Intelligent Assistants in Higher-Education Environments: The FIT-EBot, a Chatbot for Administrative and Learning Support

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ABSTRACT

The purpose of this paper is to discuss about smart learning environments and present the FIT-EBot, a chatbot, which automatically gives a reply to a question of students about the services provided by the education system on behalf of the academic staff. The chatbot can play the role of an intelligent assistant, which provides solutions for higher-education institutions to improve their current services, to reduce labor costs, and to create new innovative services. Various artificial intelligence techniques such as text classification, named entity recognition are used in this work to enhance the system performance.

CCS CONCEPTS

• Information systems~Information retrieval •Information systems~Retrieval tasks and goals •Information systems~Question answering

KEYWORDS

Smart Learning Environment, Intelligent Assistant, Chatbot.

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1 INTRODUCTION

Nowadays, higher-education learning environments have evolved significantly in the past few decades due to the inclusion of emerging Information and Communication Technology (ICT). The approaches to the Technology-Enhanced Learning (TEL) systems have been shifting from e-learning, mobile learning to smart learning environments (SLE) where innovative technologies and artificial intelligent are used to allow greater flexibility, personalization, engagement and motivation of learners [21]. It is becoming vital for such SLE to be implemented in learning institutions, in order to ensure that learners are placed at the center of the learning engine and provided with the best learning experience possible that is not diminished by an outdated and irrelevant learning environment [1]. However, one of the challenges is that individual support provided by lecturers and departments is costly and nearly impossible, and students are unable to engage in an effective learning. Several studies have revealed that this lack of individual support leads to weak learning outcomes, high dropout rates and dissatisfaction [7].

In this context, intelligent assistants can help the smart learning environment to overcome this issue by initiating communication according to the user's specific context, such as location or clickstreams, and therefore, making learners feel personally addressed [10]. The intelligent assistants, which can be also called digital assistants, conversational interfaces or just chatbots, can help users to achieve some results by conversing with a machine in a dialogic fashion, using natural language [4]. Indeed, computer-based chatbots have a growing presence in modern society, becoming integral parts of everything from personal assistants on mobile devices to technical support help over telephone lines, and even being used for health interventions [20]. They are getting to be an intuitive and successful open framework between human and machines. A chatbot is a manufactured substance that is intended to reproduce a clever discussion with human accomplices through their regular language [2]. From the user view, chatbots increase user satisfaction by speeding up response time and being available 24/7, enabling to process and communicate with multiple people at the same time, automating repetitive tasks, and supporting multi-languages.

This paper focuses on building a specific chatbot named FIT-EBot that aims at providing administrative and learning support at the Faculty of Information Technology of Ho Chi Minh City University of Science, Vietnam (FIT-HCMUS). The rest of the paper is organized as follows. The section 2 reviews our related works. The section 3 explains our motivation of this work as well as the user requirements for building the FIT-EBot. The section 4 presents in detail our proposed chatbot in terms of architecture design and component implementation. The experiments are shown in the section 5 explaining how the performance is obtained. The sections 6 and 7 highlight the main results of this work and some perspectives.

2 RELATED WORKS

This section begins with the discussion about chatbots in higher-education environments and then introduces the general chatbot structure.

2.1 Chatbots in higher-education environments

In recent years, the high demand for learning has led to a lot of pressure on higher-education institutions. A clear proof is that the number of students per teacher is increasing [16]. It means that each teacher's support for each student is significantly reduced [3]. This is one of the main reasons led to the ineffective learning and high dropout rate [7][9]. Although many solutions to this problem have been proposed, most of them cannot be successfully implemented due to financial and organizational difficulties [17].

Facing such tremendous challenges, scientists and managers have started offering chatbots for the education sector. Chatbot promises to solve a variety of problems in education today. 2018 will be the year in which chatbots are most widely used in education [11]. One of the biggest advantages of chatbot is that it can support students individually and intently [23]. This is especially useful in the large-scale learning environments at universities or in massive open online courses (MOOCs). In the higher-education, a chatbot can be trained from a wide variety of resources ranging from learning experiences to learning materials. According to [11], the main trends in learning support that chatbots are addressing as followings:

- Chatbots can functioned as an optimal learning method by repeating the old lessons as soon as learners forget them. Hence, the chatbots for learning supports should maintain knowledge by repeating it after a reasonable amount of time.
- Chatbots can be used for gathering feedback on a course. This information is a valuable source for improving learning and teaching.
- Chatbots are trained to answer common questions about the study of a subject. This motivates learning supports more quickly and conveniently.
- Students are always in need of administrative supports such as assignment submission, course registration, examination schedule, score, graduation, etc. Once these problems are resolved automatically by a chatbot, it greatly reduces the burden on the departments of the school.

Typically, the University of Georgia has built a chatbot to support students to register a course [8]. Thanks to this chatbot, the number of students enrolled on this course is increasing.

In our opinion, the next research direction could be to transform the chatbots into intelligent assistants, which can interact with users in a more intelligent way to support both administrative and teaching services.

2.2 General Chatbot Structure

There exists a variety of chatbot frameworks proposed by different communities and groups (e.g. Wit.ai – Facebook, Microsoft Bot Framework – Microsoft, etc.) [15][4][5]. Each framework is based on different programming environments, conversation types, data models, training methods, etc. However, they have the same purpose that is to actively receive the messages from users and generate answers in a convenient way.

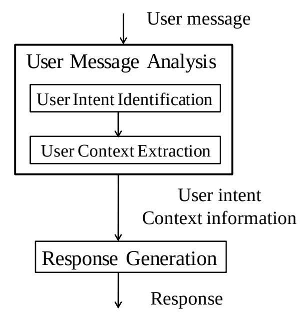

Figure 1: The general chatbot structure.

Figure 1 shows the general structure of a chatbot. Basically, a chatbot is composed of the components such as User message analysis and Response generation components [14]. The **User message analysis component** uses natural language processing techniques to comprehend what users are talking about. Specifically, it consists of two main tasks:

- *Identifying user intent:* the aim of this work is to determine the intent of users through their messages. It can be considered as the goal of the messages.
- *Extracting user context:* for each user intent, a specific set of context information is extracted from the message. It can be ranged from user clickstreams with chatbot, user profile, time, etc. to location (e.g. GPS data). Chatbots use this information to capture the current situation of the user and generate the response accordingly.

For example, based on a user message, chatbot recognizes that the use intent is to address the product warranty. To better understand the product warranty message, it requires more context information such as product name, purchase date, product problem, etc.

The **Response generation component** builds responses to the user based on the intent and context information returned from the User message analysis component. There are three models used to produce the appropriate responses: Pattern-based model [12], Retrieval-based model [24], and Generative model [18]. For the Pattern-based model, chatbots match user messages with each underlying question-answer pattern to create a response. Compared to the Pattern-based model, the Retrieval-based model offers much flexibility. Specifically, this model queries and analyzes available resources using APIs such as performing a query on the price of a product from a sale database. The Generative model is the smartest among the three models in terms of generating answers based on current user messages and previous messages. However, it encounters many difficulties in building and training. This means that it needs training with a very large set of data in order to achieve a good conversation. Because of this disadvantage, this model still has not been much used to build a chatbot in reality yet.

In the proposed approach, the retrieval-based model is used in the FIT-EBot like most of the current chatbots in order to provide more flexibilities in our services.

3 MOTIVATION AND REQUIREMENTS

3.1 Motivation

The Faculty of Information Technology of Ho Chi Minh City University of Science (FIT-HCMUS) was founded in 1994. The FIT-HCMUS has grown considerably in the last few years and become one of the leading faculties of IT in Vietnam. It is providing many education programs and degrees in computer science and IT at different levels, including masters, bachelors, continuing study, distance learning for more than 5000 students.

In order to support its administrative and teaching services, the FIT-HCMUS deployed a website (http://www.fit.hcmus.edu.vn/) and a learning management system (https://courses.fit.hcmus.edu.vn) as communication channels for supporting academic information such as education events, recruitments, program's announcements, and courses. However, they lack of individual supports, ineffectively interact with students, and cannot reuse available resources to automatically generate responses.

For example, there are some challenges the FIT-HCMUS is currently experiencing:

a) Students asking questions repeated frequently such as discipline, programs, regulations, scholarships, registration, courses, assignments, etc.;
b) Searching information is often difficult and time consuming;
c) Huge workload for administrative staff and lecturers to manually answer each student's questions, even impossible.

For this reason, the paper aims at building a chatbot named FIT-EBot that can help students at the FIT-HCMUS and solve the above mentioned issues. This chatbot can improve individual supports, provide interactive mechanism that students can continually interact with a chatbot by asking questions related to a specific matter. According to [13], when a chatbot is built based on a specific domain, it can provide suitable and accurate supports by focusing on a knowledge model when generating responses and guiding actions. In this context, the FIT-EBot is trained based on data collected from students, lecturers and available resources at the FIT-HCMUS to form the knowledge model.

3.2 Requirements

Taking into account the trends of chatbots in higher-education environments recently discussed in [11], the FIT-EBot can act as lecturers and administrative assistants to respond quickly to common inquires of students such as leaning subject, exercises, course registration, course schedules, assignments, scholarships, regulations, etc. The FIT-EBot is implemented based on the Dialogflow framework, a Google technology integrated artificial intelligence techniques in analyzing user messages and generating responses. As a consequence, the FIT-EBot can be trained from available resources and messages of the FIT-HCMUS to identify users' intents and recognize context information. That allows it to build intelligent conversations and answers. Regarding the interface, it is combined with Facebook Messenger to provide an interaction channel for users as Facebook Messenger, which is the most popular instant messenger tool for young people in Vietnam [6] and therefore, suitable for students.

We believe that our study is one of the first that focuses on building chatbots as intelligent assistants for higher-education environments that support both administrative and teaching services.

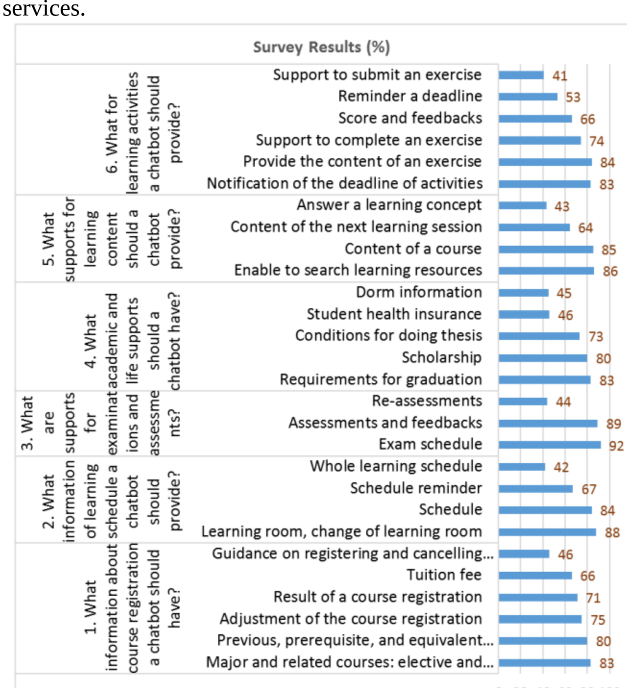

Figure 2: The survey chart.

To further explore the detailed requirements from students, we conducted a survey to find out what students needed to support from a chatbot in addition to the available resources they were counseling during their studies. We asked more than 100 bachelor students at the FIT-HCMUS from the 1st to 4th year students for answering our 6 main questions by ticking the options in each question that they think useful.

Figure 2 shows the result that can be summarized as follows:

- Most options getting a result over 40% which means that in general, a chatbot can be a promising tool for students to interact, even 43% of the result are quite high, which is over 80%;
- The result varies depending on the stage of the study, i.e. the 1st and 2nd year students care more about the information on dormitory and health insurance, while the 3rd and 4th year students focus more on the conditions for doing thesis and requirements for graduation.

This result confirms the urgent need for the FIT-HCMUS to have a system, which takes into account the user context and learns from their inputs to be able to make conversations in a more personal way.

4 FIT-EBOT APPROACH

This section presents the principles of the proposed approach for building the FIT-EBot, including the architecture, the two main components (User message analysis and Response generation), process specification and GUI development.

4.1 Architecture

The paper argues that the process of analyzing and training using artificial intelligence algorithms based on a specific knowledge model will provide the best support for users. This knowledge model, including both the static and dynamic aspect of data, plays the most important role in the architecture of the FIT-EBot as shown in Figure 3.

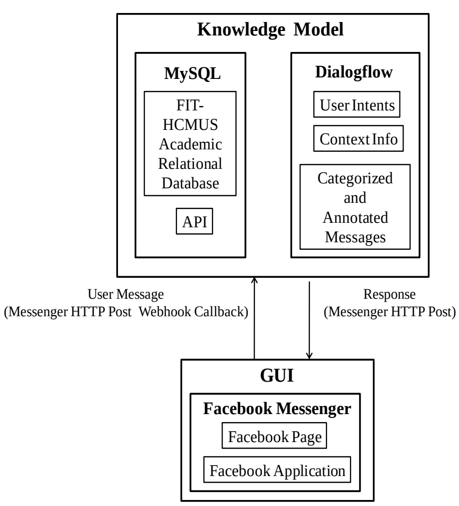

Figure 3: The FIT-EBot Architecture.

Concretely, the dynamic aspect of the knowledge model is built by learning from the categorized and annotated messages (called the training corpus) using Dialogflow, a Google technology for artificial intelligence. This aspect of the model is used to analyze user messages in the FIT-EBot. In addition, the FIT-EBot interacts with the FIT-HCMUS academic database systems via the static aspect to generate the appropriate answer. For facilitating communication, the FIT-EBot utilizes the Facebook Messenger platform to receive messages from users. All details of the above stages are presented in the remain of this section.

4.2 User message analysis

As presented in the section 2.2, for a chatbot, the user message analysis component is composed of the user intent identification and the context information extraction. In this paper, the user intent identification is studied from the perspective of the text classification. Correspondingly, user text messages are classified into the predefined topics [19] in which each topic is corresponding to a user intent. To develop a learning model for the classification, the 13 topics (each topic reflects a user intent) are manually identified based on the data from the result of the survey as mentioned in the section 3.1. These topics and their examples are listed out in Table 1. The dataset is used to train a classifier. With every new user message, the FIT-EBot approach uses this learning model to automatically classify it into a suitable topic (user intent).

Table 1: The main user intents in the FIT-EBot

User intent	Example
Exercise	What is the deadline of the final project in the course of Introduction to Programming?
Course registration	How many courses can be registered in this semester?
Course score	Please, tell me my score in the Database course.
Alternative course	What course is used to replace the Advanced Database course?
Prerequisite course	What should I study before I study Computer Vision?
Course content	Why should I study Computer Network?
Major	How many majors in the faculty of Information Technology?
Course material	Please, give me the main materials for the course of Business Intelligence?
Scholarship	What scholarships can I apply in this semester?
Examination	How long does the final exam of Computer Networking course take?
Schedule	Please tell me the schedule of the Computer Networking course?
Graduation	What is the graduation requirement of Software Engineering major?
Specialized course	Tell me all the courses for the major of information systems?

Once the intent of the user is determined, the FIT-EBot approach proceeds to extract the context information on the message. In the field of natural language processing, the researchers performed this work very effectively, known as Named Entity Recognition (NER) system [22]. In essence, it is a model of classifying a word block in a message into a given entity (label) such as the person name, location, time, etc. To apply this model, it is inevitable that there is a need to have an annotated training corpus in which each word block has exactly identified a label. The learning model based on the training corpus is used to determine the label of the word blocks in a new message.

Table 2: The main context information in the FIT-EBot

Context information	Description
@student	The student ID mentioned in the message
@course	The course the user wants to ask chatbot
@major	The major of the student

Table 2 shows three main context information that is usually extracted for most user intents. To train an NER system for the FIT-EBot, the word blocks in the dataset collected from the FIT-HCMUS students are manually located and classified. This model helps the FIT-EBot approach to annotate the context information in a new user message.

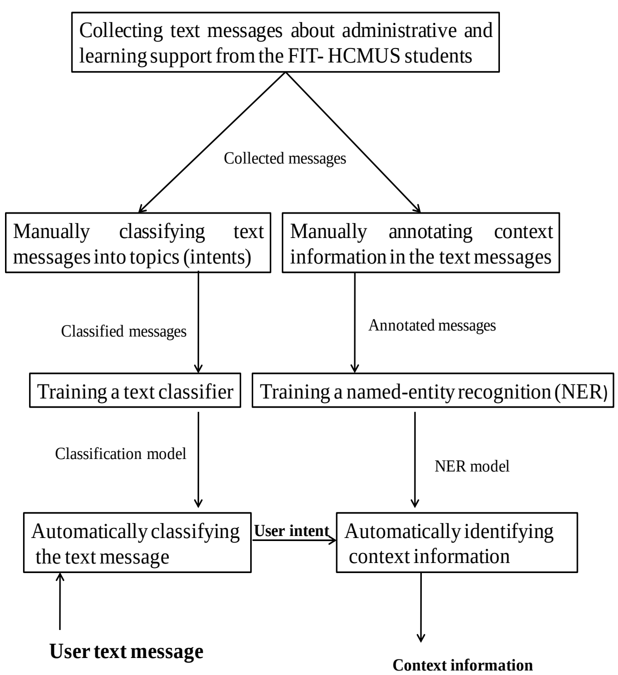

Figure 4: The user message analysis in the FIT-EBot.

Figure 4 shows the details of the user message analysis for the FIT-EBoT. For example, when a user message is "please, tell me the score of the student 1212321 in the database course", the system will automatically categorize the message to the intent of asking the course score. For this intent, two context information about the student (1212321) and the course (database) is automatically determined. In this paper, all the natural language processing operations mentioned above are implemented by Dialogflow. Dialogflow is a Google technology that supports human-computer interaction based on conversations in natural language. Unfortunately, Google has not published which algorithms are used in the Dialogflow. However, according to the Dialogflow documentation, the selected algorithms are most effective with the user message to the training phase.

4.3 Response generation

For each user intent, corresponding solutions are identified and built to generate the appropriate responses. Specifically, for non-informative intents such as greeting and good-bye, we generate fixed and unchanging responses. For example, when a user sends a message that is determined to be a greeting, the system automatically generates an answer, "Hello, I'm FIT-EBot". When the FIT-EBot receives a message intended to say good-bye, the FIT-EBot always says “bye bye” to the user.

In contrast, for the other intents, the FIT-EBot interacts with the FIT-HCMUS academic database systems to make the action appropriate to the message received from the user. Continuing the example for asking about the score of student 1212321 (@student) in database course (@course) as presented in Sec 4.2, the system executes a SQL statement, "SELECT score FROM result where student=1212321 and course= database", to return the score to the user.

4.4 Process Specification

A significant advantage of a chatbot over a question-answer application is the ability to detect missing information and then requests the additional information before producing the final answer. The FIT-EBot approach applies a retrieval-based model which can perform queries from APIs of the FIT-HCMUS database systems, renews its knowledge by analyzing resources available from the FIT-HCMUS portals, and user messages to provide a more flexible, interactive conversation for users.

A process view of the FIT-EBot in Figure 5 demonstrates how the FIT-EBot components are combined to deal with user messages. With each user intent, if the FIT-EBot cannot fully extract the required context information, the system responds to the user by asking additional context information. For example, a user asks for a course score but only provides the student information while the system specifies that each question on the course score must be extracted for two context information, @student and @course. In that case, the FIT-EBot will remind the user: “please, provide me the course in you want to ask the score”. After the user provides the course information, the system generates the answer as presented in the section 4.3.

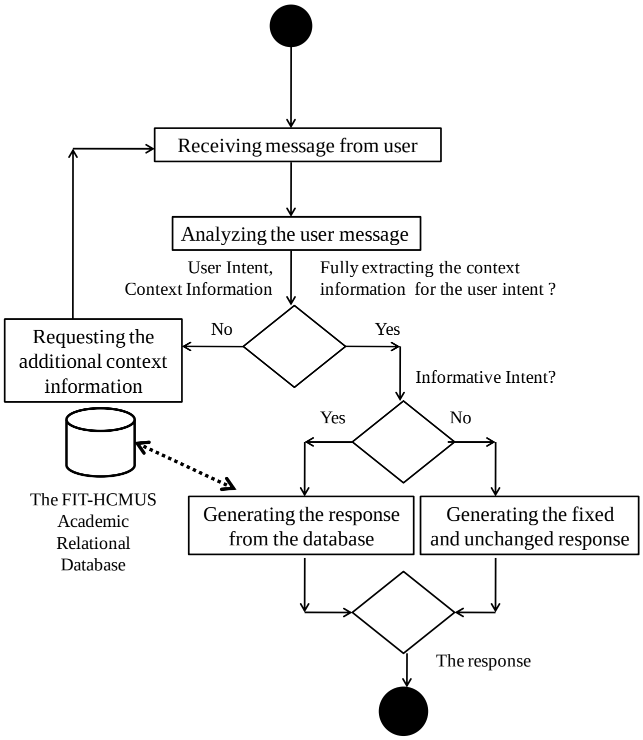

Figure 5: The FIT-EBot process.

4.5 GUI Development

Regarding the FIT-EBot interface, Facebook Messenger, a messaging platform developed by Facebook, is selected. According to a report by [6], 94% of Internet users in Vietnam usually use chat application. 42% of them install Facebook Messenger for chat. The ages of these users are mostly in the range of 18-25. This study shows that Facebook Messenger is the most appropriate interface platform to integrate into the FIT-EBot with the kind of users primarily targeted to the FIT-HCMUS students.

The interface of the FIT-EBot is implemented as follows:

- Creating a Facebook page: A Facebook page needs to be created because Facebook now only allows a Facebook page to be connected to a Facebook application.
- Creating a Facebook application: Facebook application is designed to interact with Facebook platforms through the API.
- Linking Facebook application to Facebook page: If a user sends a message to the Facebook page associated with the Facebook application, it will generate an event to the corresponding webhook. As a result, programmers can obtain user-submitted data for the subsequent processing.

Figure 6a and 6b illustrate screenshots of Facebook Messenger integrated with the FIT-EBot. While Figure 6a shows a simple chat from student asking courses compulsory for the major "Information System". Figure 6b demonstrates a more interactive conversation where the student 1412169 wants to check the registration information of the database course, the FIT-EBot recognizes the context information of the conversation (@student and @course), then enables to ask the student back to reconfirm it before answering.

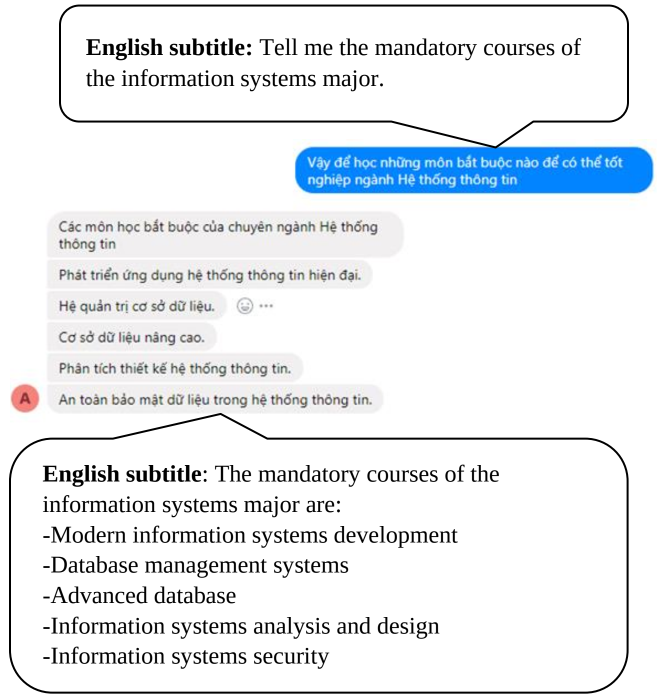

Figure 6a: Screenshot – simple query chat.

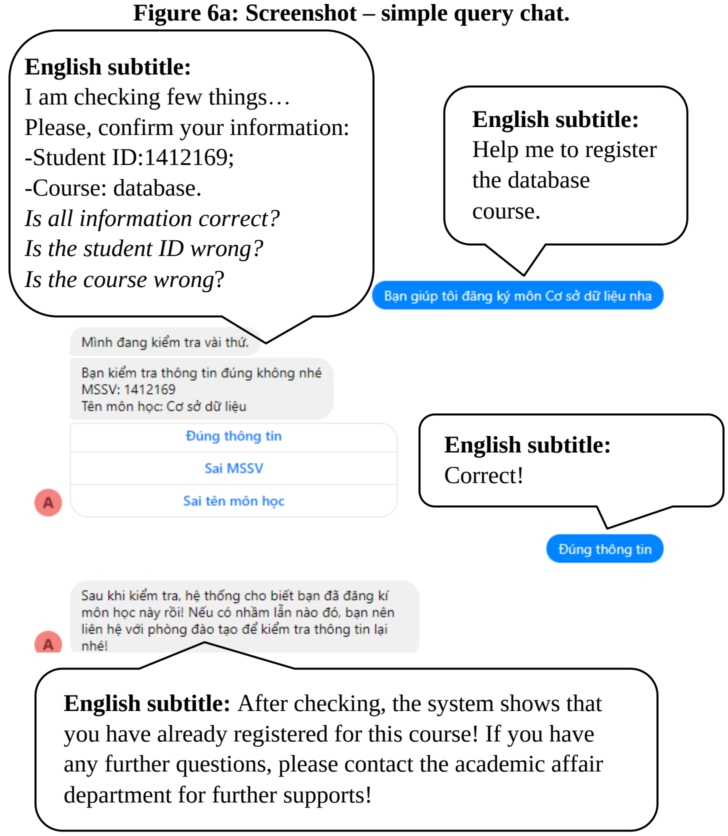

Figure 6b: Screenshot – interactive conversation.

5 EXPERIMENTATION

5.1 Experimental Setup

The aim of this experiment is to investigate the performance of the user intent identification and the context information extraction of the FIT-EBot approach. Once the user intent and the related context information are identified accurately, it is easy for the FIT-EBot to generate appropriate responses to users. As presented in the section 4, under our viewpoint of natural language processing, these two issues relate to text classification. Specifically, the user intent identification is to classify the user messages while the context information extraction is to classify the word blocks within the user message. The proposed approach uses F-score for evaluating the classification performance. It is computed based on two well-known measures, which are the precision and the recall as follows:

$$P_i = \frac{TP_i}{TP_i + FP_i} \qquad R_i = \frac{TP_i}{TP_i + FN_i} \qquad F_i = \frac{2.P_i.R_i}{P_i + R_i} \quad (1)$$

Where P_i, R_i, and F_i are the precision, recall, and F-score for the prediction of class i respectively; TP_i is the number of the items correctly predicted to class i; FP_i is the number of the items predicted incorrectly to class i; and FN_i is the number of items of class i mistakenly predicted into other classes.

Experiment has been conducted on a set of messages about administrative and learning supports collected from students of the FIT-HCMUS. The messages in this dataset are manually categorized into the 13 user intents presented in Table 1 and annotated with 3 contextual information in Table 2. Table 3 shows its statistical details. The total number of messages for training and evaluating a classifier of 13 topics (user intent) is 1560 while the total number of instances serving a NER system of 3 entities (context information) is 870. For each experiment, the approach applies the 10-fold cross-validation method for the evaluation.

Table 3: The statistic of the training corpus

User intent	The number of messages in the corpus
Every of the 13 user intents	120
Total	1560
Context information	**The number of instances in the corpus**
@student	25
@course	712
@major	133
Total	870

5.2 Experimental Results and Comments

The average results for both the user intent identification and the context information extraction are quite promising (the user intent identification: average-F1 = 82.33; the context information extraction: average-F1 = 97.3). As shown in Figure 7, regarding the user intent identification, the system gives a high F1-score over 90% for "Scholarship", "Major", "Graduation"; and over 80% for "Examination", "Course registration", "Course score", "Alternative course", "Specialized course". This is because the messages of these classes are written very specially and consistently. For example, "Scholarship" and "Graduation" are very recognizable as they show the characteristic words such as "scholarship" and "graduation" respectively. However, the results of identifying other classes such as "Exercise" and "Course content" are not very good as there is already ambiguity in the classification of these classes. In order to improve the classification efficiency of these classes, it is necessary to collect more training data for them.

For the context information extraction, the identification of the three main context information (@student @course, @major) is over 90%. In particular, student IDs are usually extracted precisely on user profile. However, in rare cases, they are extracted directly from the user message. Because the FIT-HCMUS provides a unique structure for student IDs, it is easy for the system to recognize student IDs even with very few training data. For the remaining two context information (@course and @major), the training data is sufficient for the courses and majors in the FIT-HCMUS. There is no ambiguity in extracting these two context information from the user messages.

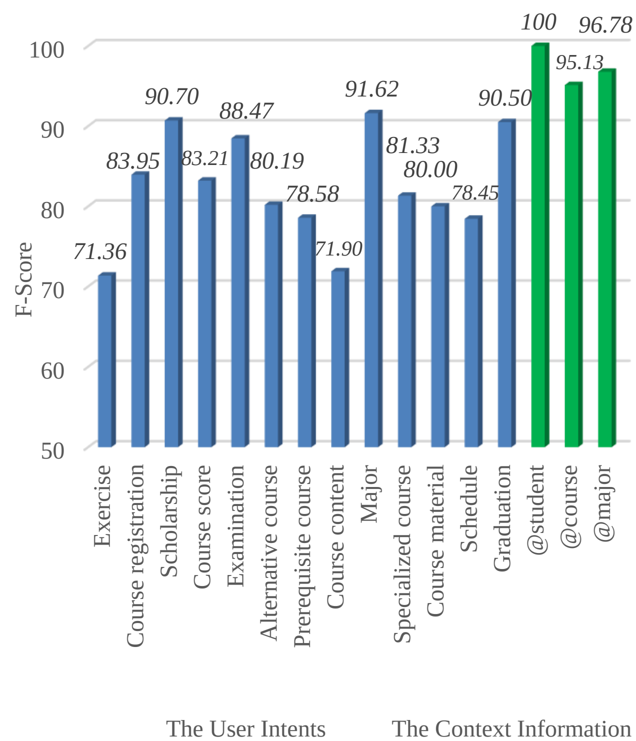

Figure 7: The F-score results.

6 CONCLUSION

This paper presents an approach for building a chatbot named FIT-EBot as an intelligent assistant to provide administrative and learning support to students in a higher-education environment. Some recent work related to the text mining domain has been used for the FIT-EBot approach. Under this viewpoint, the FIT-EBot approach exploits the studies such as text classification and named entity recognition. These functions are implemented by Dialogflow, an artificial intelligence tool developed by Google.

It is expected that the process of analyzing and training using the artificial intelligence algorithms under the data collected from the FIT-HCMUS will better support students compared to other general chatbots. Another advantage of the approach is that users can interact directly with the FIT-EBot through their Facebook pages. This is very convenient for students using the FIT-EBot. Experiments are also conducted on a training corpus consisting of 1560 user messages. The experiment results on the user intent identification and the context information extraction are quite satisfactory.

7 FUTURE WORK

The proposed approach to build the knowledge model for the FIT-EBot is heavily depending on the current database structure at the FIT-HCMUS for a specific domain of applications. The extracting relevant information from other resources via various techniques to get the exact one and to gather more knowledge is still a challenge. Moreover, there is still a lack of a knowledge structure, which can play as an integrated semantic framework for analyzing the user inputs and generating the responses. Therefore, one of our future works is to tailor and standardize the knowledge model based on the ontology technology. Ontology gives the basic concepts and the relationships to capture and train the relevant domain knowledge. With this regard, the FIT-EBot approach can be improved in terms of performance and architecture. Another concern is related to the context information. The current approach to handle the user context is limited to the three fixed elements. This data can be broadened by focusing on a more generic context model, which allows the approach to have a more flexible way to extend it to new contextual requirements in the future.

Currently, we are working to enable FIT-EBot to answer questions related to the study of a specific course offered at the FIT-HCMUS, first of all, is the course about Database Management Systems. It is very complicated to build such knowledge for chatbots from organizing knowledge to building and applying knowledge. In addition, regarding the user message analysis, the next versions of the FIT-EBot will be applied to advanced machine learning techniques such as deep learning and even building separate models to analyze each type of requests such as Why, What, How, Yes-No, etc. Obviously, for a smarter FIT-EBot, collecting the training data is ongoing.

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