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REVIEW

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Artificial intelligence applied to the study of human milk and breastfeeding: a scoping review

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Abstract

Background Breastfeeding rates remain below the globally recommended levels, a situation associated with higher infant and neonatal mortality rates. The implementation of artificial intelligence (AI) could help improve and increase breastfeeding rates. This study aimed to identify and synthesize the current information on the use of AI in the analysis of human milk and breastfeeding.

Methods A scoping review was conducted according to the PRISMA Extension for Scoping Reviews guidelines. The literature search, performed in December 2023, used predetermined keywords from the PubMed, Scopus, LILACS, and WoS databases. Observational and qualitative studies evaluating AI in the analysis of breastfeeding patterns and human milk composition have been conducted. A thematic analysis was employed to categorize and synthesize the data.

Results Nineteen studies were included. The primary AI approaches were machine learning, neural networks, and chatbot development. The thematic analysis revealed five major categories: 1. Prediction of exclusive breastfeeding patterns: AI models, such as decision trees and machine learning algorithms, identify factors influencing breastfeeding practices, including maternal experience, hospital policies, and social determinants, highlighting actionable predictors for intervention. 2. Analysis of macronutrients in human milk: AI predicted fat, protein, and nutrient content with high accuracy, improving the operational efficiency of milk banks and nutritional assessments. 3. Education and support for breastfeeding mothers: AI-driven chatbots address breastfeeding concerns, debunked myths, and connect mothers to milk donation programs, demonstrating high engagement and satisfaction rates. 4. Detection and transmission of drugs in breast milk: AI techniques, including neural networks and predictive models, identified drug transfer rates and assessed pharmacological risks during lactation. 5. Identification of environmental contaminants in milk: AI models predict exposure to contaminants, such as polychlorinated biphenyls, based on maternal and environmental factors, aiding in risk assessment.

Conclusion AI-based models have shown the potential to increase breastfeeding rates by identifying high-risk populations and providing tailored support. Additionally, AI has enabled a more precise analysis of human milk composition, drug transfer, and contaminant detection, offering significant insights into lactation science and maternal-infant health. These findings suggest that AI can promote breastfeeding, improve milk safety, and enhance infant nutrition.

Keywords Artificial Intelligence, Breast Feeding, Human Milk, Machine Learning, Neural Network

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Background

Although breastfeeding is a public health policy with various implemented actions, breastfeeding indicators remain below targets [1]. The prevalence of breastfeeding in children under six months of age in Latin America and the Caribbean is 43% [2]. In Colombia, the rate of exclusive breastfeeding in the first month of life is 50% [3]. By the first six months, this rate decreased to less than 30% [3]. It is associated with an increased risk of short- and long-term all-cause mortality and morbidities [4, 5]. Additionally, suboptimal breastfeeding during the neonatal period increases the risk of postnatal mortality by up to four-fold, especially in developing countries [6, 7].

The World Health Organization's (WHO) goal for 2025 is to increase the rate of exclusive breastfeeding during the first six months to at least 50%, a target that currently seems distant [8]. This situation necessitates the exploration of new technological developments to improve the breastfeeding indicators.

Artificial intelligence (AI) has been one of the most impactful technological advances in recent years and has been applied in various fields of medicine [9]. AI is instrumental in diagnosing clinical conditions, developing drugs, and supporting medical services in remote areas [10, 11]. During the COVID-19 pandemic, AI is crucial for tracking and predicting events [9]. In pediatrics, AI has been evaluated for its ability to diagnose sepsis and pulmonary hypertension and analyze brain images [12–16]. AI has also been used to predict low birth weight and identify risk factors for maternal health, such as anemia and gestational diabetes [17–19]. Additionally, AI enables automatic analysis of growth curves, particularly weight-for-age curves, and is valuable for diagnosing newborn jaundice [20, 21].

In this context, AI could be fundamental for improving breastfeeding indicators and for analyzing human milk. This scoping review aims to identify and present current information on the various uses and applications of AI in the study and analysis of human milk and breastfeeding patterns. Furthermore, this study evaluated the quality of the information in the selected articles and identified gaps and opportunities for new research focused on the application of AI in this field.

Methods

The scoping review followed the recommendations of the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) [22], aiming to identify, screen, and define the inclusion of relevant articles. The study protocol was registered on the *Open Science Framework* Platform (osf-registrations-r89f2-v1).

Identification of the literature

The literature search was conducted in December 2023 using electronic databases, including Medline, Scopus, LILACS (American and Caribbean Literature in Health Sciences), and Web of Science. A "snowball" search was also performed, identifying additional studies from the reference lists of publications eligible for full-text review. No language or year restrictions were applied.

The search terms included a combination of keywords, synonyms, and subject-indexing terms (MeSH and DeCS), to ensure a comprehensive search strategy. For example, the term 'milk, human' was searched alongside synonyms like 'breast milk' and 'lactation fluid,' while 'breastfeeding' included variations such as 'nursing' and 'infant feeding.' Additionally, terms related to artificial intelligence, like 'machine learning' and 'deep learning,' were included to capture a broad range of studies on AI applications in the context of human milk and breastfeeding. The following search strategy was used for PubMed and adapted to the other databases:((((((((((Milk, Human) OR (Breast Feeding)) OR (Breast Milk Expression)) OR (Lactation)) OR (Colostrum)) OR (Milk Banks)) AND ((Artificial Intelligence) OR (Deep Learning)) OR (Machine Learning)).

Study eligibility criteria

Inclusion criteria

- Studies of AI applications for the study of breastfeeding and/or analysis of human milk.
- Description of technological tools, specifically those utilizing artificial intelligence (AI) such as machine learning algorithms, predictive models, and data mining techniques, to characterize the components of all types of human milk, including the mother's own milk, donor human milk, and milk from human milk banks.
- Use of AI in clinical, environmental, and laboratory settings to study the composition of human milk.
- Clinical trial studies, observational studies, case reports, and qualitative studies
- No restrictions were applied regarding the publication dates.

Exclusion criteria

- Abstracts, conference abstracts, editors' comments, reviews of scientific literature.
- Animal studies.

Screening and inclusion of studies

Studies were blindly and independently identified and selected by the investigators (LRA, JEA, LRD, and SAP). Initially, duplicate records due to overlap between the consulted databases were detected using the Rayyan® web tool and were suppressed. Subsequently, the same tool was used to screen the titles and abstracts. Discrepancies in the initial screening were compared and resolved by consensus among the investigators. The full texts of relevant articles were independently retrieved for in-depth reading by the researchers to determine their final inclusion. Discrepancies were resolved through consensus.

Risk of bias and study quality

The risk of bias and quality of the observational studies were independently assessed by investigators. The CONSORT tool was used for clinical trials, STROBE checklist was used for observational studies, and CARE was used for case reports.

Data extraction and synthesis

The following information was extracted: (a) name of the journal, (b) author and year, (c) geographic area where the study was conducted, (d) information on the type and characteristics of the population, (d) application of AI, (f) technologies used, and (c) objectives and/or outcomes of the use of AI.

The information was organized into tables and diagrams based on the type of AI used, characteristics of the population studied, and objectives and outcomes of the use of AI. The information was synthesized according to the objectives of the study and the characteristics of the population.

Results

Initially, 1,231 articles were identified, and 180 duplicates were removed. After screening and in-depth review, 19 articles were included in the final analysis (Fig. 1). The main reasons for exclusion were studies with outcomes not directly related to the application of AI in the analysis of human milk consumption and breastfeeding. For instance, some studies have focused on general AI applications in other areas of healthcare rather than

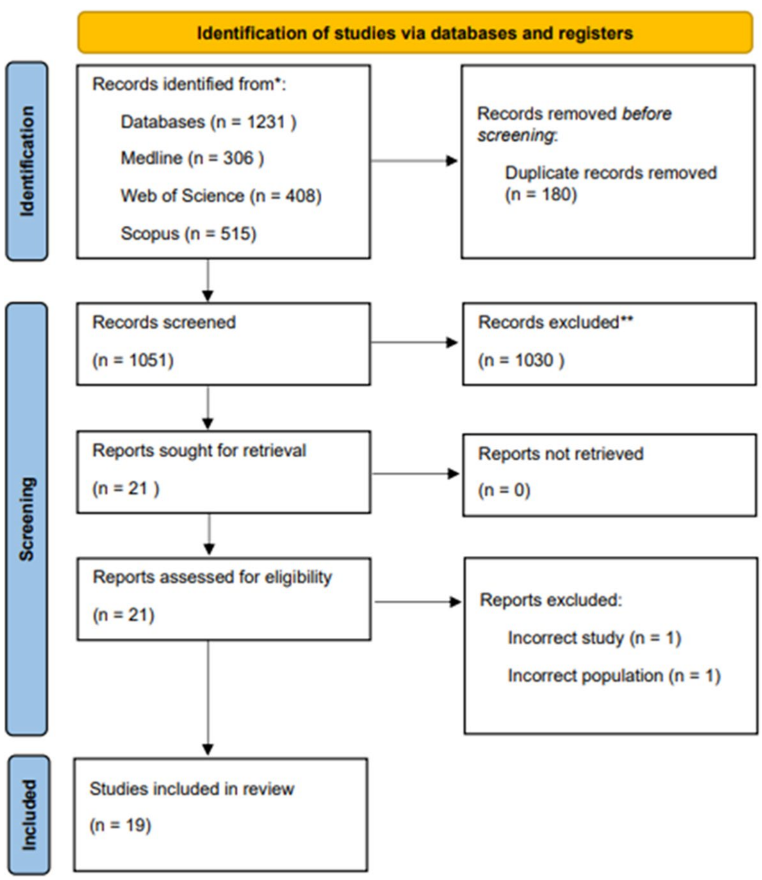

Fig. 1 Flow diagram of study selection

on breastfeeding, milk composition, or lactation-related outcomes. 'Incorrect population' refers to studies that did not focus on lactating mothers, infants, or populations directly involved in breastfeeding practices, such as studies targeting unrelated age groups or conditions not involving breastfeeding. Additionally, studies with unsuitable designs such as narrative reviews or opinion pieces that did not provide primary data were excluded.

Regarding the study methodologies, seven were observational studies, one was a case report, and the remaining studies focused on evaluating the development and integration of AI (Table 1).

Risk of bias and quality of studies

Regarding the quality and risk of bias in observational studies, most had a low risk of bias. The main causes of bias were the sample size and generalizability of the results (Fig. 2a). In addition, a low risk of bias was identified in the case reports, with the main factors being the timeline and clinical findings (Fig. 2b).

Artificial intelligence

The articles were categorized into five groups: 1. prediction of breastfeeding practices ($n=5$); 2. characterization of macronutrients in human milk ($n=3$); 3. Education and resolution of doubts and problems regarding breastfeeding ($n=4$); 4. Detection of drug concentration and passage in human milk ($n=4$), and 5. Detection of environmental contaminants in human milk ($N=3$). The most common AI approaches used were machine learning, neural networks, and chatbot development and application (Table 1).

Predicting breastfeeding practices

In a study by Oliver-Roig et al., machine learning techniques, including XGBoost and a linear support vector machine (SVM), were used to analyze data from 2,042 nursing mothers [23]. The model identified the main individual, clinical, and hospital environmental factors that predicted exclusive breastfeeding, including the mother's previous experience, admission to the neonatal intensive care unit, and institutional accreditation in breastfeeding [23]. A study conducted by Silva et al. on 1,003 infants and using decision trees to determine factors associated with breastfeeding practices in the first six months revealed that maternal and child characteristics (multiple births, maternal age, and parity), social context, work, inpatient feeding practices, and hospital policies on breastfeeding influenced breastfeeding rates [24]. The length of hospital stay was the most important predictor of feeding practices, both at hospital discharge and at the third and sixth months [24]. Using a decision tree combination algorithm, this study offers a better understanding of the risk predictors of breastfeeding cessation in an environment with a high variability in exposure [24]. Sampieri et al. used machine learning techniques to assess the influence of skin-to-skin contact on breastfeeding [25]. Using selection algorithms generated by supervised learning, this study identified a direct relationship between skin-to-skin contact at birth, prenatal breastfeeding education, initiation and duration of breastfeeding, and mothers' perceptions of breastfeeding after childbirth [25].

By using machine learning with logistic regression on imputed data, Elgersma et al. examined data from 1,944 newborns with complex single-ventricular congenital heart disease to identify the predictive factors related to breastfeeding and direct breastfeeding at the time of neonatal discharge and after palliative surgical correction [26]. They found that presurgical breastfeeding and private health insurance were associated with an increased likelihood of some types of breastfeeding after surgery [26]. On the other hand, being African American was associated with a decrease in this likelihood [26].

He et al. explored the benefits of applying common data-mining techniques to national breastfeeding surveys, where statistical analyses are common [27]. This study aimed to analyze the factors influencing the decision to breastfeed newborns using a decision tree and regression approach for classification based on selected features [27]. In addition, a risk pattern mining method was employed to identify groups at high risk of not breastfeeding. The results suggest that data mining in national surveys can identify mothers at greater risk of non-breastfeeding, which would allow their inclusion in early care and education programs to increase breastfeeding rates [27].

Characterization of macronutrients in human milk

Wong et al. developed a machine learning-based prediction model using donor mother variables, binomial characteristics, and the milk extraction process to estimate the fat and protein contents in collected mixtures of donated human milk [28]. They analyzed samples of human milk donated to a human milk bank in Canada, combining milk from two to five donors into a single bottle, and showed that the most important variables in the prediction of total fat were the body mass index of the donor, whether the neonate was preterm or full-term, and the time of day of milk production (night vs. day) [28]. In contrast, for protein prediction, the most

Table 1 Description and characterization of included studies

Author, (Year) and Country	Artificial Intelligence	Population	Objective	Outcome and Results
Prediction of breastfeedig practices				
Oliver-Roig et al. (2022) Spain [23]	Baseline; Logistic Regression; Naive Bayes; Decision Tree; Random Forest; AdaBoost (Adaptive Boosting); XGBoost, CatBoost and LightGBM; Support Vector Machine; Neural Network (Multilayer Perceptron); Nearest Neighbors	2042 healthy primiparous mothers giving birth in eighteen hospitals in Eastern Spain	To predict exclusive breastfeeding during the postpartum hospital stay using ML algorithms and explain the behavior of the ML model to support decision-making	The results showed that the XGBoost algorithm achieved the best performance in terms of AUC-ROC and Brier score. Additionally, important variables such as pacifier use, and maternal self-efficacy were identified in predicting exclusive breastfeeding. The model demonstrated the ability to predict the probability of exclusive breastfeeding for specific cases
Silva et al. (2021) Brazil [24]	Decision tree models adjusted using the CART (Classification and Regression Trees) algorithm	Longitudinal study of 1003 infants in referral centers in Brazil for high-risk fetuses and neonates	To build a tree-based analysis to determine the variables that can predict breastfeeding patterns at hospital discharge and at 3 and 6 months of age in high-risk infant referral centers	These models were used to predict infant feeding practices based on various predictor variables. The mean model accuracy in cross-validation was 83% at hospital discharge, 63% at 3 months, and 50% at 6 months; indicating that decision tree models were able to reasonably predict infant feeding practices at these three key postnatal periods using variables such as hospital stay duration, type of feeding received during hospitalization, and other maternal and neonatal characteristics as predictors
Sampieri et al. (2022) Mexico [25]	Supervised machine learning methods. Attribute selection algorithms generated by supervised learning. Bayesian networks and decision trees models for classification. Algorithms implemented by Weka (Bayes Net and J48) were used to analyze classification methods	Descriptive study analyzing data from ENADID 2018 $n = 26{,}578$ mothers between 15 and 54 years	To determine the association of skin-to-skin contact between mothers and their newborns immediately after birth with the initiation of breastfeeding within the first hour of life, breastfeeding duration ≥ 6 months, and the introduction of breast milk substitutes	Skin-to-skin contact is associated with vaginal delivery, receiving an explanation about breastfeeding after delivery, initiating breastfeeding within the first hour of life, having ever breastfed, and a breastfeeding duration of at least 6 months. Additionally, breastfeeding duration in days was greater in the skin-to-skin contact group compared to the non-skin-to-skin contact group Analyses using Bayesian networks and decision trees indicated a probabilistic dependency relationship between skin-to-skin contact and receiving an explanation about breastfeeding after delivery. In summary, AI helped identify significant relationships between the studied variables and breastfeeding
Elgersma et al. (2023) United States [26]	Supervised learning techniques: elastic net regression, multiple data imputation, and variable importance analysis. Elastic net regression was applied for predictor variable selection and final model construction for each imputed data set	Infants with complex congenital heart disease (single ventricle). $n = 1944$ for S1P analysis and $n = 1578$ for S2P analysis	Identify factors that promote or limit human milk (HM) feeding and direct breastfeeding (BF) in infants with single-ventricle congenital heart disease at neonatal discharge in stage 1 palliation (S1P) and stage 2 palliation (S2P) (4–6 months of age)	Preoperative feeding practices, demographic characteristics, and social determinants of health, along with the feeding route at discharge from the first and second intervention periods, as well as the patient's clinical course, were significantly associated with breastfeeding and human milk feeding (HM/BF) outcomes. Direct feeding before surgery was positively related to breastfeeding, while bottle or tube feeding was negatively related. Significant differences were observed based on race and type of health insurance. Additionally, the duration of hospital stays during the first intervention period showed a significant association with breastfeeding at discharge. The results varied across sites, suggesting the influence of site-specific factors on breastfeeding and human milk feeding outcomes

Table 1 (continued)

Author, (Year) and Country	Artificial Intelligence	Population	Objective	Outcome and Results
He et al. (2006) Australia [27]	Supervised classification methods: decision tree and generalized linear model. Additionally, risk pattern mining is applied to identify cohorts at high risk of not breastfeeding	Prospective study including healthy mothers: $n=625$ at hospital discharge; $n=544$ at three months; and $n=372$ at six months	To study the factors influencing the decision to breastfeed or not to a newborn	The study results show that applying data mining methods such as feature selection and supervised classification improves the accuracy in predicting the decision to feed the baby with breast milk. Classification accuracy on test data exceeds 75% when carefully selected features are used. Additionally, risk pattern mining identifies groups of mothers at high risk of not breastfeeding their babies, which could allow the implementation of targeted educational interventions to increase breastfeeding rates
Characterization of macronutrients in human milk				
Wong et al. (2021) Canada [28]	Machine learning models: Ordinary linear regression; Lasso regression by minimum angle; Random Forest regression; Gradient boosted decision tree regression	Breast milk samples from donor mothers to milk banks; $n=272$ $n=61$ mixed samples from multiple donors and $n=186$ single donor samples. The fat and protein content of each individual donation and mixed sample was measured in duplicate using a mid-infrared human milk analyzer	Develop machine learning prediction models using donation-specific variables, maternal-infant characteristics, and milk expression variables to predict crude fat and protein content in donated milk samples	Machine learning models were able to predict crude protein levels in both individual and pooled samples with good accuracy (pooled milk with significantly lower error than baseline and clinically acceptable error), while fat prediction was more challenging due to its natural variability and measurement difficulty
Jansen et al. (2010) [29]	Artificial neural network (ANN) approach combined with genetic algorithms (GA)	Human milk from three donors at the Human Milk Bank	Describe the use of an ANN-GA approach to characterize cholesteryl esters in human milk. Optimize high-performance liquid chromatography (HPLC) separation for cholesteryl ester characterization	Produced improved separation of nonpolar lipids compared to the pre-optimization method with ANNGA. The AI used allowed optimization of the analysis method using rpHPLC for efficient separation of cholesterol esters in complex biological samples like human milk without the need for prior purification steps. This will accelerate studies on the biological role of individual cholesterol esters in secretions
Ruan et al. (2022) China [30]	Machine learning techniques with linear regression algorithms. | 546 milk samples from 244 Chinese mothers (from day 1 to day 1086 postpartum)	546 milk samples from 244 Chinese mothers (from day one to day 1086 postpartum)	Generate mathematical models to adjust macronutrient and energy values in human milk	Machine learning was used to adjust the results obtained by ultrasound and make them comparable to the values obtained by mid-infrared spectroscopy (MIR). Statistically significant differences were found between sample groups measured by MIR and ultrasound methods. Machine learning was used to generate mathematical models for three macronutrients (protein, fat, lactose) and human milk energy to adjust the results obtained by ultrasound and make them as close as possible to MIR values. After applying the adjustments using machine learning, the values generated by the two methods (MIR and ultrasound) were comparable and showed high consistency

Table 1 (continued)

Author, (Year) and Country	Artificial Intelligence	Population	Objective	Outcome and Results
Education and resolution of breastfeeding questions and issues				
Corrêa et al. (2023) Brazil [31]	Deep learning-based natural language processing (DL-based NLP Pipelines) to identify user intent in interactions with the chatbot and automatically classify text messages into different user intents. Chatbots were developed using a co-design approach. These chatbots were designed to function as virtual breastfeeding consultants using text messages and illustrative images through platforms like Telegram and WhatsApp	*n* = 18 health professionals specializing in breastfeeding working in a university hospital	Present the development process of Lhia (acronym in Portuguese for "Human Milk and Artificial Intelligence"), a chatbot focused on breastfeeding education and recruiting human milk donors	Focuses on evaluating and improving the chatbot's performance throughout the co-design process, including intent identification, user engagement, number of interactions, model accuracy, and conversational flow quality. Training and validating Lhia based on feedback from health professionals achieved an accuracy of P3 with 0.82, P5 with 0.86, P5 with 0.81, and P4 with 0.93. This would increase breastfeeding rates, decrease early weaning, and increase milk donation. The accuracy of different NLP pipelines was evaluated in each co-design round. It was observed that the P4 pipeline, which uses BERTimbau word embedding, had the highest accuracy (0.93) and was selected for implementation in the production version of the chatbot. The chatbot's conversational flow was improved based on suggestions and interactions from health professionals. An increase in the number of chatbot responses was recorded in each round, reflecting the expansion of conversational flow and improvement in the quality of responses provided
Achtaich et al. (2023) [32]	1. Convolutional Neural Networks (CNN): to classify images of breasts related to breastfeeding and detect problems such as mastitis, sore nipples. Natural Language Processing (NLP): to understand and generate natural language responses. This NLP engine was used to process user text messages and generate relevant responses. 3. Artificial Intelligence Markup Language: A knowledge base was built using AIML to select appropriate responses to user requests. 4. Twilio API: The Twilio API was configured to enable bidirectional communication between the chatbot and users via the WhatsApp messaging platform. 5. Machine Learning: algorithms such as Naive Bayes (NB) and Support Vector Machine (SVM) to classify data and train models in the process of building the NLP engine and AIML knowledge base. | Availability of data collected from public online sources and not from the participation of specific individuals in the study itself	Availability of data collected from public online sources and not from the participation of specific individuals in the study itself	Develop the ALMA chatbot to support breastfeeding mothers by answering their questions related to breastfeeding and addressing their concerns about breastfeeding	Although the first version of ALMA was considered acceptable, areas for improvement were identified, particularly in expanding the knowledge base and implementing features to enhance empathy and voice support
Oyebode et al. (2021) [33]	Various AI techniques were used to perform sentiment analysis on tweets related to breastfeeding: VADER (Valence Aware Dictionary and Sentiment Reasoner); TextBlob; Pattern; VADER-EXT (an extended version of VADER). Additionally, several machine learning algorithms were employed for text classification: Support Vector Machine (SVM); Multinomial Naïve Bayes (MNB); Stochastic Gradient Descent (SGD); Logistic Regression (LR); Random Forest (RF)	Sentiment analysis of tweets related to breastfeeding	The objective of this study is to determine a range of factors positively and negatively affecting breastfeeding behaviors	VADER-EXT was the best classifier, achieving an accuracy of 89.7% for negative polarity and a recall of 90.3% for positive polarity. SVM was the best classifier, with an accuracy of 74.02% and a recall of 73.95%. SGD also performed well

Table 1 (continued)

Author, (Year) and Country	Artificial Intelligence	Population	Objective	Outcome and Results
Yadav et al. (2019) India [34]	Chatbot for breastfeeding education	Breastfeeding women and community health workers (ASHAs) in the East Delhi region, India	Understand the opportunities for chatbots in breastfeeding education for women in India	The study emphasizes the importance of addressing the barriers and challenges related to breastfeeding in contexts like India, where sociocultural and structural factors can significantly influence breastfeeding practices. Additionally, it highlights the potential of technologies such as chatbots to provide information and educational support to mothers and health professionals in this field
Detection of drug concentration and transfer in human milk				
Agatonovic-Kustrin et al. (2001) Australia [35]	- Genetic algorithm: Used to select a subset of molecular descriptors that best describe drug transfer to breast milk - Artificial Neural Networks (ANN): Employed to correlate the selected descriptors with the M/P ratio and develop a QSAR (quantitative structure–activity relationship) model	123 structurally different compounds	Simplify and update the previously developed prediction model (neural network) for the milk-to-plasma (M/P) concentration ratio, based solely on the molecular structure of the drug	Identification of the most key factors influencing drug transfer to breast milk, including molecular size, shape, and electronic properties. The developed model does not require experimentally derived parameters and could provide a useful prediction of the M/P ratio for new drugs based solely on molecular structure, which could be valuable for drug information services. It should only be used as an aid in risk assessment along with the infant's response
Mashima et al (2023) Japan [36]	- Artificial Neural Networks (ANN) - Support Vector Machine (SVM) - Genetic Algorithm (GA)	M/P ratios were collected for 403 compounds, and M/PAUC was obtained for 173	Collect data on the relationship between drug concentration in human milk (M) and plasma (P) (M/P ratio) and build a binomial classification model based on the area under the curve (AUC) of the M/P ratio to detect drugs involved in active transport in mature human milk	The ANN model showed a sensitivity of 0.969 for the training set and 0.833 for the test set, with a specificity of 0.940 for the training set and 1.000 for the test set. The SVM model showed a sensitivity of 0.971 for the training set and 0.667 for the test set, with a specificity of 1.000 for both sets. The most influential descriptors were identified for each model, providing valuable information on the factors affecting drug transfer to human milk
Zhao et al. (2005) [37]	- Ensemble learning technique: Boosting—Supervised learning methods: SVM (Support Vector Machines), LDA (Linear Discriminant Analysis)	126 common drug compounds	Develop dependable computational models to predict/classify drugs from milk to plasma (M/P). Develop SVM (Support Vector Machine) models to distinguish the potential risk of drugs for infants	The selected descriptors include characteristics such as polarity, molecular size, charge, geometry, binding energy, among others. The SVM model appears to be more effective in this specific context and might be preferable for predicting the risk of drug transfer to human milk compared to the LDA model. However, it is important to consider the specific characteristics of each model and the problem's needs when selecting the most appropriate method
Ye et al. (2022) China [38]	- Supervised learning: linear regression - Image preprocessing and backpropagation artificial neural networks	Breast milk samples from two lactating mothers	Detection of amoxicillin in human milk	The results demonstrate that the proposed system is effective for the quantitative detection of amoxicillin in breast milk samples, with good selectivity and detection capability over a range of concentrations relevant for clinical applications
Detection of environmental contaminants in human milk				
Kowalski et al. (2013) Brazil [39]	Kohonen neural network	Colostrum, transitional, and mature milk from 193 Brazilian lactating women	Detect, identify, and quantify the presence of twelve PCBs in the breast milk of 193 lactating mothers from ten cities and towns across Brazil	Higher contamination was found in the milk of mothers living in large, industrialized cities, near polluted rivers or seas, in mature milk samples, and in mothers breastfeeding for the first time

Table 1 (continued)

Author, (Year) and Country	Artificial Intelligence	Population	Objective	Outcome and Results
Nadal et al. (2004) Spain [40]	Artificial Neural Network (ANN); Self-Organizing Map (SOM) Kohonen	$n = 54$ human milk samples from different countries	The purpose of the study was to find a relationship between the profiles of different forms or chemical variants of persistent organic compounds of PCDD/PCDF in human milk and the dietary habits of the different countries where the samples were collected	The profiles of PCDD/F in human milk show high variability depending on the specific country or region. Countries with high fish consumption exhibit higher concentrations of PCDD/F in the milk. The SOM method is particularly relevant for providing an easy exploratory tool for cluster visualization
Jovanovic et al. (2019) Serbia [41]	Guided regularized random forest with implementation of AutoWeka Metalearner	Milk samples from seventy-nine healthy mothers (23 primigravida's, forty-one multigravidas, and fifteen multiparas)	Demonstrate a method to understand the relationship between organochlorine pesticides (OCP) and polychlorinated biphenyls (PCB) in breast milk and their association with the age and parity of the mother	This study revealed variations in POP levels in the milk of primiparas and multiparas. The ML methods provided relative prediction errors below 30% and correlation coefficients above 0.90, suggesting a possible nonlinear relationship between contaminants and the complexity of their pathways in breast milk

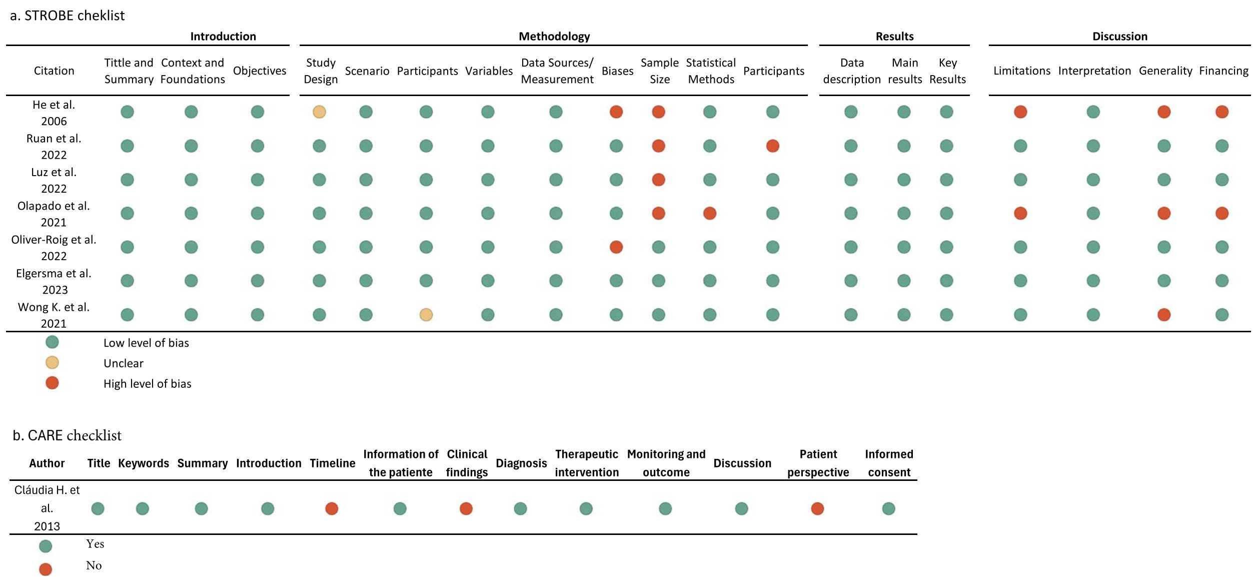

Fig. 2 Evaluation of the methodological quality of included studies. Assessment using the STROBE checklist. **b** Assessment using the CARE checklist

significant variables were the average number of days postpartum, volume of milk expressed in the bank per day, and whether the neonate was preterm or full term [28]. The model was shown to be clinically acceptable for protein-level prediction, whereas fat prediction was more difficult owing to its natural variability and measurement challenges [28].

Jansen et al. proposed a model to optimize the experimental parameters for chromatographic separation of cholesterol esters in breast milk from three samples obtained from donor mothers [29]. Using an artificial neural network-genetic algorithm (ANNGA) approach, factors such as the type of organic component in the mobile phase, column temperature, and flow rate were optimized [29]. This method led to significant improvements in the separation parameters and quality of the chromatographic results, allowing better resolution of the identified analytes [29].

Ruan et al. compared two methods for determining the macronutrient composition in the breast milk of Chinese mothers at all stages of lactation using a mid-infrared analyzer and an ultrasound-based analyzer [30]. Through machine-learning techniques using linear regression algorithms, the ultrasound results were converted to align the results from both methods, making them comparable [30]. The initial compositional results obtained using the two analysis methods differed significantly for all compounds: protein, fat, lactose, and energy [30]. However, after adjusting the values using machine learning, the data exhibited improved consistency. This approach illustrates how AI techniques enhance the accuracy and consistency of breast milk composition measurements, which is clinically important for ensuring adequate nutrition in infants, especially preterm infants [30].

Education and resolution of doubts and problems regarding breastfeeding

Correa et al. described the design process of the *Lhia chatbot*, a virtual tool aimed at breastfeeding education and recruiting breastfeeding mothers to donate human milk to milk banks, using text and images from Telegram and WhatsApp [31]. They adopted a co-design approach with lactation professionals, who simulated texts from mothers with potential breastfeeding issues, which helped refine the AI-based chatbot [31]. Five deep-learning-based NLP systems were trained to classify the various intentions of user mothers [31]. Throughout the co-design process, improvements were made to the content and structure of the conversation flow based on the data gathered during subsequent training sessions [31]. The final system, with optimal performance and enhanced conversation flow, was implemented in a *Lhia chatbot*. This tool has demonstrated high accuracy in identifying specific issues related to breastfeeding and human milk donation [31].

Achtaich et al. developed ALMA, a chatbot designed to engage in natural conversations with breastfeeding mothers via WhatsApp, using the Twilio application programming interface (API) [32]. ALMA utilizes natural language understanding and generation to respond to breastfeeding-related needs and to provide relevant information. The chatbot was evaluated by volunteer breastfeeding mothers and the results were validated with lactation consultants [32].

In a related study, Oyedove et al. explored social networks as platforms for expressing both positive and negative opinions about breastfeeding, highlighting the opportunity to analyze these perspectives [33]. They proposed using AI to identify the factors affecting breastfeeding based on an analysis of tweets [33]. Tweets on this topic were collected and analyzed for sentiment using both lexicon-based and machine-learning techniques to classify them as positive or negative [33]. Four lexicon-based sentiment classifiers were evaluated: VADER, TextBlob, Pattern, and VADEREXT. Additionally, supervised machine learning algorithms—multinomial naïve Bayes (MNB), support vector machine (SVM), logistic regression (LR), stochastic gradient descent (SGD), and random forest (RF)— have been applied for text classification. Among these, SVM showed the best performance, whereas RF performed the least [33]. This study identified factors that negatively impact breastfeeding, such as health issues (breastfeeding-related, medical, and nutritional problems), as well as social, psychological, and situational factors [33]. Positive influences included perceived benefits, maternal self-efficacy, social support, and access to educational and training resources [33].

In India, Yadav et al. evaluated the impact of chatbots on breastfeeding among mothers living in slums [34]. Initially, they developed a question-and-answer prototype by analyzing interaction patterns, perceptions, and usage contexts. The results showed that most of the nursing mothers' questions could be effectively answered using the app [34]. Additionally, the study highlighted that many of the queries made to the chatbot were influenced by beliefs and myths held by breastfeeding mothers and their families [34].

Detection of drug concentrations and transfer in human milk

Agatonovic-Kustrin et al. applied artificial neural networks to preestablished data on milk plasma concentrations and molecular structure characteristics of 123 drugs, aiming to identify factors that predict drug concentrations in human milk [35]. They used genetic algorithms to select the most relevant features describing drug transfer into breast milk, and subsequently applied an artificial neural network (ANN) to correlate these selected features with the milk/plasma ratio, developing a quantitative structure–activity relationship (QSAR) regression model [35]. This model includes nine features that predict the milk/plasma ratio of the studied drugs, considering characteristics such as molecular size, shape, and electronic properties, without requiring additional experimental data [35].

Maeshima et al. developed a prediction model for the ratio between drug concentration in breast milk and plasma concentration (M/PAUC) using the area under the curve (AUC) as a basis [36]. They also applied a quantitative structure–activity/property relationship (QSAR/QSPR) approach to predict the compounds involved in active transport during breast milk transfer [36]. Artificial intelligence (AI) tools were used to construct binary classification models, and data on the milk-to-plasma concentration ratio (M/P ratio) were collected from the existing literature [36]. Two binary classification models were developed: artificial neural network (ANN) and support vector machine (SVM). The sensitivity of the ANN model was 0.969 for the training set and 0.833 for the test set, whereas that of the SVM model was 0.971 for the training set and 0.667 for the test set [36]. These findings suggest that AI models can identify compounds with M/P ratios greater than or equal to 1 [36]. It is important to note that while these results are useful in risk assessment, alongside infants' responses, they are not sufficient to determine the safety of breastfeeding during pharmacological treatment based solely on M/P ratio [36].

Zhao et al. developed computational models to predict and classify the milk-to-plasma concentration ratio (M/P ratio) of 123 pharmacological compounds that are commonly used by lactating mothers [37]. They employed the support vector machine (SVM) method to assess the potential risks of these drugs to infants. Each drug was included in the model with a range of characteristics to determine the best predictive model and ultimately identify five key factors for its construction [37]. Two classification models were developed: linear discriminant analysis (LDA) and SVM with bootstrap validation based on selected molecular descriptors [37]. The results showed that the classification accuracies of the SVM method were 90.63% for the training set and 90.00% for the test set [37]. The overall accuracy of SVM was 90.48%, which was significantly higher than that of LDA (77.78%) [37]. This comparison suggests that SVM performed better than LDA in classifying the risks associated with drugs when experimental M/P ratio data were unavailable [37]. Additionally, steric and electronic factors appear to be important components of the drug transfer process, along with other physical descriptors that influence the ability of drugs to transfer between breast milk and blood plasma [37].

On the other hand, Ye et al. developed a process that combined colorimetric methods with artificial intelligence image preprocessing and backpropagation artificial neural network (BP-ANN) analysis to detect amoxicillin in breast milk [38]. This technique involves the coupling of gold nanoparticles (AuNPs) with aptamers (ssDNA) at various amoxicillin concentrations, producing distinct color results [38]. An image of the color was captured using a portable image acquisition device, followed by image pre-processing [38]. These findings suggest that the colorimetric process, combined with AI-based image preprocessing and BP-ANN, provides an accurate and rapid method for detecting amoxicillin in breast milk [38].

Detection of environmental contaminants in human milk

Kowalski et al. collected human milk samples from 193 mothers across different regions of Brazil to identify patterns that could predict the presence of polychlorinated biphenyls (PCBs) in milk [39]. They used high-resolution omics and separation technologies to analyze compounds, considering mothers' social, environmental, clinical, and lactational factors [39]. For the data analysis, non-automated learning techniques were applied to discover patterns and relationships, generating self-organizing maps using Kohonen neural networks [39]. The key variables predicting the presence of PCBs in breast milk included the mother's region of residence, proximity to industrial areas or contaminated rivers, lactation phase (colostrum, early milk, or late lactation), and number of previous pregnancies [39].

In a related study, Nadal et al. used Kohonen neural networks to assess the relationship between the concentrations of polychlorinated dibenzo-p-dioxins (PCDDs) and polychlorinated dibenzofurans (PCDFs) in breast milk and dietary habits across various countries [40]. Their findings indicated higher concentrations of PCDDs/PCDFs in human milk in countries with high fish consumption [40].

Using machine learning methods and the Guided Regularized Random Forest (GRRF) algorithm, Jovanovic et al. aimed to identify persistent organic compounds such as organochlorine pesticides and polychlorinated biphenyls in human milk [41]. The study included samples from seventy-nine healthy mothers along with data on their social, environmental, and occupational backgrounds [41]. The levels of organic contaminants varied between the milks of primiparous and multiparous mothers [41]. The developed model demonstrated a high capacity to reliably predict contaminants in human milk based on selected variables [41]. The primary factor influencing the model's predictions of contaminant concentrations was the chemical structure of each contaminant, particularly the number and position of the chlorine atoms [41].

Discussion

The findings of this scoping review demonstrate the growing interest in applying AI approaches to the analysis of breastfeeding and human milk, especially regarding variables associated with the prediction of exclusive breastfeeding, education of lactating mothers, and the analysis of components and contaminants in milk. The rapid advancement of AI research in other fields of medicine contrasts with the limited number of studies that have focused on its application in human milk and lactation.

The promotion of breastfeeding has emerged as a global priority, prompting numerous interventions to achieve this goal [42]. Despite global progress, breastfeeding indicators still fall short of their proposed targets [8]. The data from this scoping review underscores the potential of applying artificial intelligence to enhance the identification of factors and patterns that predict the initiation and maintenance of breastfeeding, offering a promising approach to improve these outcomes.

Traditionally, conventional statistical methods have identified key factors, such as early skin-to-skin contact, education of healthcare providers and mothers, early detection of breastfeeding challenges, and certain social determinants that contribute to improved breastfeeding rates [43–46]. However, AI-based approaches offer unique advantages and can complement the traditional data analysis methods. For example, efficient processing of large datasets, uncovering complex patterns, and enabling the integration of diverse data sources, such as clinical, genomic, and lifestyle information [47, 48]. This integration enriches existing analytical frameworks and provides deeper insights that are difficult to achieve using traditional methods alone. For instance, studies by He et al. [27] and Silva et al. [24], included in the scoping review, demonstrated that AI techniques, such as data mining, applied to national surveys can refine the identification of predictive factors for breastfeeding patterns and better understand the risk predictors of breastfeeding cessation in diverse environments.

Although AI can complement traditional methods, it is essential to recognize its limitations. The reliability of AI models depends on the quality of the training data, and non-representative datasets can introduce biases, potentially compromising care for marginalized groups [49, 50]. This is particularly critical for breastfeeding and infant nutrition, as disparities can have significant health impacts. Ensuring the selection of high-quality representative data and developing models that address biases are crucial for effective AI implementation.

Moreover, AI's ability of AI to analyze large datasets can aid healthcare providers in developing tailored strategies for promoting breastfeeding and supporting exclusively breastfed infants. However, overreliance on AI recommendations could diminish the critical judgment and personal touch that are essential in the mother–child care relationship, especially in breastfeeding support [49, 50]. Thus, AI should serve as a complement to human expertise, not as a replacement, while preserving the personalized support that remains vital for successful breastfeeding outcomes.

The use of user-friendly interfaces such as mobile health (mHealth) technologies has demonstrated the ability to provide valuable information to patients, enhance their engagement, and enable timely medical responses [51]. These technologies have proven effective in delivering breastfeeding education within communities and have become key strategies for improving exclusive breastfeeding rates [51, 52]. This is particularly relevant in light of the findings from this study, which suggest that implementing artificial intelligence through chatbots offers a valuable tool for providing education, addressing breastfeeding-related questions, and fostering support networks for breastfeeding mothers. Such technological approaches can establish accessible communication channels, reduce delays in in-person care at primary care centers, and offer guidance to postpartum women and their families [53]. Furthermore, these platforms can increase awareness of breastfeeding and support informed decision making among mothers and expectant families.

However, the use of chatbots in patient management and community health applications requires a careful approach to ensure their safety and effectiveness. It is essential to safeguard the privacy and security of collected data by adhering to data protection regulations to prevent exposure to sensitive information. Transparency is the key to maintaining patient trust, as it allows users to understand that chatbots complement, rather than replace, in-person medical consultations. Additionally, educating patients about when to seek direct medical attention is crucial to avoid the potential misinterpretation of symptoms [47]. These precautions are vital for ensuring that chatbots are safe and effective tools for enhancing the quality of care without compromising user safety.

In addition, this scoping review highlights the potential of AI for analyzing drug concentrations, toxic compounds, and nutrients in human milk. By leveraging pre-established pharmacokinetic data and considering the chemical and structural properties of these substances, AI can accurately predict their presence in breast milk and their transfer to infants. This approach circumvents the ethical and clinical risks associated with direct research on lactating mothers and infants, and offers a safe and effective alternative based on pharmacokinetic and chemical data from the existing literature.

Traditional analytical methods, such as mass spectrometry and nuclear magnetic resonance (NMR), are essential for accuracy but often require significant time, financial investment, and the participation of large groups of patients and lactating mothers [54, 55]. These requirements limit the feasibility of routine monitoring and its rapid application in clinical settings [56, 57]. In contrast, AI-based approaches can streamline the analysis process by automating routine tasks and simplifying the interpretation of results. This not only accelerates the identification of toxic compounds and nutrients but also reduces operational costs, making it a more accessible option for healthcare providers [58, 59].

Furthermore, AI's ability of AI to analyze large datasets allows for the systematic study of contaminants in breast milk across diverse populations, providing insights that are challenging to achieve through traditional methods. By offering a rapid, scalable, and cost-effective solution, AI holds significant promise for enhancing public health initiatives, supporting informed decision-making in clinical practice, and reducing disparities in access to safe breastfeeding practices [60].

Despite the numerous opportunities presented by the application of artificial intelligence (AI) in the study of human milk, several challenges and limitations persist. First, human milk is a complex and dynamic substance that varies between individuals and over time, posing a challenge to understanding and standardizing AI. Second, the lack of representative evidence limits the ability of algorithms to provide accurate results. Additionally, access to AI technologies requires significant investment of resources by research institutions, which could limit their use in resource-limited settings.

Conclusion

In conclusion, the use of artificial intelligence is experiencing promising growth and development in the analysis of breastfeeding patterns, education, and support, as well as in the analysis of the composition and contamination of human milk. The benefit of this technology in clinical practice is reflected in its rapid detection and resource optimization without the need for complex and time-consuming instruments. It is crucial to develop research that integrates AI workflows to analyze contaminants and nutrients at both laboratory and community levels.

Abbreviations

AI	Artificial intelligence
ANN	Artificial neural network
LR	Logistic Regression
MNB	Multinomial naïve Bayes
RF	Random forest
SGD	Stochastic gradient descent
SVM	Support Vector Machine
WHO	World Health Organization

Authors' contributions

SAP and DBR conceived and designed the study. SAP, LRA, JEA and LRD carried out the study selection and data extraction. SAP, DBR, LRA, JEA and LRD supported the analysis and writing of the draft manuscript. SAP, DBR, LRA, JEA and LRD reviewed the manuscript. All the authors have read and approved the final manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

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Competing interests

The authors declare no competing interests.

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