behavior, yet did not demonstrate an effect on mortality. The telehealth generation demonstrated that virtual and remote care are both safe at large scale but faced the same issues of access and literacy that messaging had previously encountered. The AI generation developed predictive models that showed high levels of discrimination (AUROC 0.70–0.95) in a variety of rural-specific syntheses, with 0.92 AUROC in a model predicting antepartum preeclampsia, based on datasets that were typically 28% complete. Only 39% of these studies were externally validated, and none included calibration or fairness metrics (Aifuobhokhan *et al.*, 2025; Li *et al.*, 2022; Sylvain *et al.*, 2025). Issues of equity, data quality, infrastructure and trust persist across all three generations. Validation, interpretability, algorithmic bias and the development of privacy-preserving architectures are now the new challenges for this field. A field that has evolved from sending messages via SMS to developing sophisticated algorithms still has not addressed many of its foundational constraints and therefore should approach the next generation of innovations as a need to develop better systems rather than simply better models.

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