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Artificial Intelligence Agents and Knowledge Acquisition in Health Information System

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ARTIFICIAL INTELLIGENCE AGENTS AND KNOWLEDGE ACQUISITION IN HEALTH INFORMATION SYSTEM

Research full-length paper

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Abstract

This research work highlights the need for AI-powered applications and their usages for the optimization of information flow processes in the medical sector, from the perspective of how AI-agents can impact human-machine interaction (HCI) for acquiring relevant and necessary information in emergency department (ED). This study investigates how AI-agents can be applied to manage situations of patient related unexpected experiences, such as long waiting times, overcrowding issues, and high number of patients leaving without being diagnosed. For knowledge acquisition, we incorporated modelling workshop techniques for gathering domain information from the domain experts in the context of emergency department in Karolinska Hospital, Solna, Stockholm, Sweden, and for designing the AI-agent utilizing NLP techniques. We discuss how the proposed solution can be used as an assistant to healthcare practitioners and workers to improve medical assistance in various medical procedures to increase flow and to reduce workloads and anxiety levels. The implementation part of this work is based on the natural language processing (NLP) techniques that help to develop the intelligent behavior for information acquisition and its retrieval in a natural way to support patients/relatives' communication with the healthcare organization efficiently and in a natural way.

Keywords: AI-Agents, NLP, Human-machine Interaction (HCI), Health Information Systems

1 Introduction

The inclusion of artificial intelligence (AI) and machine learning (ML) applications are recognized in almost every industry, where they address complex and critical issues of societies (Dandekarl and Ghodey, 2017). The importance of AI agent technologies (e.g., chatbots) is an example that serve various applications within Health Information Systems (Haftor et al., 2011) and integrates medical based information systems from trusted sources that are based on various processes, conditions, procedures and along with Triage protocols (Farrokhnia and Göransson, 2011). Chatbots are computer-based programs using artificial intelligence (AI), machine learning (ML) paradigms, and natural language processing (NLP) algorithms. They interact via interfaces with users through text or speech recognition protocols and behave a human mimic (Lalwani et al. 2018). They can act as conversational agents between patients/visitors and healthcare professionals by putting queries as inputs and providing relevant answers according to the narrative, and by implementing intelligent learning patterns using domain knowledge acquisition in a closed context especially in Pediatrics Emergency Department (PED) (Lalwani et al. 2018).

The research presented in this paper is based on a case study at Pediatrics Emergency Department (PED), Karolinska Institutet (KI) Hospital, Stockholm, Sweden. The problem at this particular department is the lack of a mechanism to get relevant information related to the emergency unit. Two research questions were raised. First, how can we obtain relevant information within emergency unit? second, how patients related unexpected experiences of long waiting times, overcrowding issues, and high number of patients leaving without being diagnosed are addressed? To address this question, an assistive technology approach was taken. In so doing, chatbots were used as helping hands to improve the information-flow processes with humans and machines interaction (HMI) abilities and preferences of healthcare workers in the medical unit. Similarly, the human-computer interaction (HCI) was decided to be helpful for digging up the most relevant information retrieval (IR) related to a specific medical context from the knowledge-based repository in the medical unit. We wanted to explore the need for a smart innovative solution with AI paradigms that may help to provide efficient communication and seamless interaction between humans and machines, and its self-learning capability for the early medical assessment for patients and ensures the urgency of medical assistance without bothering queue restriction during the overcrowded panic situation or in case of severe emergency.

The proposed solution aimed at addressing several challenges, e.g. to improve internal communication after making preliminary medical assessments through Questions and Answers (Q&A) sessions with patients/relatives; to prompt the Triage (Decision Support System (DSS)) to take immediate necessary actions to tackle patient-related conduct in the waiting area of PED; to facilitate users for providing medical services and improve information flow processes and their preferences on demand without any constraints/delays in the medical context. Finally, an important context for the design was the ongoing pandemic (e.g., COVID-19), however the design aimed at same-like situations. that is, to decrease human interaction within sensitive areas of medical centers.

To this end, this paper is organized as follows. Section two presents a brief literature review and conceptual basis of artificial intelligence (AI) based conversational interfaces (e.g., agents, etc.), intent modelling for the conversational agents and their classification, task-oriented AI agents' applications, and AI agents design approaches, techniques, and their inclusion in the healthcare context. This was followed by, a presentation of the case study, data collection, data analysis, and the pediatrics emergency department (PED) care processes. This was followed, with an illustration of various steps of methodology (Natural Language Processing (NLP)) techniques, and the building an approach for tacit knowledge acquisition, and building an approach for developing AI-enabled anatomy of chatbot architecture. After that, the paper illustrates the designing of a questionnaire related to early

assessment during the waiting area and demonstrates the visual representation of chatbot application in this discussion. Finally, conclusion and highlights for future research is summarized.

2 Literature Review and Conceptual Basis

Over the past few years, with the dynamic shifting toward natural language-based interfaces, AI-Agents (e.g. chatbots, etc.) have taken a significant place to make improved interaction between humans and machines in various industries. Especially, for the personalized interaction, the natural language processing (NLP) techniques have been considered as a compelling technology that allows each user to interact with the machine in their own freedom of words, rather than using predefined intent (Hussain and Athula 2018). The concept of NLP is defined as a Natural Language Processing is branch of machine learning (ML) that deals with text and speech. Natural Language Processing (NLP) is a way for computers to analyze, understand, and derive meaning from human language in a smart and useful way" (Agarwal and Sexena, 2019). The user usually initiated conversation either in textual form or voice-enabled in natural languages. Similarly, chatbots are used to give the answers to these questions in the same dialogue fashion (Hussain and Athula 2018).

2.1 Classification of AI Agents

The scope of AI agents with the marriage of AI paradigms and machine learning (ML) techniques is quite prominent in almost every industry, especially in healthcare sector. The classification of AI agents is based on their usage in various domains (e.g., customer service industry, education learning, etc.) but here, we are focused on health information systems (Ramesh et al., 2017). The potential role of AI agents is to mimic humans' interaction and improve users' engagements and trustworthiness while being treated in the medical unit (Kocielnik et al., 2019). The AI agents can be classified into various categories based on several criteria: conversational-interaction mode (e.g. Text-based, voice/speech-based), Applications (e.g. Task-oriented or Non-task-oriented) with domain's knowledge (either specific or open), their usage accordingly (Rule-based or AI (Machine Learning (ML)), NLP, Deep learning (DL), etc.) and some design-pattern techniques (Hussain et al., 2019) for developing AI agents (e.g. chatbots) using the response-generation method according to the needs and demands of a medical unit in healthcare sector (Ramesh et al., 2017).

2.2 AI Agents Applications in Health Information Systems

Task-oriented AI agent applications can be developed to achieve qualitatively different but defined goals, such as getting remedies, helping in location-navigation, booking prior appointments, and interpreting multilingual impressions, especially in case of a panic situation (Shafqat et al., 2019). These types of conversational applications are designed to address specific issues (such as overcrowding issues etc.) in specific scenarios and for dealing with specific use-cases and helping users to access relevant information retrieval (IR) within medical contexts (Parviainen and Rantala, 2021). Although, applications such as Alexa, Cortana, Google Assistant, Xiaolce, and Siri are already introduced into the market to facilitate the users in healthcare contexts (Parviainen and Rantala, 2021), still, these task-oriented chatbots are not efficient in restricted domains, such as Pediatrics Emergency Department (PED). These chatbots are goal-oriented and focused on helping users to achieve defined goals. These AI agents lack generic capabilities and knowledge resulting in users not being able to ask, "trivial questions" (Shafqat et al., 2019). The emergence of the first chatbot (e.g., ELIZA) (Parviainen and Rantala 2021; Wizenbaum, 1966) and digital health tools (Buoy and Omaolo; Nordheim et al. 2019) are available in the market but they are quite generic in nature and not able to incorporate the specific domain knowledge, especially in healthcare industry.

2.3 AI Agents Design Approaches and Techniques

For the development of task-oriented AI agents, there are several approaches needed to incorporate according to the nature of the scenario or problems. These approaches can be categorized into mainly three categories of AI agents. 1. Rule-Based Approaches, 2. Retrieval-Based Approaches and, 3. Generative-Based Approaches (Shafqat et al., 2019). These approaches are used for employing various techniques to develop task-oriented and non-task-oriented AI agents' applications in various domains. These techniques include parsing, pattern-matching and Artificial Intelligence Modelling Language (AIML), chatscripts, Ontologies, Markov-Chain Model and Artificial Neural Network Models (ANN) (Shafqat et al., 2019) and NLP (Lalwani et al., 2018). The natural language processing (NLP) techniques is utilized for the development of task-oriented chatbot application in the context of the pediatrics emergency department (PED) and computer science research has managed to organize and structure the knowledge to perform certain tasks such as "automatic summarization, translation, named entity recognition, relationship extraction, sentiment analysis, speech recognition, and topic segmentation. Keyword: Natural Language Processing, Speech Recognition, ML, Personal Assistant, Text-To-Speech (TTS)" (Agarwal and Sexena, 2019).

3 Research Methods

3.1 Case Study

This research work is based on the real-time observational case study within Pediatrics Emergency Department (PED), Karolinska Hospital, Solna, Stockholm, Sweden. We conducted Modelling Workshop (Fareedi and Ghazawneh, 2018) and gathered data from various healthcare professionals, who were responsible for emergency patients' treatment procedures. The current situation of the ED was observed. We traced significant problems which were related to patient-centric treatment procedures and aimed to transform from As-Is situations to To-be situations in ED. According to Arwidson (2020) it has been noticed that in 75% of patient visits, the ED is usually face unexpected experiences such as long waiting times. From the Hospital's perspective, a poorly functioned ED impacts the entire hospital's activities and workflows (Rognes and Sahlin, 2010). To get accurate medical assistance for emergency patients, there is a need for a health-oriented classified information system (e.g. decision support system (DSS) (Rognes and Sahlin, 2010) and assistive technological solutions (e.g. chatbot, etc.) which help to improve multiple steps in the front-end triage procedures with inconsistent practices, minimize the high percentage of patient handling in the waiting room during peak time, introduce single window operations to improve communication issues and harbors data silos within department and treatment areas (US-Acute, 2021). Similarly, from the patient's perspective, long waiting periods in the ED, often with a high level of anxiety, may result in patient losing trust in health services. If EDs function poorly, this jeopardizes not only the patient's health and safety but also public trust in the health service (Rognes and Sahlin, 2010).

3.2 Pediatrics Emergency Department (PED) Care Processes

In Emergency Department (ED), usually, patients are prioritized based on a 1-5 scale Triage score which is a time-taking job (Mazzocato et al., 2012). The qualified pediatrician nurse is used to enter the patient-related information in an Electronic Health Record (EHR) then patients are sent to the waiting room or roomed directly, depending on clinical urgency, and competing demand for care (Mazzocato et al. 2012).

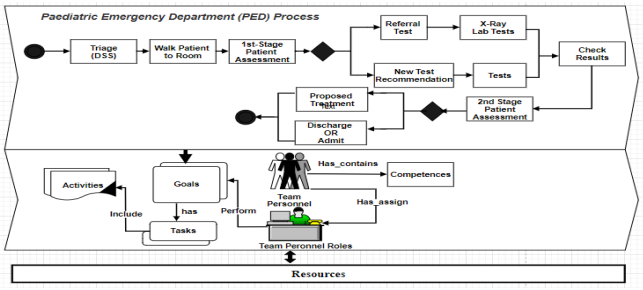

Figure 1. Pediatrics Emergency Department (PED) Model

Figure 1 describes the workflow how a qualified nurse prints the patient health record, places it in the treatment area, and escorts the patient to a room for further investigations. The assessment or treatment will be initiated by assigned physicians (usually residents) autonomously and at their own pace. When further investigations will be needed, physicians are responsible to fax referrals to other units and/or written orders on a paper chart and placing them in an "order box" at the nursing station. Any available nurse will be responsible to act according to the placed orders. When the test results are ready, a nurse again places the paper chart on the desk in the treatment area. At physician's end, the treatment's initiative, and the consultation will be continued until the patient is treated, admitted, or discharged. Often, residents are needed to consult a specialist, sometimes yielding further investigations or a change of plans. In a panic situation of Accident & Emergency (A&E), usually senior staff members are deployed, who are responsible to look after patients for their instant recovery, besides supervising residents, answering phone calls from primary care, taking referrals, and making rounds on inpatient wards for the consultation or typically delayed for further immediate decisions in treatment (Mazzocato et al., 2012).

3.3 Data Collection

For the data collection, we conducted two modelling workshops (Fareedi and Ghazawneh, 2018) with domain experts and knowledgeable mentors and one personal interview with the innovation manager at the pediatrics emergency department (PED), Karolinska Hospital, Stockholm, Sweden, who provided knowledge about guidelines and overall visions. We collected the primary data by using modelling workshop technique from the multidisciplinary personnel (see detail in table 1). For the improvement of the information acquiring process, we developed the case study which can be seen in detail in section 3.1.

Primary Data Sources	Description
Workshop I	This modelling workshop is conducted by *Karolinska Institutet* (*KI*) and *Karolinska Hospital, Stockholm, Sweden*. The primary data was collected from the innovation manager and multidisciplinary personnel such as medical nurses and medical practitioners etc.
Workshop II	• To develop the process view of the Pediatric Emergency Department (PED), Solna, Stockholm, Sweden by using the EKD modelling technique (Bubenko et al., 2001). • Assigned distinct roles to medical professionals with various competencies to initiate different processes and perform various activities to achieve defined set goals in the emergency unit.
Personal Interview	•As a team, we conducted one interview with the innovation manager/researcher there in the PED emergency unit, Karolinska Hospital, Solna, Stockholm, Sweden to get some guidelines and follow her mission to improve the long wait times and overcrowding issues in emergency units by deploying some innovative solutions e.g. health conversational agent (e.g. chatbot, etc.).

Table 1. Data Sources

3.4 Data Analysis

The data analysis section can be described as a five-phase process: knowledge elicitation, tacit knowledge modelling, developing questions and answers knowledgebase, conversational modelling (CM), deployment, and evaluation (see table 2). First, we used the tacit knowledge acquisition approach in modelling workshops and elicited knowledge from the domain experts, and medical and IT practitioners in workshops I, and II. Using our conceptual modelling basis of PED, we perceived some concepts related to the emergency unit and identified various key actors and their assigned distinct roles, various tasks, and their activities, and defined set goals. The second phase of our data analysis explains how the knowledge modeler perceives the tacit and structured knowledge from various sources, models them, and makes an analysis to adopt the solution that is the best candidate to address the identified issues in the hospital emergency unit. The third phase of our data analysis is, that the knowledge modeler establishes a questions and answers pool for the emergency department (ED) and patient treatment procedures and covers the scenario identified in the workshop, especially in a panic situation. The fourth phase of our data analysis explains how the knowledge modeler develops the conversational format of models as a dialog which is the logical flow linking between sets of intents and domain knowledge entities. These intents are usually referred to as human expressions such as "Greeting Questions: Hi, Hello" and asking some domain-related questions from the chatbot. The fifth phase emphasizes different evaluation strategies to verify that the conceptual model contains enough information to answer questions which are related to the domain (PED) and justify the conversational format of models as a dialog using the AIML technique and established pandorabot framework (Pendorabots, 2022).

Phases	Tasks	Outputs
Knowledge Elicitation	• Elicited knowledge from workshop I, II. • Construct questionnaire for the interview. • Decide knowledge modelling techniques e.g., EKD.	• Research data repository. • Identify numerous key concepts related to the PED processes. • Identify distinct roles, various tasks, activities, and defined goals. • Identify different conceptual modelling tools e.g., M.S. Visio, etc. • Make selection of frameworks e.g., pandorabot etc. for the development of the chatbot related to the health domain. • For designing the chatbot, use AIML technique with the present of programming platform e.g., python.
Tacit Knowledge Modelling	• Knowledge modelers perceive the tacit knowledge from various sources and model them.	• Process view of the PED. • Information sets. • External process. • Key processes.
Developing Question and Answer Knowledgebase	• Knowledge modeler constructs question and answers knowledgebase covering human expressions and domain knowledge.	• The set of Q&A sub-categories such as *Greetings*, *Demographic Information*, *General questions* experienced in emergency and several stages of patient-treatment in medical unit.
Conversational Modelling (CM)	• Developer is responsible for developing intent file.	• Created knowledgebase that is based on context-oriented questions and their answers. • AIML scripting file which contains the intent file

		that covers the human expressions and domain knowledge related to PED.
Deployment and Evaluation	• Design and deploy chatbot following layers architecture. • Code generation using programming APIs. • Evaluation using manual assessment with domain users and experts.	• Develop prototype of the chatbot related to the emergency healthcare services. • Execution of the accurate answers to questions tested by domain users or experts.

Table 2. Data Analysis

4 Design methodology

4.1 Building an Approach for Tacit Knowledge Acquisition

Through extensive desktop research, numerous modelling techniques (Jun et al, 2010; Völzer, 2010) have been suggested for the tacit knowledge acquisition and address the issues but the enterprise knowledge development (EKD) modelling technique (Bubenko et al., 2001) is considered one of the most promising modelling techniques especially in modelling workshop (Fareedi and Ghazawneh, 2018) for healthcare study see in figure 2.

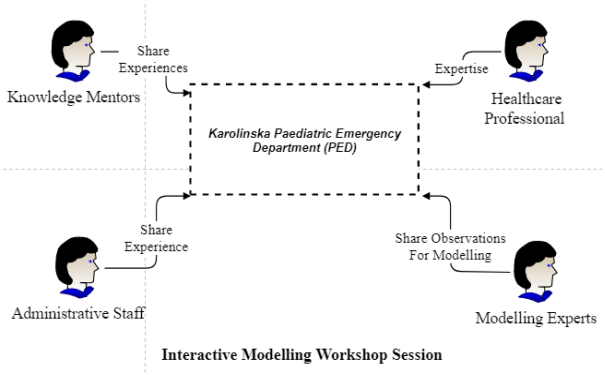

Figure 2. Modelling Workshop (Fareedi and Ahmad, 2018)

The Modelling Workshop: The modelling workshop is the platform where multidisciplinary personnel with their expertise, experiences, and competencies can share the information and tacit knowledge from their previous experiences. The EKD helps to acquire the tacit knowledge from the domain experts according to their skills, experiences, and competence during the modelling session for the systematic workflows in healthcare processes.

4.2 Building an Approach for Developing AI-Enabled Anatomy of Chatbot Architecture

In the logical layer, the AIML technique is designed to apply not only for the acquisition of domain knowledge but also helps to process the conversation knowledgebase (KB) between humans and machines. The figure-3 illustrates a brief interpretation and a practical execution of the multiple layers architecture framework which is based on a conceptual model of the Pediatric Emergency Department (PED) that is used in AIML scripting. These modelling techniques also support healthcare processes, certain activities, and different patient-oriented services in Emergency Department (ED). These layers are well connected from various data acquisition (DA) sources and interactive channels (e.g.,

webpages, chats, instant-messaging, voice-messages, etc.) and from the multidisciplinary healthcare professionals, convert this domain-oriented conversational knowledge into the understandable knowledge (machine-understandable) with the help of Artificial Intelligence Modelling Language (AIML) in a very natural way. In figure 3, The AIML is given as a feed to the chatbot which encapsulates the conversational data and stores it in small-scale database (DB) (e.g., db.sqlite3). If the users put the query in the form of text-messages or voice-messaging, the chatbot searches the specific answer through well-matched patterns, and delivers in the response to the users. This intelligence behavior of the chatbot can be improved with the help of machine learning (ML) paradigms so continuous learning makes the chatbot smarter than smarter and it seems to behave like a human.

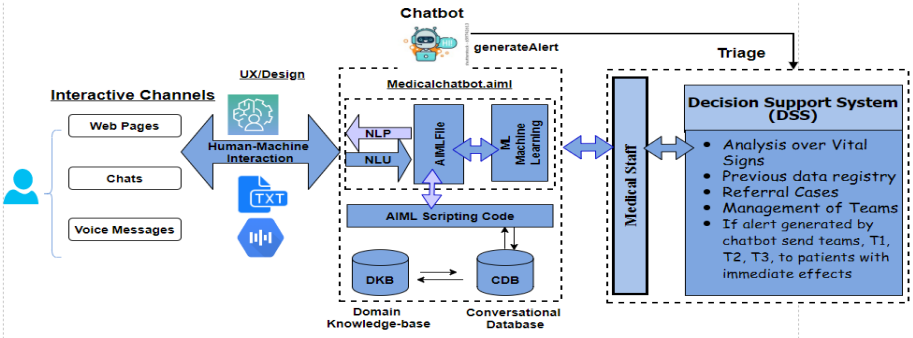

Figure 3. Multiple Layers Framework for Developing AI-enabled Chatbot

This chatbot creates an interactive session either Instant Messaging (IM) or Voice-Messaging (VM) with the patient or relatives in a panic situation before arrival at Emergency Department (ED) and helps them for reducing stress and fatigue levels in their rough panic time. Initially, the chatbot will ask some basic questions related to symptoms for inquiry and initial assessment to seek its urgency towards medical assistance. If the patient looks serious in assessment, it directly refers to Triage with triggering signals (Rognes and Sahlin, 2010).

Here, the Triage is a Decision Support System (DSS), which performs many operations and helps to improve the information-flow processes in Emergency Department (ED), usually takes vital signs and does analysis and also keeps patient medical history, and referral reports for further necessary medical actions. Similarly, the Triage also entertains various multidisciplinary professional teams such as T1 (Pediatric Nurse, Practitioner, etc.), T2 (Medical Doctor, Surgeon, etc.), T3 (Nurse, Practitioner and Medical Doctor, etc.) who are assigned to serve in various situations and panic time. In Sweden, two different systems for the triage have been developed for healthcare workflow procedures, e.g., the Medical Emergency Triage and Treatment System (METTS), and Adaptive Process Triage (ADAPT) (Rognes and Sahlin, 2010).

This conversational training helps healthcare professionals in Emergency Department (ED) for avoiding long-waiting queues and addressed overcrowding issues. Mostly in observations, many patients are used to visiting the emergency department (ED) of the medical unit with less serious situations because they are not familiar about their illness, so they only believed what they perceived. So, the chatbot technologies motivate to the patient and their relatives and also give some awareness and confidence on, how to improve panic time in case of emergency with the help of guidelines and necessary information that is already stored in the brain of the chatbot.

5 Results and Implementation

5.1 Intent File: Designing Questionnaire related to Early-assessment while Waiting Area

In this section, based on our data collection and analysis we built interactive "*questions and answers*" drills as a intent file that give an overview, *how to manufacture dialogues between humans and machines* so that the machine can mimic a human. It is also testified in Pendorabots framework see in *figure 4*.

Human Question: *Hi, Are you medical assistant?*
MediBot_Answer: Hello there!, Yes, I am glad you reached out, I am *Medical-chatbot*, I am here to answers all of your questions.
Human_Question: *Where can we find children related medical assistance in Emergency, Can we find?*
MediBot_Answer: Yes, You can find here in *Solna, Stockholm, Sweden* and Welcome to *Karolinska Institutet Hospital, Stockholm.*
Human_Question: *Can I find necessary information related Emergency Department Solna, Stockholm?*
MediBot_Answer: Yes, you can find in the following link: https://www.karolinska.se/en/karolinska-university-hospital/news/2016/12/pediatric-emergency-ward-in-the-new-hospital-building/

<!-- Medical Assessment Session -->

Human_Question: *Are you* looking for patient personal detail?
MediBot_Answer: Yes, Why not, enter your necessary information with respect to *Name, Age, Phone number, Locality, City* and *Country*.
Human_Question: *Can I find the appointment for myself or some one else?*
MediBot_Answer: Yes, you can find appointment for yourself or someone else; child.
Human_Question: *Which kind of medical assistance do you offer*?
MediBot_Answer: Here, you can find many options; 1) *Medical Doctor Appointment*, 2) *Health Diagnosis*, 3) *Health Check-up*, 4) *Admission Enquiry*, 5) *Emergency, 6) Diet Control and 7) Others.*

<!-- Medical Diagnosis Session -->

Human_Question: *I am not feeling well and look forward to seeing some medical assistance.*
MediBot_Answer: Okey, Can you tell me, what is wrong and what are the symptoms you are feeling?
Human_Question: *I am getting severe headache*
MediBot_Answer: What kind of headache you are getting, i) Migraine Headache+ ii) Cluster Headache+ iii) Tension Headache+

<!-- Medical Doctor Appointment -->

Human_Question: *I am looking for medical doctor appointment?*
MediBot_Answer: Yes, OK, We are here to serve you. Do you need appointment for yourself or someone else?
Human_Question: *I am looking for specialized doctor?*
MediBot_Answer: If yes, then we have the following doctors (*e.g. Dr. John etc.*) for you in specific time slots. So please let me know your preferences.
Human_Question: *Can you please confirm time slot?*
MediBot_Answer: Yes, we can confirm your time-slot according to your time convenience. Can you share your information; Name, Age, Social Security Number and here are the time slots; i) *09.00 A.M--11.00 A.M, ii)11.00 A.M--13.00 P.M iii) 14.00 P.M--16.00 P.M.*

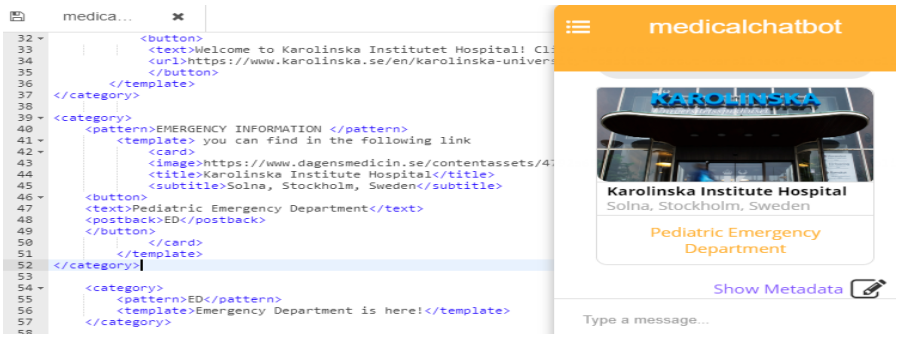

Figure 4. Execution of Medicalchatbot.aiml file in Pandorabot Platform

5.2 Implementation of the Prototype

The implementation phase of this research work emphasizes on NLP strategy and various phases of NLP-based supported chatbot 1) Development of intent-file, 2) Text-processing Approaches; Tokenization, Lemmitization, stop-word removal process Stemming, bag-of-words procedure and implementation of TF-IDF and Cosine-Similarity algorithm. This work also gives the importance of the NLP technique which helps to retrieve knowledge from the corpora (e.g., domain knowledge) and helps to make sophisticated interactions between end-users (e.g., humans) and machines (e.g., chat-bot). These chatbots technologies create intelligent behavior like a human mimic and give the same response as a human. The following results also give the depiction of the interactive session between humans and machine and this initial prototype is built in python-language APIs which is mentioned in the figure-5 and figure-6.

This research work opens new directions of Human-Machine interaction (HCI) and its self-learning strategies and abilities, and highlights how a chatbot can be used as an AI-applications in the medical sector to improve information-flow processes and what will be the effects after deploying in pediatric emergency department (PED) to facilitate healthcare practitioners and their perspectives (Palanica et al. 2019) in case of emergency or panic situations. These chatbot technologies also facilitate the patients (end-users) and their perspectives to give most of the necessary information in case of emergency without any delay and help their relatives or attendees to navigate and access of the right information with control nerves. This work also gives some motivation to developers and their technical aspects for developing methodologies (Zeineb et al. 2020) to support AI agents (e.g., chat-bots, recommended systems, etc.) and develop some innovative healthcare-related services to facilitate patients/relatives in case of emergency or panic situation.

5.3 Evaluation of the Prototype

In this paper, we have developed a prototyping evaluation process which gives a detailed interpretation of various elements in *Natural Language Processing (NLP)* techniques to deal with domain knowledge of *Emergency Department (ED)* that will be useful for the development of *goal-oriented dialogue-based interactive system* having textual and voice recognition capabilities. Although, this prototype gives us the foundation for the development of interactive software applications (*e.g. chatbots etc.*) as one of the qualifiers for addressing the above-mentioned issues in the *emergency department (ED)* in healthcare unit of *Solna, Karolinska Institutet (KI), Stockholm, Sweden*.

```
import nltk
from nltk.stem import WordNetLemmatizer
nltk.download('popular', quiet=True) # for downloading packages
nltk.download('punkt') # first-time use only
nltk.download('wordnet') # first-time use only
```

Figure 5. Natural language Processing Libraries Usage in Implementation Process

Figure 5 describes the usage of NLTK (Natural Language Toolkit) that is used for the building natural language processing applications which usually work with human language data and also provide easy-to-use interfaces to some corpora and lexical resources (e.g. WordNet, etc.) and Text-processing libraries for natural language operations such as classification, tokenization, stemming, tagging, parsing and semantic reasoning. In the following figure-4, we have tried to explain the functionality of TF-IDF approach for information retrieval-pattern which helps to retrieve from knowledge-repository and assigned within the vector-space model for the generation of possible responses from the bot (assigned named: MediBot) against input questions. Similarly, the functionality of Cosine Similarity helps to receive responses in the searching process against the user's utterance for one or more known keywords and returns one of several possible responses.

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity

def response(user_response):
    Medi_response=''
    sent_tokens.append(user_response)
    TfidfVec = TfidfVectorizer(tokenizer=LemNormalize, stop_words='english')
    tfidf = TfidfVec.fit_transform(sent_tokens)
    vals = cosine_similarity(tfidf[-1], tfidf)
    idx=vals.argsort()[0][-2]
    flat = vals.flatten()
    flat.sort()
    req_tfidf = flat[-2]
    if(req_tfidf==0):
        Medi_response=Medi_response+"I am sorry! I don't understand you, I should refer to Triage for further Medical Assistance"
        return Medi_response
    else:
        Medi_response = Medi_response+sent_tokens[idx]
        return Medi_response
```

Figure 6. Execution of TF-IDF Approach and Cosine Similarity

In the figure 6, the evaluation can be testified by using questions and answers session drills by potential domain users (e.g. patients/relatives and healthcare professionals) so that humans can get reliable information related to the domain (e.g. medical context) from the machine (MediBot) in a very natural way. According to (Meier et al., 2019), some indicators (see table 5) are observed through experiences and testing iterations. These indicators are mentioned such as perceived flexibility, friendliness, understandable, comprehension, voice clarity, consistency, pleasantness, low cognitive demand, consistent user experience, task success, system reliability, and expectation match, and verified by domain users and IT experts.

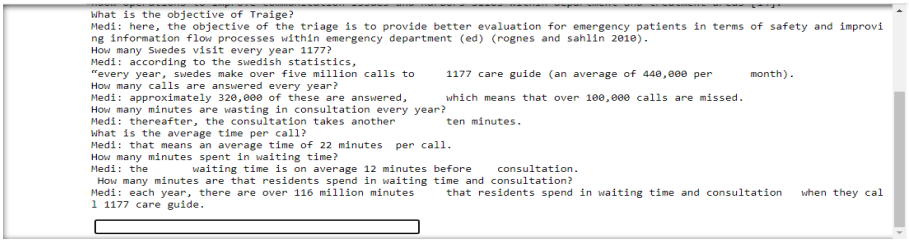

Figure 7. Developed Prototype of Medical-Chatbot (Madi)

6 Discussion

The main objective of this study was to conduct modelling workshops to achieve knowledge about mechanisms structuring domain experts' use of information related to emergency units. This study also focus on explaining various available solutions during the modelling workshops, resulting in us proposing a chatbot as an AI agent application which can be considered one of the solutions to address patients' related unexpected experiences of long waiting times, overcrowding issues, and high number of patients leaving without diagnosed are addressed within emergency unit. This study also mentions healthcare professional perspective and patient perspective. According to the healthcare professionals, this proposed solution using NLP techniques creates a platform where patients can interact with machine in a natural way and establish questions and answers sessions. This small scale (10-15 questions) conversation between patient or attendee and machine can help for establishing primarily assessment of patient's condition and need of medical urgency. This conversational training helps healthcare professionals in Emergency Department (ED) avoid long waiting queues and thus address overcrowding issues and improve multiple steps in the front-end triage procedures with inconsistent practices, minimize the high percentage of patient handling in the waiting room during peak time. Similarly, mostly in observations, many patients visit the emergency department (ED) of the medical unit with less serious situations because they are not familiar about their illness' lack of severity. In these situations, chatbot technologies can motivate the patient and their relatives and give some awareness and confidence on how to reduce panic in case of emergency with the help of guidelines and necessary information that is already stored in the chatbot.

This formal model is considered to develop natural language processing (NLP) applications which helps to establish one-to-one connection with an interactive graphic user interface (GUI) and served as text-based messaging and supports voice-recognition behaviors in natural language (NL) for making good understanding. The advantage of this model helps to engage domain-users (e.g., healthcare-workers, practitioner, etc.) and potential users (e.g., patients/relatives). They can make prior interactions through text-messaging behaviors (e.g., SMS) and get maximum information in panic-time and get some more timely information before visiting to the emergency department (ED) in medical unit. Similarly, healthcare professionals can also get some assistance to deal with patients at peak times, which is, itself a challenging situation for the healthcare workers in the medical unit. The study found that there are key factors, which are likely preferable to convince healthcare-professionals to incorporate AI agents in medical units and motivate entrepreneurs to invest and develop these types of solutions to tackle further pandemic situations in the future. These factors are discussed as follows:

- **Accessibility:** every year swedes are significantly counted due to the inefficient and negligence behavior of 1177 care-guide (Vårdguiden, 2021) and most patients are suffered due to less medical facilitation at the time of emergency or in overcrowded situation in the medical unit. By the incorporation of proposed solution Medical Chatbot (Madi) gives the opportunity to the potential users, especially patients and their relatives in emergency times, they can get pre-visit suggestions, emergency department's location information, medical remedies, initial medical assessment to avoid waiting time through the text-messaging facility because some patients are too sensitive, and they just rush to emergency after getting causal stress and traumas or frustrations. By doing these practices with chatbot communication, several patients are well-relieved and ultimately pressure on the emergency department is also reduced tremendously.
- **Entertaining Enormous Amount of Interaction Capacity:** As we know, human capacity only deals with a minimum number of patients at the same time because healthcare professionals need more concentration in response to listening patient's pains and reading their patient's history, needs and requirements. So they cannot communicate with more than one human at a time but a chatbot can have conversations with thousands of people/patients simultaneously. No matter what time of the day or night it is or how many people are contacting healthcare organizations, answering time can be significantly improved (Bajpai and Kannaujiya 2018). By deploying assistive technologies (e.g., chatbot, etc.) in practice, the healthcare deliverance can be improved with efficiency and the workflow of the emergency department can also be improved effectively.
- **Flexibility in Usage:** One of the significant advantages of chatbot technologies is, it can easily be used in any industry unlike other solutions where we have to do a lot of reverse-engineering phenomena to get desired results and made lots of development changes for testing as well (Bajpai and Kannaujiya 2018) but chatbot gives some advantages to switch in any domain, only one has to train the bot by giving the right conversation or intent as knowledgebase (Bajpai and Kannaujiya 2018).
- ***Potential User Satisfaction:*** Healthcare professionals can make mistakes during the assessment. In such situations chatbots are systematical due to their mechanically boundedness with well-defined programmable constraints. Chatbots always have the tendency to treat humans equal, no matter how rough the person is or how foul language the person uses during waiting time in *Emergency Department* (*ED*) (Bajpai and Kannaujiya 2018). The chatbot keeps the log history during interaction which can be useful for making a quick assessment in the next visit because some relative information is already stored in its *brain* knowledgebase, so it can give *suggestions* (such as home remedies, and dietary plans) before the next visit or in the emergency situation (Satu et al. 2015).

7 Conclusion

The objective of this study was to give some awareness of the increasing importance of chatbot technologies, and how conversational agents can become a first-level communication layer between patients and administration for the preliminary medical assessment and help to provide necessary information to patients in case of emergency. Similarly, human-machine interaction (HCI) can be helpful for relevant information retrieval (IR) from the knowledgebase repository in medical contexts. For future enhancement, this work can be improved at further-level to make a complete solution that facilitates the end-users and healthcare practitioners in the medical context to give the right information related to the right medical assistance in a panic situation and improve communication with multilingual support as a human-like mimic and will have implanted in the emergency department (ED) of Karolinska Hospital, Solna, Stockholm, Sweden and as per as more concise evaluation is concerned with primary stakeholders of this discussion (e.g. healthcare workers, practitioners, visitors (e.g. patients, relatives, etc.).

References

Agarwal, M. and A. Sexena (2019). "An overview of natural language processing". *International Journal for Research in Applied Science and Engineering Technology (IJRASET)* 7 (5), 2811-2813.

Arwidson, J. (2020). *Healthcare: Chatbot can streamline healthcare.* URL: https://www.pwc.se/sv/publikationer/halso-sjukvard/halso-sjukvard-chatbot.html (visited on June 12, 2022).

Bajpai, G. and R.K. Kannaujiya (2018). *Chatbot in Python: A Project Report.* Department of Information Technology, Rajkiya Engineering College, Azamgarh, India.

Bubenko, J.A., A. Persson and J. Stirna (2001). *D3: User guide of the Knowledge Management approach using Enterprise Knowledge Patterns*. Royal Institute of Technology (KTH) and Stockholm University, Stockholm, Sweden.

Dandekarl, N. and S. Ghodey (2017). "Implementation of a chatbot using natural language processing". *9th International Conference on Recent Development in Engineering Science, Humanities and Management*, 99-105.

Fareedi, A.A. and A. Ghazawneh. (2018). "An ontology approach for knowledge acquisition and development of health information system (HIS)". *27th International Conference on Information Systems Development (ISD)*, 1-13.

Farrokhnia, N. and K.E. Göransson (2011). "Swedish emergency department Triage and interventions for improved patient flows: A national update". *Scandinavian Journal of Trauma, Resuscitation and Emergency Medicine* 19(72), 1-5.

Haftor, D. M. Kajtazi. and A. Mirijamdotter (2011). "A Review of Information Logistics Research Publications". *International Workshops BIS-2011 and BPSC International Conference*, Poznań, Poland, 249-260.

Hussain, S. and G. Athula (2018). "Extending a conventional chatbot knowledge base to external knowledge source and introducing user based sessions for diabetes education". *32nd International Conference on Advanced Information Networking and Applications Workshops (WAINA),*IEEE, 1-11.

Hussain, S., O.A. Sianaki, A. Nedal (2019). "A Survey on conversational agents/chatbots classification and design techniques*". Workshops of the International Conference on Advanced Information Networking and Applications*, *WAINA,* 946–956.

Jun, G. T., J. Ward and , P. J., Clarkson (2010). System Modelling Approaches to the Design of Safe Healthcare Delivery: Ease of Use and Usefulness Perceived by Healthcare Workers, *Ergonomics* 53(7), 829-847.

Kocielnik, R., E. Agapie, A. Argyle, T.D. Hsieh, K. Yadav, B. Taira and G. Hsieh (2019). "HarborBot: A Chatbot for Social Needs Screening". *AMIA Annual Symposium Proceedings Archive*, 552–561

Lalwani, T., S. Bhalotia, A. Pal, S. Bisen, and V. Rathod (2018). "Implementation of a chatbot system using AI and NLP". *International Journal of Innovative Research in Computer Science & Technology (IJIRCST)* 6(3), 26–30.

Mazzocato, P., R.J. Holden, M. Brommels, H. Aronsson, U. Backman, M. Elg and J. Thor (2012). "How does lean work in emergency care? A case study of a lean-inspired intervention at the Astrid Lindgren children's hospital". *BMC Health Services Research*.

Meier, P., J.H. Beinke, C. Fitte, C. Behne and F. Teuteberg (2019). "FeelFit–Design and Evaluation of a Conversational Agent to Enhance Health Awareness". *Fortieth International Conference on Information Systems,* Munich*,* p.1-17.

Nordheim, C.B., B.N., A. Folstad, and C. Bjørkli (2019). "An initial model of trust in chatbots for customer service—Findings from a questionnaire study". *Interacting with Computers* 31 (3), 317-335.

Palanica, A., P. Flaschner, A. Thommandram, M. Li, and Y. Fossat (2019). "Physicians' perceptions of chatbots in health care: Cross-sectional web-based survey". *Journal of Medical Internet Research* 21(4), 1-11.

Parviainen, J. and J. Rantala (2021). "Chatbot breakthrough in the 2020s? An ethical refection on the trend of automated consultations in health care". *Medicine, Health Care and Philosophy*.

Pendorabots (2022). URL: https://home.pandorabots.com/home.html (visited on August 26, 2022).

Ramesh, K., S. Ravishankaran, A. Joshi and K. Chandrasekaran (2017). "A survey of design techniques for conversational agents". *International Conference on Information, Communication and Computing Technology*, Springer, Singapore, 336-350.

Rognes, R. and N. Sahlin (2010). *Triage and flow processes in emergency departments: A systematic review*. SBU Report, ISBN: 978-91-85413-33-1. Swedish Council on Health Technology Assessment, Sweden.

Satu, M.S., M.H. Hasnat and S.A. Mamun (2015). "Review of integrated applications with AIML based chatbot". *1st International Conference on Computer & Information Engineering*, 26-27.

Srinivasan, A. and N. Madheswari (2018). "The role of smart personal assistant for improving personal healthcare". *International Journal of Advanced Engineering, Management and Science (IJAEMS)* 4(11), 769-772.

US-Acute, C.S. (2021). *Organizational transformation at a pediatric emergency department*. URL: https://www.usacs.com/organizational-transformation-at-a-pediatric-emergency-department. (visited on June 12, 2022)

Vårdguiden. (2021). 1177 Vårdguiden- tryggt om din hälsa och vård URL: https://www.1177.se/Stockholm/ (visited on June 12, 2022).

Völzer, H. (2010). *An Overview of BPMN 2.0 and its Potential Use*, IBM Research, Zurich.

Wizenbaum, J. (1966). "ELIZA—A computer program for the study of natural language communication between man and machine". *Computational Linguistics* 9 (1), 36–45.