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ALMA: Machine learning breastfeeding chatbot

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Since the first computer, researchers always try to simulate human behave. For Chatbots, one of the first goals is to interact with the user like a human using Natural Language. For Health chatbots, another goal is as much important: be able to provide the correct answer to the user request. Over Years, many health chatbots have been developed for many fields such as cancer, diagnosis orientation, psychiatrics, etc. breastfeeding companion are, however, rare (only two breastfeeding chatbots). In this paper, we have developed ALMA, a Breastfeeding Chatbot (BC) that can converse with a breastfeeding mom throw natural language understanding (NLU) and natural language generation (NLG), and provide her – breastfeeding mom – with the relevant information using AIML knowledge base and CNN pre-trained model. We made ALMA available for a normal WhatsApp conversation throw Twilio API. ALMA was tested by volunteering breastfeeding moms and the results validated by breastfeeding consult.

Keywords: *breastfeeding chatbot; machine learning; natural language processing; artificial intelligence; artificial intelligence markup language.*

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1. Introduction

Since the first computer, researchers always try to simulate human behave. When it comes to chatbots, one of the first goals is to interact with the user like a human. Even if we can't really call it a chatbot, the credit of the first conceptualization goes to Alan Turing, who asked in 1950 "Can machines think?" [1]. In 1966, the real first chatbot named ELIZA is born [2]. The first use of Artificial Intelligence in the field of chatbots dates back to the year 1988 with the chatbot named Jabberwacky [3]. The year 2001 was a big step for chatbots with the development of the first chatbot available on existing messaging platform like MSN [4]. Since then, chatbots become able to engage conversation and establish a relationship. Moreover, Chatbots using Artificial Intelligence can also give answers to user requests in specific domain, many applications are then possible: education, industry, healthcare, etc. In health care, chatbots like Babylon Health, Sensely Molly or Start4Life for Breastfeeding are designed to provide patients with customized health and therapy information, give diagnosis and suggest treatments based on symptoms. To do so, for health chatbot (considering Breastfeeding support as a healthcare field), we distinguish between; first, human- like conversation part with NLP Algorithms and second, the expert part with other Machine Learning algorithms. In this paper, we propose ALMA chatbot (Accompagnante en Lactation de la Maman Allaitante), including dialogue and communication part in natural language processing, and expert part with pretrained deep learning model and rule-based knowledge base. When a breastfeeding mom wants to ask ALMA chatbot a breastfeeding related question, she can simply send a message in WhatsApp. The goal of ALMA chatbot is to support breastfeeding moms by answering their breastfeeding related questions and define their breastfeeding disagreements. In order to go through those points, we organized this paper as follows; Section 2 is a background study of related work where we aim to classify chatbots and describes approaches used for Health chatbots and how they work. Section 3 presents our research method, we start by presenting ALMA general architecture, then we construct the Core Engine, next we construct the NLP Engine before configurating Twilio API. In Section 4 we display the prototype of ALMA chatbot and highlight the implementation and integration steps then integrate all components of ALMA chatbot. Then Section 5 evaluates and discusses the result of testing.

2. Related work

With chatbots, researchers always try to simulate human behave. Two goals are fixed; interact with the user just like a human and provide the most relevant response. In this section, we studied researches similar to our system to understand how they meet the goals. First, we review classification and approaches of existing chatbots. Then, we examine health chatbots and breastfeeding chatbots (BC).

2.1. Chatbots classification

From ELIZA [2] to AI based chatbots, they have come a long way. They have diversified the offer as well as multiplied the used technologies. At this level, it is important for us to study the classification of chatbots to clearly define our upcoming health chatbot. Chatbots can be classified into five categories like described in Figure 1, based on simple criteria. Chatbots does not have to exclusively belong to one category or other plus these categories exist in varying proportions [5].

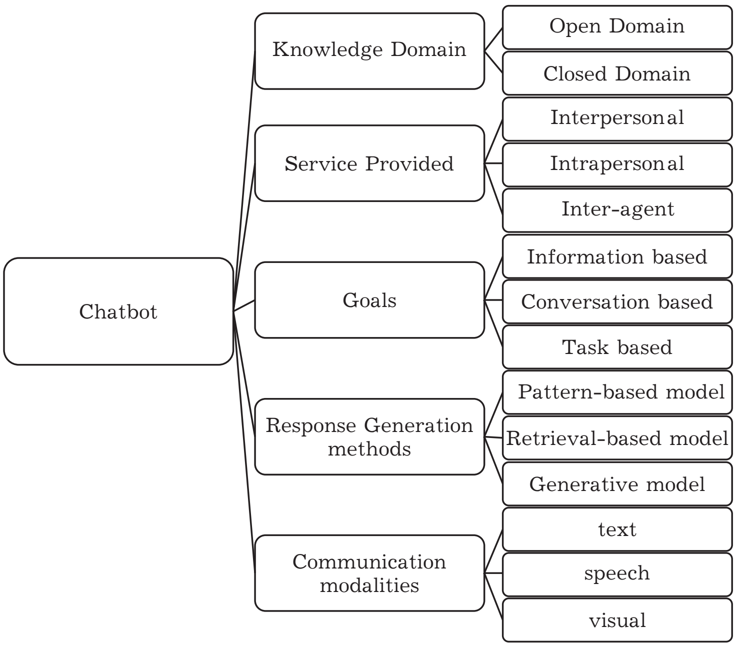

Fig. 1. Categories of chatbots.

Category 1 – Knowledge Domain: The difference between a health chatbot for example and education chatbot is the knowledge domain. Both of them could have the exact same backbone, but with different data trained upon [5]. From this perspective, two classes are listed; Open Domain for chatbots about general topics and Closed Domain for chatbots focused on a particular knowledge domain.

Category 2 – Service Provided: The Chatbots here are classified based on the sentimental proximity and the amount of intimate interaction to the user. Three classes for this category [5]; Interpersonal, mainly Chatbots providing services such as restaurant booking, flight booking, FAQ bots etc. These chatbots are not designed to be companions of the user. Intrapersonal, they exist within the personal environment of the user such as messaging platforms like Facebook Messenger or WhatsApp and perform tasks for the user like managing calendar or ask about his blood pressure. Inter-agent, the chatbot here becomes omnipresent using IOT to get the user environment, they will automatically get the heart rate from the user's smart watch or the room temperature from a smart thermostat.

Category 3 – Goals: The main role of a chatbot could be [5]; Information based: Chatbots designed to provide the user information like to respond to clients or patients FAQ, Conversation based: Chatbot talks to the user like a human being holding a continuing conversation, or task based: the chatbot here performs a task like book a restaurant or play a song.

Category 4 – Response Generation methods: The chatbot builds responses to the user based on the user context. There are three classes used to produce the appropriate response [6]; Pattern-based model, matches the user message with pre-existing pattern of question/answer to create a response. Retrieval-based model, works on the principle of graphs or directed flows. Based on a database of predefined responses, the chatbot is trained to provide the best possible response. The responses are based on existing information and Generative model, generating answers based on current user messages and previous messages. However, it needs training with a very large dataset in order to achieve a good conversation.

Category 5 – Communication modalities: Chatbots should be able to communicate with users through different modalities [7]; text, voice, image and video, as a result, they need high speech, text, and visual understanding. The user could text, speak to the chatbot or simply share an image. The chatbot needs to be able to parse the text, recognize the speech [8], or detect the salient information in the image to understand user intent. The chatbot will also respond with text, speech, or visual output, depending on the context.

2.2. Chatbots approaches

Approaches adopted in chatbots depends on the classes the chatbot belongs. Informational chatbots for example are based on predefined answers. The adapted technology here could be Artificial Intelligence Markup Language (AIML) or Artificial Intelligence Scripting Language (RiveScript). For Conversational chatbots however, as the chatbot needs to converse with the user and understand the context, technologies like Natural Language Processing (NLP) are more convenient. In general, two approaches families are used for chatbots depending on the adopted technologies: Rule-based approaches and Machine Learning Approaches trained over datasets [9].

Rule-based approaches: Chatbots positioned as rule-based basically works by matching a user request with a rule, the system then generate a response to the user [10]. The common languages for the implementation of chatbots with the rule-based approach are: AIML [11] (Artificial Intelligence Markup Language) is an extension from XML (Extensible Mark-up Language). It is designed to create conversational flow in chatbots. The elementary component of an AIML script is called an AIML element. These elements are themselves made up of categories related to the subject of the object. A category contains at least two additional components called "pattern" and "template". Each category represents a rule for matching an input to an output. The "pattern" is the user's input and the "template" is used to generate the response by the chatbot. Chatscript: is an open source chatbot creation tool. It is a combination of natural language engine and dialog management system designed for interactive conversation while maintaining user state across conversations. Chatscript is based on rules created in program scripts through dialog flow scripts. Scripts can be stored as a text file. Machine learning tools can also be used to improve dialog flows.

Machine learning approaches: Chatbots using machine learning algorithms however, have two challenges; communicate with the user and answer his questions. For the communication part, NLP algorithms are the more convenient with their two subtopics: Natural Language Understanding (NLU) to understand the user's "language", it handles and convert formless data, it allows the machine to understand users and figure out its intent for processing requests [12]. Natural Language Generation (NLG) to formulate the answer to the user, it produces a natural language containing the desired information given a semantic representation [13]. For the generation of the response, the commonly used algorithms are Deep Learning Algorithms like Convolutional neural networks (CNN), Recurrent Neural Network (RNN), Transfer Learning (TL), etc. [14]. Convolutional neural networks (CNN): mainly used for application with image recognition using a Dataset to get pre-trained and classify images with different convolution layers. Recurrent neural network (RNN): Easy to set up but the simple RNN is suffering from the short memory problem (due to a vanishing gradient), this is why both LSTM and BiLSTM are adjusted to process the sequential data and to overcome limitations. Transfer learning (TL): provides a pre-trained model with large number of data, based on attention mechanism, it uses self-attention to find the relations within sequence found dependency among words in one sequence.

2.3. General chatbots

Since the first chatbots, one of the first goals is to interact with the user like a human. Even if we can not really call it a chatbot, the credit of the first conceptualization goes to Alan Turing, who asked in 1950 "Can machines think?" [1]. In 1966, the real first chatbot named ELIZA is born [2]. The first use of Artificial Intelligence in the field of chatbots dates back to the year 1988 with the chatbot named Jabberwacky [3]. The year 2001 was a big step for chatbots with the development of the first chatbot available on existing Messengers like MSN [4]. Since then, chatbots are now able to engage conversation and establish a relationship just as humans do.

2.4. Health chatbots

Many chatbots belongs to the open domain class and have a general use have a "general use" as a virtual assistant; it can wake you up, talk to you, or do a google search for you. Other chatbots were developed as closed domain, like consumer services chatbots, travel and airlines chatbots, gaming chatbots and our concern in this paper; health chatbots. For health chatbot the objective of interacting just like a human remains. To this first goal another as important goal is added; be able to provide the most relevant response to a question or a request. Chatbots like Babylon health [15], Sensely Molly [16] or Florence [17] are designed to provide patients with customized health and therapy information, give diagnosis and suggest treatments based on symptoms [18]. To do so, for the health chatbot approaches, we distinguish between; first, human-like conversation part with NLP algorithms combined to rule-based algorithms and second, the expert part with other Machine Learning algorithms or rule-based algorithms.

2.5. Breastfeeding chatbots

Breastfeeding chatbots may be considered as health chatbot even if breastfeeding is physiological state and not pathological condition. But while the majority of newly moms had inadequate knowledge and improper techniques for breastfeeding [19], the simple use of cell phones to send regular and personalized messages to breastfeeding moms, proved to be a very useful tool for frequent and sustained support [20]. However, no sufficient literature on the usage of chatbots in the healthcare domain [21]. In this study, nevertheless, we were able to found two breastfeeding chatbots but not really documented or indexed: Start4Life adopted by UK National Health Service (NHS) [15] and Aleitamento Materno Orientado (AMO), the one and only breastfeeding chatbot indexed in Google Scholar (but not indexed in scopus for example) [16], both using Facebook Messenger as client plateform and developed using Google Dialogflow.

3. Research method

From the study we did on chatbots and their classification and getting back to the chatbot categories; we can identify ALMA chatbot classes. We justify our choice if an earlier paper [14]. Since our chatbot involves a specific knowledge field, it is a closed domain chatbot. For the service provided, we attend to create this personal relationship with the user, using existing messaging platforms, it is then an intrapersonal communication. Then, we aim to converse with the user, as it is important to feel confident to share health related information and as the psychological dimension affects the symptoms. Moreover, we will get to answer to the user, using pre-authored answers. So, the goals are, information based and conversation based. The response is generated with both pattern-based and general models, we can then say that the approach we are adopting is a hybrid approach with both rule based and machine learning. Last thing, we opt for text and images as communication modalities.

We created our chatbot ALMA respecting four components architecture [14], each component involves one step or more. After presenting ALMA general architecture (2), we, first, construct the Core Engine by constructing the dataset and the CNN module to classify breast images. Then, extract the knowledge from the reference website for breastfeeding moms, developed by the La Leche League NGO [22]. And we generated AIML files from the collected knowledge. Second, we construct the NLP Engine before configurating Twilio API and integrating all components of ALMA chatbot. Bellow we demonstrate the details of those steps.

3.1. ALMA general architecture

The general architecture of ALMA as shown in Figure 2, is split in four components. The breastfeeding mom can either write a text or send an image on WhatsApp to ALMA's number, her message (text/image) went through the API to ALMA core. A small Python script pre-process the message and: If it is a text message, it is sent to the NLP Engine, to be understanded, then to the Core Engine to extract the response from the knowledge base. The response is sent back to the NLP Engine to be generated and prepared to be sent back as a text message to the sending mom. If it is an image, the message goes directly to Core Engine to be classified by the CNN module. The classification is sent to NLP Engine to be generated and prepared to be sent back as a text message to the sending mom.

1. Client platform. Chatbots are classified into three classes: Autonomous client platform, Integrated SDK, Messaging platform based [14]. ALMA is a messaging platform based on WhatsApp. The choice of WhatsApp is induced by the fact that it is the most used messaging platform in Morocco; 84% of Moroccans use it in 2021, with 79% using it daily. A survey carried out by Sunergia Group revealed and published by the MAP (Agence Marocaine de Presse) [23].

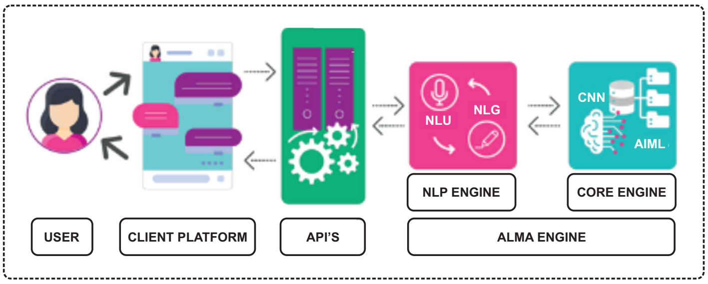

Fig. 2. 'ALMA' General Architecture.

2. Core engine. It can be qualified as the rational brain of ALMA chatbot, the expert. If on one hand the Core Engine, receives pre-formed text, it matches the request with a rule on its AIML knowledge base and generates then a response. If on the other hand it gets an image, the response is generated by the CNN module, pre-trained over a constructed dataset.

3. NLP Engine. In order to communicate with the user, the NLP engine is here to understand the user and get understanded by the user through two subtopics of NLP; NLU to handle and convert formless data to process requests [12]. And NLG to formulate the answer respecting a semantic representation [13].

4. APIs. In this work, we use Twilio as a platform for communication. It is a programmable WhatsApp API used as a powerful tool for messaging; it uses representational state transfer (REST) which relies on HTTP requests. It provides communication interface between the client platform; WhatsApp and the NLP Engine.

3.2. Core Engine construction

1. Dataset construction & CNN module. The CNN module aims, once integrated to the chatbot, to detect the breastfeeding disagreements based on a breast image. Before constructing our own dataset, out interest goes first to existing datasets.

Unfortunately, no one includes healthy images of breasts with breastfeeding related disagreements like mastitis, sore nipples, etc. All existing datasets are about cancer or breast surgery (f.e. augmentation or reduction surgeries).

In order to generate a synthetic dataset, it is important to have a large set of images of breastfeeding breast. To do so, we performed three steps: Collect the images, pre-process the images, and classify the images.

```
train_df
```

	image	label
0	..\data\train\Healthy\healthy_0_3057.jpeg	Healthy
1	..\data\train\Healthy\healthy_0_3190.jpeg	Healthy
2	..\data\train\Healthy\healthy_0_3194.jpeg	Healthy
3	..\data\train\Healthy\healthy_0_3208.jpeg	Healthy
4	..\data\train\Healthy\healthy_0_3219.jpeg	Healthy
...	...	...
687	..\data\train\CanalLactifereObstrue\canalLacti...	CanalLactifereObstrue
688	..\data\train\CanalLactifereObstrue\canalLacti...	CanalLactifereObstrue
689	..\data\train\CanalLactifereObstrue\canalLacti...	CanalLactifereObstrue
690	..\data\train\CanalLactifereObstrue\canalLacti...	CanalLactifereObstrue
691	..\data\train\CanalLactifereObstrue\canalLacti...	CanalLactifereObstrue

Fig. 3. View of the CSV file.

Image collection: we collect 1327 images by scraping images from popular image search engines; Google Images, Bing Images and Yahoo Images. We scraped images of breastfeeding breasts, we choose 4 different search queries: "mastitis", "sore nipples", "plugged duct" and "breastfeeding breast". We made our full code for scraping using Beautiful Soup library in python, the output images are stored in folders with the search name.

Image pre-processing: first, we perform a set of operations performed on the image, either to improve it, or to restore it, to reinforce the resemblance of the pixels of the same zone, or to exaggerate the differences of pixels coming from different zones. Then we apply data augmentation algorithms (flip, rotation, translation, scaling, cropping) on the images to create quite voluminous data compared to the limited start number. At the end of this step, the dataset is built-in cvs (4) files containing two columns: image url and its class.

Image classification: the dataset is used to train our neural network CNN. We first built the neural network in three layers with only one hidden layer but the accuracy was very low: 59.64%. VGG16 proposed by K. Simonyan & A. Zisserman [24] was the most appropriate to classify the breast images with 91.13% of accuracy, our team is working of making it even better. VGG16 was enough for our case, VGG19 or InceptionV3 for example went too deep into the analyze that even meaningless color modification in the breast image is meaningful for the model. We defined four breastfeeding disagrements classes: Healthy, Mastitis, Sore Nipple or plugged duct. Other classes are in process.

2. Knowledge base construction. The knowledge base aims, once integrated to the chatbot, to select the appropriate answer to user's request. As mentioned before, it uses AIML language. So before generating the AIML Files, we need first to constitute the knowledge. To do so, we performed three steps: Collect the data, pre-process the data, and classify the data [25, 26].

```
<category>
    <pattern>J'ai mal au sein</pattern>
    <template>
        Tu peux me décrire cette douleur ?
        <set name="topic">douleur</set>
    </template>
</category>
```

```
<category>
    <pattern>J'ai une zone rouge sur la partie extérieur du sein gauche</pattern>
    <template>
        C'est probablement une mastite, envoie nous une photo.
    </template>
</category>
```

Fig. 4. View of an AIML file.

Data collection: we collect breastfeeding related data from the reference website for breastfeeding moms, developed by the La Leche League NGO [22]. We went with the French version of the website and proceed using web scraping techniques by implementing our full code for scraping using Beautiful Soup library in python.

Data pre-processing: From the collected data, we used NLTK (NLTKWordTokenizer) with python to pre-process data. We first clear away all AIML dedicated characters like * and #, then we eliminate testimonials, personal information and all inconsistent data. Then, to prepare the data for classification, we proceed to a tokenization of the documents.

Data classification: Just before constructing the AIML Files, we tried classifying the data using Naive Bayes (NC) in the first place, then using support vector machine (SVM). Accuracy with SVM (92.18%) was higher that with NBC (87.48%). The big advantage of SVM also is that SVM tries to find a separating function (hyperplane) by maximizing the distance between classes [27] which is very important for breastfeeding disagreement classes, 'mastitis' and 'engorgement' for example may have many similarities in their symptoms.

3. AIML Files generation. From the data constructed in the previous step, we generate AIML files. To do so, we developed a python program to convert the text format into an AIML format. In a first time, the script converts to the basic AIML tags like <topic>, <category>, <pattern> and <template>. The rest of tags, like <srai> and <random>, are manually added using GaitoBot AIML editor in order to make the chatbot act like a human.

3.3. NLP engine construction

In order to communicate with the user, the NLP engine is here to understand the user and get understanded by the user. As NLP Framework we went with NLTK framework as it is an open-source solution for Natural Language what gives up freedom to develop our way. The most import modules we used for the NLP construction were; Tokenization, Parsing and Information extraction. We also upload WordNet knowledge files for French language.

3.4. Configuration of Twilio API

Back to ALMA architecture, we distinguish the entire chatbot part with both the NLP Engine and the Core Engine, and the client part with the breastfeeding mom and the client Platform. To interconnect the two parts, we use Twilio API. It supports WhatsApp, moreover, it allows us, without any further programming effort, integrate other client platforms like Facebook Messenger or Telegram.

Twilio is a programmable WhatsApp API used as a powerful tool for messaging, adopt representational state transfer (REST) which relies on HTTP requests. For WhatsApp, Twilio offers pre-paid phone numbers and paid message sending, except for US phone numbers.

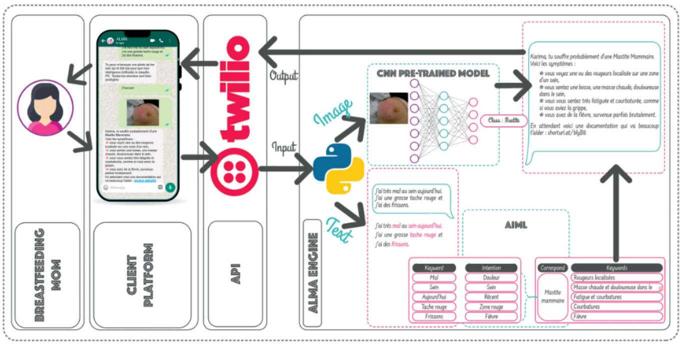

Fig. 5. Architecture and Design of 'ALMA', BC with Machine Learning.

Fig. 6. Connect the Chatbot to WhatsApp throw Twilio.

This is why for this prototype we used the US number +1 (415) 523-8886 and activate Twilio Sendbox for this number. To start communication, the first message by the breastfeeding mom should be "join swing–family" then the mom is free to send her messages. Figure 6 is an overview of how we connect the chatbot to WhatsApp throw Twilio.

4. System implementation and integration

To implement and integrate the system of ALMA we needed several steps. First of all, we configure Twilio API to connect with WhatsApp.

Secondly, we implement the NLP Engine in full stack Python development environment, setup with AWS Cloud9 and upload WordNet knowledge files, after that we test the communication. Figure 7 shows an example of NLP Engine. Then we integrate the Core Engine, in one hand, by unloading the AIML generated files, and on the other hand, by integrating the CNN module. After that, the last thing is to talk to ALMA. Figure 8 shows an example of Core Engine.

Fig. 7. NLP Engine Implementation.

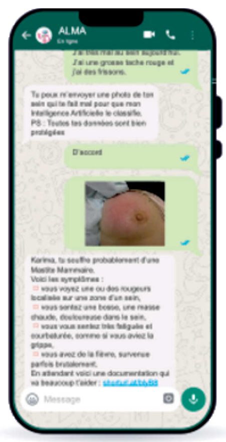

Fig. 8. Core Engine Implementation.

5. Result, evaluation and discussion

Maroengsit W. et al. came up with an evaluation method for chatbots [28] to evaluate its quality by judging efficiency, effectiveness and satisfaction [29] attributes based on ISO 9241. They base their method on three evaluation schemes: content evaluation, user satisfaction, and functional aspect. We found this study even more interesting because the authors specifically focus on closed domain chatbots among them health chatbots. Content evaluation concerns response generated by the chatbot includes both automatic evaluation, ideal for machine translation and text summarization, and expert evaluation where human experts are needed to judge the relevance of the generated data. User satisfaction is more about the conversational part of the chatbot. The user may rate some aspects like appropriateness and naturalness. The user can be asked to evaluate the entire session (Session Level Evaluation) or evaluate each response individually (Turn Level Evaluation). Functional aspect involves the evaluation of chatbot functions:

— Evaluation based on goal/task to check is a task was done by the chatbot as supposed and this evaluation only concerns goal oriented chatbots;
— Usage statistics to evaluate the performance of the chatbot on a wide period of use;
— Evaluation as building blocks for chatbots that evaluates the chatbot as technical product.

We present ALMA chatbot to 17 breastfeeding moms, 12 of them are newly moms as the breastfeeding disagreements are more frequent at the beginning. We ask them to give us their feedback by noting the entire conversation with ALMA and by answering to a questionnaire. To evaluate the content, the entire conversations are sent to a breastfeeding consultant. She is asked to evaluate each response (total of 216 responses) good, fair, poor or bad. The user satisfaction is defined based on the questionnaire into several categories: ease to use, fluency of conversation, quality of information and general satisfaction. Each category is given a mark good, fair, poor or bad. As for the functional aspect, we do not have for now enough hindsight to evaluate long term performances, however ALMA chatbot was tested by 3 colleagues working in AI field and had to answer to questions within two categories: Communication functions and Core functions. Each category is given a mark good, fair, poor or bad.

Table 1. Evaluation results after testing.

Evaluation pattern	**Category**	**Evalution mark**			
		Good	**Fair**	**Poor**	**Bad**
Content evaluation	Expert	47/216	131/216	25/216	13/126
User satisfaction	ease to use	15/17	2/17	0/17	0/17
	fluency of conversation	0/17	10/17	7/17	0/17
	quality of information	13/17	4/17	0/17	0/17
	general satisfaction	2/17	12/17	3/17	0/17
Functional aspect	Communication functions	0/3	2/3	1/3	0/3
	Core functions	2/3	1/3	0/3	0/3

After being tested and evaluated by 17 breastfeeding moms, 1 breastfeeding consultant and 3 AI experts. The results are reported in Table 1. We evaluate the content, the user satisfaction and the functional aspect.

From the breastfeeding consultant view, more than 82% of responses were good or fair, 11.57% were poor, ALMA was supposed to ask further questions to the mom to be able to better classify the disagreement. 6% of answers were false. For example, a mom sent a picture of her breast with "Vasospasm" disagreement. However, this disagreement is not classified by ALMA and ALMA classified it as "plugged duct".

From users view, all moms found ALMA easy to use and report that they particularly appreciate that they only had to use WhatsApp with nothing else to install. However, 41% found the conversation not really fluent and report that they prefer to talk to a "friend" and not to a "professional", the emotional dimension was missing. The quality of information was good enough for all users. The 17%

of unsatisfied users once again give the argument of the emotional and empathic dimension and report that they want to send voice message instead of writing.

The AI experts, found the core part fine, the functions and the technical implementation were good (67%) or fair (33%), they however suggest to automatically supply the Knowledge Base continually. For the communication part, they highlight some possible improvements; one of them suggest to add a morphological and semantic analyze to generate a less "robotic" answer, another expert recommend to add a general discussion module which signify a whole new knowledge base, the third expert focus the fact that moms should talk to ALMA in French and not in Moroccan Arabic Dialect. To sum-up, after testing ALMA chatbot and based on the evaluation results, we can say that the first experiment with ALMA chatbot was acceptable.

However, ALMA chatbot still needs to be improved. For Core Engine, work on new breastfeeding disagreements classes and increase the amount of data in the Knowledge Base. For the NLP Engine, we should find a way to make the conversation more empathic and support the Moroccan Arabic Dialect, plus, add a module of speech recognition Engine before the NLP Engine to support the voice messages.

6. Conclusion

Chatbots can really help support breastfeeding moms by providing them the relevant answer to their question, real time. In this paper we presented our breastfeeding support chatbot named ALMA. The goal of ALMA chatbot is to support breastfeeding moms by answering their breastfeeding related questions and define their breastfeeding disagreements and advise them. ALMA is the first breastfeeding support chatbot using French and the first breastfeeding support chatbot using WhatsApp, all languages combined. ALMA chatbot includes dialogue and communication part in natural language processing, and expert part with pretrained deep learning model and rule-based knowledge base. After testing ALMA chatbot and based on the results of user and expert experience, we can say that the first experiment with ALMA chatbot was acceptable. However, ALMA chatbot still needs to be improved. For Core Engine, work on new breastfeeding disagreements classes like "vasospasm" and increase the Knowledge Base content by adding other sources. For the NLP Engine, we should find a way to make the conversation more empathic and support the Moroccan Arabic Dialect, plus, add a module of speech recognition Engine before the NLP Engine to support the voice messages. In addition to that, we plan to make ALMA chatbot available on Moroccan WhatsApp number and invest our own unshared sendbox to skip the opening message.

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ALMA: чат-бот для машинного навчання грудного вигодовування

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З часу появи першого комп'ютера дослідники завжди намагаються імітувати поведінку людини. Для чат-ботів однією з першочергових цілей є взаємодія з користувачем як з людиною за допомогою природної мови. Для чат-ботів здоров'я інша мета є не менш важливою: вміти надати правильну відповідь на запит користувача. Протягом багатьох років було розроблено багато чат-ботів для охорони здоров'я для багатьох сфер, таких як рак, орієнтація на діагностику, психіатрія тощо. Однак чат-боти для грудного вигодовування зустрічаються рідко (лише два чат-боти для грудного вигодовування). У цій статті розроблено ALMA, чат-бот для грудного вигодовування (BC), який може спілкуватися з мамою, яка годує грудьми, про розуміння природної мови (NLU) і створення природної мови (NLG), і надавати їй – мамі, яка годує грудьми, – відповідну інформацію, використовуючи базу знань AIML і попередньо навчену модель CNN. Зроблено ALMA доступною для звичайної розмови WhatsApp через Twilio API. ALMA було протестовано матерями–добровольцями, які годують грудьми, і результати підтверджено консультацією з грудного вигодовування.

Ключові слова: *чат-бот грудного вигодовування; машинне навчання; обробка природної мови; штучний інтелект; мова розмітки штучного інтелекту.*