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Artificial Intelligence in Pregnancy: A Scoping Review

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ABSTRACT Artificial Intelligence has been widely applied to a majority of research areas, including health and medicine. Certain complications or disorders that can appear during pregnancy can endanger the life of both mother and fetus. There is enough scientific literature to support the idea that emotional aspects can be a relevant risk factor in pregnancy (such as anxiety, stress or depression, for instance). This paper presents a scoping review of the scientific literature from the past 12 years (2008-2020) to identify which methodologies, techniques, algorithms and frameworks are used in Artificial Intelligence and Affective Computing for pregnancy health and well-being. The methodology proposed by Arksey and O'Malley, in conjunction with PRISMA-ScR framework has been used to create this review. Despite the relevance that emotional status can have as a risk factor during pregnancy, one of the main findings of this study is that there is still not a significant amount of literature on automatic analysis of emotion. Health enhancement and well-being for pregnant women can be achieved with artificial intelligence or affective computing based devices, hence future work on this topic is strongly suggested.

INDEX TERMS Artificial intelligence, affective computing, pregnancy health, pregnancy well-being, machine learning, methodology, algorithm, framework, IT security, data privacy.

I. INTRODUCTION

Pregnancy is a complex vital period in a woman's life with potential impact on her physical and psychological health. On the one hand, it may be difficult to adapt to the important physiological changes occurring during pregnancy. On the other hand, seeking both her own well-being as well as her fetus' represents a core element in her psychological health, including emotional behavior. This search for well-being can entail the need to learn new things, lifestyle changes (nutrition, physical exercises, sleep, work, etc.), along with proper medical care and timely follow-ups. Another elemental factor that can negatively impact the pregnant woman's psychological health is the potential risk of having health problems during pregnancy, especially if there is a high possibility of developing complications. Additionally, in this case, physiological problems can be the consequence of health problems, but they can also be predisposing factors in developing disorders during pregnancy.

For example, according to Leeners *et al.* [1], emotional stress, stressful events through life (death of close relatives, trauma), sleep disorders, among others, are some of the factors associated with pre-eclampsia. Rejnö *et al.* [2] associated anxiety and depression to complications during pregnancy: higher risk of suffering pre-eclampsia and having to give birth through a cesarean section. Anxiety and depression should be considered as a relevant factor when evaluating a pregnant woman's risk of suffering complications. Other correlations have been found by [3] and [4]. In a study in which 623 new mothers participated, Kurki *et al.* [3] came to the conclusion that experiencing anxiety and depression in the early stages of pregnancy is associated with a higher risk of suffering pre-elcmapsia. Thombre *et al.* [4] presented a study with a 1371 pregnant women sample. As a result, a relation

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between anxiety or depression may be linked to the risk of developing pre-eclampsia.

With the purpose of determining the relationship between anxiety during gestation and the incidence of pre-eclampsia, Kordi *et al.* [5] studied the case of 300 pregnant women, from which 150 suffered pre-eclampsia and the other half didn't. 26.7% of women belonging to the first group and 10.7% of women belonging to the second group, suffered anxiety. Authors came to the conclusion that suffering from anxiety during pregnancy could be considered a risk factor for pre-eclampsia.

Although not directly related to anxiety or depression specifically but to other emotional aspects, Krishnamurti *et al.* [6] investigated the impact of worry during pregnancy on women's health. It is also mentioned by the authors that all actions and interventions that can help the patient worry less about health related issues or problems that may arise associated to her status can be beneficial for both the fetus and herself.

Therefore, as for the aforementioned evidence, the emotional status would seem to not only influence the risk of suffering pre-eclampsia, but also a great number of other complications. The negative effects suffered during pregnancy may potentially last long after giving birth. Thus, there is a reason to believe that the usage of technological devices capable of detecting and using emotions can be suitable, not only for preventing pregnancy disorders such as pre-eclampsia, but also for supporting patients that already had a diagnosis.

During the last decades, Artificial Intelligence (hereafter "AI") has been increasingly applied to many new disciplines, among which health is one of them. This review aims at addressing AI applications focused on the health and well-being of pregnant women, as well as the use of Affective Computing (AC). AC is a multidisciplinary field where computer science meets not only other sciences, such as psychology or physiology, but also other engineering fields: electrical, mechanical and robotics. In this context, the machine is capable of recognizing, interpreting, processing or simulating human emotion, as well as adapting its behavior in accordance to the emotion expressed by the person interacting with it.

There is a great amount of literature and reviews regarding AI applications in health. From 2019 up to date, more than 400 results can be found in the bibliographic database Scopus searching for *reviews* or *survey* and AI and AC applications in health (exact query: ((survey OR review) AND ("artificial intelligence" OR "affective computing") AND health) AND (LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019)) AND (LIMIT-TO (DOCTYPE, "re"))). There is an ongoing interest in this topic in the scientific community and the tendency is adding up. Moreover, reviews on different AI health applications are being published, such as cardiovascular health care [7], Human immunodeficiency virus (HIV) prevention [8], mental health [9], dementia [10], type 1 diabetes [11] and aging societies [12].

Although the terms AI and Machine Learning (hereafter "ML") appear much more often in the literature, the field of affective computing, on the contrary, is still uncommon. A few results related to affective computing are found using the bibliographic search previously mentioned. By searching the words *affect* or *emotion* within the titles, the results reduce to 2 studies:

- *Wearable-Based Affect Recognition—A Review* [13]
- *Emotional expression in psychiatric conditions: New technology for clinicians* [14]

When searching the term *pregnan*, only one result is returned: *Enabling pregnant women and their physicians to make informed medication decisions using artificial intelligence*. This systematic review by Davidson *et al.* [15] reviewed 31 studies in which AI techniques were used for treatment and drug intake optimization during pregnancy.

A more specific search can be conducted using the term *pregnan**: TITLE-ABS-KEY ((survey OR review) AND ("artificial intelligence" OR "affective computing") AND pregnan*) AND (LIMIT-TO(DOCTYPE, "re") AND (LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019)). From all the results found in the bibliographic database Scopus, the results more related to pregnancy are the following:

- *Enabling pregnant women and their physicians to make informed medication decisions using artificial intelligence* [15]
- *Use of artificial intelligence (AI) in the interpretation of intrapartum fetal heart rate (FHR) tracings: a systematic review and meta-analysis* [16]

With this research, we aim to address this apparent knowledge gap by asking and answering the following research questions:

- ***RQ1: "What is the current state of research on methodologies, techniques, algorithms and frameworks used in Artificial Intelligence applied to pregnancy health and wellbeing?"***.
- ***RQ2: "From these studies where AI is used in pregnancy context, how many have an AC approach and which characteristics do they have?"***.

The remainder of this article is organized as follows: In section II, related work on AI is discussed and the context of pregnancy is presented. The methods employed to develop the scoping review and the protocol are described in section III. In section IV, we analyze the sources of evidence screened, present characteristics for which data were charted and provide the citations and summarize the charting results. For readiness, results are divided in three different sections: section V for general aspects, section VI for computer science aspects and section VII for medicine aspects. In section VIII, the main results are summarized, linked to the review question and objectives, and considered the relevance to key groups, and the limitations of the scoping review process are addressed. Finally, section IX, provides a general interpretation of the results with respect to the review question and objectives, as well as potential implications and next steps.

II. BACKGROUND

AI is a computational field that over the last decades has been constantly showing its potential and gained relevance and importance in multiple disciplines, one being medicine (Jiang *et al.*, 2017) [17]. There is a large number of scientific studies demonstrating and showing how AI can contribute to significantly improve aspects related to the health and well-being of groups and individuals. In the review presented by Jiang *et al.* in which the past, present and future of AI in health has been studied, the importance of the existence of clinical data is highlighted.

The constant growth of both the capacity to store data and the amount of data that is being generated in the medical field has clearly taken a relevant part in the rise of this research area. Different types of data, such as electronic medical records, clinical studies, physical exams, images, signal recordings, administrative and demographic data can be collected (with patient consent and/or data anonymization), or can be found available on the Internet. One of the boosting factors of the vast amount of AI research applied to health is data availability.

According to a survey published in 2017 by Jiang *et al.* [17] in which the application of AI in health is reported, various applications are being highlighted: offer support to healthcare professionals by means of updated and trustful scientific information, novel medical practices or improvements on already existing practices that can help assist patient care, reduce diagnosis error, and find relevant information in big amounts of data in order to reduce health risks and make diagnosis predictions in real time.

Another survey, published in 2009 by Topol *et al.* [18], highlights three levels in which AI can be applied to health. On the first level, healthcare professionals can benefit from having the possibility to use quick and reliable methods for image analysis. Secondly, it can improve health system workflow and potentially, reduce medical errors. Lastly, from the patient's point of view, AI applications can introduce personalized monitoring, so that healthcare can be provided for each patient's individual needs through this type of applications.

Similarly to the three levels identified by [18], applied to pregnancy health and well-being, firstly, AI can assist healthcare professionals in decision making related to pregnancy processes. For this, one example could be assistance in the decision of when a cesarean section or labour induction needs to be performed so that the negative impact that this procedures can have on the mother and child are reduced [19]. Secondly, AI can provide healthcare professionals and administrators with the most optimal way to allocate health resources [20]. Thirdly, patients can benefit from using an AI based home monitoring device to provide pregnancy support [21], but also to detect possible future complications during pregnancy before they occur, such as pre-eclampsia [22].

A 2009 study published by Tran *et al.* [23] on the evolution of the scientific literature on AI applied to medicine and health illustrates the exponential increase around 2002 and 2003 of literature in this research area. Alongside the rapid growth of scientific literature in this research area, the need to elaborate reviews that allow the evaluation of the state of the art arises. However, up to date, authors of this study could not find a review on AI and AC applied to health and well-being of pregnant women and their fetus, as explained throughout this section.

III. METHODS

This study has been conducted as a scoping review. According to [24], scoping reviews are an interesting tool to determine the scope or coverage of a body of literature on a given topic. Clear indications of the volume of studies available can be obtained, as well as an overview (broad or detailed) of their focus. The Arksey and O'Malley [25] framework and further improvements on their work by Levac and Colquhoun [26], [27] and Daudt *et al.* [28] have been followed, and reporting has been elaborated in accordance with the Extended Preferred Reporting Items for Systematic Reviews and Meta-Analyses Statement for Scoping Reviews (PRISMA-ScR) [29]. Indications and recommendations from the manual published by the Joanna Briggs Institute (JBI) [30] have also been taken into consideration. A summary of the protocol is presented in the following subsections.

A. ELIGIBILITY CRITERIA

Studies were eligible for inclusion in this scoping review on the basis of the following main concepts, established by the Population, Concept, Context (PCC) framework, recommended by the (JBI) [30]: a) Population: pregnant women and fetuses (regardless of pregnancy outcomes or characteristics); b) Concept: develops, proposes, applies, evaluates or compares artificial intelligence or AC methodologies, frameworks, algorithms or techniques; c) Context: maternal-fetal health and well-being. Research included as part of this study does contain different sources of evidence, such as primary research studies, published in journals and conference proceedings. Only English and Spanish written articles were included. Review articles (scoping reviews, systematic reviews, meta-analyses, etc.) were excluded. Studies were also excluded if the full text of the article was not available (e.g. conference abstracts).

B. INFORMATION SOURCES AND SEARCH

A structured literature search has been designed to identify relevant studies from multiple bibliographic databases: Scopus, Pubmed, Web of Science (WoS), IEEE Xplore and Association for Computing Machinery (ACM). Multiple information sources have been chosen in an attempt of developing a search strategy as comprehensive as possible.

Search terms considered in this review were selected based on the main concepts of the research question: pregnancy, health and well-being and AI, ML and AC.

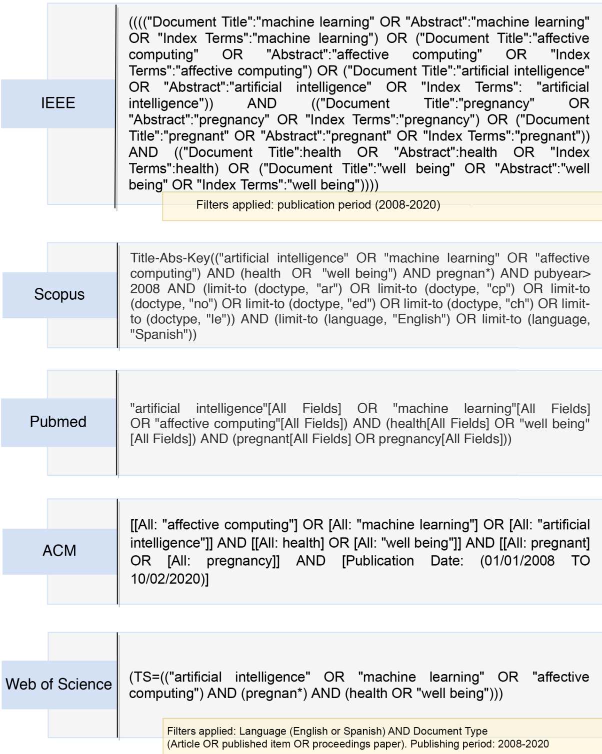

FIGURE 1. Searches conducted on IEEE Xplore, Scopus, Pubmed, ACM and web of science.

Boolean operations have been used for further personalization, so the structure of the conducted search is the following: ((''artificial intelligence'' OR ''machine learning'' OR ''affective computing'') AND (pregnan*) AND (health OR well-being)). All the returned articles from such search would comply to the condition expressed. At least one of the keywords from each AND operator in title, abstract or keywords is required.

Although the bibliographic databases search engines are similar, some differences have been found: nor ACM or Pubmed searches could be performed solely on title-abstract-keywords, so all fields were searched, Index terms in IEEE Xplore have been interpreted as keywords, and finally, in WoS, keywords were not available as a field tag, so topic (TS) field tag was used. Figure 1 illustrates the search adapted for each database.

References from each database have underwent a duplicates removal process before being exported to Mendeley for the following screening process. The search was performed on the 14th of February 2020.

C. SELECTION OF SOURCES

In a fist step and after duplicates removal, one reviewer screened the title, abstract, keywords and conclusions of each article. As outlined in the previous section, the search could not be automatically limited to title-abstract-keywords fields in all bibliographic databases, so this initial screening removed all studies that did not include at least one of the keywords in the AND operators of the search in the mentioned fields. Studies non-related to the research questions were also removed through this process.

After this first screening process concluded, the remaining studies were divided into four parts, so that each article could be reviewed by two authors. The content of the remaining article's title, abstract, keywords and conclusions were screened and tagged with one of the indicated options: *Included, Excluded* or *Unsure*. Reviewers could leave comments if necessary, however they were highly recommended, especially if studies were not included. If both reviewers tagged an article as *Included* or *Excluded*, the decision on the inclusion or exclusion was the indicated and the screen resulted in an agreement. Two *Unsure* tags or any combination of different tags represented a disagreement, which was handled by having the articles reviewed by the rest of the reviewers.

D. DATA CHARTING

For the charting process, a data charting form was developed by three reviewers (A, C, F). As recommended by the JBI [30], two reviewers (A and F) performed a pilot test on 9 studies of the charting process to assess the form before handing it over to the the rest of the reviewers. Another followed recommendation from the JBI manual [30] consisted on identifying each source of evidence with one unique identifier, for organization and communication purposes. Four different reviewers reviewed on each study, based on the two major disciplines of the team. Reviewers A, B and F only annotated in the charting form the data items related with general information, Computer Science and Information Technology (IT). Authors C, D and E annotated general information and medical data items.

Individual spreadsheets were used by each author to store the records obtained from the reviewed studies. When all reviewers finished the charting process, all spreadsheets were consolidated in one (available as appendix material). The following data charting elements were considered:

1) GENERAL DATA ITEMS

- Authors: First author's last name, first author's first name et. al.
- Title: as stated in the full-text document.
- Source: journal or conference in which the study was published.
- Publication year: as stated in the citation exported from the bibliographic database.
- Author's keywords: keywords indicated by the authors in the full-text document.
- Country: extracted from the authors affiliations, study settings and locations mentioned in the articles.
- Short summary: brief description of the study.
- Purpose or aim: describe the aims of the study.
- Final product: the proposed product stated in the reviewed study. Through synthesis of data, this category was divided into the following subcategories:

application (web, mobile or desktop), decision support system, e-health system, multi-agent system, framework, model, expert system, conversational agents, ontology, simulation, other (ultrasound system scanning, exploratory protocol, pilot study, qualitative study, proposal)
- Functions: ultimate goal proposed in the study (e.g: prediction, classification, assessment).
- Population size: refers to the type and quantity of the data handled in the reviewed study, independently of its source (primary source, in which data are collected in the study and for the purpose of the study, or secondary source, where data has been collected in the past) and type (e.g. patients or EHG recordings). It reflects the initial data size, before performing any type of data pre-processing or feature selection techniques.
- Health standards: if mentioned, medical and health standards were covered in this category, as well as information about ethical approvals.
- Social factors: if mentioned, socio-economic and demographic parameters were reported.
- Personal data protection: if mentioned, aspects related with user privacy and personal data protection, such as application of laws or regulations has been charted.
- Conclusions: relevant results mentioned in the reviewed study will be reported.

2) AI AND IT DATA ITEMS

The following items address AI data items:

- Approach: As a list of AI approaches, a shortened, personalized version of the areas described by the *European Conference on Artificial Intelligence (ECAI)* [31] has been considered: Agent-based and Multi-agent Systems (MAS), Computational Intelligence (CI), Knowledge Representation and Reasoning (KRR), Machine Learning (ML), Natural Language Processing (NLP), Robotics (ROB), Uncertainty in AI (UAI), Vision (VIS), Intelligent Decision Support Systems (IDSS), Expert Systems.
  Sources of evidence were classified in the approach (single or multiple), mentioned in the study, if any. Reviewers also classified the studies in one (or more) of the given categories, when suitable (article fits one of the stated category even if it was not mentioned in the study).
- Data acquisition: data sources and collection methods mentioned in the study (can be multiple). In this scoping review, it has been considered the following: data acquisition methods are understood from the point of view of the article reviewed: data from an online repository could have been recorded using medical equipment, but the study is accessing the repository, so its source of data will be tagged as repository. Studies that gathered data in real time have been marked with an "[R]". Data collected via direct human input (questionnaires or active interaction with an application) has been also flagged. The following subcategories have been considered:
  1) Human input: data provided, recorded and/or generated by the user, via: mobile phone, mobile/web/desktop applications, questionnaires.
  2) Repository: online and publicly available databases.
  3) Medical records: electronic or manual health records provided by hospitals, clinics.
  4) Medical equipment.
  5) Study: data recorded from other studies, independently of the type/design of study.
  6) Survey: data recorded from survey research.
  7) Experts: information provided, reviewed, classified by experts from the medical field.
  8) Sensor: data collected from sensing devices, such as bio-impedance, body temperature, accelerometer, galvanic skin response, among others.
  9) Mobile phone, including embedded sensors and mobile applications.
  10) Wearable devices.
  11) Social media.
  12) Health Institutes.
  13) Synthetic data: computer generated data.
- Knowledge representation: representation of knowledge in AI mentioned in the included studies has been charted.
- Methodology: newly proposed or standard methodologies mentioned in the included studies have been charted.
- Algorithms: if mentioned or specified, the algorithms used to develop AI related functions of the study have been charted. In the case in which the study mentions but does not specify, it will be charted as *Not specified*. Specific algorithms for feature selection have been charted under the 'Preparation' category.
- Data set: reported information about the data employed in the included studies: type of data, composition, number of instances (after data pre-processing), number of attributes, classes distribution.

The following items are a subcategory of AI addressing ML data items.

- Data preparation: reported data pre-processing, preparation and feature extraction has been annotated. In certain AI applications, it is extremely important for model performance to pre-process data, which can consist of a variety of processes: handle null/noisy data, normalization, standardization, encoding, among others. Unsupervised learning, such as dimensionality reduction techniques can also be applied. and if reported in the reviewed studies, this information has been charted in the category *Model technique*.
- Types of learning:
  1) Supervised Learning: uses labeled data for model training.

2) Unsupervised Learning: uses unlabeled data for model training. When labeled data is not available (there is no result to predict), the learning purpose is to find hidden similarities, groups or clusters among examples, or to determine characteristics in the data structure.
3) Reinforcement Learning: consists of a trained agent that learns on the basis of rewards or penalties.

- Model technique:
  1) Classification: prediction task of categorical values in supervised learning.
  2) Regression: prediction task of continuous values in supervised learning.
  3) Clustering: find groups or similarities in data in unsupervised learning.
  4) Dimensionality reduction (DR): reduce the number of variables/features in data in unsupervised learning.
- Validation and Test: information about validation and test techniques were charted, if applicable: percentage or number of instances in train/test/validation sets and cross-validation methods.
- Metrics: performance metrics applied to algorithms and models were charted. When available, information about the best performing algorithm / model according to the employed metrics was charted.
  Fig. 2 illustrated the types of learning (supervised, unsupervised, among others) and example algorithms, and Fig. 3 depicts model and feature selection techniques. This figures were created by and for the reviewing team as a guide in the charting process.

The following items address IT related items.

- Frameworks: if mentioned, information regarding the frameworks used for algorithm/model development in the studies was charted.
- Programming language: if mentioned, information regarding the programming languages used for algorithm/model development in the studies was charted.
- Information system architecture: if mentioned, the IT architecture, as well as the technologies used in the proposed systems was charted.
- Graphical User Interface (GUI): information about any graphical user interface reported in the studies has been charted, and, if mentioned, the type of architecture (web, mobile application, etc).
- IT Security: information on the IT security procedures applied to developed systems (e.g. mobile application) or personal data (demographic, administrative, clinical) has been charted.

3) MEDICAL DATA ITEMS

- Pregnancy related process: the pregnancy process (status, illness, disorder, complication, etc.) that AI has been applied to in the reviewed studies. Through synthesis of data, this category has been divided into the following items: Maternal and fetal well-being, Fetal state, Birth defects, Gestational diabetes (GDM), Preterm birth, Fetal growth, Pre-eclampsia, Hypertensive disorders, Mortality, Labour and delivery, Mental health, and *Others*: Anemia, Placental disorders, Voluntary interruption of pregnancy (VIP), Postpartum complications, Multiple sclerosis, Miscarriage, HELLP Syndrome, Human immunodeficiency virus (HIV), Blood glucose, Hypotension, Diabetes Mellitus, Systemic lupus erythematosus (SLE).
- Pregnancy characteristics: pregnancy related information, such as gestational age, stage of pregnancy, singleton or multiple, among others.
- Maternal variables and characteristics: any data mentioned in the study that is related to the pregnant woman, such as age, pre-existing pathology, clinical case, clinical history (hers and family's), health status, weight, body mass index (BMI), among others.
- Fetal variables and characteristics: any data mentioned in the study that is related to the fetus: status, position, weight, sex, biometric parameters, among others.
- Labour and delivery: any data mentioned in the study that is related to the process of labour and delivery, such as delivery type, need for induction, gestational age at birth, among others.
- Postpartum aspects: any data mentioned in the study that is related to the postpartum period, from both mother and new born's perspective: health status, birth weight, Apgar score, among others.

When no information was found about an item, it has been annotated with NS: Not specified.

E. SYNTHESIS OF RESULTS

Charted information has been synthesized to define the main points described in the review. Therefore, a proposal and interpretation of the data has been elaborated, defining and reporting the methods used. Both automated and manual processes have been used to create the figures and tables presented in this study.

Although all charted information has been used for the elaboration of this review, some items were not directly shown on tables or figures. The following items are: Short summary, Purpose/aim, Population size, Conclusions, Pregnancy characteristics, Maternal variables and characteristics, Fetal variables and characteristics, Labour and delivery, Pospartum aspects, Metrics, Information system architecture. For more details, the full charting form is available in the Appendix section.

IV. RESULTS

A. SELECTION OF SOURCES OF EVIDENCE

The reviewing team started with a total of 207 articles after duplicates removal and initial screening, from which full-text was not available for 6 studies. After the team's first screening process, a 74.1% (149 out of 201 studies) of agreement rate

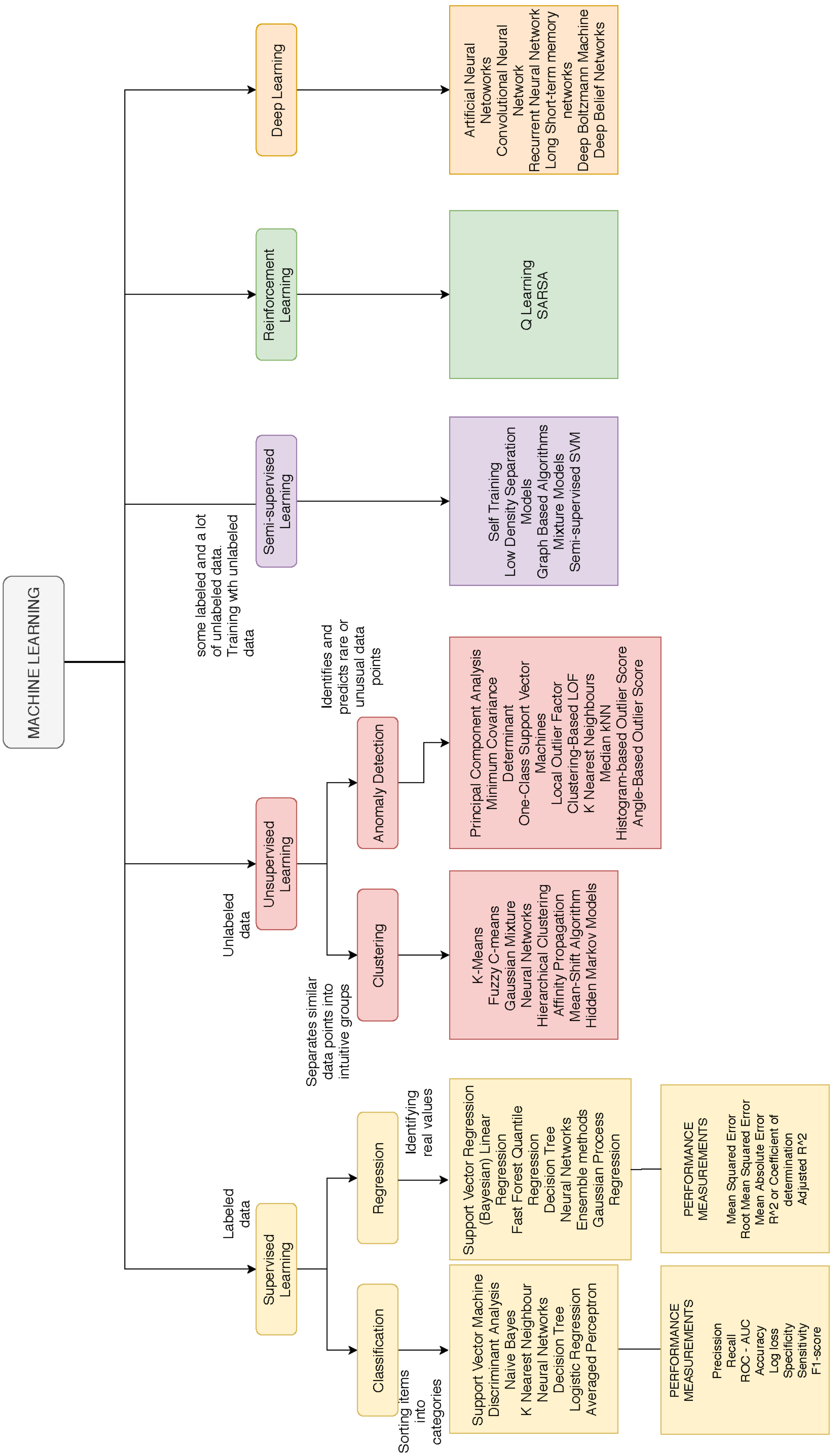

FIGURE 2. Types of machine learning and algorithms.

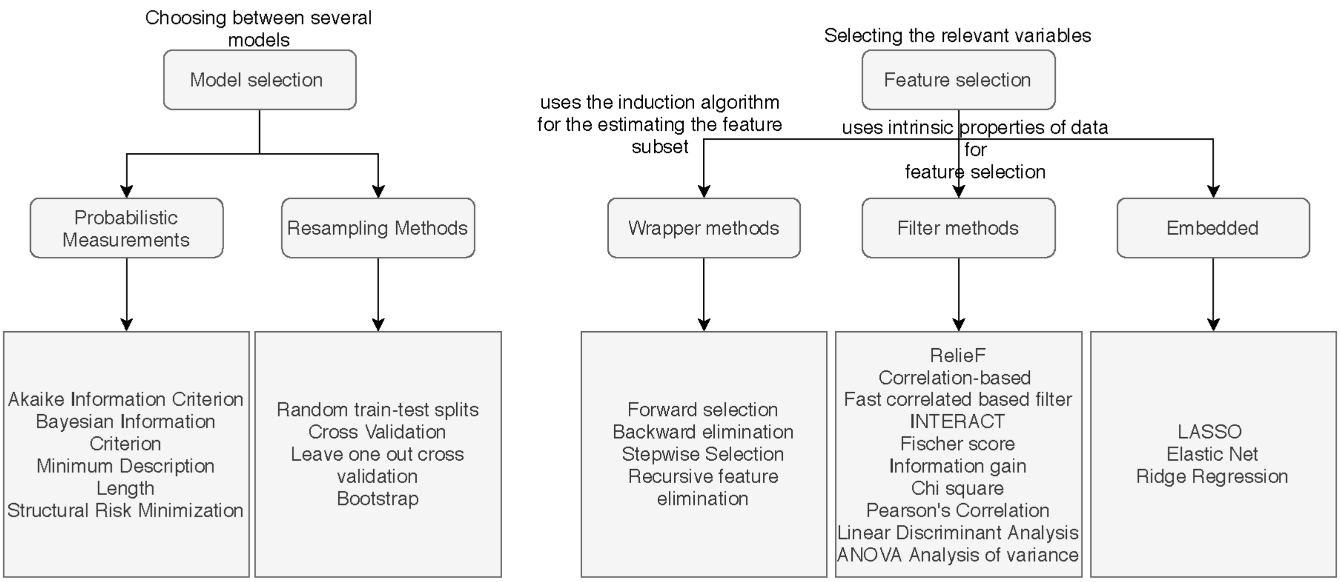

FIGURE 3. **Model selection and feature selection techniques.**

was reached. Comments provided by the reviewers on the decisions were used to find the discrepancies within the team. The major discrepancy concerned the inclusion or exclusion of studies focused solely on fetuses, and not pregnant women. This work has considered the fetal state as eligible since it is both cause and consequence of the maternal state. After this clarification, the screening process was repeated on the remaining not included studies.

After finalizing the second round of the screening process, the team achieved 97% agreement rate (195 out of 201 studies). For the studies in which an agreement was not reached, a voting system has been used. Two reviewers (that did not review the article in the first place) read the title, abstract, keywords and conclusions and decide upon its inclusion or exclusion.

At the end of the complete screening process, the reviewing team has included 169 out of the 681 studies. At this stage of the process, two reviewers iterated the screening phase, in which title, abstract, keywords and conclusions of the 512 studies (the total minus the included), were reviewed. 5 new documents were proposed for inclusion, going through the same screening process as the 169 studies. 2 out of the 5 studies were finally included in the review.

Out of the 169 studies, as mentioned, full-text was missing for 5 studies. After requesting the full-text studies (university's library and corresponding authors), 2 were obtained plus one study suggested by one of the contacted authors. This study was reviewed by the team and added to the included studies since it met all the inclusion criteria.

However, during the extraction process, several documents were finally excluded: in the case that articles were very similar and published by the same author, in which typically the most recent study includes the information in the former study, only the most recent study remained included. Another reason for exclusion was if the study mentioned using AI but no further detail about its implementation or application was provided. Fig. 4 illustrates the PRISMA-ScR [29] flowchart.

B. CHARACTERISTICS OF SOURCES OF EVIDENCE

In this section, information about the included studies is provided.

Regarding the scoping review's time period (2008-2020), studies have followed an increasing publishing trend, as illustrated in Fig. 5. In the first years, the increasing rate was slower compared to the increase rate experienced from 2018 and 2019. This shows an increasing interest on this topic in the scientific community. The 2020 results reflect the studies indexed in the bibliographic databases up until the 14th of February, when the search was conducted.

C. SYNTHESIS OF RESULTS

Throughout the next three subsections, the main categories corresponding to the review's main topics of interest are presented: General information, AI and IT Information, and Medical Information.

V. SYNTHESIS OF RESULTS - GENERAL INFORMATION

A. AUTHOR KEYWORDS

The most frequent author keywords used in the included studies have been analyzed to obtain a first impression on what authors are highlighting from their research. Fig 6 represents the most used keywords according to their frequency. Three categories can be observed, according to the topic: medical terms related to pregnancy, health related terms and AI related terms. Within the first category, the most used keywords are: pregnancy, gestational diabetes, fetal heart rate, gestational age, low birth weight, hypertensive disorders, fetal macrosomia, chromosomal abnormalities, pregnancy outcomes, preterm birth, congenital heart diseases, severe

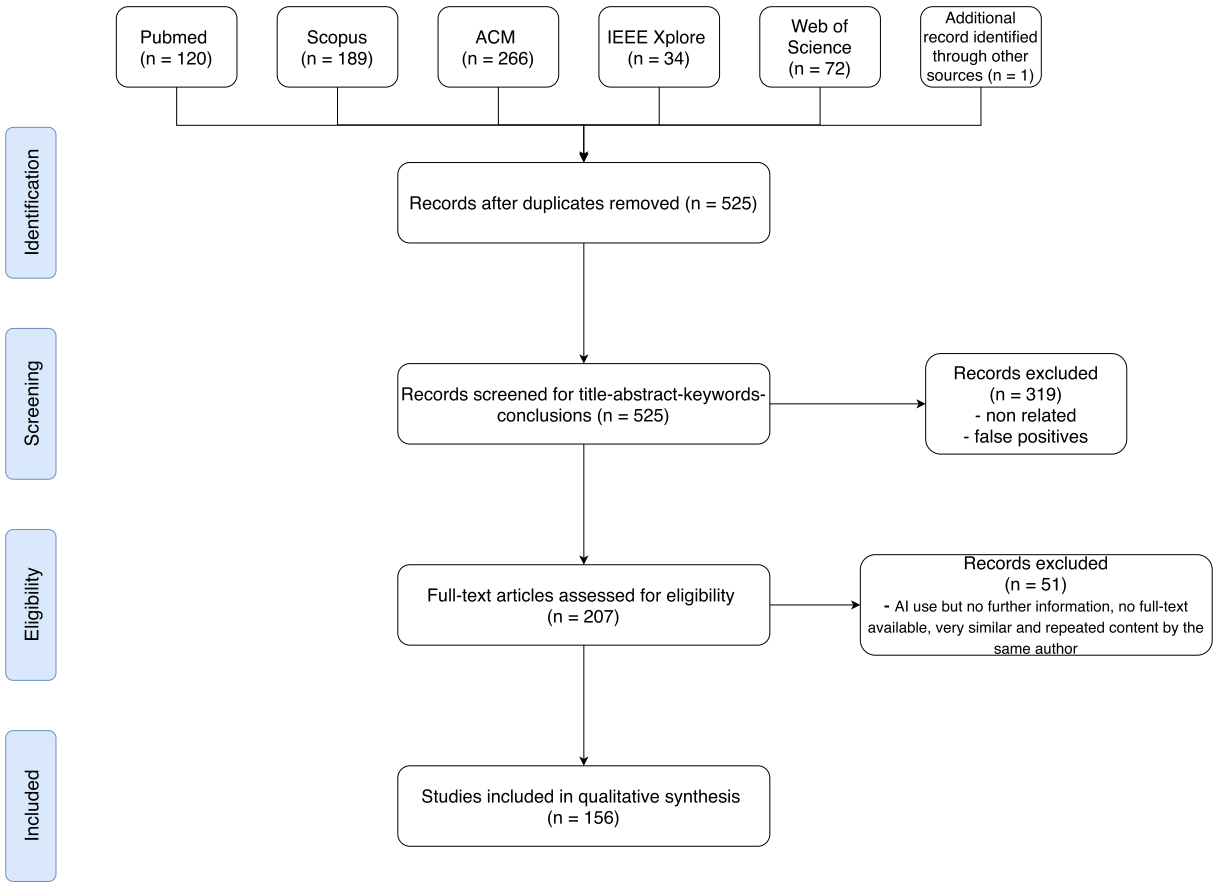

FIGURE 4. PRISMA-ScR studies flow chart developed.

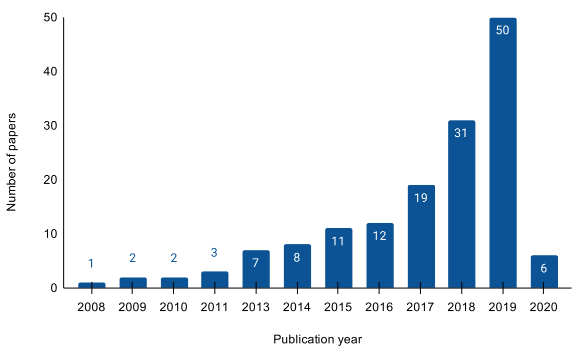

FIGURE 5. Distribution of the publication year of the included studies.

FIGURE 6. Most frequent author keywords in the included studies.

maternal morbidity, among others. Within the second category, the use of prenatal care, health care, risk prediction and medical conditions can he highlighted. Lastly, in the AI terms category, machine, machine learning, decision support system, data mining, artificial neural network, mobile health, decision tree, among others can be found.

B. PUBLICATION COUNTRIES

Included studies have been published around the world, as can be seen in Figure 7. To a greater extent, research has been conducted in United States of America 25.64% (n = 40), India 16% (n = 25), Portugal 12.2% (n = 19), Brazil and China 11.5% (n = 18) each, the United Kingdom 7% (n = 11), Russia and Saudi Arabia 5.1% (n = 8) each.

On a smaller scale, research has been published in Pakistan, Spain, Canada (4.5%, n = 7), Italy, The Netherlands (3.8%, n = 6), South Africa, Australia (3.2%, n = 5), Turkey, Israel, Sweden, Cyprus (2.5%, n = 4), South Korea, Bangladesh, Kenya, Romania (2%, n = 3), Mexico, Iran, Norway, Taiwan, Estonia, Finland, France, Switzerland, Germany (1.2%, n = 2), Northern Ireland, Morocco, Greece, Iceland, Serbia, Puerto Rico, Ecuador, Indonesia, Ireland, Austria, Sultanate of Oman, Malaysia, Zambia, Bosnia and Herzegovina, Colombia, Japan, Cuba, Tanzania, Belgium, Ethiopia, Hong Kong and Burkina Faso (0.64%, n = 1).

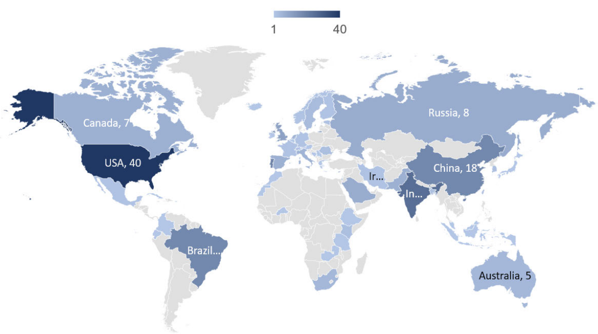

FIGURE 7. Author affiliation countries in the included studies.

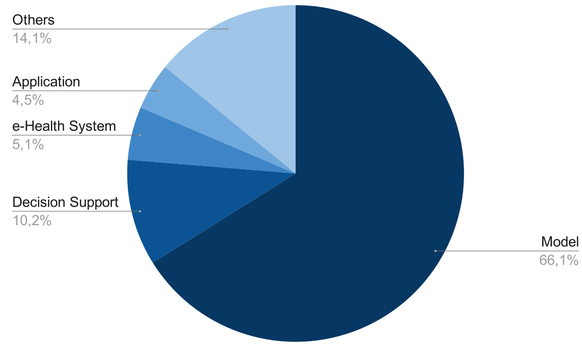

FIGURE 8. Distribution of final products proposed in the included studies.

C. FINAL PRODUCTS AND FUNCTIONS

Models have been proposed in the majority of the studies (66.1%, n = 104). Articles in this category reported mainly prediction and classification functions. Particular interest has been demonstrated in the literature in predicting GDM, hypertensive disorders and pre-eclampsia, preterm birth, mortality, birth weight, birth defects and fetal abnormalities. Classification is mainly used for fetal status and well-being evaluation purposes. Models are also developed for broader purposes such as health monitoring, but also for more specific aims, such as understanding and evaluation the relationship between pollutants and different pregnancy outcomes.

IDSS are proposed in 10.2% (n = 17) of studies for GDM monitoring, fetal state classification, mortality prediction and home pregnancy monitoring. e-Health systems have been reported in 5,1% (n = 8) of studies, presenting different functionalities: fetal state classification, miscarriage prediction, stress monitoring, pre-eclampsia prediction, congenital malformations prediction and home pregnancy monitoring. Applications have been proposed in 4.5% (n = 7) of studies, specifically: mobile applications, web applications and desktop applications. The main functions presented by this studies are home pregnancy monitoring and antenatal care providing.

In the *Others* category, comprising (14.1%, n = 22) of studies, the following products functions have been reported:

- Frameworks for fetal state classification, gestational age prediction, stress detection (n = 4).
- Simulations for delivery assistance (n = 2).
- Ontologies for risk management during pregnancy and analysis of indoor air pollution (n = 2).
- Expert systems for congenital malformation prediction and early diagnosis of GDM (n = 2).
- Multi-agent systems for GDM, blood glucose and home pregnancy monitoring and maternal care providing (n = 3).
- Conversational agents for health monitoring and maternal care providing (n = 2),
- Wearable devices for home pregnancy monitoring, gait monitoring and health resources allocation (n = 2).
- Ultrasound scanning system for health monitoring (n = 1), pilot study for perinatal depression intervention (n = 1), qualitative study for maternal care providing (n = 1), study protocol for adverse perinatal outcomes prediction (n = 1), exploratory study for healthcare programs evaluation (n = 1) and proposal study for home pregnancy monitoring and GDM monitoring (n = 1).

The distribution of the final products proposed in the included studies is depicted in Fig. 8.

D. SOCIAL FACTORS

Almost half of the included studies (45.5%, n = 71) considered socioeconomic and demographic factors. Multiple factors have been reported in most studies. The most frequent factor is patient's ethnicity, appearing in 38% (n = 27) of studies, followed by patient's educational level, mentioned in 32.3% (n = 23) of studies and patient's place of residence, mentioned in 26.8% (n = 19). Professional and marital status were considered in 11.3% (n = 8) and 9.9% (n = 7) of studies, respectively.

E. BIO ETHICAL ASPECTS AND HEALTH STANDARDS

A total of 26.9% (n = 42) of studies have considered ethical aspects by submitting and obtaining the approval of an institutional ethical committee. Since in some cases studies are conducted on real patients, bio ethical aspects are important and need to be considered.

44.2% (n = 69) of studies have mentioned the use of Health Standards. Among the different health standards mentioned in the studies, the most used have been: the International Classification of Diseases (different versions) (n = 12) [32]–[43], World Health Organization (n = 6) [37], [44]–[48] and Health Level-7 (n = 4) [39], [49]–[51].

F. PRIVACY OF PERSONAL DATA

Aspects regarding personal data privacy and protection have been discussed in 23% (n = 36) of studies, from which 86.1% requested patient consent and the rest used data anonymization techniques.

VI. SYNTHESIS OF RESULTS - AI AND IT INFORMATION

A. ARTIFICIAL INTELLIGENCE TOPICS

The majority of the included sources of evidence reported using a single AI topic (63.5%, n = 99), whilst the rest used several by combining different topics to achieve their results.

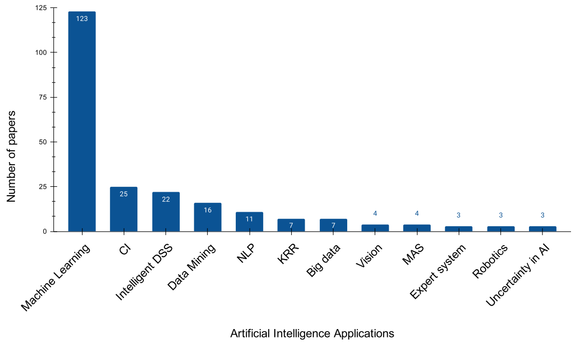

FIGURE 9. Distribution of AI topics in the included studies.

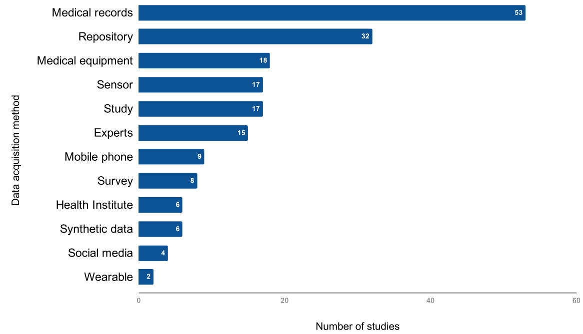

FIGURE 10. Distribution of data acquisition methods in the included studies.

ML has been by far the most implemented AI topic (78,8%, n = 123). Most studies from this category proposed developments based on supervised learning (94.3%, n = 116), in which the model is trained with labeled, known data. Of these, the majority (93.1%, n = 108) performed classification tasks for predicting values from a discrete set, i.e. classify delivery into term or pre-term. To a lesser extent, studies (8.6%, n = 10) performed regression tasks for predicting values from a continuous set, i.e prediction of gestational age. Classification and regression tasks together were performed by (2.6%, n = 3) studies. For classification and regression tasks, ensemble ML techniques can be used in which the decision of multiple models is combined, aiming to achieve better predictive performance. This aggregative technique has been used in 26.7% (n = 33) of studies.

Among studies using unsupervised learning (22%, n = 27), clustering techniques, in which the main idea is to group unlabeled, unknown data into groups, i.e. calculate the heart rates for different stress levels, have been implemented in the majority of cases (55.5%, n = 15). Lastly, (44.4%, n = 12) studies performed DR, a technique used to reduce the number of input variables in a data set, i.e. selecting the data from cardiotocography (CTG) recordings that provide more information. Only 0.8% (n = 1) studies reported using reinforcement learning.

Deep Learning (DL) techniques were employed in (7.3%, n = 9) studies.

The remaining AI topics detected in the included studies are distributed as follows: CI (16%, n = 25), IDSS (14.1%, n = 21), DM (10.2%, n = 16), NLP (7%, n = 11), KRR (4.5%, n = 7), Big data (4.5%, n = 7), MAS (2.6%, n = 4), UAI, Expert systems, Robotics and Vision (1.9%, n = 3) each.

Fig. 9 shows the distribution of AI topics used in the included studies.

B. DATA ACQUISITION

Data used in the included studies have multiple origins and collection methods, as can be seen in Fig. 10. This information has been available and charted for 154 out of the total of 156 studies, and most studies have used data from more than one source.

Mainly, data were collected from medical records (hospitals or clinics) (34.4%, n = 53), in the form of clinical and/or administrative data. The second most used data acquisition method are database repositories (20.7%, n = 32), being the most popular *UCI Machine Learning* repository cardiotocography data set (n = 7) and *Physionet Term-Preterm Electrohysterogram (EHG)* database (n = 5).

Medical equipment were used for data acquisition in 11.7% of the studies (n = 18), being the most used ultrasound machines and blood draw equipment.

Data from studies, mainly population based, were used in 11% (n = 17) of documents.

Sensors were used as data collection methods in 11% (n = 17) of the studies. From this source, a variety of data were recorded, mainly from the fetus and the pregnant woman: glucose levels, body temperature, blood pressure (BP), activity levels, among others, and from their environment: temperature, humidity, pollution.

In 9.1% (n = 14) of the studies, experts (mainly, healthcare professionals) served as a source of information by providing knowledge and expertise. Their contributions have been registered in different ways: conducting interviews, performing clinical testing, collection and structuring of data, among others.

Mobile phones served as data collection methods in 9.1% (n = 14) studies, by direct human input or by collecting the data automatically from other type of devices.

In total, 13% (n = 20) of studies used real time data acquisition methods, mainly sensors and mobile phones. Human input was used in 13.6% (n = 21) of the studies, under different forms: questionnaires (n = 13), mobile phones and mobile phone applications (n = 8), and lastly, web applications (n = 1).

C. METHODOLOGY AND KNOWLEDGE REPRESENTATION

Different methodologies were used or proposed in 15.3% (n = 24) of studies. The most employed methodology was the Cross-Industry Standard Process for Data Mining (CRISP-DM) in [52]–[55]. This hierarchical process model divides the process of DM into six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation and Deployment.

Authors in [56] employed Multiple Kernel Learning methodology to fuse and order multi variate heterogeneous data. Ontology Development 101: A Guide to Creating Your First Ontology was used in [45]. A hybrid methodology of a specialized system is proposed in [35]: BN, AI and Multiple-criteria decision analysis (MCDA).

Agent-Oriented Modelling (AOM) was reported in [57] to create a scalable multi-agent architecture for environments with limited connectivity.

The rest of studies typically proposed own developed methodologies for model development, prediction systems and benchmarking. As an example, authors in [58] described the prediction process methodology: Prediction process: 1) Gather and store data in database server in files. 2) Extract data from the database server to the Cloud. 3) Transform data. 4) Analyze data transformed. 5) Make predictions. 6) Evaluate and validate the model. 7) Present the final response.

Knowledge representation has been described in 11% (n = 17) of studies. The most used approach were knowledge representation based on rules and probabilities and ontologies.

The full list of methodologies and knowledge representation can be found in the full data charting form.

D. DATA PREPARATION

Data preparation has been reported in 60% (n = 94) of studies, from which (n = 34) mentioned using feature selection techniques. Although not all studies specified the algorithms, the most implemented feature selection algorithms were Principal Component Analysis (PCA), Univariate, Bivariate or Multivariate Logistic Regression and Analysis of Variance (ANOVA).

Imbalanced data sets have been reported by 34% (n = 32) of studies. Different approaches to address the imbalanced data have been reported: over-under sampling techniques, Synthetic Minority Oversampling Technique (SMOTE), K-means clustering and DR.

Missing data have been identified in 24% (n = 22) of studies and have been addressed by excluding the data or applying mode imputation (multiple mode imputation, similarity-based heuristic algorithm, fully conditional specification, completion with average values).

E. ALGORITHMS

The majority of included articles (92.3% n = 144) reported implementing algorithms, from which 66% (n = 95) used more than one algorithm.

One of the most implemented algorithms were decision trees (DT) and variants, including random forests (RF), classification and regression trees (CART) and boosted trees, accounted for in 45.8% (n = 66) of studies. Some of the most used implementations were C4.5, J48 and ID3.

Other popular algorithms were support vector machines (SVM), reported in 36.1% (n = 52) of studies, logistic regression (LR) used in (27.7%, n = 40) and artificial neural networks (ANN) reported in (24.3% n = 35). K-nearest neighbors (k-NN) algorithm has been used in 12.5% (n = 18) of studies.

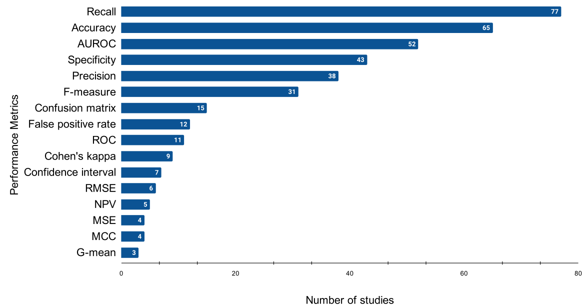

FIGURE 11. **Performance metrics used in the included studies.**

The most used clustering algorithm was k-means (7%, n = 10).

Generally speaking, even though there are a series of algorithms that are implemented the most across the included sources of evidence, a wide variety of algorithms have been used: linear regression, naïve Bayes (NB), extreme machine learning (EML), genetic algorithms (GA), among others.

F. MODEL VALIDATION

From all included studies, 70% (n = 109) reported using validation techniques. Test/train splitting technique has been used in 37,6% (n = 41) of studies. K-fold cross-validation technique has been reported in 61 studies, from which, specifically, 10-fold-cross-validation (n = 42) and 5-fold cross-validation (n = 18). In the rest of the studies in which k-fold cross-validation was used, data was split in other number of folds (k = 3, k = 4, among others). Hold Out Cross-Validation and Leave One Out Cross-Validation techniques, were reported in 6 and 4 studies, respectively.

G. PERFORMANCE METRICS

The 80% (n = 126) of all included studies reported using metrics for evaluating model performance. The majority of the charted metrics are usually employed for evaluation of classification and regression models. As can be seen in Figure 11, 61.1% (n = 77) of studies have relied on metrics such as recall (sensitivity or true positive rate), 51.6% (n = 65) of studies have used accuracy, and 41.3% (n = 52) of studies reported area under the receiver operating characteristics (AUROC). Specificity (true negative rate) measurements have been used as metrics by 34.1% (n = 43) of studies, precision (positive predictive value) has been described in 30.1% (n = 38) of studies and F-measure (F1-score or F-score) in 24.6% (n = 31) of studies. To a lesser extent, metrics used were confusion matrix, false positive rate, receiver operating characteristic curve (ROC), Cohen's kappa, confidence intervals, root mean square error (RMSE), negative predictive value (NPV), mean squared error (MSE), Matthews correlation coefficient (MCC) and Geometric Mean (G-mean).

H. FRAMEWORKS AND PROGRAMMING LANGUAGES

The use of frameworks has been identified in 56.4% (n = 88) of studies. Mostly, AI or ML related frameworks have been mentioned (n = 68): Scikit-learn for Python (n = 12), WEKA software (n = 11), IBM's SPSS software (n = 10), STATA software (n = 5) and SAS software (n = 4). Other non-AI frequent frameworks were Bluetooth or Internet of things.

Information regarding programming languages can be found in 33.8% (n = 62) of studies, being R the most used language (32.2%, n = 20), followed by Python (27.4%, n = 17), MATLAB (17.7% n = 11) and Java (9.67%, n = 6). Other programming languages mentioned in the studies were C++, Spark, Scala, C#,.NET, Fortran 95, Perl, Ruby, Blender and Unity.

Reported functions or packages from the R programming language were: *randomforest, dismo, gbm, rpart, paralell, doparalell, cared, libsvm, mice, hmisc, glmnet, prcomp, glmulti, dsa, gcdnet*.

I. GRAPHICAL USER INTERFACES

A 22.4% (n = 35) of studies developed GUIs for patients, healthcare professionals or administrators to interact with. GUIs have been incorporated to IDSS (n = 10), applications (n = 7), e-health systems (n = 5), expert systems, multi-agent systems, frameworks, conversational agents (n = 2), model, ontology, demonstration and wearable (n = 1). In addition, one pilot study mentioned the intention of using a GUI.

From this category, (n = 10) studies have been identified to propose a GUI for both patient and healthcare professionals. This is relevant because it can be understood that an online communication between patient and doctor exists. A total of (n = 20) studies reported the patient to be the end user and (n = 23) studies designed the GUI for healthcare professionals.

Lastly, healthcare administrators have been targeted as end user in (n = 3) studies.

J. IT SECURITY

Only 7% (n = 11) of all included studies addressed IT security. Proposed methods are: use of Hypertext Transfer Protocol Secure (HTTPS) and web certificates for web and mobile applications, data encryption, virtual private network, firewalls, onion routing, white-box testing and implementation of Health informatics - Electronic health record communication - Part 1: Reference model (ISO 13606-1:2008) standard.

VII. SYNTHESIS OF RESULTS - MEDICAL INFORMATION

A. PREGNANCY RELATED PROCESSES

As illustrated in Fig. 12, in this scoping review it has been identified that AI has been applied to a wide spectrum of pregnancy related processes. 18% (n = 28) of studies have been considered by the authors to be labeled as part of the maternal/fetal well-being (M/F well-being) category, where no specific process has been addressed or reported and the main purpose was to improve maternal/fetal well-being. Fetal state has been addressed in 12.2% (n = 19) of studies, followed by birth defects (9%, n = 14), GDM, preterm birth (8.3%, n = 13), fetal growth (7.7%, n = 12), pre-eclampsia (6.4%, n = 10), mortality (6.4%, n = 10), hypertensive disorders (6.4%, n = 10), labour and delivery (5.1%, n = 8) and mental health (5.1%, n = 8).

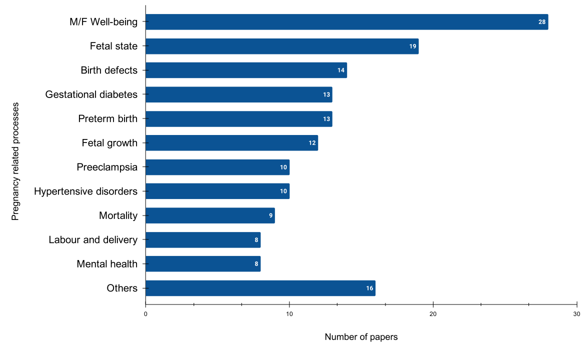

FIGURE 12. Distribution of pregnancy process in the included studies.

Other processes category is formed by studies addressing anemia, placental disorders voluntary termination of pregnancy (VIP), postpartum complications (PP complications) (1.2%, n = 2) each; multiple sclerosis miscarriage, HELLP syndrome, human immunodeficiency virus (HIV), blood glucose, hypotension, diabetes mellitus and systemic lupus erythematosus (SLE) (0.64%, n = 1) each.

4 articles have been recognized to have studied more than one pregnancy process: preterm birth and fetal growth in [33], hypertensive disorders and pre-elcmapsia in [59] and [60], and pre-eclampsia and mental health in [6].

Interestingly, the majority of the reviewed studies examined physical health related issues, whereas only 5.1% of studies carried out investigation related to mental health issues, such as depression or stress.

In the following subsections, each pregnancy process category will be examined.

B. FETAL STATE

Studies in this category (11.5%, n = 18), mainly reported the potential of AI applications in classifying fetal state and well-being. Monitoring techniques can be used to assess maternal and fetal health and well-being, as well as possible fetal outcomes (e.g. anomalies detection). ML has been applied in the majority of studies (72%, n = 13), followed by CI (44%, n = 8), DM (16,6%, n = 3), IDSS (16.6%, n = 3), NLP (5.5%, n = 1) and VIS (5.5%, n = 1).

Repositories as data source have been used by 78% (n = 14) of studies. Articles within this group have reported to use CTG recordings (n = 12). Among these, (n = 11) gathered the recordings from the UCI ML Repository CTG data set, which consists of 2126 measurements of fetal heart rate (FHR) and uterine contraction (UC). Samples in this data set are imbalanced, since it contains 70% measurements of normal fetal state, 20% suspect state, and 10% pathological state. Within this category, (n = 6) studies applied some form of data preparation: feature selection [61]–[63], SMOTE [64], and removal of noisy data [65]. One study [66] gathered CTG data from the CTU-UHB Intrapartum Cardiotocography Database, consisting of a total of 552 CTG recordings and applied feature selection techniques for data preparation. In [67], data were collected from the Daisy database in the form of fetal ECG recordings, and data used in [68] was gathered from the Massachusetts Institute of Technology (MIT) database in the form of maternal abdominal ECG recordings.

Supervised learning classification tasks have been performed by all articles in this group, and [61], [62], [65] and [66] also applied unsupervised learning in the form of DR techniques. Clustering techniques (also unsupervised learning) have been reported in [69].

NLP techniques have been applied in [70] to investigate patient's sentiments and reactions on prenatal tests (invasive and non-invasive). Data have been collected in the form of user posts from social media (Reddit).

In the above mentioned studies, reported sources of data are considered to be offline, since data have been recorded at a past moment. Real time data gathering has been reported in (n = 3) studies. Firstly, [21] used Doppler ultrasound for remote surveillance (home monitoring) of the fetal state and well-being, combining the Doppler's sonographic assessment of fetoplacental blood flow and fetal heart rate. Secondly, in [71], the prediction system (part of the e-health system) employed data collected from medical equipment (Doppler Ultrasonography device). The mobile application (also part of the e-health system), intended to be used by patients and healthcare professionals, collected real time data directly from the human input. Lastly, [72] recorded real time gathered data from mobile phones and sensors for fetal ECG recordings.

A 16.67% (n = 3) of studies from this category mentioned that the proposed final products could be used by the end patient [72] (e-health system), by healthcare professionals [68] (framework) or both [71] (e-health system).

Table 1 summarizes detailed information for each study.

C. BIRTH DEFECTS

Among 9% (n = 14) of studies that considered birth defects, the focus is set on aneuploidy detection (n = 4), prediction of congenital defects (n = 3) and fetal macrosomia prediction (n = 3). A smaller number of studies addressed prediction of gastroschisis (n = 1), evaluation of the relationship between pollutants and macrosomia (n = 1), fetal heart rate classification (n = 1), assessment of birth defects reporting on social media (n = 1) and classification of drugs safety in pregnancy (n = 1).

Half of the studies from this category considered more than one AI application for their purposes, and in most studies (n = 11) ML has been applied. Other AI applications found are DM (n = 4), CI (n = 3), expert system, VIS and NLP (n = 1) each. Most studies presented classification tasks (n = 10), and two studies applied clustering techniques. Proposed products by the included studies are models with the exception of [78], which presented an expert system for predicting congenital malformations in live births, along with a desktop application directed to healthcare professionals.

The complete list of algorithms is presented in Table 2, however LR and RF are among the most implemented algorithms in this category.

Different data collection sources have been used. In 42.9% (n = 6) of studies more than one source has been employed. Data are gathered from medical records (n = 4), studies (n = 3), health institutes (n = 2), repositories (n = 2), medical equipment (n = 2), social media (n = 1) and computer generated data (n = 1). Human input data have been collected via questionnaires in 2 studies, from which [78] collected data in real time.

35.7% (n = 5) of studies reported using imbalanced data sets [40], [44], [79]–[81]. K-means algorithm (unsupervised learning, clustering technique) was reported to be used in [79] for reducing the population of the majority class, and over-under sampling techniques have been used in [40].

Table 2 summarizes detailed information for each study.

D. GESTATIONAL DIABETES

A 8.3% (n = 13) of all included studies have conducted research on GDM, presenting the following purposes: prediction (n = 8) and monitoring (n = 5).

In this category, more than half of the studies developed models for GDM prediction (n = 7), followed by decision support systems (n = 2) for GDM monitoring from home and an expert system (n = 1) for early diagnosis of GDM. Among the rest of studies categorized as *Others*, it can be found one proposal study of a wearable device (n = 1), also meant for GDM monitoring from home and one demonstration study (n = 1) for monitoring purposes.

Interestingly, comparing with other pregnancy processes categories, in this category more studies 38.4% (n = 5), have provided information about the possible usage of the proposed tools by patients and healthcare professionals via a GUI.

Classification is the predominant task among the studies in this category (n = 9) and in two of the accounted studies, clustering techniques have been applied. Most research applied ML techniques (n = 9), followed by IDSS, CI (n = 2), KRR (n = 2), MAS (n = 1) and Expert system (n = 1).

The most common classification algorithms are DT, LR, RF, BN and SVM.

Regarding the source of used data, (n = 7) studies collected data from medical records. Sensing devices have been used for glucose measurements in [51] and [50]. Similarly, in [88] sensing devices have been employed as well as wearable devices for activity tracking and mobile phone to take pictures of patient's food intake. Other data sources reported are: synthetic data in [89], data set from the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) in [90], medical equipment (for blood samples) in [91], patient data from a prospective hospital-based birth cohort study called Early Life Plan in [92] and risk factors defined by experts from the National Institute of Health (NIH) in [93]

Human input was reported on (n = 5) studies, and the means to collect this data were: [93] and [92] via questionnaires, mobile application [88] and [89], and web application [94]. 23% (n = 3) of studies [50], [51], [88] reported real time data gathering for patient monitoring.

TABLE 1. Artificial Intelligence applied to fetal state. Acronyms used in this table: aECG (abdominal Electrocardiography), Decision Jungle (DJ), Electromyography (EMG), fECG (fetal Electrocardiography), Improved Adaptive Genetic Algorithm (IAGA), RBF (Radial basis function) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML	Cla	Medical equipment: 4D Color Doppler Ultrasonography device; Human input via mobile application; [R]	Feature selection: Tree-based algorithm	Boosted DT, Bayes Point Machine, DT, DJ, Locally-Deep SVM, SVM, LR, ANN, Averaged Perceptron	e-Health system (web app: healthcare professionals; mobile app: patient)	Fetal state classification	[71]
ML	Cla	Repository: UCI ML CTG data set	NS	CART	Model	Fetal state classification	[73]
ML, IDSS	Cla, DR	Repository: UCI ML CTG data set	Feature selection: PCA based on Ranker search	SVM, AdaBoost	IDSS	Fetal state classification	[61]
ML, CI	Cla	Repository: UCI ML CTG data set	Data labeled as noise, interference or artifacts were removed	ANN, EML	Model	Fetal state classification	[64]
ML	Cla, DR	Repository: UCI ML CTG data set	SMOTE	SVM (Linear, RBF kernel), k-NN, XGBoost, AdBoost, RF, LR, Gaussian NB, DT	Model	Fetal state classification	[65]
ML, CI	Cla	Repository: UCI ML CTG data set	NS	Modular NN	Model	Fetal state classification	[74]
IDSS, CI	Cla, DR	Repository: UCI ML CTG data set	Feature selection: IAGA, PCA	SVM, BN, EML, k-NN	IDSS	Fetal state classification	[62]
ML(DL)	Cla	Repository: UCI ML CTG data set	NS	Multilayer perceptron ANN	Model	Fetal state classification	[75]
ML, IDSS, CI	Cla	Repository: UCI ML CTG data set	Gaussian RBF; Feature selection: GA	SVM, ANN, Adaptive Neuro Fuzzy inference system	Model	Fetal state classification	[63]
ML, CI	Cla	Repository: UCI ML CTG dataset	NS	ANN, SVM, LR, RBF Network, CART, C4.5 DT, RF, k-NN	Model	Fetal state classification	[76]
ML, CI	Cla, Clu	Repository: UCI ML CTG data set	Statistical features extracted	ANN, SVM, Fuzzy C-means, K-means	Model	Fetal state classification	[69]
VIS	NS	Repository: fECG (Daisy)	Signal processing: EMG low pass filter, baseline wander high pass filter	Least Mean Square based Adaptive Noise Cancelling	Model	Fetal state classification	[67]
CI	Cla	Repository: aECG (MIT)	Files are converted from .dat to .txt	Back-propagation ANN, Adaptive Linear ANN	Framework (GUI: healthcare professionals)	Fetal state classification	[68]
ML	Cla, DR	Repository: CTU-UHB Intrapartum CTG database	Feature selection: PCA	SVM, Deep Gaussian Processes	Model	FHR classification	[66]
CI	NS	Medical equipment: Doppler ultrasound [R]	NS	Fuzzy logic, ANN	e-Health system (proposal)	Home pregnancy monitoring; fetal state classification	[21]
ML	Cla	Repository: UCI ML CTG data set	NS	DT, SVM, NB	Model	Fetal state classification	[77]
ML, DM	NS	Mobile phone; Sensor: fECG [R]	NS	NS	e-Health system (patient)	Home pregnancy monitoring; fetal state classification	[72]
NLP	NS	Social media	NS	OpinionFinder; Natural Language Toolkit	Model	Sentiment analysis on invasive and non-invasive prenatal tests	[70]

Table 3 summarizes detailed information for each study.

E. PRETERM BIRTH

A 8.3% (n = 13) of studies were identified to study preterm births. An extensive homogeneity is found in the screened literature, being mainly oriented to preterm birth prediction and determination of relevant factors, with the exception of 2 studies: in [98], authors aim to establish the relationship between preterm birth and exposure to pollutants, meanwhile in [99], researchers aim to discern EHG recordings acquired

TABLE 2. Artificial Intelligence applied to birth defects. Acronyms used in this table: Air Quality System (AQS), Food and Drug Administration (FDA), Generalized additive models (GAM), Markov chain Monte Carlo (MCMC), National Free Preconception Health Examination Project (NFPHEP), Online Mendelian Inheritance in Man (OMIM), Spatio-temporal image correlation (STIC) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML, CI	Cla	Medical records; Medical equipment: Ultrasound, blood samples	Each unknown case is assigned into a class between "euploid" and "aneuploid" using a cut-off value	Feed-forward ANN	Model	Aneuploidy detection	[82]
ML, CI	Cla, Clu	Health Institute: Fetal Medicine Foundation	Normalization and reduction, clustering: K-means	Feed-forward back-propagation ANN, K-means	Model	Aneuploidy detection	[79]
ML, CI	Cla	Medical records	Statistical analysis	SVM, ANN, k-NN	Model	Aneuploidy detection	[83]
ML	Cla	Synthetic data: simulated to mimic the targeted sequencing data of pregnant women's cfDNA samples	NS	DT, SVM, Hidden Markov	Model	Aneuploidy detection	[84]
NLP, DM	NS	Social media	Manual process	Rule-based bootstrapping approach	Model	Assessment of birth defects reporting on social media	[36]
ML, DM	Cla, DR	Study: designed by the Population and Family Planning Commission of Shanxi Province	NS	Weighted SVM, RF, LR	Model	Prediction of congenital heart defects	[80]
ML	Cla	Study: population-based birth defects surveillance system; Study: Ambient PM10 observations	Over-under sampling techniques	RF, LR, Gradient Boosting	Model	Prediction of congenital heart defects	[40]
VIS	NS	Medical records; Medical equipment: STIC technology to acquire fetal heart images	NS	NS	Model	Prediction of congenital heart defects	[85]
ML	Cla	Study: successive Small-for-Gestational-Age Births (NICHD)	NS	MCMC sampling, Skewed multivariate random effects, Polynomial regression spline, Bayesian	Model	Prediction of macrosomia	[86]
ML	Cla	Medical records	Missing or erroneous records were excluded	Multivariable LR, RF	Model	Prediction of macrosomia	[87]
ML(DL)	Cla	Health Institute: PM2.5 concentrations; Study: NFPHEP	Missing data was excluded	Ensemble ML, RF (XGBoost, GAM), LR, Spatial clustering	Model	Relationship evaluation between PM2 exposure and macrosomia	[44]
ML, DM	Cla	Human input via questionnaire; Repository: United States Environmental Protection Agency's AQS	Missing data was excluded	LR, RF	Model	Prediction of gastroschisis	[81]
ML	Cla	Medical records; Repository: OMIM and FDA pregnancy drug categories	NS	LR, RF	Model	Classification of drugs safety	[32]
Expert System, DM	Clu	Human input via questionnaire: collected from hospital [R]	Cleaning, duplicates removal, discretization	Modeling Association Rules	Expert system (desktop application: healthcare professionals)	Prediction of congenital malformations	[78]

during labour from EHG acquired during normal pregnancy activity.

ML models have been applied and developed for all the studies. A web application targeted for healthcare professionals has been additionally proposed in [100], which focused on determining the features potentially responsible for a high preterm birth rate. Supervised learning classification ($n = 11$) and regression ($n = 2$) tasks have been identified

TABLE 3. Artificial Intelligence applied to GDM. Acronyms used in this table: Body Area Network (BAN), Chi-square automatic interaction detection (CHAID), Gradient Boosting Methods (GBM), Radial Basis Function Network(RBFN) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML	Cla	Medical records; Human input via questionnaire; Experts: risk factors defined by the NIH	Missing values: inherently handled (Gradient boosting); Feature Attribution: framework of Shapley values	DT, GBM; LR	Model	Prediction of GDM	[93]
ML	Cla	Medical records; Human input via questionnaire; Study: Early Life Plan	Statistical analysis, Odds ratio	Multivariate Bayesian LR using MCMC; Metropolis-Hastings algorithm	Model	Prediction of GDM	[92]
ML	Cla	Medical equipment: blood samples	Feature selection	LR, RF, AdaBoost	Model	prediction of GDM	[91]
ML, CI	Cla, Clu	Health Institute: NIDDK	K-means custering, discarded missing data	Guassian RBFN	Model	Prediction of GDM	[90]
ML(DL)	Cla	Medical records	Reduce noise, remove redundant features, duplicates, complete missing data; Feature selection: stepwise regression analysis	DT, LR, DenseNet	Model	Prediction of GDM	[95]
ML, CI	Cla	Medical records	Normalization to comply with the Euclidean distance	AIRS, k-NN; LR, DT, SVM	Model	Prediction of GDM	[96]
ML(DL)	Cla	Medical records	Missing data processing, discretization and normalization	Cost-sensitive Hybrid Model, LR, BN, ANN, SVM, CHAID tree	Model	Prediction of GDM	[97]
ML, KRR, IDSS	Cla, Clu	Human input via web application	NS	C4.5 DT, Expectation Maximization	IDSS (mobile app: patients, healthcare professionals)	Home pregnancy and GDM monitoring	[94]
IDSS	NS	Mobile phone; Sensor: glycometer; Medical records [R]	NS	Statistical analysis	IDSS (patients)	Home pregnancy and GDM monitoring	[51]
ML	NS	Sensor: glucose; Wearable: FitBit activity tracker; Human input via mobile phone: food diary (camera) [R]	Preparation and cleaning	Statistical, computational analysis, ML algorithms (NS)	Others: No development (wearable proposal)	Home pregnancy and GDM monitoring	[88]
IDSS	NS	Sensors: BAN (Glucose meter, sphygmomanometer) [R]	NS	Intelligent data analysis (NS)	IDSS (patients and healthcare professionals)	GDM monitoring	[50]
MAS	NS	Synthetic data; Human input via mobile phone	NS	Deductive rules using Event Calculus	Others: Multi-agent system (patients, healthcare professionals)	GDM monitoring	[89]
KRR, Expert Systems	Cla	Medical records	NS	BN	Expert System (healthcare professionals)	Early diagnosis of GDM	[35]

in the studies. The complete list of the implemented algorithms can be found in Table 4, however the more frequently mentioned are RF, DT and SVM.

It is interesting to notice that 30.7% (n = 4) of studies have employed the same data set consisting of EHG recordings from the Term-Preterm EHG data set (Physionet). Data from medical records, collected by external studies and health institutes have been used in the remaining studies with the exception of [101], which collected data from human input via questionnaires and medical equipment. Overall, studies focused on preterm delivery did not gathered real time data, but previously recorded data.

The majority of studies (61.5%, n = 8) within this category have performed learning tasks using imbalanced data sets [34], [100]–[105]. Oversampling and undersampling techniques to adjust the class distribution have been performed in most studies (n = 5). Feature selection process has been applied in 69.2% (n = 9) of studies.

Table 4 summarizes detailed information for each study.

F. FETAL GROWTH

Fetal growth has been researched in 7.7% (n = 12) of studies. In this category, studies mainly presented ML models for: prediction of birth outcomes (term birth weight, small for

TABLE 4. Artificial Intelligence applied to preterm birth. Acronyms used in this table: Generalized additive models (GAM), Moderate Resolution Imaging Spectroradiometer (MODIS), National Free Preconception Health Examination Project (NFPHEP), Precose Resolution of Optimal Titration to Enhance Current Therapies (PROTECT), Polynomial Classifier (POLYC), Uncorrelated Normal Density (UND) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]), Regression (R).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML	Cla	Repository: EHG signals (TPEHG dataset in Physionet)	SMOTE, Signal filtering, Feature Selection	RF, Penalized LR	Model	Prediction of preterm birth	[103]
ML, Big data	Cla	Medical records	Missing values imputation, normalization, Feature selection: Map-reduce	RF, DT, SVM, Ensemble	Model	Prediction of preterm birth	[104]
ML	Cla	Repository: EHG signals (TPEHG dataset in Physionet)	SMOTE, Signal filtering, Feature selection	Linear and Quadratic Discriminant, UND, POLYC, Logistic Classifier, k-NN, DT, SVM, Parzen	Model	Prediction of preterm birth	[106]
ML	R	Study: The Zambian preterm birth prevention	NS	Super Learner, Linear Regression, RF Regression, GAM	Model	Prediction of preterm birth	[107]
ML	Cla	Health Institute: National Institute of Child Health and Human Development and Maternal-Fetal Medicine Units Network	Varying Sample Size, Skewed Class Distributions	SVM (linear and RBF kernels), LR	Model	Prediction of preterm birth	[108]
ML	Cla	Study: PROTECT (high preterm birth phenomena)	Feature selection: Linear Correlation, Normalized Mutual Information, DT; Missing data: similarity based heuristic algorithm	DT, LR	Model (web app: healthcare professionals)	Determination of potentially responsible factors for preterm birth	[100]
ML	Cla	Repository: EHG signals (TPEHG dataset in Physionet)	Feature selection: Intrinsic mode functions Hilbert transformation; SMOTE, Butterworth filter and signal discretization	k-NN, RF, SVM	Model	Prediction of preterm birth	[105]
ML, NLP	R	Medical records	Undersampling, Feature selection	NLP, Regularized LR, SVM, Gradient boosting, Recurrent NN	Model	Prediction of extreme preterm birth	[34]
ML	Cla	Study: NFPHEP	NS	Cox Proportional-Hazards	Model	Relationship evaluation between PM2.5 exposure and preterm birth	[98]
ML,IDSS	Cla	Medical records	NS	SVM (smooth linear kernel function)	Model	Prediction of preterm birth, Apgar score prediction	[99]
ML	Cla	Medical records; Repository: MODIS satellite data	NS	Super Learner	Model	Prediction of birth outcome in greener areas	[33]
ML	Cla	Repository: EHG signals (TPEHG dataset in Physionet)	Feature selection: Hilbert-Huang Transform; Butterworth filter, Manual segmentation of bursts	EML	Model	EHG recordings: labour or pregnancy	[102]
ML	Cla	Human input via questionnaires; Medical equipment	SMOTE, Feature selection	LR, RF, Adaptive Elastic Net	Model	Prediction of preterm birth	[101]

gestational age, preterm birth, and low 5 min Apgar score) in [33], prediction of fetal weight in [109], prediction of large for gestational age (LGA) or small for gestational age (SGA) in [110]–[112], prediction of fetal growth abnormalities in [113], prediction of birth weight in [114], prediction of low birth weight (LBW) in [54] and [115], measurement of head circumference (HC) in [116], prediction of fetal HC in [117], and evaluation of the relationship existing between pollutants exposure and low weight at birth in [118].

The vast majority of studies reported using ML techniques, except for [54], in which DM techniques were developed. 75% (n = 9) of studies implemented classification tasks, meanwhile regression was reported in one study [114]. In this study, the task in hands was to predict the newborn's weight at birth (continuous value).

It is worth mentioning the fact that all studies presented models and none of the studies used data gathered in real time. Data source were medical records (n = 6), repositories (n = 4), medical equipment in the form of ultrasound scanners (n = 2), experts (n = 2), study (n = 1), health institute (n = 1) and human input via questionnaire (n = 1).

The majority of studies reported data preparation processes. In [54], [113]–[115] and [118], missing or incomplete data was excluded, meanwhile in [112], missing values were replaced with the median of the rest of the observed values. Feature selection techniques were implemented in [110], [111], [115] and [116].

Table 5 summarizes detailed information for each study.

G. PRE-ECLAMPSIA AND HYPERTENSIVE DISORDERS

Both pre-eclampsia and hypertensive disorders have been addressed (n = 10) in studies, from which 2 studies [60] and [119], focused on both. This category represents 11.5% (n = 18) of studies. Regarding pre-eclampsia, most studies tend to focus on its prediction, whilst the purpose behind studies on hypertensive disorders is varied: monitoring and prediction, association with mortality and negative impact on pregnancy and fetal growth.

Classification is the main task performed by the included studies in this category (88.9%, n = 16), and although models are still the most proposed final product in 66.67% (n = 12) of studies, remaining studies proposed decision support systems (n = 2), mobile applications (n = 2) and e-health system (n = 2).

A 44.4% (n = 8) of studies from this category collected data from medical records. In 22.2% (n = 4) of studies sensors were employed for data acquisition (BP measurements), and data from human input was collected in 11.1% (n = 2) of studies, via maternal questionnaires and mobile phone usage. 16.6% (n = 3) of studies used survey data and 11.1% (n = 2) of studies used medical equipment. Experts knowledge was used in 11.1% (n = 2) of studies. Remaining studies used data from repositories (n = 1) and surveys (n = 1).

In 22.2% of the analyzed studies application of a data preparation process was mentioned: 3 studies reported working with missing data, from which multiple imputation technique has been used by [120], single-chained imputation with mean value was applied by [42] and completion with average value of data by [42]. Only one study used feature selection techniques [121].

From all studies in this category, 22.2% proposed usable systems. In [49], a complete IDSS was presented for pre-eclampsia prediction and maternal care alongside three different applications for each role (mobile phone or tablet application for patients and healthcare professionals, web application for healthcare professionals and a desktop application for healthcare administrators). In [22], a mobile application was reported for pre-eclampsia prediction and home monitoring. In [122], authors proposed a mobile application with the purpose of monitoring the health status of pregnant women suffering hypertensive disorders. The mobile application could be used by both patients and healthcare professionals. An e-health system proposed in [59] for hypertension detection could also be used via a web application by healthcare professionals. In all mentioned studies, BPsensing devices were used by the pregnant woman.

LR, RF, SVM, and NB are among the most frequent algorithms.

Table 6 summarizes detailed information for each study.

H. MORTALITY

Studies researching mortality related to pregnancy focused solely on prediction (5,7%, n = 9).

Prediction of severe maternal morbidity (SMM) has been addressed in (n = 2) studies: [127] and [41] as ML models (classification). Neonatal mortality has been studied in (n = 3) studies: [128]–[130]. The first study, which also addressed maternal and infant mortality, proposed an IDSS. A framework was presented in [129], developed using ML and CI techniques, and [130] combined ML, DM and IDSS to create an e-health system. It is worth mentioning that the 3 aforementioned studies created tools with GUIs (mobile or web applications) targeting as end users healthcare professionals or administrators.

Perinatal mortality has been addressed in (n = 4) [56], [131], [132] and [133] (stillbirth), using ML techniques. Classification tasks have been applied throughout the three studies. [56] additionally proposed dimensionality reduction and clustering techniques, meanwhile in [133], spatial regression models were used.

55.5% (n = 5) of studies employed medical records for their data, and (n = 3) studies used repository data. In [130] and [128], data was collected from *DATASUS*, a public data repository in the form of data about infant mortality and live birth, and [133] used several database repositories: United Nations, UNDP, World Bank and the WHO. Medical equipment (Doppler patterns of the fetal cardiovascular, cerebral and placental flows and HemoCue photometer), along computer generated data were described in the study protocol of [56]. Data collected via a survey has been used in [132].

Most reported algorithms in this category are logistic regression, random forests and Bayesian networks. More than half of the studies (n = 5) indicated using data pre-processing: feature selection in [41], [127] and [130]. Additionally, the first two studies had to deal with imbalanced data sets: data sub-sampled and random sampled, respectively. Mode imputation strategy has been reported in [131].

Table 7 summarizes detailed information for each study.

TABLE 5. Artificial Intelligence applied to fetal growth. Acronyms used in this table: D/S/A (Deletion, Substitution, Addition), Gradient Boosting Machines (GBM), Information Gain (IG), Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-task learning with deconvolution network (MTL-DN), Pregnancy Physical Activity Questionnaire (PPAQ), Radial Basis Function (RBF), Recursive Feature Elimination with Cross-Validation (RFECV) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML	Cla	Medical records; Repository: MODIS satellite data	NS	Super Learner	Model	Prediction of birth outcome in greener areas	[33]
ML	R	Repository: Magee-Womens Obstetric Maternal and Infant data	NS	Linear and Quantile Regression, Bayesian additive regression trees, GBM, RF	Model	Prediction of fetal weight	[109]
ML	Cla	Repository: LGA dataset from National Program	Feature Selection: GridSearch-based RFECV + IG, RFECV + IG + Stacked generalization	LR, RF, DT, SVM with Linear and RBF kernel	Model	Prediction of LGA	[110]
ML(DL)	Cla	Medical equipment: ultrasound	Manual process by experts (feature extraction), Feature selection: Haar-like	Non-iterative ellipse fitting method; RF	Model	Prediction of LGA	[111]
ML	NS	Human input via questionnaire: PPAQ; Medical records	Missing values replaced with the median of observed values; missing covariate data	Super Learner	Model	Prediction of LGA/SGA	[112]
ML	Cla	Repository: Nova Scotia Atlee Perinatal Database	Missing data were excluded	Multiple LR, Elastic Net, DT, RF, ANN, Gradient Boosting	Model	Prediction of fetal growth abnormalities	[113]
ML	R	Health Institute: National Institute of Perinatology of Mexico; Experts	Incomplete or poorly captured data were eliminated	SVR: Linear, Polynomial, RBF and Nu	Model	Prediction of birth weight	[114]
DM	Cla	Medical records	Null values removed, normalization, Oversampling: duplicate all data instances	AdaBoost, DT, k-NN, NB, RF, SVM	Model	Prediction of LBW	[54]
ML	Cla	Medical records	Feature ranking: RF, XGBoost, verified with PCA. Normality of features: Chi square test, Covariance matrix; Missing data were excluded; Feature selection: Recursive feature elimination	BN, XGBoost	Model	Prediction of LBW	[115]
ML	Cla	Experts: manual extraction of data; Medical equipment: ultrasound	Normalization, Feature selection: Haar-like	LR, Ellipse fitting	Model	Measurement of HC	[116]
ML(DL)	Cla	Medical records: ultrasounds	Augmentation: image processing	MTL-DN based on Link-Net	Model	Prediction of fetal HC	[117]
ML	Cla	Medical records; Study: Air Pollution, Genetics and Early Life Events	Missing data and not included clinical cases were excluded	Targeted maximum likelihood estimation, D/S/A algorithm, LR	Model	Relationship evaluation between pollutants exposure and LBW	[118]

I. LABOUR AND DELIVERY

Research investigating labour and delivery (5.12%, n = 8) focused mainly on prediction tasks (n = 6): prediction of delivery type (c-section or vaginal delivery) [134]–[136], prediction of the likelihood of a woman using skilled delivery service [137], prediction of the success of conducting an induction procedure [138] and prediction of the need for performing labor induction [139]. In the rest of studies (n = 2), [140] aimed to perform a tool for decision assistance during labour and delivery, and [141] focused on analyzing the reason behind the high rate of home birth in the study location.

TABLE 6. Artificial Intelligence applied to pre-eclampsia and hypertensive disorders. Acronyms used in this table: Averaged one-dependence estimators (AODE), Gradient Boosting (GB), Linear Discriminant Analysis (LDA), Monitoring Mothers-to-Be (nuMoM2b), Multilayer perceptron (MLP), Multivariate Adaptive Regression Splines (MARSplines), Particle swarm optimization (PSO), Radial Basis Function (RBF), Ribonucleic acid (RNA) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]), Regression (R).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
IDSS, UAI	NS	Human input via mobile application; Sensors: glucose, temperature, Weight, BP, FHR [R]	NS	Bayesian Networks	IDSS (patient, healthcare professionals, administrators)	Providing maternal care, prediction of pre-eclampsia	[49]
ML	Cla, Clu	Medical records: Demographic and laboratory data	Multiple imputation for missing data using fully conditional specification	LR, DT, NB, SVM, RF, Stochastic GB k-means	Model	Prediction of pre-eclampsia	[120]
UAI	NS	Medical records; Sensor: BP [R]	NS	Bayesian Networks	Mobile app (patient)	Prediction of pre-eclampsia, home pregnancy monitoring	[22]
ML	Cla	Study: Stockholm-Gotland Obstetric Cohort	Missing data: single-chained imputation with mean value	LR, RF, Backward Selection, Decision rules	Model	Prediction of pre-eclampsia	[42]
ML	Cla	Study: nuMoM2b	NS	LR, Regularized Regression	Model	Relationship between worry and pre-eclampsia	[6]
ML	Cla	Medical equipment: Illumina's TruSeq small RNA	Removal of erroneous samples, Feature selection	LR	Model	Prediction of pre-eclampsia	[121]
ML, NLP	Cla, R	Medical records	NS	LR, SVM, RF, Gaussian NB	e-Health system	Dietary habits assessment	[46]
ML	Cla	Study: Improving Health and Development Outcomes for Children	Missing data completion with the average value of the data	Boosted LR, k-NN, LDA, SVM (Linear and RBF), RF, C4.5, C5 Trees, Stochastic GB, MARSplines, Adaboost	Model	Prediction of pre-eclampsia	[123]
ML	Cla	Survey: National Health and Nutrition; Sensor: BP [R]	NS	LR, Gaussian NB, RF, SVM	e-Health system (web app: healthcare professionals)	Detection of hypertension	[59]
ML	Cla	Medical records	NS	AODE	Model	Prediction of pregnancy outcome	[60]
KRR, IDSS	Cla	Repository: clinical knowledge manager and national health; Medical records	NS	Ontology-based model	IDSS	Health monitoring	[39]
ML, CI	Cla	Medical records	NS	PSO, Conventional MLP	Model	Health monitoring	[124]
ML	Cla	Medical records	NS	AODE, C4.5, RF, NB, NB Tree, SVM, Multilayer Perceptron, RBF Network	Model	Prediction of maternal mortality; birth outcome	[119]
ML, IDSS	Cla	Experts	NS	ID4, NB Tree, J48 DT	Model	Prediction of hypertensive disorder	[125]
CI	Cla	Medical equipment: EHG recordings; Human input via questionnaire	NS	ANN	Model	Prediction of Hypertensive disorder	[126]
ML	Cla	Experts; Sensor: BP measurement [R]	NS	NB	Mobile app (patient, healthcare professionals)	Health monitoring	[122]
ML	Cla	Medical records	NS	J48 DT, NB	Model	Health monitoring	[38]
ML	Cla	Medical records	NS	DT, SVM, k-NN, Boosted and Bagged trees	Model	Prediction of SGA	[37]

TABLE 7. Artificial Intelligence applied to mortality. Acronyms used in this table: Linear Discriminant Analysis (LDA), United Nations Development Program (UNDP), World Health Organization (WHO) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]), Regression (R).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML	Cla	Medical records	Control group (non-SMM) sub-sampled (imbalanced data); Feature selection: ANOVA	LR, L1 Regularized LR	Model	Prediction of severe maternal morbidity	[41]
ML	Cla	Medical records	Control group (non-SMM) randomly sampled (imbalanced data), Feature selection: Filter method	Regularized LR	Model	Prediction of severe maternal morbidity	[127]
ML, IDSS, DM, KRR, NLP	Cla	Repository: SIM (infant mortality) and SINASC (live birth data)	NS	NS NLP; NS predictive models	IDSS (mobile and web app: health administrators)	Prediction of maternal, prenatal, infant mortality	[128]
ML, DM, IDSS	Cla	Repository: SIM (infant mortality) and SINASC (live birth data)	NS	DT (ID3, C4.5), RF, BN	e-Health system (mobile app: healthcare professionals)	Prediction of neonatal mortality	[129]
ML, CI	Cla, DR	Medical records	Feature selection: computational (wrapper) methods and human input	ANN, SVM	e-Health system (GUI: healthcare professionals)	Prediction of neonatal mortality	[130]
ML	Cla	Medical records	Mode imputation strategy for missing data	RF, LDA, LR (L2 penalty), NB	Model	Prediction of perinatal mortality	[131]
ML	Cla	Study	NS	k-NN	Model	Prediction of perinatal mortality	[132]
UAI, ML	Cla, R	Repository: United Nations, UNDP, World Bank, WHO	NS	BN, Spatial regression	Model	Predict the determinants of stillbirth	[133]
ML	Cla, Clu, DR	Medical equipment: Hemocue Pholometer, Doppler; Medical records; Synthetic data	NS	Multiple LR	Study protocol	Prediction of perinatal mortality	[56]

The majority of studies in this category developed models (n = 5), followed by (n = 2) studies that proposed intelligent decision support systems using IDSS techniques and one study that developed a simulation. The IDSS proposed in [138] also developed a web application for healthcare professionals to use.

Classification tasks have been performed in 75% (n = 6) of studies, and dimensionality reduction has been applied to the medical records used as data in [138] and [135]. Also 75% of studies reported applying pre-processing methods, such as data cleaning, filtering, trimming [135], [137], [138], [141], feature selection [137]–[139], unbalanced distribution and SMOTE technique [137].

Data sources are medical records (n = 4), surveys (n = 2), experts (n = 1) and electrode sensors (for ECG recordings in real time, n = 1). Algorithms reported by study in this category are support vector machines, artificial neural networks and decision trees (C4.5, J48), among others.

Table 8 summarizes detailed information for each study.

J. MENTAL HEALTH

Research on mental health during pregnancy (5.1%, n = 8) is mainly focused on depression and stress using ML (n = 7), Big Data (n = 1), Robotics and NLP (n = 1) techniques.

Studies that researched stress (n = 3) developed models for predicting complications that could occur during pregnancy and defects of fetus due to stress [142], framework for detecting stress [143] and e-health system for stress monitoring [144], based on ML. Both the framework and e-health system were designed to be used by the patient and gathered real time data through: heart rate, electrocardiograph, galvanic skin response sensors and human input via questionnaire, and activity sensors, respectively.

Depression, has been studied in (n = 4) studies, mainly postpartum depression (n = 3). Prediction of postpartum depression has been the main purpose of studies [43], [145], [146] based on ML (classification tasks) and Big data techniques, meanwhile [147] presented the pilot study for a perinatal depression intervention based on Robotics and NLP. Mainly medical records and survey data have been used [43], [145], [146].

In [6], authors focused on trying to establish a relationship between an emotional state, worry, and pre-eclampsia, by the means of classification tasks (ML), using data from a medical study.

Most implemented algorithms in this category are: support vector machines, k-nearest neighbors, decision trees, among others. 62,5% (n = 5) of studies implemented some type of

TABLE 8. Artificial Intelligence applied to study labour and delivery. Acronyms used in this table: Comma-separated values (CSV), Ethiopian Demographic and Health Survey (EDHS), Information Gain (IG), International Centre for Diarrhoeal Disease Research, Bangladesh (ICDDR,B), Linear Discriminant Analysis (LDA), Minimum Redundancy Maximum Relevance (mRMR), Multilayer Perceptron (MLP) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
IDSS, ML, CI, NLP, Big Data	Cla, DR	Medical records	Cleaning and filtering; Feature selection: ReliefF, mRMR, Gain Ratio and IG, Correlation based	NB, DT, ANN (MLP), SVM, RF, Decision Making Rules	IDSS (web app: healthcare professionals)	Prediction of the success of induction procedure	[138]
ML	NS	Medical records	NS	Linear Regression, LR	Simulation	Labour and delivery decision assistance	[140]
DM	Cla	Survey: Maternal neonatal and child health program by ICDDR,B	Trimming: missing and irrelevant data were excluded	C4.5, NB, SVM, Probabilistic ANN, MLP	Model	Analysis of reasons for home birth	[141]
ML	Cla	Sensor: EHG recordings using Ag/AgCl disposable electrodes [R]	Manual segmentation of EHG bursts; Signal processing: bandpass Butterworth filter and downsampling, Feature selection: Sequential Forward	SVM	Model	Prediction of the need for labour induction	[139]
ML	Cla	Medical records	Conversion to CSV format	ANN, SVM, RF, DT	Model	Prediction of delivery type (c-section or not)	[134]
ML	Cla, DR	Medical records	Cleaning	LR, LDA, SVM, k-NN, NB, ANN, Adaboost	Model	Prediction of delivery type (c-section or not)	[135]
CI, IDSS	NS	Experts	NS	Timed Fuzzy Cognitive Map	IDSS	Prediction of delivery type (c-section or not)	[136]
ML, CI	Cla	Survey: EDHS	Unbalanced distribution, missing data excluded, Feature selection: Bivariate analysis and multivariable LR, SMOTE	J48 DT, NB, SVM, ANN	Model	Prediction of seeking skilled delivery assistance	[137]

data pre-processing. Specifically, feature selection techniques have been used in [43] on medical records and in [143] on sensor and questionnaire data. Other techniques like SMOTE were reported on [146], normalization [142]–[144], and segmentation and cleaning in the last mentioned study.

Table 9 summarizes detailed information for each study.

K. MATERNAL AND FETUS WELL-BEING

There is a variety of functions and purposes among the studies in this category (18%, n = 28). Most studies present more than one purpose:

- Providing maternal, prenatal, antenatal or infant care (n = 10): [48], [148]–[156].
- Health monitoring (n = 5): [148], [151], [155], [157], [158], from which specifically home monitoring [151], [158].
- Evaluation of health programs [159] (exploratory protocol), reducing health care variability [160] (IDSS) and health resources allocation [158] (wearable).
- Analysis of indoor air pollution (ontology) [161] and association between PM2,5 exposure and pregnancy outcomes [162], [163] (models).
- Detection of fetal QRS complex [164] (model).
- Prediction of pregnancy complications [53] (model).
- Classification of drugs safety during pregnancy [165] (model).
- Identification of pregnancy time frames [166] (model).
- Promotion of healthy lifestyle and prevention of female feticide [149] (IDSS).
- Gait monitoring [167].
- Prediction of gestational age [47] (model), [168] (framework).
- Pregnancy detection [169] (ML model).
- Prediction of risk in pregnancy [170] (IDSS), risk management during pregnancy [45] (Ontology to be used as part of an IDSS) and risk factor identification [171] (model).

From the subcategory of studies focused on providing maternal care and health monitoring, only one study developed only a model. 5 studies proposed applications (web, mobile or desktop), 2 studies proposed conversational agents, other 2 studies proposed wearable devices, one study proposed an intelligent decision support system, another study proposed a multi-agent system.

Table 10 and Table 11 summarize detailed information for each study.

TABLE 9. Artificial Intelligence applied to study mental health. Acronyms used in this table: Galvanic Skin Response (GSR), Monitoring Mothers-to-Be (nuMoM2b), Radial Basis Function (RBF) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
ML	Cla	Medical records	Feature selection: univariate LR	L2-regularized LR, SVM, DT, NB, XGBoost, RF	Model	Prediction of postpartum depression	[43]
ML, Big Data	Cla	Medical records	NS	DT, SVM, k-NN, Ensemble	Model	Prediction of postpartum depression	[145]
ML	Cla	Survey	SMOTE	NB, J48 DT, SVM, LR, AdaBoost, Bagging, Gradient boosted trees	Model	Prediction of postpartum depression	[146]
ROB, NLP	NS	NS	NS	Existing AI system for automated psychological support	Pilot study	Perinatal depression intervention	[147]
ML	Cla, Clu	Sensors: BiostampRC, Polar H7, Neulog GSR; Human input via patient questionnaire [R]	Segmentation, normalization and cleaning, Feature selection: CfsSubsetEval	SVM with RBF, DT, AdaBoost, NB, ANN	Framework (wearable: patient)	Stress detection in pregnant women	[143]
ML	Cla	Medical records; Human input via questionnaire	Rescale data algorithm (normalization)	SVM, NB, k-NN, DT	Model	Prediction of labour complications and birth defects due to stress	[142]
ML	Cla	Study: nuMoM2b	NS	Regularized Regression, LR	Model	Relationship between worry and pre-eclampsia	[6]
ML	Cla, Clu	Sensor: Garmin vívosmart smart bands [R]	Normalization	k-means, RF, ANN	e-Health system (patient)	Stress monitoring	[144]

L. OTHER PREGNANCY PROCESSES

From all included studies, 9% (n = 14) were charted under the *Others* category. A wide variety of processes can be found:

- Social media posts were used in [172] to analyze concerns related to pregnancy while suffering MS, using ML and NLP techniques.
- A real time prediction system using wearable devices and mobile generated data was proposed by authors in [58] to help pregnant women make quick decisions in case of miscarriage or probable miscarriage.
- Maternal anemia was addressed using ML models by [173] and [174].
- Postpartum complications were reported by [175] (health administrative data and ML techniques were applied to predict the risk of common maternal postpartum complications) and [52] (DM models were used to create to predict the need for neonatal resuscitation)
- DM model was developed in [55] to identify the risk associated to the patients that decide to voluntarily terminate their pregnancy.
- Risk of hypotension in a needle-based epidural procedure was studied by authors in [176] using ML techniques.
- ML model for predicting the risk of suffering diabetes mellitus in life after suffering GDM during pregnancy has been developed in [177]
- Authors in [57] created a scalable multi-agent system for healthcare resources allocation and individualized care. Blood glucose control has been used as a case study.
- In [19], a CI based prediction system for the best delivery timing on a pregnant woman duffering of SLE was proposed.
- Placental disorders identification was the focus in [178], [179]. ML, CI and VIS techniques were employed for this purpose.
- Model for early diagnosis of HELLP syndrome was proposed in [178].
- A geospatial collective intelligence model for health planning (GCIMHP) in regions in which HIV infections affect pregnant women was proposed by authors in [20].

VIII. DISCUSSION

The purpose of this scoping review is to asses the nature and extent of the body of research (published since 2008) on AI and AC for pregnancy health and well-being. This study aims to provide an overview of studies in which AI methodologies, techniques, algorithms and frameworks are applied to pregnancy health and well-being (RQ1: *What is the current state of research on methodologies, techniques, algorithms and frameworks used in Artificial Intelligence applied to pregnancy health and wellbeing?*) and to find AC approaches applied in this studies (RQ2: *From these studies where AI is used in pregnancy context, how many have an affective computing approach and which characteristics do they have?*).

To answer the presented research questions, several topics have been proposed for detailed analysis in this literature review: author keywords, publication countries, social

TABLE 10. Artificial Intelligence applied to Maternal and Fetal Well-being. Acronyms used in this table: Adaptive Resonance Theory (ART), Convolutional Neural Network (CNN), Independent Component Analysis (ICA), International Fetal and Newborn Growth Consortium (INTERGROWTH), Residual Neural Network (ResNet), Supervised Gaussian Mixture Models (SGMM), Statewide Planning And Research Cooperative System (SPARCS) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]), Regression (R).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
KRR	NS	Sensor: temperature, humidity, PM10/PM2.5, carbon monoxide [R]	NS	NS	Ontology	Analysis of indoor air pollution	[161]
ML, IDSS	Cla	Medical records	Feature selection	BN, Pairwise association rule mining	IDSS (GUI: healthcare professionals)	Reducing health care variability	[160]
ML	Cla, R	Repository; Human input via questionnaire; Sensors	Resampling, cleaning, multiple imputation mode for missing values	RF	Model	Association between PM2,5 exposure and pregnancy outcomes	[163]
ML	Cla	Medical records; Sensor: HK-2010/1 single channel pulse; Experts: data collection	Filtering process	CNN (1D ResNet and BasicBlocks, 1D MgNet); SVM, LR	Model	Pregnancy detection	[169]
ML	Cla, DR	Sensor: signal of fetal movement (accelerometer) [R]	Sequential feature algorithms, Forward feature construction	Fuzzy ARTMAP	Wearable (mobile app: patients)	Home pregnancy monitoring; health resources allocation	[158]
ML, IDSS	Cla	Synthetic data; Experts: manual validation of data	NS	CART	IDSS	Prediction of risk in pregnancy	[170]
IDSS, KRR	NS	Experts: information regarding high risk pregnancy, antenatal care	NS	NS	Ontology	Risk management during pregnancy	[45]
ML	Cla	Experts; Medical records	Validation, normalization, standardization and transformation	C4.5 DT	Model	Health monitoring	[157]
ML, DM	Cla, DR	Sensor: electrodes fixed on wearable coat [R]	Feature selection: Segmented Pigeon Hole algorithm	Iteration Reduced Threshold based classifier	Wearable (mobile app: patients)	Monitoring gait	[167]
ML	Cla, Clu	Study: SPARCS	NS	SGMM, L1-regularized LR, K-means, RF, ANN, AdaBoost, Gradient boosting	Model	Risk factor identification	[171]
ML	Clu	Medical equipment	ICA, Signal processing: impulsive artifact and baseline wandering removal, power-line canceling	Autoregressive model based on the learning management system	Model	Detection of fetal QRS complex	[164]
ML(DL)	Cla	Synthetic data; Medical equipment: ultrasound; Repository: fetal ultrasound	NS	CNN	Framework	Prediction of gestational age; Providing antenatal care	[168]
ML, CI	NS	Study: INTERGROWTH-21st	NS	GA	Model	Prediction of gestational age	[47]
ML, CI, VIS, Big Data	R	Synthetic data	NS	ANN	Application (web and mobile: patient)	Home pregnancy monitoring; providing maternal care	[151]
IDSS	NS	Human input via questionnaire; Survey	NS	Embedded algorithm	Application (desktop: healthcare professionals)	Providing maternal care	[48]
ML, Big Data	Clu	Human input via questionnaire	NS	DT	Application (mobile and web: patient)	Providing maternal care	[152]

TABLE 11. Artificial Intelligence applied to Maternal and Fetal Well-being (II). Acronyms used in this table: Linear Discriminant Analysis (LDA), National Library of Medicine (NLM), Questions and answers (Q&A), Sequential Minimal Optimization (SMO) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]), Reinforcement learning (Reinf).

Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
Expert System	NS	Human input via mobile phone	NS	NS	Application (mobile: patients)	Providing antenatal care	[154]
ML, DM	Cla	Experts: Q&A	Bloom filters	DT, SVM, k-NN, LR, Zero Rule	Application (web: patients)	Providing maternal care	[153]
ML, ROB, NLP, MAS	Reinf	Mobile phone [R]	NS	NS	Conversational agent (GUI: patients)	Providing maternal care, health monitoring	[148]
ML(DL), NLP, ROB	NS	Human input via mobile phone	NS	NS ML and DL algorithms	Conversational agent (GUI: patients)	Providing maternal care, health monitoring	[155]
IDSS	NS	Medical records	NS	Rule-based algorithm	IDSS (healthcare professionals)	Providing maternal care; healthy lifestyle promotion; prevention of female feticide	[149]
ML, Big Data	Cla, Clu, DR	Repository; Health institute; Survey	Reduction and noise removal	LDA, PCA, LR, NB, CART, SVM, NN, K-means	Exploratory protocol	Health programs evaluations	[159]
IDSS	NS	Experts	NS	NS	Qualitative study	Providing maternal care	[156]
MAS	NS	Medical records	NS	NS	Multi-agent system	Providing maternal care	[150]
IDSS, DM	Clu	Medical records	Null or noisy data were removed, normalization	K-means, Expectation-Maximization, Farthest First	Model	Prediction of pregnancy complications	[53]
ML, NLP	Cla	Repository: NLM	Regular expressions, manual process	SMO, NB, SVM	Model	Classification of drugs safety	[165]
NLP, DM	NS	Social media	Tweets were tokenized using ARK Twokenizer	Self-developed heuristic algorithm	Model	Identification of pregnancy timeframe	[166]

factors, bio ethical aspects and health standards, personal data protection, proposed systems and their functions, AI topics, data acquisition, methodology, data preparation, algorithms, model validation, performance metrics, frameworks and programming languages and IT security.

Next, the first research question (RQ1) will be addressed. ML is the most prolific AI field among the identified research, thus, a great number of studies developed models based on ML. Generally speaking, included studies that developed ML models followed a scheme similar to the following: data is collected and prepared using data preparation techniques (normalization, removal, transformation, etc.), relevant features are selected through feature engineering techniques and a classification or regression algorithm is applied. The model then undergoes validation techniques (sometimes validation with real or external data) and performance evaluation.

Research has also demonstrated its interest in CI techniques, capable of performing a great variety of tasks. Some state-of-the-art CI applications observed in this scoping review were developed for various prediction purposes (GDM prediction, labour and delivery related prediction, among others). ANN is the most implemented algorithm for CI applications.

This review has found that IDSS can be very interesting for both the patient and the medical practitioners, since they can improve patient care, as well as reduce healthcare related costs. IDSS based studies have focused mainly on pregnancy aspects such as maternal and fetal well-being, fetal state, gestational diabetes, pre-eclampsia and hypertensive disorders and labour and delivery. All this processes require close monitoring since they can really benefit from quick intervention. Remote health assessment and remote medical follow-ups, timely treatment, reduce of mis-diagnosis and treatment error, widespread medical assistance, are just some of the benefits that this type of system can provide. Moreover, this type of solutions can be very interesting for women living in developing countries and rural areas, since their access to healthcare assistance can be limited mainly by socio-economic factors.

TABLE 12. Artificial Intelligence applied to other processes (I). Acronyms used in this table: Generalized Linear Model (GLM), Gradient Boosting (GB), Medical Resonance Imaging (MRI), Multiple Sclerosis (MS), Recursive feature elimination (RFE) and abbreviations: Classification (Cla), Clustering (Clu), Real time gathered data ([R]), Regression (R).

Pregnancy process	Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
MS	ML, NLP	Cla	Social media (forums)	Content analysis techniques and filtering	NB, NLP models	Model	Analyze pregnancy concerns while suffering MS	[172]
Miscarriage	ML, DM, Big data	Clu	Wearable: healthcare sensors; Mobile phone: accelerometer; Human input via mobile application [R]	Transformation into specific types	K-means	e-health system (patient)	Prediction of (patterns) miscarriage	[58]
Anemia	ML	R	Medical equipment: non-invasive multi wavelength spectroscopic device [R]	Signal processing; Feature selection	Stacked Regressor	Model	Detection of maternal anemia	[173]
Anemia	ML, CI	R	Medical equipment: blood draws	Train/test samples with the minimal ratio for the test sample due to imbalanced data set	Linear Regression; Multilayer NN	Model	Prediction of the impact of anemia treatment in pregnant women	[174]
PP complications	ML	Cla	Medical records	NS	Gradient boosted trees	Model	Prediction of postpartum complications	[175]
PP complications	DM, IDSS	Cla	Medical records	Normalization; Oversampling	Linear Regression, NB, k-NN, RF, SVM	IDSS	Predicting the need of neonatal resuscitation	[52]
VIP	DM	Cla	Medical records	Oversampling; Missing data were excluded	DT, SVM, NB, GLM	Model	Prediction of the risk of voluntary termination	[55]
Hypotension	ML	Cla	Experts: data collected by trained observers	NS	DT, LR, NB, RF, k-NN, SVM, Discriminant Analysis via Mixed Integer Program	Model	Prediction of hypotension in a needle-based epidural procedure	[176]
Diabetes Mellitus	ML	Cla	Medical records; Survey: telephonic	NS	SVM, NB, DT, RF, AdaBoost	Model	Prediction of diabetes mellitus predisposition post GDM	[177]
Blood glucose	MAS, KRR	NS	Medical equipment: glucose meter; Human input via mobile phone	NS	NS	Multi-agent system	Health resources allocation	[57]
SLE	CI	NS	Medical equipment: Doppler	NS	GA	Model	Prediction of best delivery timing on women suffering SLE	[19]
Placental disorders	ML, CI	Cla	Medical equipment: MRI	RFE, variance threshold, maximum absolute scaling, PCA, ANOVA	Online learning-based semi-automated algorithm, GA, RF, XGBoost, LR, GB, Extra trees	Model	Identification of placental alterations	[178]
Placental disorders	ML, VIS	Cla	Medical equipment: ultrasound	Automatic (expert dot annotations);	ANN	Model	Identification of placental alterations	[179]

Fetal health and well-being can benefit from this type of systems since close monitoring can provide rapid diagnosis and evaluations.

For pregnant women suffering GDM, glucose levels need to be constantly monitored in order to prevent hyperglycemia and correctly administrate insulin therapy. It can be very

TABLE 13. Artificial Intelligence applied to other processes (II). Acronyms used in this table: Adaptive neuro fuzzy inference system (ANFIS), Generalized Linear Model (GLM), Radial Basis Function (RBF) and abbreviations: Classification (Cla).

Pregnancy process	Approach	Task	Data acquisition	Preparation	Algorithms	Final product	Functions	Ref
HELLP syndrome	ML, CI	Cla	Medical records:	NS	ANFIS, Fuzzy logic-based algorithms, RBF network, GLM, SVM, DT, NB	Model	Early diagnosis of HELLP syndrome	[178]
HIV	IDSS	NS	Experts: questions and answers	NS	NS	IDSS (web app: healthcare administrators)	Health resources allocation	[20]

useful, especially for women that have limited access to healthcare, to use a system that is remotely connected with her doctor, thus reducing the risk of developing other pregnancy complications. Similarly to gestational diabetes, women suffering of pre-eclampsia or hypertensive disorders can benefit from close monitoring, but also healthy women in terms of anticipation and reassuring a healthy state.

Labour and delivery can be confusing and worrying for the pregnant woman. As already mentioned, a complicated labour experience can have many postpartum complications that can affect both mother and child. Moreover, how this process develops and results has very close relation with how quickly and easily the pregnant woman will recover after giving birth. There are situations in which both patients and obstetricians could benefit from a decision support system that could improve patient health outcomes and costs (medication, hospitalization, healthcare professionals), as well as perceived quality of care.

NLP approach has also been reported by researchers for analyzing maternal concerns, habits and sentiments. This approach can be very useful for developing conversational agents and intelligent systems that can directly interact with the patient, providing care and assistance.

As for methodologies, only a small number of the included studies reported using a standard methodology. CRISP-DM is the most widely employed. Other studies proposed their own methodology in which step by step explanations of their work were provided. This is an important issue since it improves research reproducibility.

Algorithms have been implemented in the vast majority of studies, independently of the AI technique applied. It has been observed in the included research that a wide variety of algorithms have been implemented. A great number of studies used more than one algorithm which allows for performance comparison between algorithms. In studies in which a more advanced technique (CI, DL) was used, usually other baseline models were implemented for performance comparison purposes.

Diverse data collection sources have been observed throughout the research. There are studies in which authors acquired their own data set and studies in which the data was already collected. Data concerning health is of a very sensitive nature and its acquisition and manipulation requires of ethical boards and reviewing teams consent, which is a delicate process. When data is acquired from publicly available repositories, the control that authors have on this data is naturally very low, and more often than not, the type of data (e.g. labeled or not) will determine the type of learning to be applied. It can also affect the performance of the models due to various reasons: missing, incorrect or noisy data, unbalanced data set, among others. One example of this could be the studies in which the publicly available UCI Machine Learning CTG data set is used. Studies working with CTG recordings from this data set, focused solely on fetal state classification using classification tasks (data was labeled), and since the cases (normal, suspect or pathological) were imbalanced, some studies applied different types of feature selection, dimensionality reduction or clustering techniques.

Remarkably, R and Python are the most used programming languages, and Sci-kit for Python the most popular framework. A reason behind this could be the fact that both R and Python (especially within Sci-kit learn) have multiple built-in functions and packages that are very useful for implementing, especially ML models, feature selection, validation techniques, among many others.

Overall, main findings of this scoping review regarding AI use show that more than half of studies applied the AI techniques for model development. Studies marked as models did not report any further development (unless specified) regarding its use by an end user in controlled environments for experiments or real life settings. In this specific cases, usually further work is required for building usable systems for the model to function in, which could be mobile applications, for example, wearable devices or e-Health systems.

Next, the second research question (RQ2) will be addressed. Affect detection is one of the main components of AC. Therefore, affect is commonly used as data input in AC approaches. This type of data is mainly acquired by sensors, wearable devices and mobile applications, among others. Data can be acquired automatically (sensors: galvanic skin response, heart rate) or from manual human input (psychological questionnaires, emotional report). This type of application is to be directly used by the patient in a passive or active form.

Only a few studies have reported patient emotions as data input. Two studies included in this literature review used emotion as input data. Firstly, in [6], researchers looked into the relationship between pre-eclampsia and worry. Secondly, in [70], authors researched patients reactions on prenatal invasive and non-invasive tests using sentiment analysis techniques. However, none of the studies mentioned developing any kind of device to make possible the interaction between the patient and the machine. Remarkably, although AC and emotional terms have been included in the search strategy, there are no significant studies on AC applied to pregnancy health and well-being.

Another interesting topic that emerged from the qualitative analysis is the relationship that can be observed between AI solutions and the patient's socio-economic context. Approximately half of the studies considered at least one social factor. Throughout the reviewing process, information reported on social factors (developing and low-middle income countries, environments with limited resources and connectivity, rural areas, low educational level, among others), study locations and author's countries, has reveled that there is an important body of literature focused on developing AI-based healthcare solutions for pregnant women who have difficulties accessing medical attention. It is important to acknowledge that AI-based systems can significantly improve health and well-being conditions of women living in such situations. Social factors have been reported in studies in which the authors' affiliation correspond to the following countries, ordered by frequency: United States of America, China, India, Portugal, Brazil, Pakistan, England, Canada, Israel, South Africa, Saudi Arabia, Australia, Russia, Cyprus, Italy, The Netherlands, Spain, Kenya, South Korea, Mexico, Bangladesh, France, Oman, Ethiopia, Colombia, Puerto Rico, Ecuador, Iran, Romania, Ireland, Sweden, Zambia, Germany, Tanzania and Belgium. This can also be observed in Fig. 7, which illustrates author affiliation countries for all included studies.

To summarize, the main objective of the AI techniques applied to pregnancy health and well-being is prediction, detection or classification of a disease, disorder or state, followed by health care providing and health status monitoring. Therefore, the analysis of the sources of evidence indicates that a high number of studies focused on model development, mainly ML (supervised learning, classification tasks), in many occasions without a clinical validation. Wearable devices or mobile applications directly used by the pregnant woman are reported to a lesser extent. The emotional state has been considered as relevant or even a factor worth mentioning in only a few studies. With a few exceptions, this review has not found affect to be a studied variable in the pregnant woman's health and well-being status. Although there is an extensive body of literature on AI for pregnancy health and well-being, no significant results on AC have been found.

A. STRENGTHS AND LIMITATIONS

Strengths of this review include a comprehensive search strategy, as well as a detailed scoping review protocol, in which all decisions and assumptions made have been stated. Additionally, the iterative nature of this type of review, especially during the screening process, has been detailed and reported under the methods section. Another strong point of this review has been the use and consideration of multiple scoping review guidelines and methodologies.

There are several limitations to this study. No quality assessment of the included studies has been performed. Studies regardless of the development stage have also been incorporated in this review, however, it is mentioned (e.g. proposal, protocol study). No grey literature has been considered in this scoping review.

IX. CONCLUSION

This study evidences a growing interest in the scientific community for the potential that artificial intelligence have in the field of medicine in general, and obstetrics and gynecology in particular. Research in AI applied to health has resulted in very interesting discoveries in recent years, giving way to a synergy that can benefit many people. The support it can offer to those who are in disadvantaged or inequality situations is especially interesting.

A scoping review is presented, based on a systematic search, which identified research trends on the topics of artificial intelligence for pregnant health and well-being applications. The evaluation of final products, methodologies, frameworks, tools, and design guidelines related to many pregnant processes extracted from the literature provide a knowledge base, which can be consulted and applied when developing intelligent systems that seek to improve and support pregnancy.

Once all the studies have been processed and reviewed, the following set of ideas serve as part of the conclusions for the study:

- AI applications in pregnancy can improve universal healthcare and reduce healthcare variability by decreasing the difficulties imposed by the socio-economic factors, place of residence or transport capabilities of the pregnant woman.
- AI applications can be used to closely monitor health during pregnancy. This can make the patient feel more secure and closer to her health service and reduce feelings of anxiety or worry.
- AI applications can help reduce maternal-fetal morbidity in two ways:
    1) Monitoring applications in wearable devices and mobile phones enable rapid detection of risk factors.
    2) Data automatic analysis help doctors develop more efficient decision trees.
- AI would allow early detection of changes in the pathology of the pregnant population.
- AI application can improve the process of evaluation of any health program, as well as its efficiency regarding human and material resources.
- Despite increasing awareness and research activity addressing the intelligent solutions in health

interventions in recent years (as addressed in the Background section), there are still substantial gaps in the field. More specifically, a research gap has been identified where AC has not been explored yet to support pregnant psychological health and, in consequence, pregnant physical health. Specific evaluation techniques could be applied: from the design and creation of a system to the testing and finally, adoption and recommendation to patients. Furthermore, this field is very novel and brings with it ethical implications that must be carefully studied and considered.

A promising direction for future research could focus on embedding those tools further into the digital health development process and bring multidisciplinary development and design teams closer to compliance with regulatory and standard frameworks.

Additionally, despite its relevance, only the 7% of the studies included data security and only the 23% privacy issues, which is another current research shortcoming and an opportunity for future studies.

It is also clear that a community effort towards validating and reproducing findings will help in providing more solid and actionable research guidelines.

Finally, this article provides insights for researchers and practitioners interested in deepening their knowledge for artificial intelligence and affective computing applications in obstetrics and gynecology fields. By providing these insights, we contribute to the development of future innovations in this fast-paced field problem.

APPENDIX

The data charting form used in the review process is available in the GitHub repository. The academic research (master's thesis) [180] that served as base for this article is also available in the GitHub repository.

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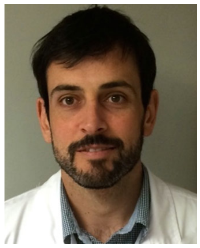

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