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Maternal Recommender System Systematic Literature Review: State of the Art and Future Studies

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Abstract

Aim/Purpose	This paper illustrates the potential of health recommender systems (HRS) to support and enhance maternal care. The study aims to explore the recent implementations of maternal HRS and to discover the challenges of the implementations.
Background	The sustainable development goals (SDG) aim to reduce maternal mortality to less than 70 per 100,000 live births by 2030. However, progress is uneven between countries, with primary causes being severe bleeding, infections, high blood pressure, and failed abortions. Regular antenatal care (ANC) visits are crucial for detecting and managing complications, such as hypertensive illnesses, anemia, and gestational diabetes mellitus. Utilizing maternal evaluations during ANC visits can help identify and treat problems early, lowering morbidity and death rates for both mothers and fetuses. Technology-enabled daily health recording can help monitor pregnancy by providing actionable guides to patients and health workers based on patient status.
Methodology	A systematic literature review was conducted using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to identify maternal HRS reported in studies between November 2022 and December 2022. Information was subsequently extracted to understand the potential benefits of maternal

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HRS. Titles and abstracts of 1,851 studies were screened for the full-text screening, in which two reviewers independently selected articles and systematically extracted data using a predefined extraction form.

Contribution
This study adds to the explorations of the challenges of implementing HRS for maternal care. This study also emphasizes the significance of explainability, data-driven methodologies, automation, and the necessity for integration and interoperability in the creation and deployment of health recommendation systems for maternity care.

Findings
The majority of maternal HRS use a knowledge-based (constraint-based) approach with more than half of the studies generating recommendations based on rules defined by experts or available guidelines. We also derived four types of interfaces that can be used for delivering recommendations. Moreover, patient health records as data sources can hold data from patients' or health workers' input or directly from the measurement devices. Finally, the number of studies in the pilot or demonstration stage is twice that in the sustained stages.

We also discovered crucial challenges where the explainability of the methods was needed to ensure trustworthiness, comprehensibility, and effective enhancement of the decision-making process. Automatic data collection was also required to avoid complexity and reduce workload. Other obstacles were also identified where data integration between systems should be established and decent connectivity must be provided so that complete services can be administered. Lastly, sustainable operations would depend on the availability of standards for integration and interoperability as well as sufficient financial support.

Recommendations for Practitioners
Developers of maternal HRS should consider including the system in the main healthcare system, providing connectivity, and automation to deliver better service and prevent maternal risks. Regulations should also be established to support the scale-up.

Recommendations for Researchers
Further research is needed to do a thorough comparison of the recommendation techniques used in maternal HRS. Researchers are also recommended to explore more on this topic by adding more research questions.

Impact on Society
This study highlights the lack of sustainability studies, the potential for scaling up, and the necessity for a comprehensive strategy to integrate the maternal recommender system into the larger maternal healthcare system. Researchers can enhance and improve health recommendation systems for maternity care by focusing on these areas, which will ultimately increase their efficacy and facilitate clinical practice integration.

Future Research
Additional research can concentrate on creating and assessing methods to increase the explainability and interpretability of data-driven health recommender systems and integrating automatic measurement into the traditional health recommender system to enhance the anticipated outcome of antenatal care. Comparative research can also be done to assess how well various models or algorithms utilized in these systems function. Future research can also examine creative solutions to address resource, infrastructure, and technological constraints, such as connectivity and automation to help address the shortage of medical personnel in remote areas, as well as define tactics for long-term sustainability and integration into current healthcare systems.

Keywords
health recommender system, maternal care, antenatal care, systematic literature review

INTRODUCTION

The Sustainable Development Goals (SDG) set a target for the global Maternal Mortality Ratio (MMR) to be less than 70 per 100,000 live births by 2030 (World Health Organization, 2019). However, the World Health Organization (WHO) study on maternal mortality reveals that although the rate of maternal deaths has decreased significantly, there is still a considerable gap to close before reaching this target, and progress is uneven between countries. The primary causes of maternal deaths are severe bleeding, infections, high blood pressure during pregnancy, and failed abortions (Say et al., 2014). While some of these issues may already exist before becoming pregnant, the majority of complications arise during pregnancy and can be avoided through regular antenatal care (ANC) visits. The WHO recommends promoting health-related behavior, nutritional supplements, community mobilization, and midwife-led continuity of care to ensure the recommended eight ANC contacts for regular monitoring are met (World Health Organization, 2021).

ANC visits are crucial for detecting and managing complications, including hypertensive illnesses, anemia, asymptomatic bacteriuria (ASB), intimate partner violence (IPV), and gestational diabetes mellitus (GDM), as well as evaluating fetal development and health (World Health Organization, 2016). Utilizing maternal evaluations during ANC visits may enable the early identification and treatment of problems, hence lowering morbidity and death rates for both the mother and the fetus (World Health Organization, 2016). Technology-enabled daily health parameter monitoring under free-living conditions may shorten hospital stays and lower medical expenses. Through non-invasive sensor technology, user behavior can be tracked to determine how everyday lifestyle choices affect an individual's health. On the other hand, recommender systems in healthcare have the potential to offer resources and assistance to doctors and patients, aiding in the constant monitoring and diagnosis of chronic diseases (J. Saha et al., 2020). Selected patients and healthy individuals are the primary end-users, with healthcare professionals (such as doctors, nurses, clinicians, and physicians) serving as the secondary end-users (Tran et al., 2021).

Such technologies could offer resources and assistance to doctors and patients, extending appropriate advice and predicting disease risk (Cochran et al., 2019; Humphries et al., 2021; Peleg, Shahar, Quaglini, Fux, et al., 2017; Pustozerov et al., 2018; Venkateswaran et al., 2022). Those technologies also enable users to explore and find conditions associated with their disease regarding their specific medical conditions. Studies by J. Saha et al. (2020) have shown that monitoring daily behavior can help people become more aware of the importance of leading healthy lives, which is crucial for treating patients with chronic diseases. Additionally, tracking user efforts over time may reveal relevant information that can be used by recommender systems to help treat chronic health conditions.

In a survey of health recommendation services aimed at non-medical professionals, De Croon et al. (2021) divided them into four broad categories: lifestyle, diet, general health information, and specific health issues. They found that the fact that the majority of health recommender systems (HRS) employ mixed recommendation algorithms and that evaluations differ widely indicates that the area is gradually evolving. Additionally, they suggest certain design principles that might be applied to HRS research. Moreover, insights on recommendation scenarios and recommendation methodologies were supplied by Tran et al. (2021). Tran et al.'s study covers subjects such as food advice, medicine recommendation, health status prediction, physical activity recommendation, and healthcare professional recommendation. End-users and healthcare professionals received various kinds of recommendations. Recommendations for end-users might offer, for instance, diagnostics and disease forecasts, while health professionals could gain support based on medical resources to acquire more accurate recommendations for patients (Tran et al., 2021).

Another review of the health recommender system was also performed by Pincay et al. (2019), which compared methods and techniques used in health recommender systems identified in these four recommendation areas: wellness, diagnosis and medication, healthcare services, and medical resources. Pincay et al. also emphasized the importance of how the recommendation must be delivered to the users. Pincay et al. concluded that finding a suitable method for HRS development can be a challenge due to the complexity of health-related issues. Therefore, it is necessary to consider certain design principles to enhance HRS research.

Review papers have evolved into crucial tools for condensing, synthesizing, integrating, or critically evaluating existing information in the field of eHealth (Lau & Kuziemsky, 2017). When carefully constructed, review papers serve as valuable information sources for eHealth researchers and professionals seeking cutting-edge research (Lau & Kuziemsky, 2017). However, earlier research in this area has less discussion on health recommender systems used in maternal care. To better understand the current implementations and open issues, this study comprehensively analyzes prior research on maternal recommender systems. Therefore, the following study topic is of special interest to us:

RQ: What are the recent implementations and challenges of Maternal Recommender Systems?

There are six sections in this article. The research background is explained in the first section. The next section is an explanation of the literature evaluation of HRS. Related technologies and the research methodology is covered in the third section. The findings and analyses of this study are then further developed in the fourth and fifth sections. The study's findings and recommendations for further research are covered in the concluding section.

LITERATURE REVIEW

HEALTH INFORMATICS IN MATERNAL CARE

Studies in maternal health informatics covered maternal and child health monitoring where a comprehensive informatics monitoring framework was presented to track progress towards priorities for ending preventable maternal mortality and enhancing child health (Henao et al., 2019). Studies in this area also identified key functionalities of pregnancy apps and telehealth platforms as digital technology-enabled health interventions (Moise et al., 2023).

Other key studies in maternal health informatics focus on mHealth applications for improving antenatal care, such as client education and communication for behavior change of patients (Feroz et al., 2017). The development of mobile health technology (mHealth) has improved emergency obstetric referrals, empowered women during pregnancy by providing access to knowledge and resources they need, encouraged cooperation among medical professionals, and improved the delivery of healthcare as a whole (Mishra et al., 2023). Even though all of the included studies demonstrated that mHealth tools can increase prenatal care attendance, the quality of the evidence varied greatly, necessitating a stronger emphasis on mHealth tool evaluation and dissemination of findings to guide policy and program design (Watterson et al., 2015). Furthermore, rather than designing an integrated system that tracks women and children through the maternal, neonatal, and child health continuum, many current programs concentrate on just one aspect of preventative care for mother and child health (Watterson et al., 2015).

Furthermore, research on artificial intelligence (AI) in healthcare for pregnant women has discovered that AI can be applied to predict pregnancy disorders, assess risk factors, and safety monitoring (Abuelezz et al., 2022; Ramakrishnan et al., 2021). Additionally, machine learning algorithms can also be used to predict and assist medical practitioners in diagnostics and determine pregnancy outcomes (Gulzar Ahmad et al., 2022). While there is a lot of potential for AI applications in pregnancy research and healthcare, there has not been much of it realized in clinical settings, according to previous reviews (Davidson & Boland, 2021). It is also possible to use certain evaluation approaches at each stage of the process, from system design and development to testing and patient adoption and recommendation (Oprescu et al., 2020).

HEALTH RECOMMENDER SYSTEM

Recommender System (RS) is an application that suggests an item that will meet a user's need based on a variety of data sources (Aggarwal, 2016). The recommendations may be based on prior user-item interactions or merely on the user's explicit requirements. Common techniques for giving recommendations include collaborative filtering, content-based analysis, and knowledge-based analysis. To achieve the greatest results, several recommender systems would combine different kinds of recommender systems. Some methods have also been created to take into account more data types and settings, such as time, place, and social data. According to Aggarwal (2016), two different types of spatial locality can also be taken into consideration: first, the locale or region that is important to the user specifically; and second, the geographic location of an item that will be recommended to the user. As shown in Figure 1, a health recommender system comprises various phases following the fundamental design of a health informatics system (J. Saha et al., 2020).

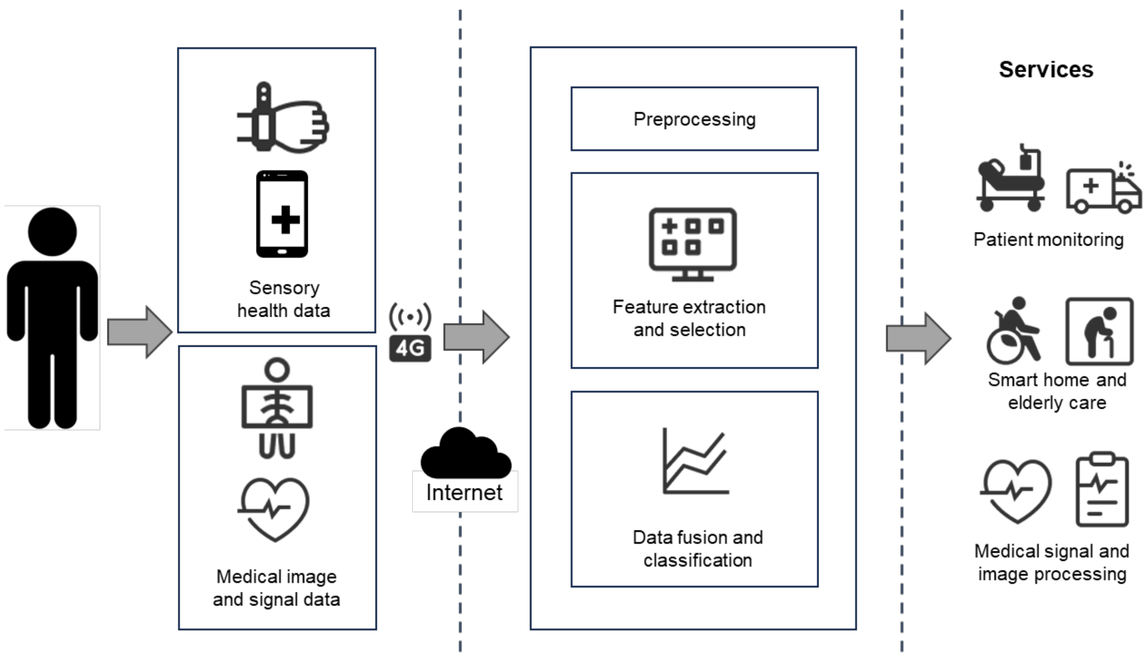

Figure 1. System architecture of health recommender system (J. Saha et al., 2020)

According to J. Saha et al. (2020), recommender systems in health applications offer two scenarios regarding the kind of end-users: first, health professionals can get additional information like research articles or clinical guidelines through the system; and second, the patients as final consumers of high-quality content that is supported by evidence. Additionally, existing Health Recommender Systems (HRS) could also be divided into two categories based on how they are used. First, HRS continuously monitors and diagnoses chronic disease. Such technologies could offer resources and assistance to doctors and patients, extending appropriate advice and predicting disease risk (Cochran et al., 2019; Humphries et al., 2021; Peleg, Shahar, Quaglini, Fux, et al., 2017; Pustozerov et al., 2018; Venkateswaran et al., 2022). Second, content-based HRS allows users to explore and find conditions associated with their disease via semantic analysis. While there are two main types of user interfaces used to connect with people by health recommender systems, graphical user interfaces are not always employed to do so (De Croon et al., 2021). Information can be distributed through mobile applications or mobile web applications by a health recommender system with a mobile interface (Abejirinde, Douwes, et al., 2018; Akbulut et al., 2018; Peleg, Shahar, Quaglini, Broens, et al., 2017; Perry et al., 2021; Pustozerov et al., 2020; Rahman et al., 2021; Simbolon et al., 2020). On the other hand, others can display the recommendations via a web interface (De Croon et al., 2021).

HEALTH RECOMMENDER SYSTEM FOR MATERNAL CARE

There is a wide range of topics that can be covered in the health-care domain which define the nature of items that are being recommended. In maternal care, pregnant individuals using the system could receive recommendations for things like diet, exercise, medicine, or consultations (Akbulut et al., 2018; Nsugbe et al., 2021; Palmer et al., 2021; Pustozerov et al., 2018; Rahman et al., 2021). HRS for maternal care could use portable diagnostic tools and mobile sensors to offer automatic measuring (Abejirinde, Zweekhorst, et al., 2018; Palmer et al., 2021; Pustozerov et al., 2018). Data from linked medical devices, as well as user input into patient health records, may be used to provide recommendations that help in diagnosis and monitoring pregnancy during ANC (Abejirinde, Zweekhorst, et al., 2018; Akbulut et al., 2018; Cochran et al., 2019; Humphries et al., 2021; Lindahl et al., 2019; Nsugbe et al., 2021; Peleg, Shahar, Quaglini, Fux, et al., 2017; Perry et al., 2021; Pustozerov et al., 2018; Rahman et al., 2021; Simbolon et al., 2020; Venkateswaran et al., 2022). Although earlier research has demonstrated the potential of health recommender systems for maternal care to monitor pregnancies and reduce risks, the challenges associated with putting these systems into practice have been examined from the perspective of physicians (Priambodo et al., 2022). Priambodo et al. (2022) identified technological issues concerning simplicity, compatibility, and the provision of all necessary functionalities, precise and consistent information, alongside critical information which are exacerbated by normative pressure, necessitating the existence of regulation and policy for amplified impact.

METHODOLOGY

This review adhered to the recommended reporting items for Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) reporting guidelines (Page et al., 2021). This systematic review was carried out from November to December 2022. Various steps in this study followed PRISMA reporting guidelines used by Handayani et al. (2018, p. 1) determining: (1) inclusion criteria; (2) information sources; (3) research selection; (4) data collection; and (5) data item selection. Figure 2 shows the procedures we used to perform the systematic review.

ELIGIBILITY CRITERIA

For the review guidelines, the following inclusion criteria (IC) were established:

- IC1: English-language, original, peer-reviewed research; and
- IC2: Primary research or reports on the development or evaluation of a system used by clinicians or patients for giving recommendations during pregnancy.

Since English is a widely used language among scientists, we only chose papers that were written in English (IC1). To address the research questions, IC2 was included. Our interests extended beyond just health applications in developing countries and to those in developed nations as well. Additionally, we were looking for publications that examined a health recommender system or decision support system focusing on or having the ability to give actionable guides to patients or clinicians in accordance with ongoing pregnancies. The inclusion criteria were initially examined before thoroughly screening the chosen publications. These publications were finally grouped into several criteria of health recommender system functionalities and factors.

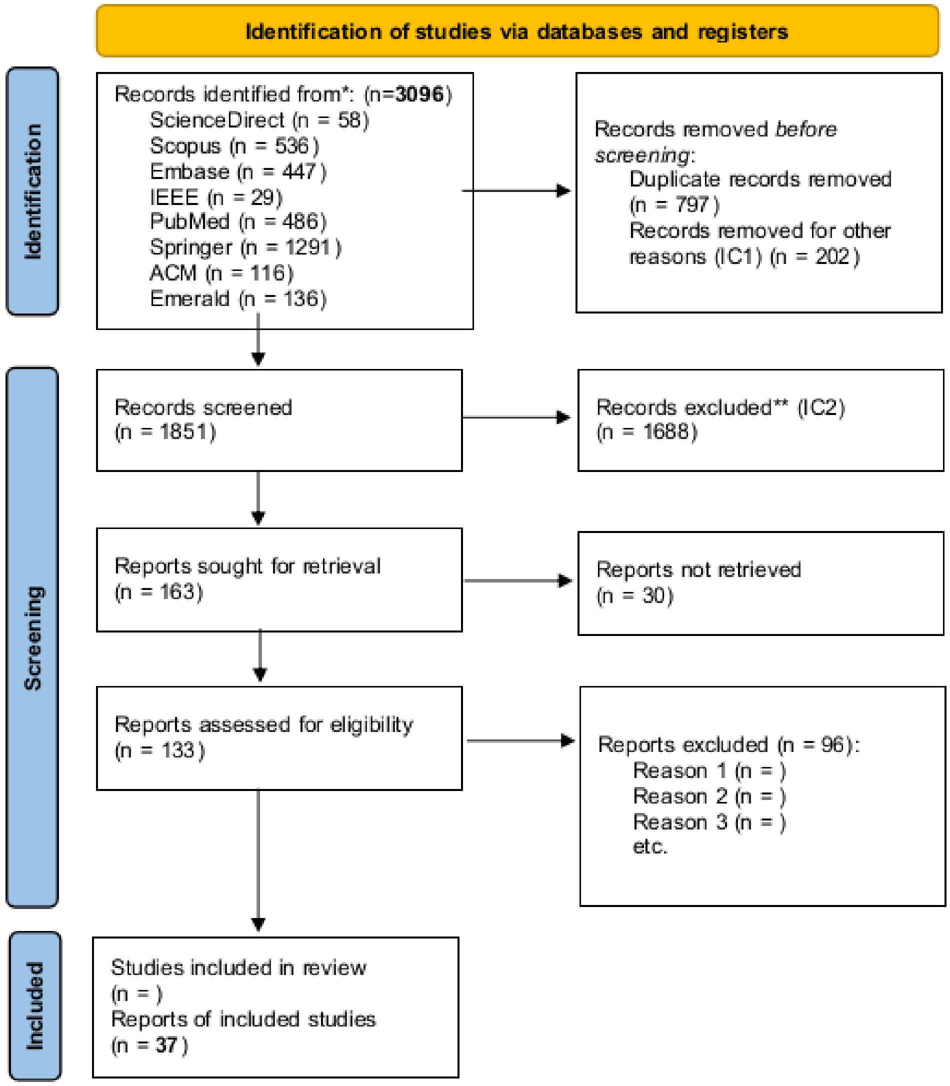

Figure 2. PRISMA flow diagram

INFORMATION SOURCES

ACM Digital Library, Springer, Elsevier (SCOPUS), Emerald, IEEE Xplore, ScienceDirect, Embase, and PubMed were among the online databases we searched that have sizable libraries of scholarly articles. Articles that the authors could not access fully were removed. We also looked through the articles' reference lists to locate related studies.

STUDY SELECTION

The selection of the studies was done in the following four stages:

(1) The keyword search, or search string, was relevant to both computer science and health research themes since it was related to our interest in analyzing health recommender systems for maternal care. The search string was the combination of "recommender system", "recommendation system", or "decision support system", and "maternal", "maternity", "antenatal", "prenatal", or "pregnancy" including terms such as "telemonitoring", "telehealth", "online monitoring", "remote monitoring", and "pregnancy application". In each of the

online databases mentioned in the Information Sources section, those precise search terms were looked up one by one.

(2) Based on the eligibility requirements, the titles, abstracts, and keywords of the identified articles were investigated and chosen.
(3) To determine whether the articles should be included in the review in accordance with the eligibility requirements, a full or partial reading of those that were not eliminated in the earlier phases was carried out.
(4) In order to begin this phase from Phase 2, related studies were sought out by searching the reference lists of the articles.

The authors worked together to complete these stages through an iterative process of author assessments. As a result, any disagreements were discussed by the three authors until they all agreed.

DATA COLLECTION PROCESS

Data extraction forms with the following contents were used to manually collect the necessary information: article type, name of the journal or conference, year, topic, title, abstract, keyword, country, research technique, and if it has discussion on a system giving recommendation to patients/clinicians during pregnancy. Each author evaluated publications that might be pertinent. Reading both the full text and the extracted data served as the assessment. Any disagreements were discussed among the authors in order to be resolved.

DATA ITEMS

The following information was taken from each article:

1) Demography of selected articles with the following information:
   i. Distribution of study
   ii. Countries involved in a study
   iii. Sources of selected study
   iv. State of development
2) Information related to the recommender system:
   i. Description of recommendation scenario
   ii. Domain (therapeutic area)
   iii. Recommended items
   iv. Type of targeted users
   v. Recommendation techniques
   vi. Data source
   vii. User interface types

RESULTS

STUDY SELECTION

There were 3,096 studies authored in English between 2017 and 2022 found through the search results in the chosen databases, all of which were matched with the relevant keywords. Following a screening of those publications based on their title, abstracts, and keywords, the remaining 133 articles underwent a full-text examination. Due to IC2, 1,784 articles were eliminated in total (most of those articles did not discuss pregnancy or maternal care). We also removed 30 articles that the authors could not access entirely. Finally, 37 papers in total were chosen for the review.

Demography of Selected Studies

This section describes the demography of selected studies. Figure 3 shows the distribution of the study in the last five years. The chart shows that there were 4-9 research of maternal recommender systems in a year in the last five years. Although not many, the number shows consistency on this topic of interest.

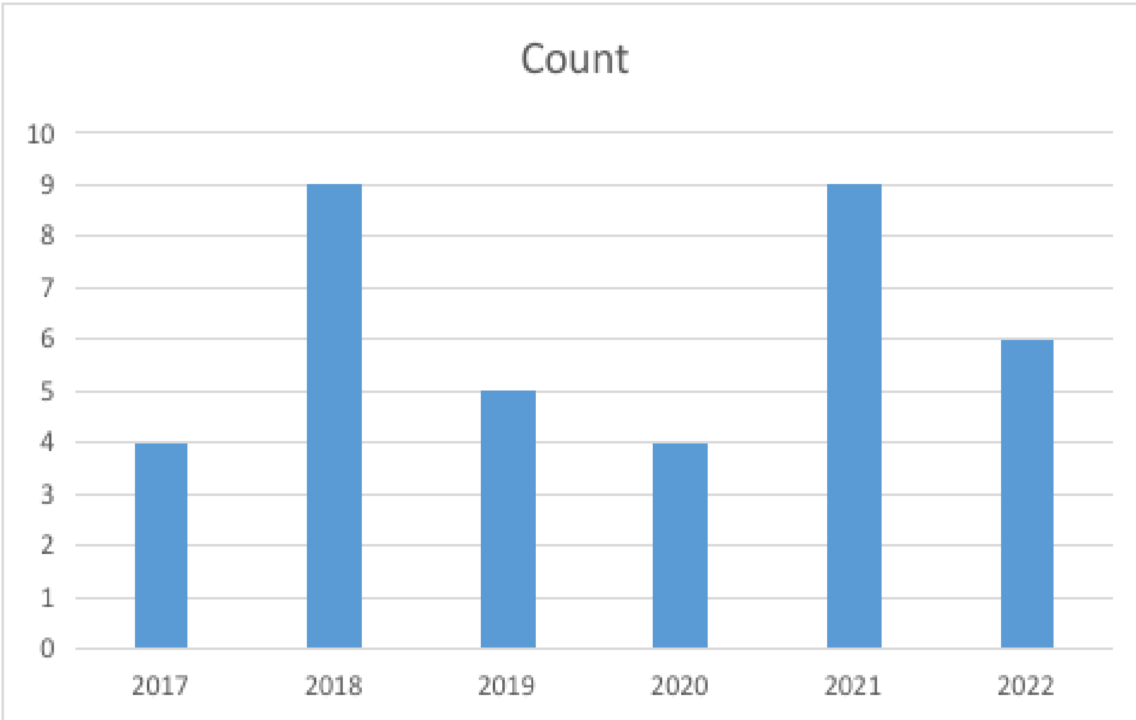

Figure 3. Distribution of study

Tables 1 and 2 show that the studies of health recommender systems for maternal care are published in international journals and proceedings. Almost all of them are indexed in Scopus and the rest of them are indexed in Springer, ScienceDirect, Embase, ACM, and PubMed.

Table 1. Source of studies

Database	# of Publications
Scopus	25
Springer	4
ScienceDirect	3
Embase	2
ACM	2
PubMed	1

Table 2. Sources of publication

Article Type	Journal	# of Publications
Journal	JMIR mHealth and uHealth	3
Journal	JMIR Research Protocols	3
Journal	BMC Medical Informatics and Decision Making	2
Journal	BMC Pregnancy and Childbirth	2
Journal	International Journal of Medical Informatics	2
Journal	Trials	2
Proceeding	2020 International Symposium on Community-Centric Systems, CcS 2020	1
Journal	Archives of Endocrinology and Metabolism	1
Journal	Artificial Intelligence in Medicine	1
Journal	Biomedical Engineering	1
Journal	BMJ Open	1
Journal	Frontiers in Global Women's Health	1
Journal	Frontiers in Public Health	1
Journal	IAES International Journal of Artificial Intelligence	1
Journal	Journal of Decision Systems	1
Journal	Journal of Diabetes Science and Technology	1
Journal	Journal of Global Health	1
Journal	Journal of Medical Internet Research	1
Journal	Machine Learning with Applications	1
Journal	Midwifery	1
Journal	National Medical Journal of India	1
Journal	Pregnancy Hypertension	1
Proceeding	Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems	1
Proceeding	Proceedings of the Third International Conference on Advanced Informatics for Computing Research	1
Journal	Reproductive Health	1
Journal	Studies in health technology and informatics	1
Journal	The Lancet Digital Health	1
Journal	User Modeling and User-Adapted Interaction	1
Journal	Wireless Personal Communications	1

Based on the data, the literature review on health recommender systems for maternal care included publications from a wide range of countries. Seven publications did not specify a country of origin, The remaining publications were conducted in 15 different countries, with the majority of the publications originating from Palestine (Western Asia) and Spain (Southwestern Europe), each with four publications. Ghana (Western Africa) and India (Southern Asia) had three publications each, while the UK had three publications as well. Other countries with more than one publication include Bangladesh (Southern Asia), the Netherlands (Western Europe), and Russia (Northern Asia), each with two publications. The remaining countries had only one publication each, including Brazil, China, Ethiopia, Guatemala, Israel/Italy/Spain/USA (a multinational study), Kenya, and Malaysia. Table 3 shows the list of the distribution of the countries.

Table 3. Countries involved in health recommender system study

Countries	# of Publications
(not specified)	7
Palestine	4
Spain	4
Ghana	3
India	3
UK	3
Bangladesh	2
Netherlands	2
Russia	2
Brazil	1
China	1
Ethiopia	1
Guatemala	1
Israel, Italy, Spain, USA	1
Kenya	1
Malaysia	1

Some of the major causes of maternal mortality are severe bleeding, infections, and high blood pressure (Say et al., 2014). In general, the health recommender system for maternal care was targeted to antenatal care (ANC) where cases can vary such as pre-eclampsia (high blood pressure), gestational diabetes, and anemia. However, as one of the most common complications of pregnancy, Gestational Diabetes Mellitus (GDM) and/or Atrial Fibrillation (AF) was found as the second most common therapeutic area with 10 publications. Other domains are less common, with only 3 publications focusing on preterm birth prevention, 2 on preeclampsia, and 1 each on general health including maternal and Nausea and Vomiting during Pregnancy (NVP). Table 4 shows the number of publications for each therapeutic area.

The six stages of maturity for a digital health intervention include the pre-prototype stage, prototype stage, pilot stage, demonstration stage, scale-up stage, and sustainability stage (World Health Organization, 2016). Table 5 shows the list of the distribution by the stage of maturity. In the pre-prototype stage, hypotheses are built, needs and context are assessed, and usability and technical stability are tested (World Health Organization, 2016). Furthermore, the prototype stage involves iterative testing of user-focused designs to enhance functionality, technical stability, usability, and relevance (World Health Organization, 2016). The 9 publications in the design/prototype stage indicate that significant research and development efforts have been dedicated to conceptualizing and building the initial version of the maternal health recommender system.

Table 4. Domain (therapeutic area)

Domain (therapeutic area)	Description	# of Publications
Antenatal Care (ANC)	The application provides all recommendations required during the antenatal period	20
Gestational Diabetes Mellitus (GDM) and/or Atrial Fibrillation (AF)	A glucose tolerance issue that begins during pregnancy is known as gestational diabetes mellitus (GDM), and it is linked to an elevated risk of fetal and maternal morbidity as well as long-term consequences for both mother and child (Kautzky-Willer et al., 2019). One of the most prevalent cardiac arrhythmias is AF. Pregnancy's increased cardiac workload may make AF less tolerable and raise the risk of heart failure (Lee et al., 2016).	10
Preterm birth prevention	Preterm birth refers to the delivery of a baby before 37 weeks of gestation. This is a significant health concern as preterm babies are at higher risk of health complications and mortality compared to babies born at full term (Carlisle, Watson, Seed, et al., 2021).	3
Pre-eclampsia	High blood pressure during pregnancy. Pre-eclampsia is one of the major complications that lead to maternal mortality (Say et al., 2014).	2
General health including maternal	The apps generated recommendations not for specific diseases but can support maternal health.	1
Nausea and Vomiting during Pregnancy (NVP)	Refers to the feeling of sickness and the act of vomiting during pregnancy. Even mild NVP can significantly reduce quality of life (QoL), and it can become an economic burden for both the woman and society (Ngo et al., 2022).	1

Table 5. Stage of maturity

Stage of Maturity (WHO, 2016)	# of Publications
Design/Prototype	9
Pilot	12
Demonstration	11
An integrated and sustained program	5

In the pilot stage, the intervention is deployed in a controlled setting to evaluate its desired effect (World Health Organization, 2016). There are 12 publications of studies conducted in the pilot stage. Moreover, the demonstration stage expands the intervention beyond controlled conditions, focusing on implementation requirements, costs, and replicability in new contexts (World Health Organization, 2016). We found 11 publications in the demo stage which suggests that the maternal health recommender system has been expanded beyond controlled conditions and tested in real-world settings. The higher number of publications in the pilot and demo stages suggests that the maternal health recommender system has shown promising results in terms of feasibility, acceptability, and effectiveness. This indicates that the system has demonstrated the potential to address the challenges related to lowering maternal mortality rates.

Finally, in the integrated and sustained program stage, efforts are directed toward creating an enabling environment that supports the intervention's impact at a large scale, including policy integration, financing, human resources, and interoperability, ensuring its long-term integration into the broader health system (World Health Organization, 2016). The lower number of publications in the sustained stage points to a potential gap in research on the long-term integration, policy alignment, and sustainability of the maternal health recommender system. This highlights the need for more attention and investigation into these areas to ensure the successful implementation and continued impact of the system. The findings in Table 5 underscore the importance of considering the broader healthcare ecosystem and the integration of the maternal health recommender system into existing maternal healthcare services. This implies that a comprehensive approach, including policy integration, financing mechanisms, and sustainability planning, is crucial to ensure the long-term success and impact of the system.

As seen in Table 6, the most commonly studied approach for health recommender systems for maternal care is the knowledge-based approach with 27 publications. The knowledge-based approach utilizes constraints and rules to generate recommendations for users (Ameen, 2019). The second most commonly studied approach is the hybrid approach with 5 publications. The hybrid (mixed) approach combines multiple recommendation techniques, such as collaborative filtering and content-based filtering, to generate more accurate recommendations (P. Rana et al., 2020). Content-based filtering, which involves recommending items based on their similarity to items previously rated positively by the user (Aggarwal, 2016), is the third most commonly studied approach with 4 publications. Finally, there is one publication where the approach used is not mentioned.

Table 6. Recommender system approach

Recommender System Approach	Description	# of Publications
Knowledge-based (constraint-based)	Generate recommendations based on explicitly specified constraints or rules (Ameen, 2019)	27
Hybrid (mixed)	Combines multiple recommendation techniques (e.g., collaborative filtering and content-based filtering) (P. Rana et al., 2020)	5
Content-based	Generate recommendations based on the similarity of the user's attribute and the item's attribute (P. Rana et al., 2020)	4
Not mentioned	No specific approach was mentioned	1

As seen in Table 7, the majority of the studies (24 out of 40) used a rule-based matching technique to generate recommendations for maternal care. Other techniques mentioned include cosine similarity (2 studies), linear regression (2 studies), support vector machine (SVM) (2 studies), decision tree (1 study), genetic algorithm (1 study), prediction algorithm (1 study), soft voting-based ensemble learning and cosine similarity (1 study), and statistics (1 study) and Multilayer Perceptron neural network (MLP) (1 study). In addition, 4 studies did not mention the matching technique or algorithm used.

The health recommender system for maternal care keeps an eye on the physiological state so it can make the best recommendations for risk prevention (Abejirinde, Zweekhorst, et al., 2018). It uses portable diagnostic equipment and mobile sensors to provide automatic measurement and offers pregnant people recommendations for things like diet, exercise, medicine, or consultations (Akbulut et al., 2018; Nsugbe et al., 2021; Rahman et al., 2021). The user's input, the patient's health record, connected medical devices, and other data sources may all be used to make suggestions (Cochran et al., 2019; Humphries et al., 2021; Lindahl et al., 2019; Peleg, Shahar, Quaglini, Fux, et al., 2017; Simbolon et al., 2020).

Table 7. Matching technique (algorithm to generate recommendations)

Matching Technique	Description	# of Publications
Rule-based	Recommendations are generated based on rules defined by experts or guidelines provided by health authorities (e.g., government, Ministry of Health, WHO)	24
Not mentioned	The studies did not mention specific matching techniques or algorithms used to generate recommendations	4
Cosine similarity	The method used to measure similarities between users and items (P. Rana et al., 2020)	2
Linear regression	Statistical modeling technique used in recommender system to find a linear relationship between items to make predictions and generate recommendations based on the prediction (Pustozerov et al., 2018)	2
Support Vector Machine (SVM)	A classification algorithm that can be used to give recommendations based on predicted class (Nsugbe et al., 2021)	2
Decision tree	A hierarchical partitioning of data based on split criteria results in branches of classes (Aggarwal, 2016). A decision tree can be developed based on available guidelines (Haddad et al., 2020)	1
Genetic algorithm	An optimization algorithm that selects the best individual or element from a pool of population and iteratively mates and produces better offspring until it achieves the best product. The genetic algorithm is used to predict the recommended meal intake for GDM patients based on their blood glucose levels (Mohd Rosli et al., 2020).	1
Prediction algorithm	A prediction algorithm was used in this study without specifying any known algorithm	1
Soft voting-based ensemble learning	An ensemble method combines the prediction of multiple individual classifiers (Simbolon et al., 2020)	1
Statistics	The recommendation is given based on a risk score calculated using statistical methods	1
Multilayer Perceptron (MLP)	A classification algorithm that can be used to give recommendations based on predicted class or condition (Nsugbe et al., 2021)	1

As shown in Table 8, the most commonly used source of data for generating recommendations in health recommender systems for maternal care in the studies is the patient health record, where the data were input by health workers. This suggests that health workers are key stakeholders in the design and implementation of these systems and that their input and involvement are critical for the successful adoption and use of the systems.

Next, the patient health record input by patients and measurement devices are tied for second place. This highlights the importance of including patient-generated data in these systems, as well as data from measurement devices, such as wearables and medical devices, which can provide more objective and accurate data for personalized recommendations. Measurement devices used in the studies can be operated by the patient herself or with the help of health workers such as physicians in health facilities or midwives, cadre, or Traditional Birth Attendants (TBA) by visiting the patients at home.

Table 8. Source of data

Data Source	# of Publications
Patient health records	
Input by health workers	22
Input by patients	13
Input from measurement devices (e.g., ECG, blood glucose monitor, blood pressure monitor, heart rate monitor, pulse oximeter, doppler ultrasound)	13
Dataset	2

Recommender systems in the healthcare domain can be used by health professionals and patients as well. J. Saha et al. (2020) stated that, regarding the type of end-users, the health recommender system offers two scenarios. First, health professionals as the users who can retrieve additional information through the system. Second, patients as the users who can get health-related content based on evidence. The WHO (2019) definitions of health professionals, associate professionals, and personal care workers in health services which cover maternal care include doctors in obstetric and gynecological specialties, nurses, midwives, and birth assistants or attendants. In this study, 18 publications reported health recommender systems targeted to health workers as users. This included doctors, nurses, midwives, and traditional birth attendants (TBA). They received recommendations regarding the condition of a patient or retrieved information based on the patient's medical record. On the other hand, 8 publications reported health recommender systems targeted patients as users. In this case, patients were not only able to browse relatable content but also received alerts, notifications, risk predictions, or any other actionable guides throughout the application. While these two scenarios only offer recommendations exclusively to one of the types of users, there is also the third scenario where the application provides recommendations for both types of users. Table 9 shows the number of publications for each scenario.

Table 9. Targeted user

User	# of Publications
Health workers (doctors, nurses, midwives, traditional birth attendants (TBA))	18
Patients	8
Health workers and patients	11

De Croon et al. (2021) found that, while there are two main types of user interfaces used by the user of the health recommender systems, graphical user interfaces are not always employed to do so. Health recommender systems using mobile interfaces can disseminate information through mobile applications or mobile web applications while others can use web interfaces to show recommendations (De Croon et al., 2021). Table 10 shows the variety of interfaces used to deliver recommendations to the user. Although most of the research uses a mobile application as an accessing device, some applications only provide web-based applications (14 publications) or desktop applications (3 publications) for their users. Additionally, text messaging, or Short Message Service (SMS), and email are also used to send the personalized message (3 publications).

Table 10. Interface to deliver recommendations

User Interface	# of Publications
Mobile app	26
Web-based app	14
Desktop app	3
Email/SMS	3
Not specified	1

Antenatal care recommended by WHO suggests regular visits and routine screening for early detection of complications. During pregnancy, patients are also required to follow guidelines to keep healthy and to prevent diseases that can worsen and risk the delivery. The health recommender system helps diagnose and monitor patients over time. It uses personal health records collected from measurements made by health workers or patients themselves. It can be integrated into automated diagnostic devices to automate routine data input. As a recommender system, this application uses a machine learning algorithm to find the best match of the recommended items for the patient. However, there are guidelines usually provided by health authorities that they must adhere to. Therefore, the algorithm must combine with knowledge-based rules regarding the guidelines. Figure 4 depicts the ecosystem of the health recommender system for maternal care. Data collected from measurement devices can be stored in the server or locally in the device to anticipate intermittent data connection. The same reason can also be considered for the use of communication channels that require no data plan such as Short Message Service (SMS) and Unstructured Supplementary Service Data (USSD).

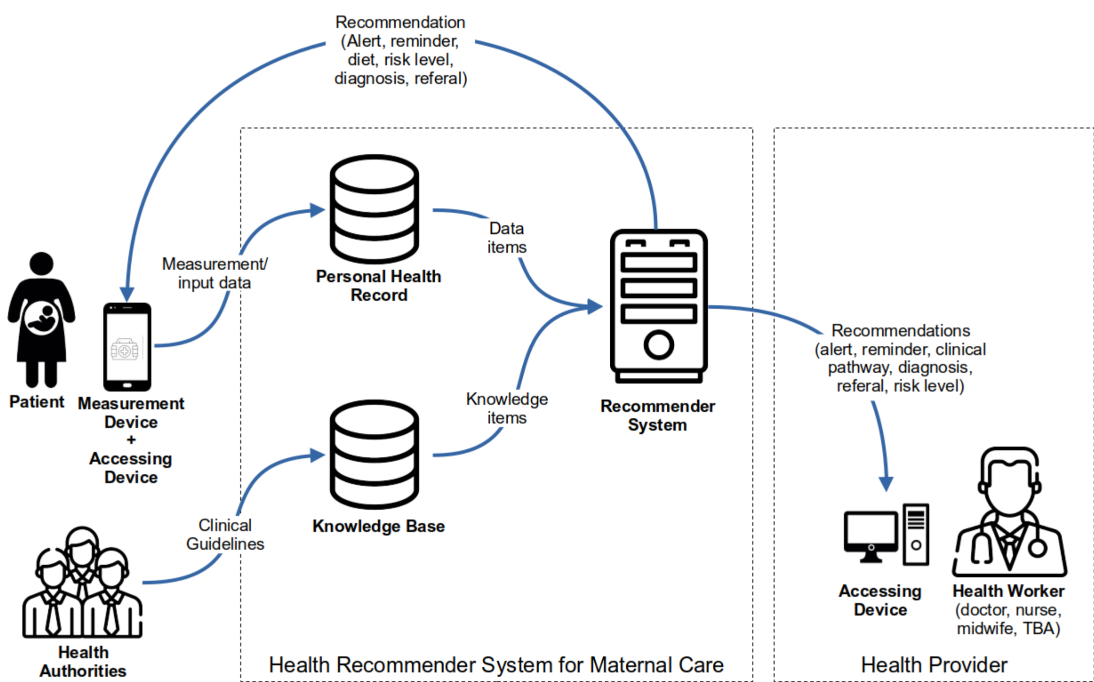

Figure 4. The ecosystem of Health Recommender System for Maternal Care

CHALLENGES

Health recommender systems for maternal care have gained attention in recent years as a promising solution to improve the quality of healthcare services for pregnant women. These systems aim to provide personalized recommendations to support patients and healthcare providers in making informed decisions about the management and treatment of maternal health conditions. However, the design and implementation of such systems face several challenges, as revealed in our systematic literature review.

Handayani et al. (2015) discovered that both hospital management and patients share the belief that human resources, procedure, policy, and infrastructure are the aspects that can improve hospital service quality. The term "human resources" or people refers to an organization that is supported by both professional and amiable medical and non-medical staff. The process dimension suggests that the company needs to respond quickly and be dependable to provide the promised services. According to the infrastructure dimensions, the facility must have a suitable structure and equipment. The final aspect of the policy is giving assurance for all the promised services. In our systematic literature review, we discovered 12 themes of challenges that were mapped to 7 sub-criteria, 4 criteria, and 3 dimensions afterward. Figure 5 shows the map of the findings, which visualizes the connection between dimensions, criteria, sub-criteria, and themes.

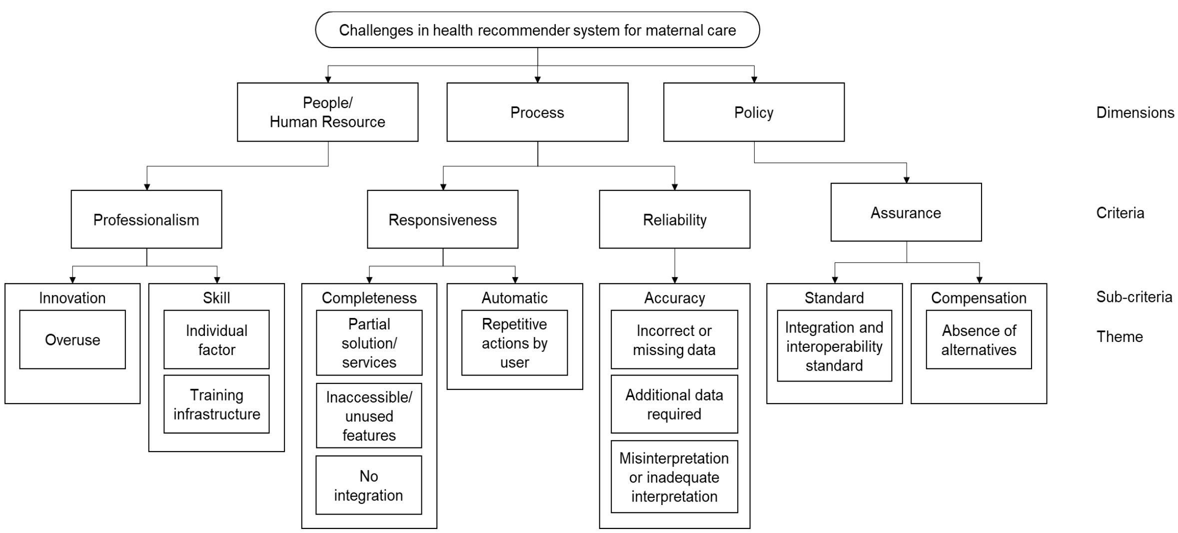

Figure 5. Challenges in the health recommender system for maternal care

Human resources

To guarantee the effectiveness of technology deployment, social- or human-related elements should be considered (Harahap et al., 2019). Professional healthcare workers should be highly skilled and experienced, actively engaged in ongoing innovation in line with the most recent advancements in technology and the health sciences, and readily available to patients whenever they need them (Handayani et al., 2015). Lewis et al. (2023) discovered that staff members in health facilities who were given the chance to improve skills through training programs could improve their performance. Both the central government and local governments should put more effort into training medical professionals, which involves growing the staff's numbers, skills, and knowledge as well as how they are distributed (Handayani et al., 2015). Table 11 shows challenges in human resources or people dimension.

Table 11. Challenges in the human resource/people dimension

Criteria	Sub-Criteria	Theme	Challenge Description	Reference
Professional-ism	Innovation	Overuse	The technology's potential to hinder holistic assessment may cause clinicians to overly rely on the app's recommendations, neglecting other vital aspects of the patient's condition, necessitating education to view the app as a supportive tool rather than a substitute, although most physicians found it helpful for confidence and communication, some struggled to perceive it as such.	(Carlisle, Watson, Carter, et al., 2021)
	Skill	Individual factor	Despite perceived usefulness and user motivation Abejirinde, Zweekhorst et al. (2018) found individual factors suppressed utilization mechanisms, such as low technological self-efficacy and knowledge	(Abejirinde, Zweekhorst et al., 2018)
			More than half of the users were first-time smartphone users in their fifties. Despite everyone's quick acceptance of the new technology, many had trouble using the system.	(S. Saha & Quazi, 2022)
			More than half of the participants were reluctant to use the application as they had never used a smartphone before while some of them maintained a manual register due to the fear of losing mobile data.	(S. Saha & Quazi, 2022)
		Training infrastructure	Performed training using online infrastructure because it was difficult to organize in-person training for field employees across the state. The preference for in-person training highlights the importance of personal interaction and hands-on experience in training healthcare workers. It also emphasizes the need for adequate infrastructure and resources to provide effective training to field staff in remote areas.	(S. Saha & Quazi, 2022)

Process

Reliability and responsiveness should be reflected in the process dimension (Handayani et al., 2015). DeLone and McLean (2016) mentioned that reliability, completeness, and accuracy can be used to measure information quality in an information system. Thus, hospitals should be able to operate and deliver promised services on schedule, offer an automated process, and be able to deliver all types of services needed by patients to provide outstanding public services (Handayani et al., 2015).

Table 12 shows challenges in the process dimension. Handayani et al. (2015) defined hospital responsiveness as the ability of the hospital to provide the promised services on time that are supported by the hospital information system, which could make the process more effective and efficient, as well as the willingness of the hospital to assist patients whenever necessary and to have all necessary services on hand.

Priambodo et al. (2022) also found that the implementation of HRS for maternal care concerns simplicity so that the app can provide information promptly, promote awareness, and be easy to use.

While a lot of information must be entered, the recording process should be straightforward and uncomplicated so that important messages won't be overlooked and patients and doctors may make the right choices as well.

Table 12. Challenges in the process dimension

Criteria	Sub-Criteria	Theme	Challenge Description	Reference
Responsiveness	Completeness	Partial solution/ services	Facilities with high volumes of ANC attendees, multiple service delivery demands, or high staff turnover or shortages had lower utilization of the recommender system. This was related in part to the fact that the system was used in addition to the usual ANC routine because it was regarded as a pilot intervention, therefore it was seen as a partial solution to a larger diagnostic need and was not fully integrated into ANC workflow, which led to duplication of processes and made utilization burdensome.	(Abejirinde, Zweekhorst, et al., 2018)
	Skill	Individual factor	Personnel shortages, despite the high volume of patients, appeared to have an impact on the level of success in meeting patient demands.	(Carlisle, Watson, Carter, et al., 2021)
			Employee turnover at medical facilities and health offices, particularly the absence of a vital member of the technology and monitoring and evaluation teams, hampered the development of the application's adaptation to local needs and further customization.	(Shiferaw et al., 2018)
		Inaccessible/unused features	When the apps needed internet connectivity to manage beneficiaries' details, clinicians found it hard to operate the application while offline.	(S. Saha & Quazi, 2022)
		Training infrastructure	The system was able to function properly most of the time but faced occasional disruptions due to poor network connectivity or power outages.	(Shiferaw et al., 2018)
			Despite the capability of the system to recommend a range of laboratory testing, treatment options, and medication choices, clinicians frequently ignored this suggestion because of the limitations of the facility.	(Wang et al., 2021)
			The app includes an information section with a detailed guide to the field definitions, but some users may not have utilized it.	(Carlisle, Watson, Carter, et al., 2021)
		No integration	The system was less useful according to the clinicians since it was not synchronized with other systems, such as pharmaceutical systems that provide information on available medicine. Therefore, sometimes the given recommendation was not useful due to the unavailability of the recommended prescriptions.	(Wang et al., 2021)

Criteria	Sub-Criteria	Theme	Challenge Description	Reference
			Maternal care was provided solely and was not connected with other crucial service elements including child health services like immunization. As a result, health professionals were expected to use both the new system and the manual system, which added to their workload.	(Shiferaw et al., 2018)
	Automatic	Repetitive actions by the user	The recommender system requires specific data from electronic health records to produce suggestions where clinicians need to inquire about patients' medical histories, assess their current medication consumption, and assess their emotional state before recording all of this data in the electronic health record.	(Wang et al., 2021)
			Due to high patient volume and time constraints, clinicians frequently lack the time to ask these in-depth inquiries and accurately document the answers.	(Wang et al., 2021)
			Clinicians also encounter difficulties when updating beneficiary information because the software repeatedly requests beneficiaries' basic information.	(S. Saha & Quazi, 2022)
Reliability	Accuracy	Incorrect or missing data	Due to oversight on the part of users, information requiring manual entry was often not entered or had errors, which means that the users did not pay enough attention to the accuracy and completeness of their entries.	(Abejirinde, De Brouwere et al., 2019)
			A glitch resulted in incorrect dates for many records from one of the facilities.	(Abejirinde, Brouwere et al., 2019)
			Technical issues in data entry caused inconsistencies in data, such as the inability to correct the mistakes upon data entry or the software that stopped working frequently while entering the data.	(S. Saha & Quazi, 2022)
			Found some cases of accidental removal of data, loss of data stored on memory cards, and dysfunctional phones that made it unusable when needed.	(Shiferaw et al., 2018)
		Additional data required	Needed to assign unique identification numbers to pregnant women so that the woman's health progress can be tracked throughout the pregnancy, delivery, and postnatal care, even if she shifts from one health facility to another.	(Shiferaw et al., 2018)
		Misinterpretation or inadequate interpretation	Some issues with the app's usability, such as misinterpreting the obstetric definitions in the app fields.	(Carlisle, Watson, Carter, et al., 2021)

Criteria	Sub-Criteria	Theme	Challenge Description	Reference
			The suggested diagnoses were generally good, but the top recommendation's lack of accuracy due to the system's ineffective information gathering and inability to capture subtle clinician-recognized clues made the recommendations less useful and time-consuming.	(Wang et al., 2021)
			Clinicians are not sure if they can rely on the system's recommendations, they have to spend time evaluating the recommendations given by the system and the system does not provide enough explanatory information, such as why it gave such alerts.	(Wang et al., 2021)

Policy

Adherence to standards ensures that healthcare services are provided consistently and meet the patient's needs and expectations (Mosadeghrad, 2013). To ensure that all hospital activities adhere to the relevant standards for persons, processes, and infrastructure that are used, the policy dimension is the most crucial dimension that should be defined first in comparison to other dimensions. Without a clear, comprehensive, standardized, and defined policy, two dimensions – human resource and process – cannot be carried out effectively. To boost patient confidence and provide services that are affordable for all patients, the policy dimension should also include assurances in line with the principle of decency, as well as the provision of compensation or warranties for patients who experience problems. Table 13 shows challenges in policy dimensions.

Table 13. Challenges in the policy dimension

Criteria	Sub-Criteria	Theme	Challenge Description	Reference
Assurance	Standard	Integration and interoperability standard	To ensure the viability of scale-up in the long run, it will be crucial to create standards for the mHealth ecosystem that takes service integration and interoperability into consideration.	(Shiferaw et al., 2018)
	Compensation	Absence of alternatives	Low to moderate adoption was caused partly by the absence of alternatives while on the other hand, there was enthusiasm and high expectation of the service delivery because of the perceived benefits of the device, as well as the context in which it is introduced.	(Abejirinde, Zweekhorst, et al., 2018)

DISCUSSION

The systematic literature review conducted on health recommender systems for maternal care revealed several key findings that have important implications for both research and practice. First, the dominance of the knowledge-based approach could indicate that the development of HRS for maternal care must strictly follow available guidelines. The limited exploration of other approaches suggests that there may be opportunities to expand the range of recommendation techniques applied in this domain, which could potentially improve the effectiveness of recommender systems for maternal care. Therefore, further analysis may be needed to understand the strengths and limitations of each approach, and how they may be best applied to improve maternal health outcomes.

The findings on the matching techniques also suggest that while rule-based matching is the most used technique, there is a wide variety of techniques and algorithms used in health recommender systems for maternal care, such as cosine similarity, decision trees, and genetic algorithms. There are a few reasons why rule-based systems are more commonly used in healthcare.

1. *Interpretability:* Aggarwal (2016) emphasizes that rule-based systems offer a high level of interpretability. In healthcare, interpretability is crucial as it allows healthcare professionals to understand and explain the reasoning behind recommendations or decisions made by the system. This transparency builds trust and confidence in the system's outcomes, making it more likely to be used.
2. *Trust and clarity:* Contempré et al. (2022) point out that healthcare professionals may lose trust in a system if its underlying processes are unclear and unexplained. Rule-based systems provide explicit rules that can be understood and validated by healthcare professionals. This clear and transparent nature of rule-based systems helps maintain trust and confidence in the system's recommendations.
3. *Integration into the clinical workflow:* Gräßer et al. (2022) mention challenges regarding the integration of clinical decision support systems (CDSSs) into the clinical workflow. Rule-based systems can be easily integrated into existing systems and workflows, as they rely on a set of predefined rules and conditions. This makes it more feasible for healthcare professionals to incorporate rule-based CDSSs into their daily practice without major disruptions.
4. *Availability of clinical data:* Gräßer et al. (2022) also highlight challenges related to accessing relevant clinical data in a processable format for data-driven CDSSs. Rule-based systems do not rely heavily on extensive clinical data analysis, making them more accessible and easier to implement. The rules in a rule-based system can be derived from existing medical guidelines, protocols, or expert knowledge, which are often readily available.

Explainability or providing a rationale for the generated recommendations or decisions is crucial for Clinical Decision Support Systems (CDSS) to ensure trustworthiness, comprehensibility, and effective enhancement of human decision-making processes (Antoniadi et al., 2021). While rule-based systems have advantages in terms of interpretability and ease of integration, it is important to note that data-driven approaches, such as machine learning-based systems, are also gaining recognition in healthcare (Mittal & Hasija, 2020). These approaches can leverage large-scale clinical data for more accurate predictions and recommendations (Sandeep Kumar & Satya Jayadev, 2020). However, challenges related to interpretability and explainability need to be addressed to ensure the acceptance and adoption of these data-driven systems in clinical practice (Antoniadi et al., 2021).

Another key finding is that the sources of data for the recommender system may come from user input or directly from measurement devices. For example, Caballero-Ruiz et al. (2017), Volanski et al. (2019), Ngo et al. (2022), and Bateja et al. (2019) had the patients input the data while others had the data input by health workers, such as doctors (Carlisle, Watson, Seed, et al., 2021; Veena & Aravindhar, 2021), physicians (Caballero-Ruiz et al., 2017; Pustozerov et al., 2020), clinicians (Carlisle, Watson, Seed, et al., 2021; Nsugbe et al., 2021), midwives (Abejirinde, Douwes, et al., 2018), and traditional birth attendants (Martinez et al., 2018). These sources of data may come from users manually reading the devices or by user observation. On the other hand, diagnostic devices could also provide automatic reading where data from sensors could be sent directly to the remote computer (Peleg, Shahar, Quaglini, Broens, et al., 2017; Pustozerov et al., 2020), providing benefits for users not to input the data by themself. This Internet of Things (IoT) based device helps doctors and physicians acquire the necessary data needed to continuously monitor throughout pregnancy (Oti et al., 2018). Additionally, the workload of doctors would be reduced by the use of automatic data input (S. Saha & Quazi, 2022; Wang et al., 2021).

The typical health recommender system framework collects information about a patient's current health status from many resources, such as electronic medical records (EMR) or electronic health records (EHR) through secure network protocol to form personal health records or PHR (S. P. Rana et al., 2020). Pustozerov et al. (2020) developed a health recommender system for pregnant women where various sources of data are linked and stored in remote databases as electronic records. These collected data are used to generate recommendations back to the patient and the physicians. Providing decent connectivity to a recommender system is necessary since data analysis requires data from many resources (Wang et al., 2021). Doctors/experts need to be in the loop to give feedback to refine the resulting recommendation (S. P. Rana et al., 2020). So that providing connectivity or integration between systems could also provide more complete services (Shiferaw et al., 2018; Wang et al., 2021) by covering other departments (e.g. pharmacies, labs, and child health service), and intermittent connections could cause some features inaccessible or unusable at all (S. Saha & Quazi, 2022).

However, providing proper connectivity was not easy for implementation in low and middle-income countries (LMICs) (Labrique et al., 2018). Transport mediums range from ordinary broadband in cities to satellite connections, cellphone data, and Short Message Service (SMS) messaging (Chiang et al., 2021). Although SMS was least used as communication media in this study, it is worth considering that this interface can be sufficient for delivering recommendations. Schwebel and Larimer (2018) found that SMS is a widely used communication method due to its ubiquity, customizability, low cost, rapid and automated delivery, and acceptability. Therefore, text reminders could improve medication adherence and appointment attendance (Schwebel & Larimer, 2018). Ebuenyi et al. (2021) also found that SMS interventions have been used successfully to encourage patient self-management, patient awareness, and treatment adherence in these chronic diseases. Ebuenyi et al. (2021) discovered as well that SMS is a cost-effective and feasible way to improve patient outcomes and can be used to provide education, reminders, and support to patients. In addition, simple solutions are less reliant on the external environment, frequently depending on more resilient cellular channels such as short message service (SMS), interactive voice response (IVR), unstructured supplementary service data (USSD), or voice rather than internet or data (Labrique et al., 2018).

Finally, to ensure the long-term feasibility of scale-up, it will be crucial to develop standards for the mHealth ecosystem that take service integration and interoperability into account (Shiferaw et al., 2018). This involves financial assistance to enable long-term sustainable operations as well as regulatory standards and procedures to guarantee compliance with national health recommendations and strategies (Labrique et al., 2018).

CONCLUSION

In conclusion, the findings discussed in this study highlight the importance of explainability, data-driven approaches, automation, and the need for integration and interoperability in the development and adoption of health recommender systems for maternal care. As we reflect on the significance of these advancements, we acknowledge the urgent need to address the limitations and gaps in this research to reach the global health impact, laying the groundwork for a time when data-driven innovations can bridge healthcare disparities, lower the rate of maternal death, and provide universal access to high-quality prenatal care. One of the study's limitations is that the methods utilized to generate the recommendations were not thoroughly compared. The research question, which we ought to be able to investigate further on this subject, is likewise limited in this study.

Consequently, further studies can focus on developing and evaluating techniques to enhance the explainability and interpretability of data-driven health recommender systems and adding automatic measurement to the conventional health recommender system to improve the projected outcome of antenatal care. Comparative studies can also be conducted to evaluate the performance of different algorithms or models used in these systems. Future studies can also explore innovative approaches to overcome technological, infrastructure, and resource limitations, such as connectivity and automation to help overcome the lack of health professionals in remote areas, as well as identify strategies for sustainable long-term operations and integration into existing healthcare systems.

Finally, this study underscores the importance of a comprehensive strategy to integrate the maternal recommender system into the broader maternal healthcare ecosystem, highlighting the absence of sustainability assessments and the potential for scalability. These insights lay the groundwork for further research in health informatics, offering a way to enhance the effectiveness and seamless integration of health recommender systems in clinical settings. The task at hand is to translate these findings into pragmatic informatics solutions, shaping the trajectory toward safer and more efficient maternal care. It is a pivotal moment, where our knowledge must evolve into actionable informatics solutions that have the potential to transform the landscape of maternal healthcare, ultimately leading to healthier outcomes for both expectant mothers and their children.

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