Conversational Artificial Intelligence (AI) in the Healthcare Industry

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Abstract

The study presents an innovative approach to incorporating AI-driven conversational agents (CAs) or social robots technologies into healthcare information systems (HISs) and revolutionizing healthcare delivery systems. The study aims to improve accessibility and personalization, and minimize adverse risks, especially in the emergency departments (EDs). The study investigates patient-related experiences, long waiting times, and overcrowding issues during peak hours in EDs. Design science research methodology (DSRM) principles were tailored with modelling workshop method to capture domain contextual knowledge and include practitioners' cognitive-tacit knowledge-ability into HIS to address the above-mentioned issues. The developed social robot artifact incorporates an artificial intelligence markup language (AIML) technique as a model to restore domain knowledge of EDs, which serves as a foundation for developing goal-oriented interactive conversational system artifact between humans and machines. As a result, the study contributes that CAs, considered value-added AI-driven applications such as CAs or social robots, serve as a coworker to facilitate healthcare practitioners and patients, catering to patients' needs and communication to enhance care delivery experience and improve information flow processes using interactive services within EDs. The research presents a promising solution to improve patient outcomes, reduce waiting times, and enhance communication between patients and practitioners in EDs.

Keywords: Conversational agents (CAs), Social robots, Artificial intelligence markup language (AIML), Design science research (DSR), Health information system (HIS)

1 Introduction

Over the last two decades, studies have shown the role of conversational agents (CAs) or social robots and their potential benefits of using customized CAs for health-related activities in digital workplaces (von Wolff et al., 2020; McTear et al., 2016; Weizenbaum, 1996; Bickmore, 2013). Advances in voice recognition, natural language process (NLP), and artificial intelligence (AI) have led to a foundation for the integration of CAs (*e.g., social robots, chatbot, etc.*) systems that mimic human conversation using text or spoken language (Laranjo et al., 2018). Some familiar examples of CAs include voice-activated systems like *Apple Siri*, *Google Assistant, Microsoft Cortana*, and *Amazon Alexa* (McTear et al., 2016).

CAs, also known as social robots or chatbots, are computer software programs designed to simulate human text or verbal conversations and are increasingly used in various fields, including the healthcare sector (TudoCar et al., 2020). These systems use a chat interface to diagnose a specific disease based on an individual's input (Laumer et al., 2019). They also facilitate by enabling better accessibility, personalization, and efficiency, assisting clinicians with counselling, helping users to change their behaviour, and helping clinicians to minimize adverse risks in emergency departments (EDs) (Laranjo et al., 2018). In particular, the development of conversational user interfaces (CUI) is helping to enable new forms of human-machine interaction (Marietto et al., 2013).

Although the service industry is increasingly technology-driven than people-driven, this has led to the development of CAs to support health-related activities. CAs assist with behavior change, treatment support, health monitoring, education, triage, and screening. CAs also help minimize adverse risk factors in hospital settings (Pinxteren et al., 2020). Automating these tasks could free healthcare professionals to focus on more complex tasks through collaboration that could mitigate the shortage of qualified healthcare workers, assist overworked medical professionals and improve the quality of healthcare services in healthcare organizations (von Wolff et al., 2020; Lai et al., 2021). It also helps to improve access to health services with networked health information systems *(HIS)* for the general public, especially in panic situations (Milne-Ives et al., 2020).

Studies have highlighted the benefits of using AI-driven CAs in the broader healthcare setting, such as coaching to support healthy lifestyles, monitoring chronic conditions, supporting therapy patients, and supporting the personalization of healthcare through CAs (Montenegro et al., 2019). However, still, a significant research gap needs to be covered. There is a roam by testing and deploying customized CAs that include contextual and tacit knowledge (TK) in the ED to improve *information flow processes*, *improved inaccurate assessment* and *social stigma* (Yan and XU, 2021) and minimize adverse risk factors related to patient care, and serve as a coworker with practitioners in an emergency unit of the medical hospital (Sawad et al., 2022).

According to the statistics (US-Acute, 2021), there is a *75%* increase in patient visits yearly. ED typically faces challenges: unexpected patient experiences such as bed capacity issues, long waiting times, overcrowding, high numbers of patients leaving without diagnosis or treatment, patient safety concerns, and patient and family dissatisfaction. This study focuses only targeting **RQ:** *how CAs/social robots address unexpected patient-related experiences, exceptionally long waiting times, and overcrowding issues and elevate information flow processes during peak hours in ED?* In *ubiquitous computing*, the development of interactive interfaces makes communication more intuitive.

The study aims to develop intelligent assistance solutions (*e.g. CAs, social robots, chatbots, etc.*) that incorporate contextual knowledge, provide contextual services and also help to improve information flow processes and healthcare outcomes within ED. It also explores the extent to which CAs could be a helpful tool to capture healthcare professionals' knowledge to guide patients more efficiently and enable health workers to spend more time with patients with severe conditions in the ED. The goal is to design a customized CA using *artificial intelligence modelling language* (AMIL) that accurately responds to patients with less urgent needs. The CA will include contextual knowledge and perform interactive dialogue-based information stored in a local data repository for analysis and improved personalized health services in various scenarios.

The proposed solution can be considered a mediator between patients and healthcare providers, enabling practical and useful interactions before or upon arrival at the medical department to address some overcrowding issues in ED (*e.g., pediatrics emergency department (PED)),* which are a global challenge. The proposed solution helps to reduce waiting times and improve the flow of healthcare information in the ED significantly. To develop the CA, the team used AIML and incorporated recognition (PR) and pattern matching (MP) (Abu-Shawer and Atwal, 2003; Ahmad and Singh, 2015). The stimulus-response approach was also followed, and natural language modelling was used to construct dialogue management between humans and machines, as outlined in (Marietto et al., 2013).

This paper is structured with the following sections: *Section 2* provides a brief overview of desktop research, the conceptual basis of conversational agents (CAs) and AI in information systems (IS), Conversational agents trends, practices, and frameworks for ISs. *Section 3* presents the methodology: the case study, data collection, data analysis, problem identification and motivation for tacit knowledge acquisition, comparative analysis of CAs frameworks, and design and development of the *AIML* approach for a goal-oriented dialogue system. *Section 4* describes the Anatomy of AI-powered CA and its architecture. *Section 5* explains the evaluation cycles of the prototype. *Section 6* presents the results and discussion. Lastly, *Section 7* offers a conclusion and future possibilities and directions.

2 Theoretical Background

2.1 Conversational Agents and Artificial Intelligence in Information Systems (IS)

In the field of computer science (CS), as well as in the information systems (IS) domain, the idea of having dialogues between humans and machines has been around since the development of the *Turing Test* in 1950 (Ebel et al., 2020; Pryss et al., 2019). It is fascinating to evaluate whether machines can exhibit intelligent behavior compared to humans. Artificial intelligence (AI) brings intelligence to machines and enables them to behave intelligently to solve complex problems. Mostly, AI-powered systems use machine learning (ML) algorithms to train data for *analysis*, *prediction*, *clustering, and classification* into HIS, especially in the healthcare sector (Michiels, 2017). Conversational agents (CAs) usually refer to social robots or chatbots that develop an interface layer between humans and machines to provide the best possible results from their knowledge bases (KBs) and are used for monitoring and self-reporting data to enable flexible and personalized services in EDs (Resenbacke et al., 2022). The CAs knowledge base is analyzed for matching patterns when a user sends a request. If no matching patterns exist in the available data set, the database is re-initiated in iterations for optimal results. CAs possess three essential characteristics - *understanding*, *thinking*, and *acting* - that enable interactive sessions between humans and machines. By searching the knowledge base in iterations with optimally tuned patterns, the machine produces real-time *natural language understanding* (NLU) for human messages (Saveeth et al., 2018).

2.2 Conversational Agents Trends and Practices in Information Systems (IS)

The integration of CAs technologies (*e.g., social robots, chatbots, avatars, etc.*) has been acknowledged in organizations and academic research, gaining traction in almost every industry, especially in the healthcare sector (Lewandowski et al., 2021). The role of CAs is promising, especially in care-demanding situations. Including CAs and their interfaces help improve patient *medication adherence* (MA) to treatment (Jimmy and Jose, 2011). They also help patients with personalized medical treatment (Fadhil, 2018). They also help improve *digital communication*, *social media interaction*, *channel marketing*, *integrated campaigns*, *content creation, and delivery* in a natural language (Michiels, 2017). In recent times, experts in various domains are developing assistive tools like CAs (*e.g., CAs for diabetes care*) (Nguyen et al., 2021) to help healthcare professionals and other stakeholders in specific situations in the hospital setting. These tools are integrated with other digital platforms such as IoT, mobile, cloud, and HIS to model workflows and facilitate communication. leading vendors like *Facebook* and *Slack* also focus on the messenger and business bots to integrate with various information systems (ISs) (Michiels, 2017).

2.3 Conversational Agents Frameworks for Information Systems (IS)

Conversational agent (CAs) frameworks have been known as software frameworks, provide predefined functionalities that summarize the developmental complexities of building a CAs (*e.g., chatbots or social robots*), new kinds of ISs (Lewandowski et al., 2021) using an NLP engine phenomenon (Zahour et al., 2020). According to (Raj, 2019), from time to time, various CAs frameworks presented: *QnA-Maker*, *Dialogflow, Rasa-NLU & Core, Wit.ai, Luis.ai, Wit.ai, Botkit.ai, Pendorabots* (Pandorabots, 2008). Some other frameworks for developing CAs are also used in any specific fields and contexts (*e.g., healthcare, etc.*) depending on the needs and requirements of CAs development (Janssen et al., 2020). These frameworks, such as *Microsoft Bot Framework*, *IBM Watson*, and *Tensorflow*, are also known as frameworks for knowledge-base CAs development and help to execute domain knowledge in the form of queries and responses (Biswas et al., 2017). These CAs frameworks also provide one-click integration of customized domain-oriented CAs with various applications, including the most popular instant messaging applications such as *Facebook Messenger*, *Slack*, *Twitter*, *Kik*, *Line*, *Skype*, *Telegram*, *Twilio* and *Viber*. These apps are considered an enabler to work with voice assistants such as *Google Assistant*, *Amazon Alexa*, or *Microsoft Cortana* with NLP behaviour (Raj, 2019). AIML technique is used for knowledge acquisition (KA) in the *Pandorabots* framework and for sharing domain knowledge between potential users and healthcare professionals. The implementation of this technique will be discussed in the following sections.

3 Methodology

This study employs a tailored and holistic approach (*illustrated in figure-1*) which involves iterative processes to elaborate on different phases of the design science research method (DSRM) (Hevner et al., 2004; Peffers et al., 2007; Gregor and Hevner, 2013). The objective is to design and evaluate a novel digital artifacts inspired by theory of knowledge design (Muller and Thoring, 2010) within a PED setting. We utilized a customized approach of DSR and modelling workshop method (Fareedi and Tarasov, 2011; Fareedi and Ghazawneh, 2018) that helps to understand contextual knowledge management (KM) and dialogue management between humans and machines. This approach provides a systematic way to understand the problem and motivation, presentation, and demonstration of AI-powered artifact. It evaluates it from the domain expert to justify the context of PED in the hospital setting.

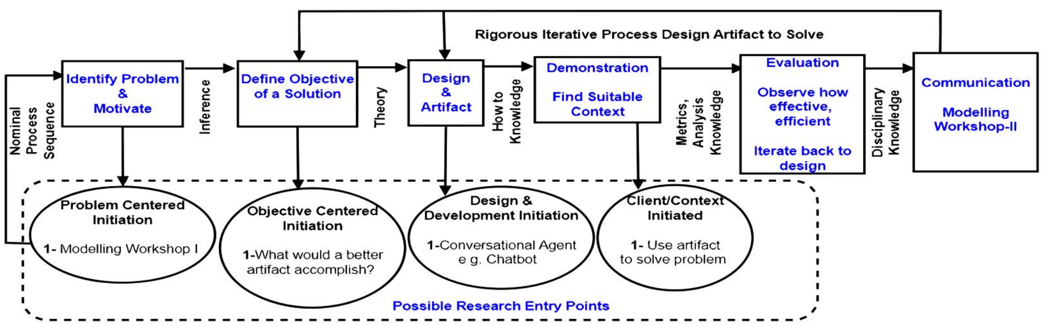

Figure 1. Customized Design Science Research (DSR) Approach

Numerous modelling techniques (Völzer, 2010; Jun et al., 2010) have been developed for acquiring tacit knowledge from domain experts and potential users to address the bottleneck issues of information flows within different contexts. This study also narrates how the AIML can manage knowledge acquisition (KA) and dialogue management processes between humans and machines using the *Pandorabots'* framework. Here, we used the enterprise knowledge development (EKD) modelling technique (Bubenko et al., 2001), considering the most promising design technique for modelling workshops, especially at *Karolinska Hospital, Solna, Stockholm, Sweden*, for the observational study on patient care in PED.

The Modelling Workshop: The modelling workshop has been partly carried out as a collaborative activity platform where multidisciplinary personnel with their expertise, experiences, and competencies with skill sets can share 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 competencies during the modelling sessions to improve the systematic workflows in healthcare.

3.1 Activity 1 & 2: Problem Identification and Motivation for Tacit Knowledge Acquisition - Construct Artifact

3.1.1 The Karolinska University Hospital Case

This study is based on a case study and direct observations in the PED of *Karolinska Hospital in Solna, Stockholm, Sweden* and inspired by the case study of *USACS* (US-Acute, 2021). As a team with multidisciplinary expertise, we conducted modelling workshops and followed specific steps (Fareedi and Ghazawneh, 2018) to facilitate better communication with domain users, medical professionals and experts responsible for emergency patient treatment procedures and explain ED workflows. Initially, we observed and tried reverse engineering the whole situation of the ED. We analyzed the information flows procedures related to the patient's treatment and admission procedure at the time of arrival at PED. After some assessment and establishing consensus, we traced some critical problems associated with patient-centric treatment procedures. We aimed to transform from an *As-Is situation to a To-be situation* in ED. From extensive desktop research, *75%* of patient visits increase yearly at ED and affected patients are used to confronting unexpected experiences such as *long waiting times and overcrowding issues* (US-Acute, 2021).

From the *Hospital's perspective*, a poorly functioning ED affects overall activities and workflows within the emergency unit, so it must be well organized (Rognes and Sahlin, 2010). To get appropriate medical assistance, we need to deploy classified information systems (IS) such as *Triage* (*e.g., decision support system (DSS)*) (Rognes and Sahlin, 2010), electronic health records (EHR), and electronic medical records (EMR). The EHR focuses on the patient's overall health and sharing information with other healthcare practitioners. Similarly, the EMR incorporates and follows the medical and treatment history of the patient. Here, Triage's role is quite promising because it helps prioritize the patients for care and treatment. Unfortunately, a massive amount of patients and a long waiting queue creates a bottleneck at Triage in ED. So we need some supporting technological solutions (*e.g., CAs, social robot, chatbots, etc.*) that help improve multiple steps in front-end Triage procedures with inconsistent practices and minimize the high percentage of patient handling in the waiting room during peak hours in the ED. They also help to initiate single-window operations to improve communication issues and harbour data silos within departments and treatment areas (US-Acute, 2021).

From the *Patient's perspective*, the long-waiting times in the ED, often accompanied by high anxiety levels, can cause the Patient's lose trust in health services. When EDs function poorly, this jeopardizes the patient's health and safety and public confidence in the healthcare system (Rognes and Sahlin, 2010).

3.1.2 Pediatrics Emergency Department (PED) Care Process

In the emergency department *(ED)*, patients are used to dealing with *Triage (Decision Support System)* on arrival by a qualified nurse or physician. Patients prioritize triage based on a *1-5 scale Triage score,* which is a bit time-taking job (Mazzocato et al., 2012). The qualified pediatric nurse enters the patient-related information into an electronic health record *(EHR)*. Patients are then sent to the waiting room or accommodated directly, depending on clinical urgency and competing care needs

(Mazzocato et al., 2012). In the *figure-2*, a qualified nurse prints out the patient's medical records, places them in the treatment area, and escorts them to a room for further examinations and investigations. The assigned physicians initiate the assessment or treatment (*usually residents*) independently and at their own pace. If further investigations are required, the physicians are responsible for faxing referrals to other departments, recording orders on a paper chart, and placing them in an "*order box*" at the nursing station. Any available nurse is responsible for following the orders in the PED area. When the results of the tests are available, a nurse puts the paper chart back on the desk in the treatment area. The treatment initiative and consultation continue on the physician's side until the patient is treated, admitted or discharged. Residents often need to consult a specialist, which sometimes leads to further investigations or a change of plans. In panic situations especially, in accidents and emergencies (A&E), senior staff usually are assigned to look after patients so that they recover quickly. They only supervise residents, answer primary care calls, take referrals, and make ward rounds for consultation or delay further immediate treatment decisions (Mazzocato et al., 2012).

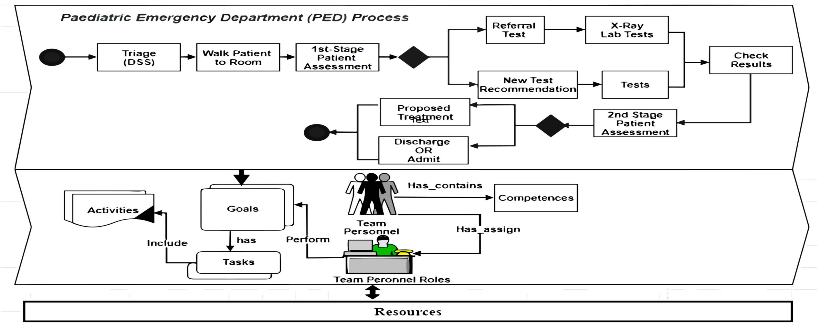

Figure 2. Pediatrics Emergency Department (PED) Conceptual Model Artifact

3.1.3 Data Collection

For data collection, we conducted two modelling workshops with domain experts and knowledgeable mentors and one personal interview for sophisticated guidelines with the innovation manager of the PED, *Karolinska University Hospital, Solna, Stockholm, Sweden*. We collected the primary data from the multidisciplinary personnel using the modelling workshop technique (*see table-1*). To improve the improvement gathering process, we developed the case study described in detail in *section 3.1.1*.

Primary Data Sources	Description
Workshop I	A student group conducted this modelling workshop session studied at the *Karolinska Institutet* (*KI*) and *Karolinska Hospital, Solna, Stockholm, Sweden*. Initially, they collected the primary data from the innovation manager and multidisciplinary personnel at PED, such as medical nurses, medical practitioners etc. • The most valuable data collected related to the patient's care pathways and resources, such as electronic health record *(EHR), Triage (Decision Support System) and* workflow procedures, were used in the emergency unit. • Different multidisciplinary participants with various competencies and skills are responsible for dealing with patients in the emergency unit; a qualified paediatrics nurse is accountable for receiving the patient upon arrival. Usually, patients are prioritized based on a 1-5 scale Triage score. • Usually, a qualified pediatrician nurse is used to enter patient-related information into an electronic health record (EHR) then patients are sent to the waiting room or sent to the emergency room directly depending on their clinical needs, urgency, and competing demand for care. • A qualified pediatrician nurse is used to print out the patient's health record, place it in the treatment area, and escort the patient to an emergency room

	for further investigations. The assessment and initial treatment will be initiated by assigned physicians (usually residents) autonomously and at their own pace. • When the results of the tests were ready, a nurse again placed the paper chart on the desk in the treatment area. The consultation continued on the physician's initiative until the patient was treated, admitted, or discharged. • Senior staff members have usually deployed in *Accident & Emergency (A&E)* panic situations. They are responsible for looking after patients for their instant recoveries, supervising residents, answering phone calls from primary care, taking referrals, and making rounds on patients' wards for consultation.
Workshop II	• To develop the process view of the *Pediatric Emergency Department (PED), Solna, Stockholm, Sweden,* using the *EKD modelling technique* (Bubenko et al., 2001) and evaluates different design artifacts with valuable feedback. • They assigned distinct roles to medical professionals with various competencies to initiate different processes and perform multiple activities to achieve defined goals in the emergency unit.
Personal Interview	• We conducted one interview with a *Nurse* (innovation manager or researcher) in PED at *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 innovative solutions such as a conversational health agents (*e.g., social robot, chatbot, etc.*).

Table 1. Data Sources

3.2 Activity 3: Defining the Objective for a Solution and Relevance

3.2.1 Data Analysis

Data analysis describes as a five-phase process: *knowledge elicitation*, *modelling of tacit knowledge*, *development of knowledge base for questions and answers*, *conversation modelling (CM)*, *deployment*, *and evaluation* (*see table-2*). *First phase*, we used the implicit knowledge acquisition approach in modelling workshops and elicited knowledge from domain experts and medical and IT practitioners in *workshop I*, and *workshop II*. Based on our conceptual modelling foundation from PED, we perceived some concepts related to the emergency unit. We identified key actors and their assigned roles, tasks, and activities and defined goals. The *Second phase* of our data analysis explains how the knowledge modeller perceives the tacit and structured knowledge from different sources, models it, and performs an analysis to adopt the innovative solution that is one of the best candidates to address the issues in the hospital emergency. The *Third phase* of our data analysis relates to the knowledge modeller concerned with creating a set of questions and answers for the emergency department *(ED)* and treatment procedures for patients and covering the scenario, especially in a panic situation. The *fourth phase* of our data analysis explains how the knowledge modeller develops the conversational format of the models as a dialogue. i.e. as a logical flow link between sets of intent files and domain knowledge entities. These intent files referred to as human expressions such as "*Greeting Questions: Hi, Hello*" and asking domain-related questions to the CAs. The *fifth phase* emphasizes different evaluation strategies. These are applied to check whether the conceptual model contains enough information to answer these domain-related questions related to PED and to justify the conversation format of the models as dialogue using the AIML technique and the established *Pandorabots* framework.

Phases	Tasks	Outcomes
Knowledge Elicitation	• Elicited knowledge from workshop I, II.	• Research data repository and Identify numerous critical and key concepts related

(Construct Level Artifact)	• Construct questionnaire for the interview. • Decide knowledge modelling techniques e.g. EKD.	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 a selection of frameworks (e.g., pandorabots etc.) for developing the CAs related to the PED domain. • For designing the CAs, use the AIML technique with the presence of the programming platform (*e.g., Python, etc.*)
Tacit Knowledge Modelling *(Neuronal Level Artifact)*	• Knowledge modeller perceives the tacit knowledge from various sources and models them.	• Process view of the PED. • Information sets, External process, Key processes.
Developing Question and Answer Knowledge-base	• Knowledge modeller constructs question and answers knowledge-base covering human expressions and domain knowledge.	• Q&A set is categorized into sub-sets such as *Greetings*, *Demographic Information*, *General questions* experienced in the emergency, and several stages of patient treatment in the medical unit.
Conversational Modelling (CM) *Symbolic Level Artifact* *(Explicit Knowledge)*	• The developer is responsible for developing the intent file.	• The knowledge base creation is based on context-oriented questions and their answers. • AIML scripting file contains the intent file that covers the human expressions and domain knowledge related to PED.
Deployment and Evaluation *Physical Level Artifact* *(Prototype/Instantiations)*	• Design and deploy CAs following layers architecture. • Code generation using programming APIs. • The evaluation process will initiate using manual assessment with domain users and experts.	• Develop a prototype of the CAs related to emergency healthcare services. • Domain users or experts can test the accurate execution of the answers to questions.

Table 2. Data Analysis ingrained Topology of Design Knowledge (Muller and Thoring (2010)

3.2.2 Analysis of Conversational Agents (CAs) Frameworks for a Proposed Solution

As part of a systematic literature review (SLR), we have reviewed a variety of CAs development concept frameworks and discussed them in the theoretical *section 2.3*. According to the reader's curiosity, we preferred to choose the pandorabots framework, which uses the AIML technique for designing CAs development in the context of this study. We have conducted comparative studies (*see table-3*), taken a foundation from (Shah and Shah, 2019), and adapted it to the best of our knowledge, so we chose the pandorabots framework for developing the health CAs in the context of this study. In the following *table-3*, we have mentioned some indicators: customized, context-aware, community learning and open-source, speech processing ability, cross-channel integration, flexible and extensible capability, machine learning support, and multilingual behaviour CAs design and development. According to the evaluation, the pandorobots framework is quite simple and flexible to accommodate AIML techniques in the form of scripts in XML format. Therefore, we agreed in the team to choose the pandorabots framework to execute the intent file with extension .aml (*dialogue management related to domain knowledge*). The execution procedure can be seen in *figure-6*.

Name	Custom.	Context Aware	Comm. Open-source	Speech Process.	Cross Channel Integ.	Flexible & Extens.	Machine learning	Multi-lingual
IBM Watson	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
QnA-Maker	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Dialog-flow	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rasa-NLU	Yes	No	Yes	No	No	No	No	No
Wit.ai	Yes	No	Yes	Yes	No	No	Yes	Yes
Luis.ai	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Botkit.ai	Yes	No	Yes	No	Yes	Yes	No	Yes
Pendorabots	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agent bot	Yes	No	Yes	No	No	Yes	Yes	No
Gup shup	Yes	Yes	Yes	No	Yes	Yes	No	No
Kitt.ai	Yes	No	Yes	Yes	Yes	Yes	No	No

Table 3. Systematic Literature Analysis of Conversational Agents (CAs) Frameworks

3.2.3 Design and Development of AIML Approach for Goal-oriented Dialog System

In this section, the *AIML approach* (Marietto et al., 2013) is based on various steps of the proposed layered architecture, which can be seen in *figure-2*. This layered architecture performs numerous functionalities, discussed in the following sections. The *First layer* is reserved for the knowledge acquisition of cognitive and tacit using acquisition methods (*e.g., Modelling Workshop Technique, Interviews, etc.*) (Fareedi and Tarasov, 2011) from the domain experts/practitioners. Here, knowledge modellers are responsible for developing conceptual models using modelling techniques (e.g., *EKD*) (Bubenko et al., 2001) to showcase them in front of domain experts. The *Second layer* is reserved for establishing intent files containing focused dialogues between humans and machines. These intents files include varieties of knowledge such as contextual knowledge of PED, greetings and domain knowledge expressed in the context of PED. These intent files help write AIML scripts following XML format in an AIML-based editor (*e.g., Pandorabots AIML Editor, etc.)* (Pandorabots, 2008). The *Third layer* explains the role of the *startup-file* with the extension *std-startup.xml* as the main entry point for loading AIML files. The *Fourth layer* is reserved for creating the human-machine interface (HMI) for voice conversation and text-base messaging using CAs and machine learning (ML) *API* in programming language platforms (*e.g., Python etc.*). The *Fifth layer* is reserved for writing code in a file that is used to load the CAs brain. It is written in the development phase in the editors of the *Python* programming language (*e.g., Pycharm, Jupyter Notebook editors, etc*.)(Fareedi et al., 2022).

4 Activity 4: Anatomy of AI-driven CA - Architecture Artifact

At the logical level, the AIML technique is not only for acquiring domain knowledge but also helps in processing the conversational knowledge base (KB) between humans and machines. The following *figure-3* illustrates a brief interpretation and a practical execution of the multiple-layered architecture framework based on the conceptual model of the PED used in AIML scripting. These modelling techniques also support healthcare processes, specific activities, and various patient-centred services in the ED. These layers are well connected with multiple knowledge acquisition (KA) sources and interactive channels (*e.g., web pages, chats, instant messaging, voice messages etc.*). Multidisciplinary healthcare professionals are used to transforming domain-oriented conversational knowledge into understandable knowledge (*machine-understandable*) with the help of AIML in a very natural way.

AIML is fed to the CAs, encapsulating the conversational data and storing it in a small-scale database (DB) *(e.g. db.sqlite3, etc.*). When the users put the query in the form of text or voice messages, the CAs search for the specific answer based on well-matched patterns and deliver the response to the users. This intelligent behaviour of the CAs can be improved using AI and machine learning (ML) paradigms so that CAs become more intelligent and competent through continuous learning and appear to behave like humans. This CA creates an interactive session either through *instant messaging* (IM) or *voice messaging* (VM) with the patient or relatives in panic situations before arrival at the emergency department (ED) and also helps them for reducing stress and fatigue levels in their difficult time of panic. Initially, the CA asks some fundamental questions related to symptoms in the initial assessment to determine the urgency of medical help. If the patient looks serious during the evaluation, they are referred directly to a Triage with triggering signals (Rognes and Sahlin, 2010).

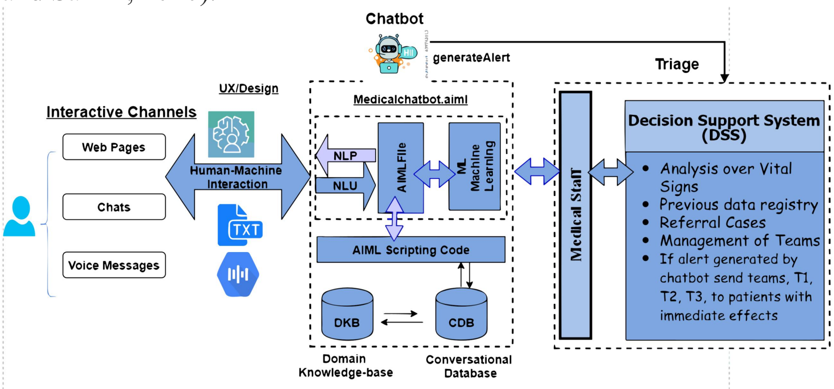

Figure 3. Multiple Layers Framework for Developing AI-driven Conversational Agent (CA)

Triage is a decision support system (DSS) that performs many operations and helps improve the PED information flow processes. It usually takes vital signs, performs analysis, and keeps patient medical history and referral reports for further necessary medical actions. Similarly, *Triage* also entertains different multidisciplinary professional teams such as T1 (*Pediatric Nurse, Practitioner, etc.*), T2 (*Medical Doctor, Surgeon, etc.*), and T3 (*Nurse, Practitioner and Medical Doctor, etc.*) who are assigned to serve in various situations and panic times. In *Sweden*, two different systems for Triage have been developed to entertain healthcare flow procedures, for instance, the *medical emergency triage and treatment system* (METTS) and *adaptive process triage* (ADAPT) (Rognes and Sahlin, 2010). This informal training helps healthcare professionals in the PED for avoiding long waiting queues and address overcrowding issues. In observations, many patients are used to visiting the ED of a medical unit with less severe medical conditions because they are unfamiliar with their illness, so they only believe what they perceive. So, CAs technologies motivate patients and their relatives and give them some awareness and confidence of *how to improve the abnormal situation and panic times in an emergency using guidelines and necessary information already stored in the brain of the CA*.

5 Activity 5: Evaluation of Conversational Agent - Prototype Artifact

In this study, we have developed a prototype artifact for the evaluation process as proof-of-a-study that provides a holistic view of an AIML as a model to capture for capturing PED domain knowledge. This modelling exercise helps develop a goal-directed dialogue-based interactive system with text and speech recognition capabilities. However, this prototype forms a foundation for developing interactive software applications *(e.g., CAs, social robots, chatbots, etc.*) as one of the qualifiers for addressing the overcrowding issues in PED in the medical unit of *Karolinska Institutet (KI), Solna, Stockholm, Sweden*.

5.1 Evaluation Cycle

In this phase, the integrated CA prototype shown in the *figure-4* results from three design cycle iterations. Within this process, we followed the FED framework (*artificial and formative strategy*) to evaluate different digital artifacts at different evaluation phases and provide some essential feedback regarding improvements to the application (Venable et al., 2016). The evaluation cycle is based on two steps: *technology and conversational agent*, *task completion and technology acceptance* (Meier et al., 2019; Makkonen et al., 2022) during the second modelling workshop with domain experts and technical personnel for valuable feedback.

5.1.1 Evaluation Cycle: Technology and Conversational Agent (CA)

In the evaluation cycle, workshop II was conducted with experts from the field of technology and domain experts with different competencies and skill sets. In the workshop, we followed the theoretical technology acceptance model (Makkonen et al., 2022) and the development team presented different stages of the prototype (*illustrated in figure-4*) to domain experts for feedback and testing (Fareedi et al., 2022). The experts gave value-added feedback, suggestions, and technical support in improving language understanding, dialogue management, and response generation. The development team also discussed possibilities for improvement and detailed performance indicators of the applications' GUI aspects (Meier et al., 2019).

Figure 4. Developed Prototype of Medical Conversational Agent (Madi)

5.1.2 Evaluation Cycle: Task Fulfillment and Technology Acceptance

This evaluation cycle was focused on technology acceptance and task fulfillment to investigate the application's perceived benefits. The domain experts and users testify to the dialogue statements management in the form of questions and answers. According to (Meier et al., 2019), some indicators 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 (Meier et al., 2019). The following *table-4* interprets the accurate depiction of this evaluation cycle related to task fulfillment and technology acceptance with the Likert scale; poor, reasonable, and excellent related to this study.

Indicators	Not satisfied-Poor	Acceptance Reasonable	Excellent
Perceived Flexibility	×	√	×
Friendliness	×	×	√
Understandable	×	×	√
Comprehension	×	×	√
Voice Clarity	×	√	×
Consistency	×	√	×
Pleasantness	×	√	×
Low Cognitive demand	×	×	√
Consistent User Experience	×	×	√

Task success	×	×	√
System reliability	×	√	×
Expectation match	×	×	√

Table 4. Observational Results of the Evaluation

6 Results and Discussion

6.1 A Process Model Artifact of Pediatric Emergency Department (PED)

In *figure-5*, we have attempted to present the workflow process model or holistic view of the PED. We have used the EKD modelling technique (Bubenko et al., 2001) to design the model related to PED. This section describes some key processes, external processes and information sets that make up the process view shown in *figure-6*.

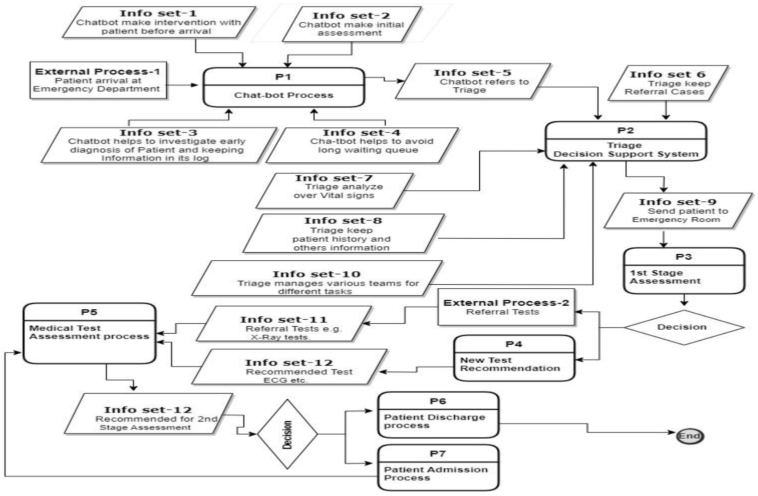

Figure 5. Process View of Pediatrics Emergency Department (PED)

Patient Arrival at ED (External Process): This process highlights the procedures or patterns for reaching ED for medical assistance. ***Triage (Decision Support System) Process:*** Triage is a decision support system (DSS) that helps improve patient care decision-making after critically analyzing medical tests, symptoms, and conditions data. ***1st Stage Medical Assessment Process:*** In 1st stage medical assessment process, the CAs or social robot is asked some essential questions to the patient relative to assess the need for serious medical help or to avoid long queues. ***Referral Tests (External Process):*** Triage also handles referral tests referred from secondary or primary medical centers. New-Tests Recommendation Process: After a critical analysis of the patient, Triage refers to medical trials for new patients. ***Medical Tests Assessment Process:*** After receiving the result of the new tests and referral tests, the medical professionals make assessments for further medical actions. ***Patient Discharge Process:*** The medical staff follows some necessary steps for discharging the patient from the medical unit. ***Patient Admission Process:*** This process includes some steps required for admission purposes to treat the patient.

6.2 Artificial Intelligence Modelling Language (AIML) Scripting Artifact

In this section, we have written Intent files based on the AIML modelling techniques following rule-based *frequently asked questions* (FAQ) and *pattern-matching* schemes. So, we have written an AIML-based file that processes only one pattern, load AMIL *medicalchatbot.aiml*. When we give the bot some commands in written/text form or based on speech recognition in the UX interface, it first loads essential intent files *(medicalchatbot)* with *aiml.extension* until it stops working. We have created a KB based on the context-related questions and answers presented in *medicalchatbot.aiml.* It follows *pattern-matching principles* (Abu-Shawer and Atwal, 2003) and responses schema phenomenon in the execution procedure. It also follows an evaluation procedure demonstrated in the *Pandorabots* platform in *figure-6*.

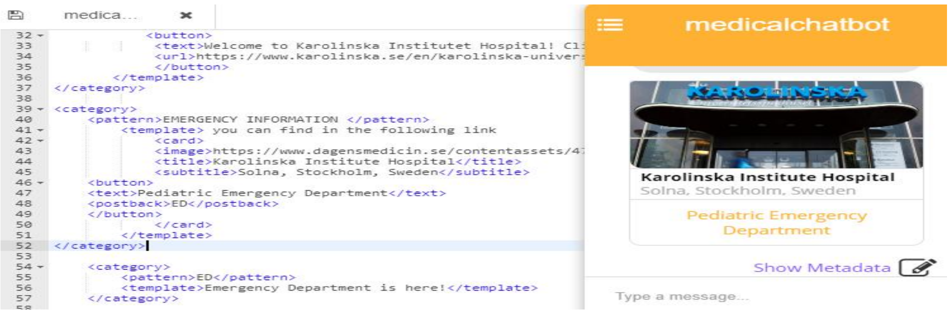

Figure 6. Execution of Medicalchatbot.aiml file in Pandorabots Platform

Our findings present an innovative approach to incorporating AI-driven CAs or social robots technologies in the IS domain. The study aimed to improve accessibility and personalization and minimize adverse risks such as long waiting times and overcrowding issues in hospital settings. One of the significant strengths of the study is the use of DSRM tailored with modelling workshop methods to capture domain contextual knowledge and include practitioners' cognitive-tacit knowledge-ability into HIS. This approach helped to ensure that the developed CA or social robot artifact was tailored to meet the specific needs of EDs, improving the accuracy and effectiveness of the conversational system. The use of the *artificial intelligence markup language* (AIML) technique as a model to restore domain knowledge of EDs and related dialogues is another significant strength of the study. AIML is an effective tool for developing goal-oriented conversational systems, which can improve communication between patients and healthcare practitioners. The study's use of conversational agents or social robots as value-added AI-driven applications to facilitate practitioners and patients is also noteworthy. However, the study also has some limitations. *First*, the study's focus on EDs means its findings may need to be more generalizable to other healthcare settings. *Second*, the study's design did not allow for comparing the developed social robot artifact with other conversational systems, which limits the assessment of its effectiveness compared to other AI-driven applications such as CAs or social robots. In conclusion, the study presents a promising solution to improve patient outcomes, reduce waiting times, and enhance communication between patients and practitioners in EDs. Its innovative approach to incorporating AI-driven CAs or social robot technologies into healthcare information systems has opened new possibilities for improving healthcare delivery systems. However, further research is needed to evaluate and validate the developed social robot artifact's effectiveness and extend the study's findings to other healthcare settings.

7 Conclusion and Future Directions

This study focuses on how CAs can be used to improve unexpected patient-related experiences and address exceptionally long waiting times and overcrowding issues during peak hours in EDs. The objective of this study was to give some awareness of the increasing importance of CAs technologies and how CAs 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. We followed a rigorous customized DSR approach to aim to design, model using AIML and evaluate digital artifacts demonstrating the conversational interaction between humans and machines, especially patients who visit the ED upon arrival. The proposed solution (*a prototype*) acts as a coworker (*assistive tool*) and facilitates patients and healthcare practitioners in a medical context to give the right information related to the right medical assistance in a panic situation and improve information flow procedures during peak hours in ED. For future enhancement, this work can be improved at a 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.

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