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Lhia: A Smart Chatbot for Breastfeeding Education and Recruitment of Human Milk Donors

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Featured Application: The chatbot developed in this study can be used by human milk banks in the process of breastfeeding education and recruitment of mothers to donate human milk.

Abstract: Human milk is the most important way to feed and protect newborns as it has the components to ensure human health. Human Milk Banks (HMBs) form a network that offers essential services to ensure that newborns and mothers can take advantage of the benefits of human milk. Despite this, there is low adherence to exclusive breastfeeding in Brazil, and human milk stocks available in HMBs are usually below demand. This study aimed to co-develop a smart conversational agent (*Lhia* chatbot) for breastfeeding education and human milk donor recruitment for HMBs. The co-design methodology was carried out with health professionals from the HMB of the University Hospital of the Federal University of Maranhão (HMB-UHFUMA). Five natural language processing pipelines based on deep learning were trained to classify different user intents. During the rounds in the co-design procedure, improvements were made in the content and structure of the conversational flow, and the data produced were used in subsequent training sessions of pipelines. The best-performing pipeline achieved an accuracy of 93%, with a fallback index of 15% for 1851 interactions. In addition, the conversational flow improved, reaching 2904 responses given by the chatbot during the last co-design round. The pipeline with the best performance and the most improved conversational flow were deployed in the *Lhia* chatbot to be put into production.

Keywords: chatbot; conversational agent; breastfeeding; human milk; co-design; deep learning; natural language processing

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1. Introduction

Breastfeeding is a process that involves interaction between mother and infant, with implications for the infant's nutritional status, ability to defend against infectious diseases, cognitive and emotional development, and long-term health. Also, it has positive implications for the physical and mental health of mothers [1]. Breastfeeding improves the survival, health, and development of all children [1], prevents breast cancer, reduces postpartum bleeding in women, and contributes to the development of human capital [2].

Exclusive breastfeeding consists of offering only Human Milk (HM) to infants, without introducing any other solid or liquid food [3]. The World Health Organization (WHO) recommends that exclusive breastfeeding should be practiced until the infant's sixth month of life, and then supplemented with other foods until the second year of life [4]. The introduction of other foods in the infant's diet to complement HM before the infant reaches the sixth month of life is defined as early weaning [5]. Despite the benefits of breastfeeding for mothers and infants, there is a low adherence to exclusive breastfeeding in Brazil [1].

Different public policies have been developed around the world to encourage, support, and promote breastfeeding, such as: the Innocenti Declaration, the United Nations Convention on the Rights of the Child, and the Baby-friendly Hospital Initiative. Although such initiatives have been established since the last century, in low & middle income countries, only 37% of children are exclusively breastfed [1] (45.8% in Brazil [6]), and these are lower values than the minimum recommended by the WHO, which is 50%.

Providing donated HM to vulnerable newborns without access to their mother's milk, in addition to directly saving lives, raises awareness of the value of breastfeeding by improving overall breastfeeding rates in society. These increases in breastfeeding rates are important because they can prevent up to 12% of infant mortality [7]. When the mother's milk is insufficient, unavailable or contraindicated, the recommendation is to use donated HM as the food of choice [8]. However, despite incentives through public policies to donate HM to mothers who have difficulty producing their milk, few mothers are willing to donate milk.

As the global community strives to reduce infant mortality and help neonates thrive, the commitment to the Human Milk Bank (HMB) has rapidly expanded. In the Brazilian Human Milk Bank Network (BR-HMBn), HMBs are responsible for promoting breastfeeding and conducting activities of collection, processing and quality control of the HM for later distribution to a Neonatal Intensive Care Unit (NICU).

Pregnant women and mothers of young children interact with computers in different ways and, although there are several solutions for breastfeeding mothers [9], there has been little research on how to design ICTs for breastfeeding education and HM donation. Developing successful internet interventions for mothers requires an intimate knowledge and understanding of their behaviors, feelings, problems they face and their use of technology [10].

Conversational agents, also known as chatbots, are systems able to talk with users using natural language, so simulating interactions with humans [10]. They have gained prominence due to their ability to provide automated conversational experiences, and are implemented in several fields, such as health, education, commerce, industry, and entertainment [11]. To develop them, Artificial Intelligence (AI) techniques can be used to improve the interactions with end users and, especially in the area of health, AI-based chatbots have been applied in training, education, prevention, educational support, diagnostic aid, and elderly assistance [12]. Therefore, healthcare chatbots have emerged as a promising tool and seem to be a well-suited solution for delivering interventions for breastfeeding education and recruitment of HM donors.

This study presents the development process of the *Lhia* (an acronym in Portuguese language for "Human Milk and Artificial Intelligence"), a chatbot focused on breastfeeding education and recruitment of HM donors. *Lhia* was developed using a co-design approach, in which 18 experienced health professionals contributed to the development of the conversational flow, and produced data to train Natural Language Processing (NLP) pipelines based on Deep Learning (DL) [13] to classify texts related to different types of problems faced by mothers who breastfeed and identify the intention of mothers who want to become HM donors.

The remainder of this paper is organized as follows. Section 2 describes a background related to the interdisciplinary topics covered in this study. Section 3 presents related works. Section 4 describes the process performed for *Lhia* implementation. Section 5 presents the results achieved, while Section 6 discusses them, contributions, limitations and future work. Finally, we conclude the paper in Section 7.

2. Background

2.1. Breastfeeding Education

Breastfeeding education aims to increase mothers' knowledge and skills in breastfeeding, help them see breastfeeding as normal, and help them develop positive attitudes towards breastfeeding [14]. While the audience is usually pregnant or breastfeeding women, it may include fathers [15] and others who support the mother who is breastfeeding [16]. It can be given in any space or time, as long as it is given with experience and specific knowledge in breastfeeding management [14].

Different breastfeeding support strategies can be used, always taking into account the individual needs of each mother during the breastfeeding process, thus seeking to improve their feelings, power capacity and their self-efficacy in breastfeeding [17]. The breastfeeding education is an effective strategy to promote exclusive breastfeeding [18]. Postnatal home support provided by community health workers increases breastfeeding duration and knowledge [19]. Education via mobile text messages and Internet (e.g., smartphone applications) has also been considered an effective tool to promote exclusive breastfeeding. Along with classical support methods, Internet-based tools provide another possible method for promoting positive long-term breastfeeding outcomes [20].

2.2. Human Milk Donation

HM donation is essential to increase the chances of recovery of preterm infants and/or low-birth-weight newborns who are hospitalized in NICU, in addition to providing a healthy development for them. Human milk protects against necrotizing enterocolitis, late onset sepsis, retinopathy of prematurity, bronchopulmonary dysplasia, and aids in neurodevelopment in babies born with $\leq$28 weeks gestation or with a mean birth weight of $\leq$1500 g [21].

A difficulty in prematurity is associated with the immaturity of the gastrointestinal tract of the premature newborn. In preterm infants, the development of the gut microbiota is disrupted by events related to prematurity, such as mode of delivery, antenatal and postnatal use of antibiotics, minimal exposure to maternal microbiota, and low intake of HM [22]. Human milk is better tolerated by preterm infants than artificial formulas, as it contains immunobiological nutrients that stimulate intestinal maturation and motility [23]. The sooner babies start breastfeeding, the greater their chances of survival and healthy growth [24].

Every healthy woman who breastfeeds and has more than enough milk for the full development of her baby can be an HM donor, and any donation of HM can help premature newborns [25]. Despite the benefits of HM for preterm infants, HM stocks available in HMBs are usually much smaller than the demand for NICU and, with the coronavirus pandemic, the demand for HM for high-risk newborns admitted to NICU increased [26]. Therefore, new strategies to encourage HM donation are needed.

2.3. Conversational Agents

Chatbots are software solutions that can interact with humans through a conversational interface [27]. They are also known as talkbots, smartbots, bots, chatterbots and conversational agents. Chatbots tend to communicate with the user and behave like a human being. They are usually connected to messaging services (e.g., Telegram, WhatsApp), web pages and mobile applications. Chatbots may be classified into two types [28]: based on rules and AI techniques. Rule-based chatbots use the concept of a state machine, which consists of a rule engine that determines the set of inputs needed to transition from one state to another. Question and answer structures are pre-defined to enable the chatbot to control conversations; thus, the chatbot only performs pre-established actions [29].

AI-based chatbots can understand natural language and not just predefined commands [27]. In addition, they manage to maintain different contexts of conversations and provide the user with richer and more engaged conversations [30]. This type of chatbot can use AI techniques for Natural Language Understanding (NLU) [13]—in particular, in the tasks of intent classification and entity recognition [31]—and Natural Language Generation (NLG) [32]. Chatbots with a NLU component can analyze natural language by extracting concepts, entities, emotions, keywords, and interpret it into a computer language [13]. Chatbots with an NLG component, called generative chatbots (e.g., ChatGPT by OpenIA, Bard by Google, Bing Chat by Microsoft), use a Large Language Model (LLM) to generate responses in a fluid and coherent way for each interaction made by the user [33].

3. Related Work

Internet interventions have been effective in supporting breastfeeding [34,35], mainly to provide breastfeeding education, through persuasive systems designed to encourage mothers to breastfeed [9] or provide advice during the entire breastfeeding process [36]. Specifically, studies have reported positive outcomes related to the usability and effectiveness of chatbots in healthcare, but the evidence is not yet strong [37]. An increasing number of chatbots for healthcare have been developed and studied, including those focused on health education [12]. Also, deep/machine learning-based approaches have been used frequently for developing chatbot systems in the health domain [10]. However, although chatbots for healthcare are evolving, to the best of our knowledge, little has been achieved specifically using chatbots as an intervention in breastfeeding education and recruitment of donor mothers [9].

A first initiative of chatbots for educational support in breastfeeding was Tanya [38]. It was a female, multiracial, computer-animated character that was displayed on the computer screen. A pilot study with 15 mothers in the perinatal period demonstrated that Tanya may be helpful in improving rates of exclusive breastfeeding, particularly when there is no adequate healthcare professional support [38]. When evaluating the ability of the chatbot to longitudinally maintain continuity of care on postnatal, Zhang et al. [39] observed that home use of Tanya may help mothers with stability, reliability, and comfort during breastfeeding.

Yadav et al. [40] aimed to understand the potential of chatbots for breastfeeding education in India. They conducted a Wizard of Oz experiment (i.e., a human emulating functionalities of a chatbot) that made participants believe they were chatting with a real chatbot. Results demonstrated that a majority of breastfeeding-related questions can be answered by a chatbot.

In Brazil, a first related effort was performed by Barreto et al. [41] when developing and evaluating the *GISSA Chatbot Mamãe-Bebê* (*GISSA chatbot*). This chatbot is concerned with maternal and child health in Brazil, and has a module developed for mothers/caregivers of children under two. The module provides information related to breastfeeding, food introduction, immunization, growth and development milestones. An experimental evaluation with 142 puerperal women using the GISSA chatbot demonstrated good results in relation to its use by the participants regarding simplicity, quality of information, clarity of content, usefulness and satisfaction.

As opposed to the previous proposals, *Lhia* is a tool designed to offer an innovative way to support breastfeeding mothers, through education and, in addition, recruit mothers to donate HM to the HMB. It is proposed for the Brazilian Portuguese language (PT-BR), the official and most spoken language of Brazil, and it is focused on aspects of breastfeeding culture in the Brazilian context. *Lhia* was developed from technical knowledge using a co-design approach, in which experienced health professionals collaborated to build the conversational flow. Moreover, a DL-based NLP pipeline was deployed to enable the chatbot to answer questions related to breastfeeding.

4. Methodology

Lhia is proposed as a virtual breastfeeding consultant that uses conversations based on text messages and illustrative images through Telegram and WhatsApp. It was developed using a co-design approach in partnership with the HMB of the University Hospital of the Federal University of Maranhão (HU-UFMA), a center focused on the promotion, protection and support of exclusive breastfeeding, which has been operating for over 20 years in a maternity hospital. *Lhia* allows the identification of different types of problems faced by mothers who breastfeed. It is able to identify when a mother has a problem that could lead to early weaning and thus intervene, by guiding her correctly or indicating the appropriate professional care to ensure successful breastfeeding. Furthermore, *Lhia* provides incentives for HM donation through an active notification mechanism (i.e., it autonomously initiates conversations aimed at recruiting mothers).

4.1. Development Based on Co-design

This study involved eighteen (n = 18) health professionals who work at the HU-UFMA, specifically with breastfeeding. Professionals who worked in the specialized breastfeeding ambulatory clinic for at least two years were included, and those who worked in different sectors of ambulatory care for mothers were excluded. The study was approved by the scientific committee and institutional review board of the HU-UFMA (number 5.770.812).

A co-design approach [42] was used to develop the proposed chatbot, which consisted of listening to health professionals and using their requirements and insights in the design and improvement of the conversational flow. Also, since the participants interacted with the chatbot continuously in each new version launched, they produced texts (i.e., conversations simulating mothers) used to train DL-based NLP pipelines to build intent classification models. Figure 1 presents the timeline of the co-design procedure step by step, described as follows.

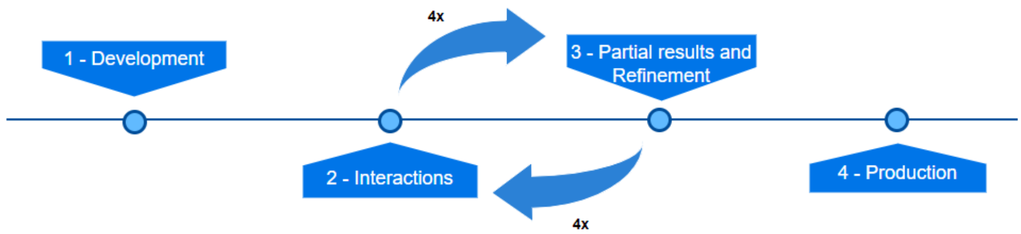


Figure 1. Co-design procedure timeline.

1. Development: At this stage, the first version of *Lhia* was developed and made available to be used by the participants;

2, 3. Interaction and Partial Results/Refinement:this stage took place in four rounds, as explained in Table 1, the first three lasting seven days and the last one hundred twenty minutes during a face-to-face brainstorming workshop. During this interactive process, we performed several training sessions with different DL-based NLP pipelines to identify the one with the best accuracy result to be deployed in *Lhia*. Also, this iterative development process allowed us to improve the conversational flow based on participants' suggestions. The flow was improved in the following manners: content improved by adding figures and better explanations, adjustment of used vocabulary, and increase in the number of chatbot answers (i.e., utterances). During each round, we collected a number of fallback triggers—i.e., a fallback is triggered by a low confidence score ($\leq$0.4; the chatbot is not able to classify a user intent) on the user intent classification—the confidence scores on the user intent classification, the number of user interactions, the number of participants interacting with the chatbot and, in the last two rounds, the Net Promoter Score (NPS) [43] on a 3-answer Likert scale;

4. Production: finally, after the interactive process, *Lhia* reached a version that could be put into production.

Table 1. Co-design rounds.

Round	Channel	Intents	Duration	Flow Improvement
1	Telegram	4	7 days	Fluidity and friendliness
2	Telegram	6	7 days	Content
3	WhatsApp	6	7 days	Specific improvements based on suggestions of the participants
4	WhatsApp	6	2 h	N/A

As we have collected the number of fallback triggers, we were able to calculate the fallback index, which is the percentage of messages that the chatbot was not able to understand. Fallback index is obtained using the Equation (1). The lower the percentage, the lower the chances of the chatbot not understanding the user's message.

$$Fallback\ index = \frac{number\ of\ fallback\ triggers}{total\ number\ of\ chatbot\ interactions} \tag{1}$$

4.2. Chatbot Conversational Flow

The conversational flow of *Lhia* was initially based on the book of primary care (child health - breastfeeding and complementary feeding) of the Brazilian Ministry of Health [44]. Also, we considered the model chapter for textbooks for medical students and allied health professionals - infant and young child feeding [3] to develop the conversational flow.

4.3. Chatbot Architecture

Figure 2 displays the architecture of *Lhia*, which was built on the *Rasa* platform [45], an open source chatbot development platform. The architecture has five components, as follows:

- *Lhia-Core* component is responsible for recognizing user inputs. It used a DL-based NLP pipeline, so classifying intents and providing responses;
- *Lhia-Action* processes requests sent from the *Lhia-Core* component. For example, during a conversation, *Lhia-Core* can send a request to identify if the user is interacting for the first time (i.e., to check if there is a history of past conversations). *Lhia-Action* can also schedule tasks in the *Lhia-Events* component, such as notification messages to be sent to the user;
- *Lhia-Events* is a publish–subscribe broker, in which *Lhia-Action* acts as a producer and *Lhia-Task* as a consumer;
- *Lhia-Task* is a component for scheduling tasks and sending notifications. It consumes tasks from the *Lhia-Events*, which are scheduled according to time parameters. After they are processed, notifications encouraging donation and guidance on exclusive breastfeeding are sent to the *Lhia-Core* component.
- *DB Atlas* is a component used to store all interactions between users and the chatbot;
- *Connectors* are components that provide communication channels between users and the chatbot. *Lhia* architecture has implemented connectors for WhatsApp and Telegram.

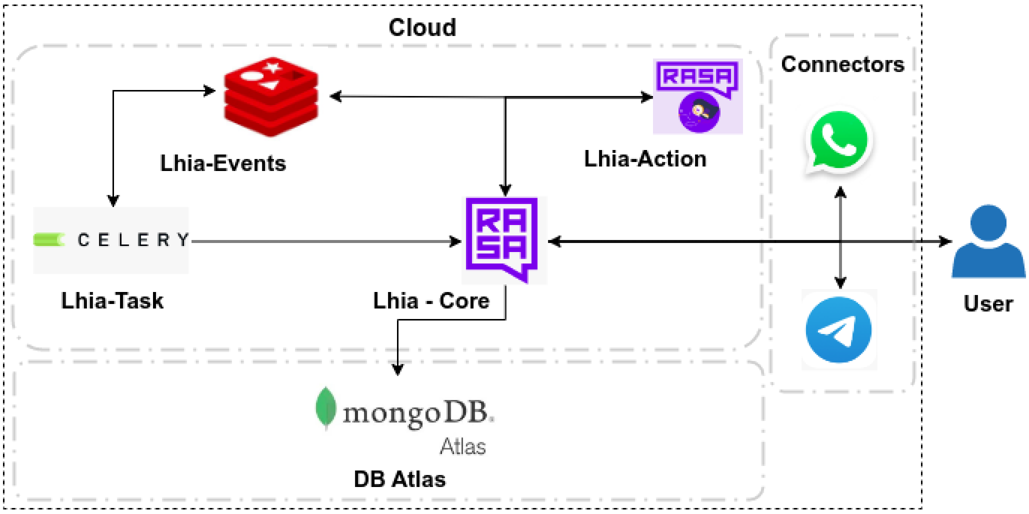


Figure 2. *Lhia* Architecture.

4.4. Enabling Lhia to Answer Questions

Every user interaction has a purpose, called user intent [46]. Intent classification is the automatic categorization of text data based on user goals. An intent classifier analyzes the texts and categorizes them into intents. Intent classification can use DL-based NLP pipelines to automatically associate words or sentences with a given user intent (i.e., NLU).

Rasa needs to understand user input messages, and the understanding of messages occurs by using pipelines responsible for sequentially processing user messages. A pipeline has components that handle different tasks, such as entity management, intent classification, and response selection. In the *Rasa* platform, pipelines are configured in the config.yml file using five components [47]: language models, tokenizers, featurizers, intent classifiers, and response selector.

In the first version of the chatbot (i.e., before starting the co-design procedure), sentences related to each problem faced by mothers who breastfeed (i.e., classes in a machine learning multiclass classification problem) were collected through interviews with 18 health professionals, and then used to perform the pipeline training before the first co-design round. During the entire co-design process, the dataset was improved from the data collection during user interactions. *Rasa* uses the following three files to perform the pipeline training:

- *nlu.yml* has all problems faced by mothers categorized as intents, and each intent contains sentence samples;
- *domain.yml* contains the answers and actions for each corresponding intent in the *nlu.yml* file;
- *stories.yml* contains the conversational flow based on stories, in which each story contains one or more intents.

As described in Table 2, we defined five different *Rasa* pipelines to carry out experiments to find the one with the best performance, considering accuracy as a metric (Equation (2)), which is based on the confusion matrix. The dataset was divided into 80% for training/validation and 20% for testing. In each co-design round, we deployed the pipeline that performed best in the training session that used data added from the previous round. However, after all rounds in the co-design procedure and after the pipeline that performed best has been identified, we trained it with 100% of the data to be deployed in the *Lhia* chatbot.

$$Accuracy = \frac{correct\ classifications}{all\ classifications} \tag{2}$$

Table 2. DL-based NLP pipelines evaluated.

Pipeline	Description
P1	WhitespaceTokenizer, LexicalSyntacticFeaturizer, CountVectorFeaturizer, DIETClassifier
P2	WhitespaceTokenizer, RegexFeaturizer, LexicalSyntacticFeaturizer, CountVectorFeaturizer, DIETClassifier
P3	WhitespaceTokenizer, BERTimbau-base, LexicalSyntacticFeaturizer, CountVectorFeaturizer, DIETClassifier
P4	WhitespaceTokenizer, BERTimbau-large, LexicalSyntacticFeaturizer, CountVectorFeaturizer, DIETClassifier, FallbackClassifier
P5	WhitespaceTokenizer, BERT-multilingual, LexicalSyntacticFeaturizer, CountVectorFeaturizer, DIETClassifier

Each component present in pipelines described in Table 2 is described below.

- *WhitespaceTokenizer* component is responsible for the initial pre-processing step, in which texts are divided into smaller units (words or characters), i.e., unique tokens. This separation occurs from the white spaces between each word or character, and has user messages as input, and a list of unique tokens as output;
- *LexicalSyntacticFeaturizer* is a component responsible for extracting features such as keywords, sequences of relevant words, grammatical categories, n-grams, and lexical properties. Furthermore, it uses word processing techniques to analyze the grammatical structure and lexical properties of the input sentences;
- *CountVectorFeaturizer* identifies the frequency of words, without considering their contextual or semantic meaning in the sentences;
- *DIETClassifier* is the component with the Dual Intent and Entity Transformer (DIET) [31], which is a multitasking architecture for intent classification and entity recognition. It outputs the confidence scores for each possible intent associated with the user message;
- *FallbackClassifier* component is responsible for handling occasions when the chatbot cannot classify an intent. It provides a default response when a fallback is triggered (i.e., the fallback response).

We tested pipelines with the pretrained model DIET acting as classifier, which already has demonstrated high performance [31]. We also tested three different word embeddings of the Bidirectional Encoder Representations from Transformers (BERT) for Portuguese language [48]: multilingual BERT (base) [49,50] and BERTimbau [51–53] (base and large). BERTimbau is a specialized version of BERT for PT-BR, which was trained using data from Brazilian Portuguese Web as Corpus (brWaC) [54,55], a large and diverse corpus of web pages in PT-BR. Textual data were submitted as input for training DL-based NLP pipelines using the *Rasa* platform.

5. Results

5.1. Participants

A total of 18 subjects (16 female) participated in this co-design procedure. All subjects were Brazilian citizens, and aged between 35 and 74 years (AVERAGE = $\approx$48.33, SD = $\approx$9.56). The subjects were nurses (n = 11), physicians (n = 2), nutritionists (n = 2), speech therapist (n = 1), biomedical scientist (n = 1), and social worker (n = 1). All participants stated that they had experience in the clinical management of breastfeeding, ranging from 2 to 25 years of experience (AVERAGE = $\approx$9.59, SD = $\approx$6.16).

5.2. Indicators

Table 3 presents the intents used in each round of the co-design procedure. The first round had four intents, and the remaining rounds had six intents. Although the number of intents in the last three rounds is the same, we rearranged the organization of problems into intents, and modified the content to improve the conversational flow. This rearrangement allows us to improve the chatbot performance. Table 3 also presents the average of the confidence scores for intents used in each round of the co-design procedure.

Table 3. Average of the confidence scores for intents used in each round of the co-design procedure.

Intent	1	2	3	4	Average
Human milk donation	–	1.0	0.74	0.73	0.82
Active notification of participants	–	–	–	0.65	0.65
Satisfaction survey	–	–	0.81	0.70	0.75
Position and handle	0.95	0.98	0.86	0.73	0.88
Engorgement	0.98	1.0	–	–	0.99
Hypogalactia and insecurity	0.93	0.97	0.96	0.73	0.89
Fissure	1.0	0.94	0.70	–	1.32
Breast abscess	–	0.98	–	–	0.98
Breast engorgement and abscess	–	–	0.77	–	0.77
Breast abscess, engorgement, and fissure	–	–	–	0.73	0.73

Figure 3 presents the number of participants in each round, in which we consider only those who finalized the chatbot interaction (i.e., arrived at the end of the conversational flow). There was an increase in the number from the first to the fourth round, which occurred for the following reasons: (1) the interaction platform, in which WhatsApp, the most popular mobile messaging application in Brazil, was used by the participants in the last two rounds; and (2) face-to-face support and motivation in the last round, in which the researchers acted in person explaining how the chatbot works and guiding participants in using the chatbot.

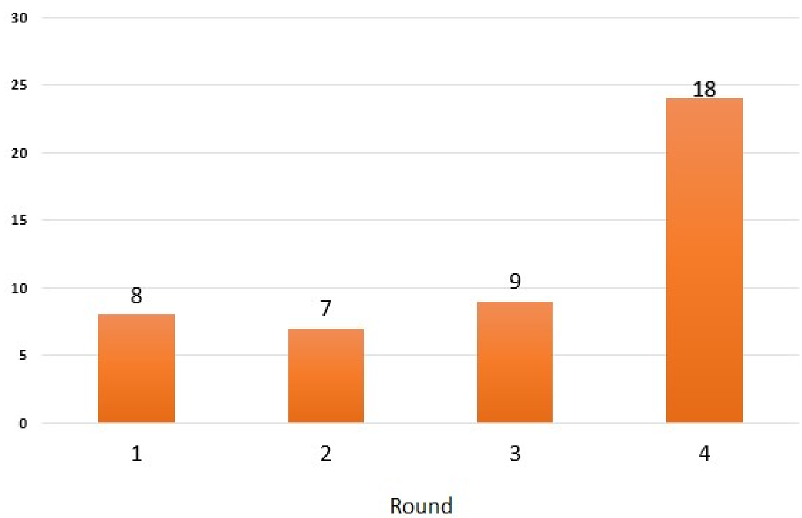


Figure 3. Total of participants in each round of the co-design procedure.

Figure 4 presents the number of interactions during the co-design approach. In the first and second round, there were few interactions, due to a smaller number of participants (Figure 3). On the contrary, there were many interactions in the fourth round due to the participation of a greater number of health professionals in the face-to-face workshop.

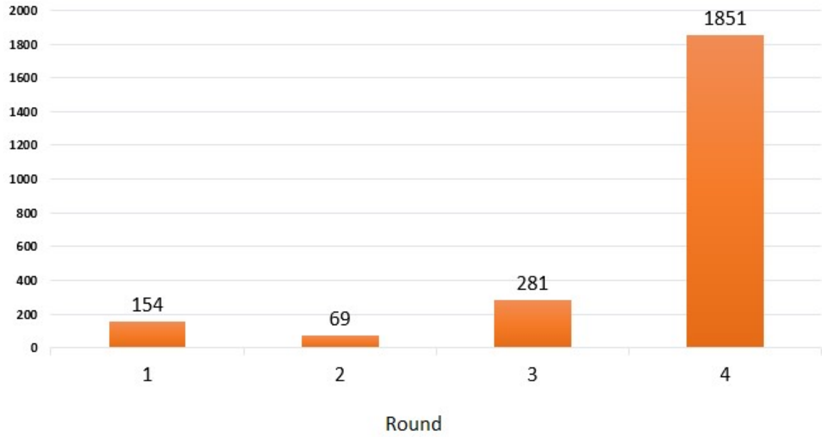


Figure 4. Number of interactions in each round of the co-design procedure.

5.3. Evolution of Performance Results

Figure 5 presents a line plot with results for the accuracy metric of the pipelines in each round of the co-design procedure. Based on the results, the pipelines deployed in all rounds were, respectively, P3 with 0.82 of accuracy, P5 with 0.86, P5 with 0.81, and P4 with 0.93. Finally, pipeline P4, which uses the word embedding of the BERTimbau, was trained with 100% of the data to be deployed in the production version of *Lhia* chatbot.

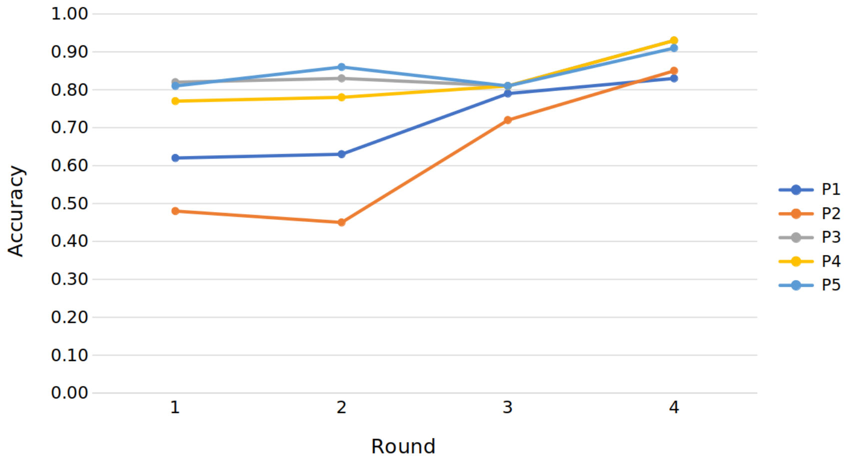


Figure 5. Performance results of each pipeline for the accuracy metric in the co-design rounds.

Figure 6 displays the number of fallback triggers in the co-design rounds. Based on the results presented in Figures 4 and 6, the fallback index for all rounds were, respectively, ≈21%, 0%, ≈7%, and ≈15%.

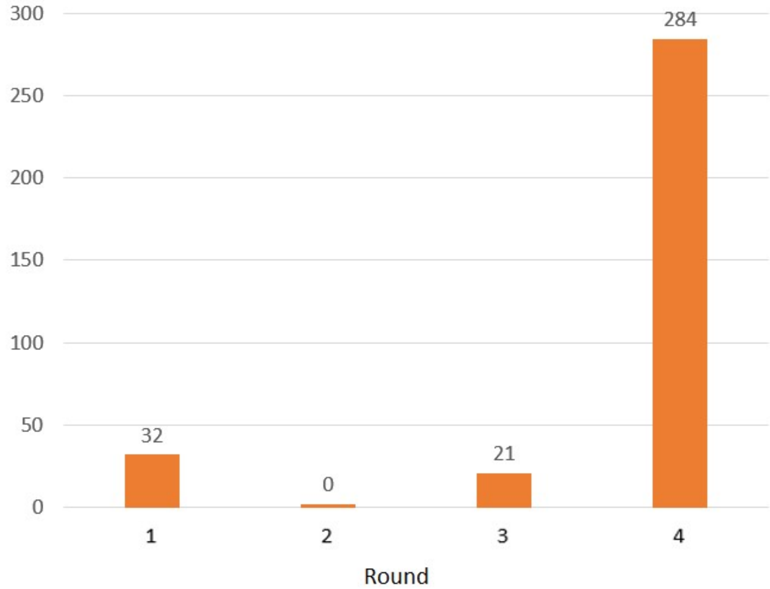


Figure 6. Number of fallback triggers in each round of the co-design procedure.

5.4. Improvement of the Conversational Flow

The conversational flow used in the chatbot was improved based on the suggestions and interactions of the health professionals. The conversational flow had the following numbers of utterances for each round, respectively: 217, 73, 457, and 2904, as shown in Figure 7. This increase in the number of answers was caused not only because of the increasing number of participants, but also by the increase in the size (i.e., number of utterances) of the conversational flow. Although the last round of the co-design procedure had a duration of only 120 min (as opposed to previous ones that lasted 7 days), we can see numerous answers from the chatbot. We believe this was also due to our face-to-face support and motivation, when we could act in person explaining the chatbot features.

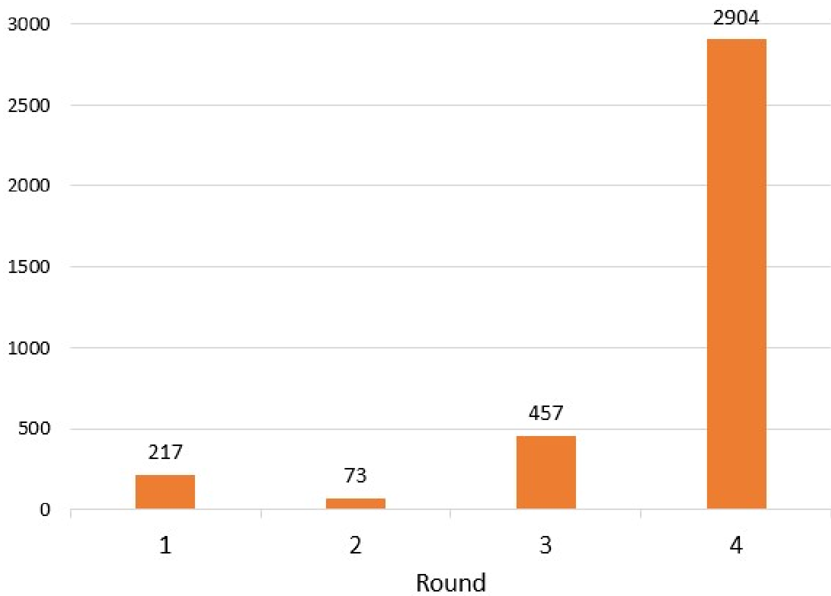


Figure 7. *Lhia* answers in each round of the co-design procedure.

Figure 8 presents the NPS results ranging from 1 to 3 in the last two rounds, in which 3 is the best score given by a participant. Results show an evolution of the score, in which a greater number of scores 3 is observed in the fourth round.

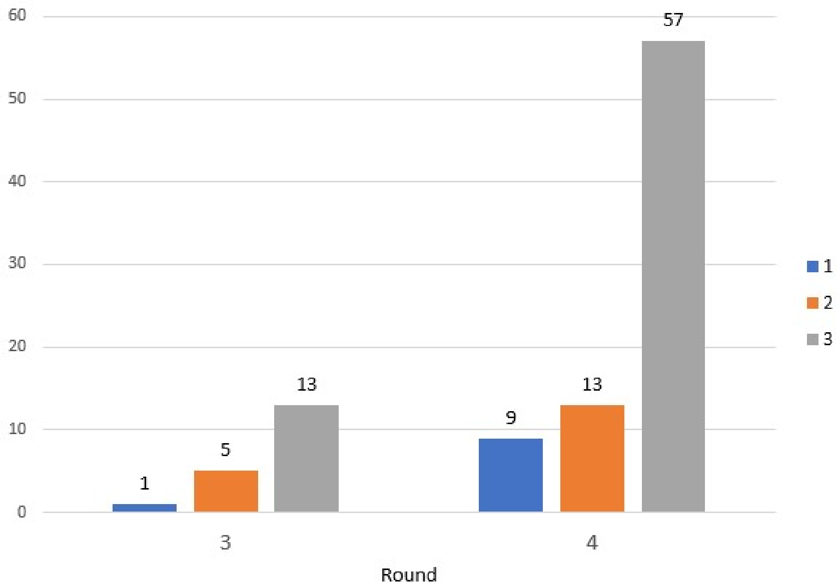
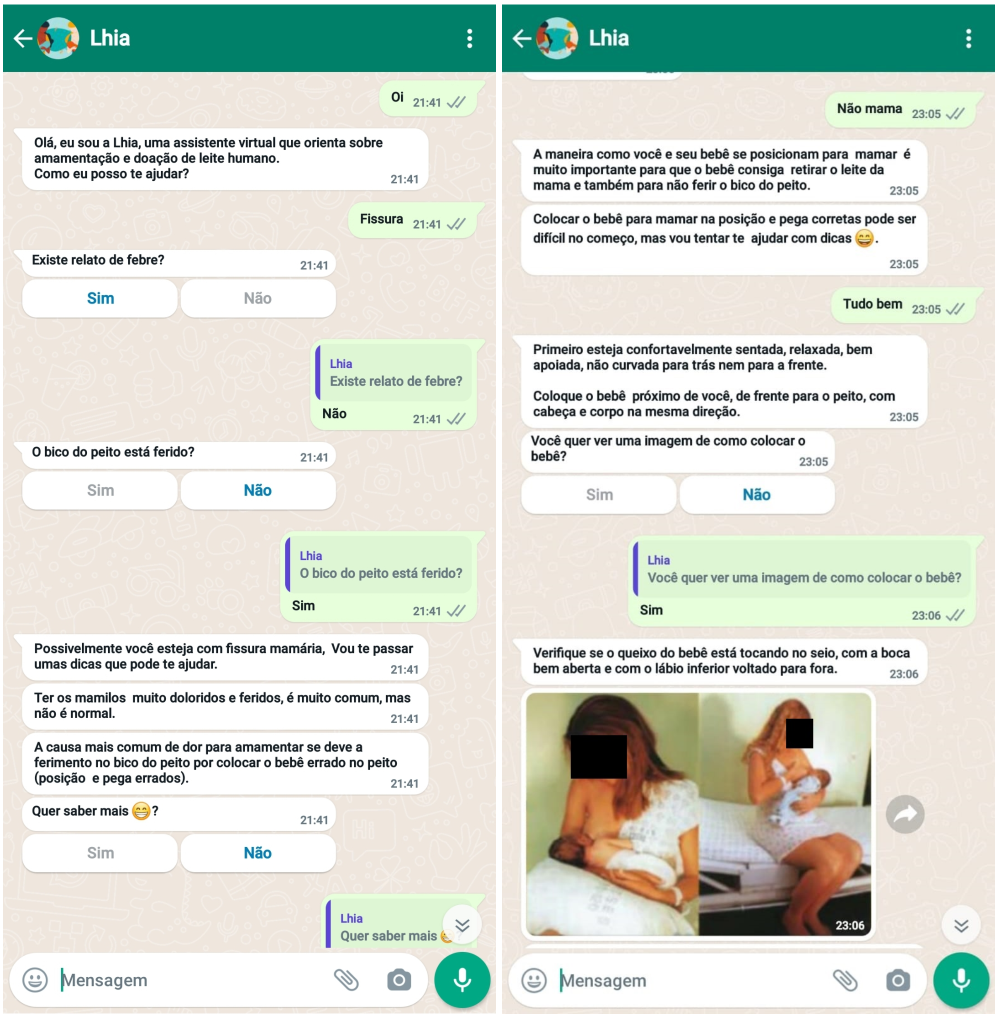


Figure 8. NPS results in the last two rounds of the co-design procedure.

5.5. Case Study

To illustrate the usage of the *Lhia* chatbot, we selected conversations from one of the participants in the co-design procedure, which are in Brazilian Portuguese language. The first conversation shown in Figure 9a shows the user starting contact with *Lhia* by sending a "Oi" (Hi) message, to which *Lhia* responds using a greeting message. The user then informs the problem she is experiencing during breastfeeding: "Fissura" (fissure). *Lhia*, upon receiving the message from the user, asks two new questions to better understand which intent the reported problem falls into, namely "Existe relato de febre?" (Is there a fever report?) and "O bico do peito está ferido?" (Is the breast nipple hurt?). Finally, based on the answers given by the user, *Lhia* is able to identify the problem, and then presenting detailed textual information about it, its causes and tips on how to deal with the discomfort caused by it.



(**a**) (**b**)

Figure 9. *Lhia* guiding the user with texts and images; (**a**) Starting a conversation with *Lhia*; (**b**) Guidance using texts and images.

Figure 9b displays a second conversation in which the chatbot guides the user on how to put the baby in the right shape to breastfeed. For this purpose, guidelines are transmitted using text and image messages. In the conversation, the chatbot asks whether the user would like to receive an illustrative image related to the topic addressed: "Você quer ver uma imagem de como colocar o bebê?" (Do you want to see an image of how to place the baby?). At the end of the conversation, *Lhia* presents an image in which a mother is sitting with her baby in the correct breastfeeding position.

Figure 10 shows *Lhia* starting a conversation, i.e., the active notification mechanism, in which the chatbot itself starts the interaction without the need for a previous message from the user. In this interaction, *Lhia* interacts by providing information about the importance of HM and its donation to the HMB: "Você sabia? Um frasco de 100 mL de leite materno doado pode alimentar até 10 bebês internados na UTI!" (Did you know? A 100 mL bottle of donated breast milk can feed up to 10 babies admitted to the ICU!). Health professionals (i.e., participants) believe that such a mechanism can encourage mothers to understand and practice HM donation. Finally, *Lhia* concludes the conversation by informing that if the user is interested in learning more about HM donation, she can contact the HMB of the HU-UFMA via telephone number or go to the address of the HMB, both data forwarded in messages of the conversation.

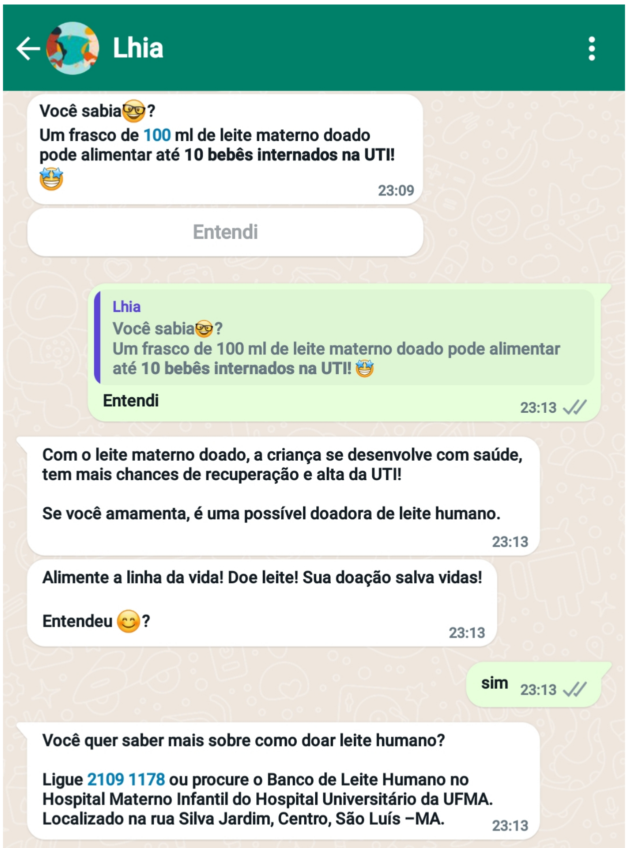


Figure 10. Example of active notification mechanism.

Figure 11 shows an interaction in which *Lhia* cannot understand the participant's message (i.e., a fallback trigger). It replies to the participant using a standard message (i.e., the fallback response) informing the user that their message was not understood, and then providing guidance for the conversation to resume: "Desculpe, mas eu ainda estou aprendendo e por isso não consegui te entender. Para continuar, você pode digitar novamente o que deseja, mas em poucas palavras. Ex: "Dor nos seios". (Sorry, but I'm still learning and that's why I couldn't understand you. To continue, you can retype what you want, but in a few words. E.g.: "Pain in the breasts").

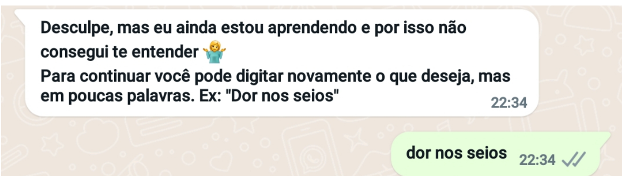


Figure 11. Example of fallback response.

6. Discussion

6.1. Principal Findings

Our proposed solution uses a DL-based NLP pipeline to identify when the mother seeks care at the HMB for a specific breastfeeding problem or HM donation. In the development of the *Lhia* chatbot, a co-design approach was used, which consisted of listening to health professionals and using their insights to improve the AI-based chatbot, simulating the texts produced by mothers with possible breastfeeding problems and using the generated conversation data for successive rounds of training and testing of different DL-based NLP pipelines. In addition, during co-design, there were adjustments to the content of the chatbot's conversational flow (Figures 7 and 8) based on suggestions from health professionals.

By looking at the last round of the co-design, we can observe that although the accuracy result of the pipeline P5 reached 0.93 (Figure 5), the number of fallback triggers increased to 284 (Figure 6) in the fourth round, but maintaining a fallback index at ≈15%. This was certainly due to the increase in the number of messages sent by users and sentence variability, which were caused by the number of participants interacting with *Lhia* and our face-to-face support and motivation during the last round. When observing these numbers, it is possible to verify that the number of participants (Figure 3) and interactions (Figure 4) may be seen as proportional, as well as the chances for *Lhia* to be improved, since we had new data to be used in subsequent training sessions of pipelines and, therefore, the greater the ability of *Lhia* to identify the reported problems by users.

During the co-design procedure, the health professionals who participated in the study indicated that *Lhia* chatbot is a promising tool to prevent early weaning of mothers. Also, participants suggested that the chatbot is an interesting technology for supporting breastfeeding education of health professionals, caregivers, and family members. This was confirmed by the NPS results (Figure 8). Therefore, although *Lhia* is resulting from an initial study, it has the potential to have good adherence by end users, and be constantly improved even after being put into production.

6.2. Lhia Contributions

The goals of breastfeeding education are to increase mothers' knowledge and skills, help them see breastfeeding as normal, and help them develop positive attitudes towards breastfeeding [14]. Developing a chatbot that helps mothers who breastfeed or people who support breastfeeding can improve breastfeeding rates in the general population, and this can be accomplished by combining knowledge of internet interventions and breastfeeding education.

Recently, Kung et al. [56] pointed out that generative chatbots, such as ChatGPT, Bard, and Bing Chat, may have the potential to aid in medical education and, potentially, clinical decision-making. *Lhia* differs from the current generative chatbots because it was developed in a co-design process with the participation of health professionals specialized in breastfeeding, so it provides technical content validated by them. *Lhia* uses a DL-based NLP pipeline to assist in addressing specific breastfeeding problems and, through education, teaches the correct management of such problems. It also identifies the intention of mothers who want to be HM donors and encourages mothers to donate HM through autonomous notifications. Moreover, *Lhia* differs from generative chatbots by using multimedia content, including not only texts, but also emojis and illustrative images.

During the COVID-19 pandemic scenario, social distancing was required, with restrictive measures that reduced patient access to health professionals, which compromised breastfeeding education in health units. Despite the benefits of using chatbots to help with agility and continuity of patient care [12], we are the first initiative that presents a chatbot proposal to improve breastfeeding indicators in the Brazilian population and in PT-BR [37]. This is the first proposal to create a smart chatbot with training directed by health professionals who work at a HMB, corresponding to a reference public policy in the promotion, protection, and support of breastfeeding. Therefore, *Lhia* is considered an innovative proposal for breastfeeding education in Brazil, which may represent an important health promotion tool.

6.3. Limitations

The present study is subject to a number of limitations. First, our study was mainly limited by the adherence of the participants in the first three rounds of the co-design procedure, demonstrated in the results. Second, from a clinical point of view, barriers to breastfeeding may occur at different levels (e.g., social, cultural, and political) and under different contexts, often beyond maternal control. *Lhia* was conceived and developed considering the context of HMB of the HU-UFMA and using the PT-BR language. Therefore, our proposed chatbot may not be able to deal with breastfeeding issues in different populations, not only by HMBs outside Brazil, but also by users in Brazil, since it has a continental geographic area, with many heterogeneous regions.

Third, the data provided by health professionals to train pipelines were texts simulating messages produced by mothers with possible breastfeeding problems, which might not have been faithful to what they would type. Therefore, we understand that additional studies involving mothers are necessary not only to confirm the performance of the chatbot, but also to improve it. Fourth, as *Lhia* seeks to educate using information on the management of the main problems related to breastfeeding, in practice, it is not able to address problems that require intervention by a health professional.

6.4. Future Work

Since we have a more stable version of the chatbot, we plan to put it into production to be used by breastfeeding mothers cared by the HMB of the HU-UFMA. Future plans for further studies include carrying out evaluations related to usability and user experience exploring the production version with mothers and health professionals and, at the same time, applying a process called Conversation-Driven Development (CDD) [57,58]. CDD consists of sharing the chatbot with end users, reviewing regularly generated conversations, taking notes of the conversations, and using them as training data, testing the chatbot to verify that its behavior is as expected, tracking chatbot failures, measuring its performance, and correcting when cases of unsuccessful conversations occur. Clinical studies with mothers are also expected to clarify the impact of the chatbot on people's perception and attitude towards breastfeeding.

7. Conclusions

The chatbot developed in this study can be used by HMBs in the process of breastfeeding education and recruitment of HM donors. *Lhia* was developed using a co-design approach with the participation of professionals specialized in breastfeeding. So, the result of this study is an internet intervention capable of clarifying the main problems related to the interruption of breastfeeding, in a non-face-to-face manner, 24 h a day, 7 days a week. As a consequence, the proposed chatbot is able to strengthen the public policy proposal of the HMB of the HU-UFMA because it will expand its frontiers of assistance to even remote regions where there is no access to this specialized service of support, promotion, and protection of breastfeeding.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the scientific ethics committee and institutional review board of University Hospital of the Federal University of Maranhão (protocol code 5.770.812).

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Abbreviations

The following abbreviations are used in this manuscript:

CDD	Conversation-Driven Development
HMBs	Human Milk Banks
DIET	Dual Intent and Entity Transformer
HM	Human Milk
WHO	World Health Organization
BR-HMBn	Brazilian Human Milk Bank Network
Lhia	Human Milk and Artificial Intelligence
NLP	Natural Language Processing
DL	Deep Learning
NICU	Neonatal Intensive Care Unit
AI	Artificial Intelligence
HU-UFMA	University Hospital of the Federal University of Maranhão
NLU	Natural Language Understanding
brWaC	Portuguese Web as Corpus
NPS	Net Promoter Score
LLM	Large Language Model
NLG	Natural Language Generation

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