Development Of Conversational Agent To Enhance Learning Experience: Case Study In Pre University.

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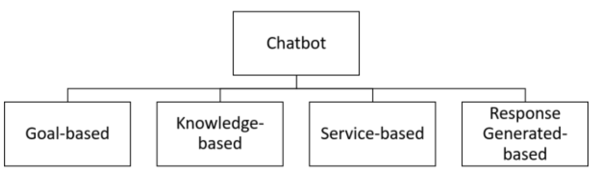
Abstract: Chatbot is an artificial intelligent application that can converse with a user through textual or auditory method. The chatbot can give a response according to their characteristic and domain knowledge. This study aims to evaluate the use of chatbot named eLVA among students at the Centre for Pre University Studies. A series of 10 questions was distributed to 40 students to evaluate the use of eLVA after they have experienced it. The results indicated that chatbot are most likely to be very helpful in teaching and learning because it has helped students getting an instant response. However, results showed that the main reason for students to stop using chatbot involved getting incorrect information and worried about Chatbot making mistakes. The result further show that there is no significant difference in the use of eLVa between male and female students. The study also found that there is no significant correlation between study program (Physical Sciences/Life Sciences) towards the use of eLVA.

Index Terms: NLP; NLU; Response Generation method; Chatbot

1 INTRODUCTION

Chatbot's application have boomed during the past few years with the presence of Siri, Alexa, Microsoft Cortana, and many more that attract the attention of the user towards chatbot's topic. Chatbot is basically an Artificial Intelligence (AI) application that conduct a conversation via auditory or textual method [1] and be enable a person to ask question in the similar manner that they would address a human being [2].

***Fig. 1**. Chatbot's Taxonomy*



A chatbot can be categorized as four main characteristics which are Goal-based, Knowledge-based, Service-based, and Response generated based [3]. Goal-based chatbot are classified based on the aim of the chatbot. Goal-based chatbot can be based on informational, or task-based where the chatbot need to accomplish a task based on the user request. Knowledge- based chatbots are classified based on the type of the domain knowledge they accessed. It could be open-domain or closed domain. An open domain chatbot can talk and respond appropriately to an open topic. A closed domain chatbot focuses on specific knowledge and may fail to answer an unrelated question. Service-based chatbot can be classified based on the task it can accomplished per user request. It could be interpersonal, intrapersonal, or inter-agent [4]. Interpersonal usually provide service to user, intrapersonal usually exist within the personal domain of the user, and inter-agent usually involving two communication system such as IOT. As for Response generated, it is classified based on the method of processing input and generating response [4]. Retrieval-based methods retrieve response candidates from a pre-built index, rank the candidates, and select a reply from the top ranked one [5]. Generation-based methods leverage natural language generation (NLG) techniques to respond to a message [6][7]. The ascent of chatbot has been influenced by the growth of Natural Language Processing (NLP) area where a lot of techniques has been discovered and enhanced to ensure the capability of chatbot to deliver an accurate and acceptable response to the user's queries.

2 PROBLEM STATEMENT

Chatbots are programmed to operate according to predefined instructions. If chatbot interact and learn more new stuff, then chatbot will get much smarter. Previously, chatbot are commonly used in e-commerce in figuring out how to automate task of answering repetitive question asking by customers such as in customer service. Therefore, extending the concept to e-Learning could mean using a chatbot for student engagement. As in learning environment, engaging with the students play important role to keep student motivate and focus into their learning in order to enhance learning outcomes of all students. Some researchers think implementing chatbot might increase engagement and enhance learning, as some students who are ashamed to ask a lecturer a question in front of their peers might prefer to talk to a software robot. On the other hand, students have a lot of the repetitive questions and they have similar type of questions regarding their subject. Considering all these reason, this project aims to improve student-learning experience through chatbot named eLVA by utilizing student profile in student databases such as in Facebook messenger.

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3 RELATED WORK

The response generation method is important in a chatbot pipeline since it will determine what kind of responses or actions will be generated. The classification of the method of how the response generated is heavily influenced by the technique applied in the processing and understanding of natural language. However, there is no fixed claim that every technique applied are bounded with how it classified the response generation method. This section highlighting the multiple studies from [4], [3], [9], [10] that discussed the taxonomy of the chatbot, focusing on the classification of the response generation method. [3] proposed that the response generation method consists of four category response models which are the Template- based model, Generative Model, Retrieval based model, and Search Engine model. The paper suggests that every model has its technique applied in the chatbot. A comparison also has been made on the technical specification and the study shows that every technique at least has one problem within it. For example, Elizabot's response generation method is one kind of template-based model. The drawback of Elizabot is to keep a conversation going and incapable of learning a new pattern [3]. A study from [4] however simplified that chatbot can be classified into two kinds of type response generation method models which are Retrieval based model and Generative model. It studies how the classification is made by proposing a general chatbot pipeline where the response is generated after the query input is structured into a predefined format or via machine learning. The structured is referred to as input that converted into a desirable structure by using some techniques such as Entity extraction and Intent detection. In this paper, the author classified the method of response as Retrieval-based model when there are rules that fetch responses from pre- determined set of responses. Meanwhile, Generative model is when the system is trained on the data, often by using NLP and NLU algorithms. [9] made a study on the latest chatbot approach based on the ability to generate an appropriate response perspective. The paper proposed a Retrieval-based model and the Generation- based model is a new data-driven approach that falls under the category of the non-task oriented chatbot. It stated that the early version of non-task-oriented dialogue system does not use data for learning purpose and the data-driven approach is proposed to overcome the limitations that appear within the response generated. In this study, no comparison is made on a certain technique or method of response generation because the author claimed that there is still no standard framework to measure the quality of chatbot on the problem and limitation metrics. Another study conducted by [10] proposed that chatbot can be categorized into two of chatbot based on the response generation method. The types are Rule-based or AI-based. The type is determined according to how chatbot responds to the user base from the information in each conversation [10] called Natural Language Generation (NLG). The author suggests that the Rule-based chatbot is classified under of Retrieval-based model where it searches a user query through a data corpus while the AI-based classified under the Generative model where it typically based on recurrent neural network. The paper has done a literature review that shows the NLG method is generated and distinguished from the Natural Language Processing (NLP) or Understanding (NLU) techniques applied in the chatbot such as Pattern Matching and Intent Classification

4 CHATBOT PIPELINE

4.1 General Architecture

Before going further down to analyze the NLP techniques that can be applied in a chatbot application, it is important to become familiarize with the general architecture of a chatbot first. While there are many kinds of architecture for chatbot, their main components are the following:

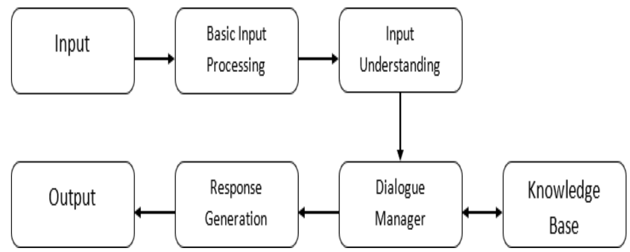

***Fig. 2**. Chatbot's General Architecture*

- Basic input processing: some basic algorithm will take place to process and breakdown a sentence into a form of important keyword only. The algorithms involved are part of NLP technique.
- Input Understanding: A process to extract the keyword into a structured that a bot can understand. The process usually involved a complex model or algorithm to convert the text into desirable form. All the models and algorithms are part of Natural Language Understanding (NLU) technique. Input understanding can be said as the component of the combination NLP and NLU techniques.
- Dialogue Manager: Analyze the input that has been transformed into intelligible structured by the bot, maintained the dialogue history, and controls the flow of the conversation.
- Knowledge Base: Stored or retrieved information and data that is used by Dialogue Manager.
- Response Generator: Once there is a set of candidate response, the suitable response can be returned. From the response generation, chatbot can be classified into two kind of models which are Retrieval based model and Generative model.
- Output: A set of response, returned to the user.

4.2 Natural Language Processing (NLP)

NLP primarily collect the data external text data for the data corpus or collecting new data from conversation dialogue between user and system. Through the review, most of the techniques involved that fall under NLP category are Pattern Matching or Tokenization that match the input from the user with the database. Parsing that take text input and parse each text into a part corresponding to a predefined rule of algorithms such as left-right and bottom-up algorithms. TF- IDF that works by converting the text input to a matrix array containing frequencies, and Word2vec which is the process of changing text corpus turns into a numerical form and plot into a vector space to create a knowledge base.

4.3 Natural Language Understanding

NLU primarily collect and manage the conversation base on the data that was input from a user that already pass the step of pre-processing. NLU is the subset of NLP. So NLU is closely related with NLP, and just differ on how it perceives the underlying data. NLU consists of Intent classification that classify and label the intention of input from a user to use with a knowledge base. Dialogue planning hat be able to manage the conversation between multiple users or the ability to understand the context of a conversation. Vector recognition with cosine similarity that become the measure of content- based similarity between two non-zero vectors represents text summary and reference system summary based on the vector space model. Lexicon which is the collection of words and word elements that carried meaning and used as a dictionary. LSTM a layered algorithm that helps the model/agent to classify the text input from user base on a conversation which divides into two types of memory which are Long-term and Short-term.

5 EXISTING CHATBOT

AliMe Chat [11] is an open domain chatbot working in the e-commerce industry. AliMe Chat architecture focused on a hybrid approach incorporating both a model for information retrieval and a model based on generation using Attentive Sequence to Sequence based rerank approach and was de- veloped using Tensorflow. The model works by training the QA Knowledge-based or conversation corpus, then after the training, it will generate an answer for each input. The novel approach outperforms both models. However, the approach still cannot solve the problem of scaling up the context of interaction. The author still working on finding a solution by combining with other models. SuperAgent [12] is a customer service chatbot that used data from in-page product descriptions as well from user- generated content from the e-commerce website. To be simply, SuperAgent is a third party chatbot that used open-source data or does a crowd-sourcing data from many resources to support open domain Q&A from the customer. All of the input queries from the customer will be processed in parallel by the different engines such as Fact QA engine, FAQ Search engine, and opinion mining and text answering engine. The engine that scores a high confidence level, will output the answer to the customer. But if none of the engine scores above the acceptable score, the chit chat engine will generate a reply from a predefined permitted response set. The techniques applied to implement SuperAgent are deep learning-based matching framework, keyword matching, neural network, and attention-based LSTM Seq2Seq model. It is proven that it can solve the problem of data scaling. But the techniques applied are still cannot solve the problem with multi-turn queries where it is related to the context of interaction. Mandy [13] is a primary care chatbot system that created to assist healthcare staffs by automating the patient intake process [3]. The whole concept of Mandy application is about how Mandy simply can provide a humanized interface to the patient, understand their needs, and provide valuable information to the physician. Mandy works from the patient that interacts with Mandy through a mobile chatbot. All algorithms are executed, and all data are processed in a web service (cloud). After the intake interview, Mandy scores the patient's record and generate a report regarding the patient's conditions. The doctor then login into the e-health information management system to access the personalized reports generated for the patient. This chatbot system architecture consists of three section which are, the chatbot app, web service, and E-health Management System. The drawback of Mandy however is sometimes Mandy cannot simplify the task at hand due to the high level of natural language from the user. Li et al [14] proposed a movie-ticket booking chatbot that leveraged supervised learning and Reinforcement Learning (RL) in their chatbot. The chatbot is a closed domain and a task-based chatbot. The framework includes two parts which are user simulator and neural dialogue system. User simulator part will control the conversation exchange conditioned on the generated user goal, to ensure the user behaves in a consistent, goal-oriented manner. A neural dialogue system part, an input sentence passes through an LU module and becomes a corresponding semantic frame, and an DM, which includes a state tracker and policy learner, is to accumulate the semantics from each utterance. From the approach that focusing on the dialogue planning technique, the chatbot becomes robust, flexible, and consistent. At early implementation, a rule-based agent is used before it further trained with RL. NLU is heavily used especially the LSTM model. However, the function of the slot value used as one of the components in the dialogue planning technique is too critical. The dialogue agent will pass wrong information if the slot value not identified correctly. FarmBot [15] is a closed domain chatbot where users can chat with a bot specifically on agriculture information such as about farming and future market prediction of agriculture products. Farmbot will FarmBot applies both rule-based and generative based method to get the prediction result. It used NLP and Neural network to process input and output data and for prediction algorithm. Basically, the NLP will help to classify the algorithm to make the prediction output. One of the algorithms applied in the FarmBot is ARIMA model. As the application of Farmbot rely on the classification of input and pre-trained data to make prediction, the output is restricted to predetermined data training and the chatbot cannot answer to the question that has different context. Chatbol [16] for Spanish La Liga is a closed domain chatbot that has domain knowledge on the sport. It is an informative based chatbot that used a retrieval-based conversational engine. The data retrieval process is based on the semantic similarity scores turn according to detected intent and dialogue history. Chatbol's approach is by combining task-oriented bot with chitchat engine and it relies on NLP and machine learning libraries. It will map natural language questions into SPARQL queries to retrieve data from Wikidata. But the chatbot some- times fails to recognize intents correctly. Ranoliya et al [17] proposed a closed domain and informative based chatbot for university-related FAQs. The chatbot used AIML and Latent Semantic Analysis (LSA) methods. The concept of these methods is all the unanswered queries by AIML will be viewed as a reply by LSA. The function of LSA is to discover the likeness between words as vector representation. But the problem with Ranoliya is the responses given is restricted to predetermined rules. The problem is the common problem that facing by other rule-based chatbot application. Divya et al [1] proposed a closed domain chatbot based on the data extraction method for self-diagnosis medical chatbot. The chatbot will validate the user before extracted the symptoms from the conversation. The symptom later will be mapped into the documented symptoms (pre-determined data) before it developed a personalized diagnosis or if necessary, the user will be provided with specialist details from the database. They utilized natural language processing methods before the chatbot further trained with the natural language generation (NLG) template. Although this is a good practice of healthcare's chatbot, the problem of this chatbot as a rule- based chatbot, the responses are restricted on the pre-determined dataset where it cannot identify the symptom that out of the pre-training context. Arts bot [18] is a closed domain chatbot that works in the rule-based method. The architecture is solely relying on predetermined data that is stored in a knowledge base. The area of knowledge for this bot is based on a museum where the bot will prompt user to ask about the art that is exhibited in the museum. The response later will be based on the keyword matching method. Like other rule-based chatbot. Arts bot can only give responses based on the pre-determined dataset. DBpedia Chatbot [19] is an open domain chatbot where the area knowledge of the bot is based on open knowledge. DBpedia chatbot used TF-IDF vectorization and K-Means clustering to translate the incoming query or request from user. After the process, it will generate the response based on the rule-based module. Mainly, DBpedia applied NLP algorithm to process and generate responses to user queries.

6 OBJECTIVE

The objective of the study are as follows:

a) To evaluate the use of chatbot technology among pre-university students.

b) To determine the difference in the use of chatbot technology between male and female pre-university students.

c) To determine the difference in the use of chatbot technology between program of study (Physical Sciences/Life Science) in pre-university.

7 METHODOLOGY

7.1. eLVA as a chatbot

The concept of eLVA was similar to a Messaging Application conversation. In eLVA, the conversation was between the students and bot in eLVA itself. Before accessing eLVA, students were required to enter their validated matric number for them to start asking the question or choose the option from the menu function. eLVA via Facebook Messenger used GET request algorithm to call for API service from Dialogflow, and the question then was translated using Natural Language Processing (NLP). Once the question was translated in the eLVA into understandable structure for the bot, the question was sent to the student database via webhook service to Firebase, and the query was generated into a set of answers.

7.2. Development of chatbot

The chatbot used in this study named eLVA consisted of the front-end services of Facebook Messenger, Firebase (the student database), and Dialogflow API. Students are the clients who used eLVA via Facebook Messenger while Dialogflow offers an API service. The Dialogflow integration service connects eLVA database to the Facebook Messenger which channeling the bot to its publication. As for Dialogflow fulfilment, it offers an API service to connect database query from eLVA to the student database. The implementation of eLVA chatbot focused on having access to parse JSON code from the Dialogflow to the Firebase database and retrieve back into Dialogflow via webhook. The connection to get the link between two parties of APIs was made using JSON code. The issues at this stage involved the intent that need to be code specifically and a lot of NLP knowledge needed to parse one intent. Considering the limitation of time and project priorities that focus on proving concept only, a dummy database system was developed internally in Firebase console to replace the official system and provides the data to the chatbot. The students' personal data used in this study were not retrieved from the institution's official database system due to the confidential concerns.

7.3. Evaluating the use of chatbot named eLVA

Quantitative method was used through data collection from survey of 40 students of Pre University Studies. A series of 10 questions were included in the questionnaire which was distributed to students to evaluate the use of chatbot after they have experienced it. The data collected was on demographic information as well as data on the use of chatbot.

8 RESULT

8.1. Descriptive statistics

A total of 40 students were participated in the survey. They were 19 (47.5%) male and 21 (52.2%) female students. For this study, 19 (47.5%) students were from Life Science Program and 21 (52.2%) students from Physical Science Program as shown in Table 1.

Table 1 *Gender and study program of students*

		Frequency	Percentage
Gender	Male	19	47.5%
	Female	21	52.5%
Study program	Life Science	19	47.5%
	Physical Science	21	52.5%

Additionally, students were asked to do ranking for each of the channel used within the period of 12 months as shown in Table 2. A majority of students would choose eLEAP, one of the e-Learning platform in pre university studies as their channel of communication which reported the highest score of 6.65, while Email recorded the least channel used by the students with lowest score of 3.2 compared to other channels as shown in Table 2.

Table *2 Ranking for each of the channel used within the period of 12 months*

Answer Choices	1	2	3	4	5	6	7	8	Total	Score
eLEAP	17	8	8	2	3	1	0	1	40	6.65
Email	1	2	4	1	8	7	7	10	40	3.2
Website	0	8	6	8	3	7	6	2	40	4.47
Face-to-face	7	4	5	11	7	1	2	3	40	5.18
Online chat	2	5	6	3	11	8	4	1	40	4.47
Mobile app	1	3	2	8	3	11	10	2	40	3.7
Social media	4	7	7	7	3	3	8	1	40	4.9
Chatbot	8	3	2	0	2	2	3	20	40	3.43

8.1.1 Engagement in Chatbot

On the question of the students' engagement in chatbot, 35% students were engaged in chatbot. While, students that were not engaged in Chatbot recorded about 65% as shown in Table 3.

Table 3 *Engagement in chatbot*

Engagement in chatbot	Frequency	Percentage
Yes	14	35%
No	26	65%

8.1.2 Using Chatbot for learning

On the number of students using chatbot for learning, most of the students only used chatbot for learning if it was on mobile phones, which reported for about 72.5%. Besides that, students engaged in chatbot for learning via WhatsApp, Facebook messenger, Website recorded about 12.5%, 7.5% and 5% respectively as shown in Table 4.

Table 4 *Using chatbot for learning*

Using Chatbot for learning	Frequency	Percentage
Yes, if on Mobile	29	72.5%
Yes, if on website	2	5%
Yes, if on Facebook Messenger	3	7.5%
Yes, if on WhatsApp	5	12.5%
No, I would prefer to use the standard eLEAP	0	0
Other (please specify)	1	2.5%

8.1.3 Using chatbot for education

On the number of students using chatbot for education, 72.5 % did not use chatbot for education while, only 27.5% students used chatbot for education as shown in Table 5.

Table 5 *Using chatbot for education*

Using chatbot for education	Frequency	Percentage
Yes	11	27.5%
No	29	72.5%

8.1.4 Availability of chatbot in searching information

On the availability of chatbot for searching information, the highest was "sometimes", 85%. Followed by 12.5% students always available use chatbot for searching information as shown in Table 6.

Table 6 *Availability of chatbot in searching information*

Availability of chatbot in searching information	Frequency	Percentage
Always	5	12.5%
Sometimes	34	85%
Never	0	0%
Other (please specify)	1	2.5%

8.1.5 Understanding chatbot

Students were asked on their understanding of chatbot, there was 72.5% recorded mixed understanding in chatbot. Besides that, 15% students understood in using chatbot as shown in Table 7.

Table 7 *Understanding Chatbot*

Understanding Chatbot	Frequency	Percentage
Well	6	15%
Mixed	29	72.5%
It was painful	1	2.5%
Other (please specify)	4	10%

8.1.6 Chatbot helpful in teaching and learning

On the questions on how helpful chatbot in teaching and learning, "getting an instant response" recorded as the highest percentage, 72.5%, followed by "24-hour service", "answer to simple questions", and "easy communication" which reported 70%, 55% and 65% respectively as shown in Table 8.

Table 8 *Chatbot helpful in teaching and learning*

Chatbot helpful in teaching and learning	Frequency	Percentage
24 hour service	28	70%
Getting instant response	29	72.5%
Answer to simple questions	22	55%
Easy communication	26	26%
Other (please specify)	0	0%

8.1.7 Reasons stop using chatbot

Students were asked on the reasons why they would stop using chatbot. The highest reasons of the students to stop using chatbot was because they were worried about making mistake which was about 47.5%. Followed by the students preferred to deal with real-life assistant and not able to 'chat' in a friendly manner which was 37.5% and 3% respectively. There are about 7.5% who would prefer to use a normal website. However, there are 27.5% who would prefer using a chatbot and nothing would stop them from using it as shown in Table 9.

Table 9 *Reasons stop using chatbot*

Reasons stop using chatbot	Frequency	Percentage
I would prefer to deal with a real-life assistant	15	37.5%
I would worry about it making a mistake	19	37.5%
I would prefer to use a normal website	3	7.5%
It was not able to 'chat' in friendly manner	12	3%
Nothing would stop me from using chatbot	11	27.5%
Other (please specify)	3	7.5%

8.2 Inferential statistics

8.2.1 Correlation between variables

Pearson correlation is applied to measure the relationship between two variables under study. The value of correlation ranges from -1.0 to +1.0. A negative sign indicated a negative correlation between the variables under study while, a positive sign indicated a positive relationship.

Table 10 *Chi-square test result for gender and respondents' study program*

	Chatbot	Gender	Study program
Chatbot	1		
Gender	-0.164 (0.312)	1	
Study program	-0.013 (0.938)	-0.103 (0.528)	1

Table 10 reports that there is negative and no correlation between gender and the use of chatbot (0.312, $p > 0.01$). The null hypothesis of no correlation between gender and the use of chatbot is accepted. Besides that, there is also negative and no correlation between respondents' study program and the use of chatbot (0.938, $p > 0.10$). The null hypothesis of no correlation between respondents' study program and the use of chatbot is accepted. Thus, the variables under study are insignificant. The magnitude or strength of the relationship is relatively weak among the variables.

8.2.2 Regression result for the use of chatbot

The result in the estimated regression model empirically tested the use of chatbot as a dependent variable and gender and respondents' study program as independent variables. Table 11 reports the baseline model result of the use of chatbot, gender and respondents' study program. Also, it shows the R2 and F-test of the model. Based on the finding, the value of R2 is 0.037, which explains that the result model is 3.7% of the variance of the use of chatbot technology. Besides that, the model of the F-test reported insignificant results. This is because when the p-value is more than 0.1, the F-test result is insignificant.

Table 11 *Baseline Model Result*

Variables	Coefficient of Variation	t-value	Sig
(Constant)	2.042 (0.359)	5.686	0.000
Gender	-0.083 (0.155)	-0.536	0.595
Study Program	-0.174 (0.155)	-1.123	0.269
N	40		
R2	0.037		
Adj R2	-0.015		
F-test	0.720		0.493

Based on the pooled Ordinary Least Square (OLS) result, a 1% increase of gender will decrease the use of Chatbot by 0.083%. The variables between gender and the use of Chatbot are negative and insignificant at 1% level. Besides that, respondents' study program and the use of Chatbot are negative relationship and not statistically significant. A 1% increase in respondents' study program will decrease 0.174% in the use of chatbot.

9 CONCLUSION

Based on all the results that had been discussed, we can conclude that majority of the students indicated that they will use chatbot for learning if it was on mobile phone. The result further indicated that chatbot are most likely to be very helpful in teaching and learning because it has helped students getting an instant response. Besides that, the result shows that there is no significant difference between male and female students towards the use of chatbot technology. Not only that, the result shows that there is no significant relationship between the study program towards the use of chatbot technology.

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