Proactive Chatbot Framework based on the PS2CLH model: An AI-Deep Learning chatbot assistant for students

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Abstract. Nowadays, universities are using more technologies dealing with students' interactions. The chatbot supported with Artificial Intelligence (AI) – Deep Learning (DL) technology exhibited a better ability and efficiency in various assistant situations. However, the effectiveness of the education chatbot is still not satisfactory. This paper proposes a new chatbot framework that integrated students' learning profiles and enhanced chatbot components to improve student interaction. The new chatbot framework uses knowledge from the PS2CLH model and AI - DL to build a proactive chatbot for assisting students' learning on their academic subjects and controllable learning factors. One of the principal novelties of the chatbot framework lies in the student-lecturer/assistant facilitator. The proactive chatbot applies multimodality to students' learning process to retain students' attention and explain the content in different ways using text, image, video, and audio to assist students and improve their learning experience effectively. Furthermore, the chatbot proactively suggests controllable learning factors for students to work on, improving their academic performance. The testing results demonstrated that the proactive chatbot offered sound accuracy and more effective learning support than other chatbots.

Keywords: AI-Deep Learning Chatbot, Framework, Students' Assistant.

1 Introduction

Universities are using more technologies dealing with students' interactions. In fact, for decades, new ways to convey the message to teach students has been slowly incorporated into education [1]. This pattern started decades ago, with the spread of electronic e-mails and the web [2]. On the other hand, effective learning required more innovative and efficient technologies to couple with natural learning challenges, which presented the need to make more effective tools establishing the interaction between human-computer, lecturers and students. Researchers tried to develop such tools for more than decades but were not very successful. However, in the last decade, 2010 to 2020, there was a significant evolution in computer hardware, which made possible AI-Deep Learning advancements to make tools such as chatbots more usable [3]; [4]. Then also advancements in applications in various sectors, such as Health, Customer Service, Security, Leisure. In the same way, practical applications have been pointed out in the generic field of Education [5].

The last years presented additional new challenges to lecturers and students' university assistance. For instance, the pandemic forced students to study from home facing new problems in their learning, which affected their results. This situation caused significant needs for such tools, but there are still usability, ethical and ecosystem chatbot issues to tackle or improve. The traditional assistance system fails to tackle this new learning environment rollbacks.

This paper reviewed the state-of-the-art technology in chatbot development and proposes a new chatbot framework that integrated students' learning profiles and enhanced chatbot components to improve student interaction. The new chatbot framework uses knowledge from the authors proposed PS2CLH model (combines the perspectives of Psychology, Self-responsibility, Sociology, Communication, Learning and Health & wellbeing) [6] and AI - DL techniques. To build a proactive chatbot framework to assist students' learning on their academic subjects and controllable academic factors from the PS2CLH model, which affect students' performance.

2 Literature Review

The traditional Universities approach to handling students' frequently asked questions is a physical help desk, welcoming visitors and assisting students with a mailbox and a website. Hence, to manage the number of daily requests, subsequently, dedicated staff are required for that task. Research [7] shows that chatbots have uncovered positive benefits of the academic environment ecosystem for students, lecturers, and employees. As a result, using a chatbot can lead to a valuable and effective solution for students due to the chatbot's conversation synchronicity.

Chatbots could be defined as agent systems, which engage a conversation with human using natural language. The firsts chatbots ELIZA [8] and ALICE [9], have experimented with pre-programmed questions-answers that fooled people into thinking that they were talking to humans. In recent days, the chatbot is used in various areas in the real-world, such as information retrieval, education and e-commerce. With years the chatbot focus changed from perfect human imitation to more valuable tools to help people in their tasks using a natural language [10]. Research suggests that Internet users use more social media to ask for assistance than call or write an e-mail [11]. Virtual assistants chatbots are a candidate to replace old-style customer service [12].

A systematic review of the chatbots applications in education was made by Chinedu Okonkwo and Ade-Ibijola in 2021 [13], they explain as it follows. Chatbots are utilized in the education system to improve students' interaction skills and assist teaching personnel through automation [14]. Chatbots can also be used in education to increase efficiency and connectivity and reduce uncertainty while interacting with the system [15]. Therefore, it can straightforwardly deliver a personalized, focused, and result-oriented online learning platform [16], which is precisely what today's educational institutions require.

Usually, the academic environment uses chatbots in two categories: To perform specific area tasks or question-answers [17]. For example, they use a questions-answers chatbot application to involve students in Computer Science topics [18]. These chatbots are task-oriented, as the issue they try to tackle is related to specific problems.

Universities chatbot assistant usually provides generic information, such as courses information, admissions and University's facilities. Answering certain request information usually offered by chatbots is about University facilities, upcoming events, and academic information [19]. During the academic year, different scenarios of the chatbot are presented. At the application process, a bot could help students during enrolment, payment of their fees. The objective is for students to retrieve information without browsing several web pages searching for frequently asked questions. Often, users find it challenging to locate relevant information fast [20].

Advisory interactions in education are another crucial aspect where Chatbot technology has been applied. Analyses indicate that Chatbots are being used to help students make vital decisions on their various academic programmes or activities by providing recommendations on academic matters. Ho, Ismail and D'Silva [21]; [22]; [23] built a Chatbot with the intent of helping individuals gain a better understanding of themselves as well as employment trends, allowing them to make more informed career and education selections.

Presently, a chatbot is perceived as a valuable tool in educational settings to deliver an engaging experience to students. [24]; [25]; [26].

Artificial Intelligent chatbots simplify students' learning process by making it more engaging, short and sharp and attention-grabbing and assisting lectures by easing their teaching methods. Additionally, chatbots can also help to take off the workload of the administrative staff [27].

According to Rapp, A., et al. [28] it is not sufficient to evaluate a chatbot design just based on its ability, utility and effectiveness. Paschoal, L. N., et al. [29] draw similar observations and justifications, stating that the process to evaluate a chatbot mainly uses a small and insignificant data sample to justify the effectiveness of the chatbots systems.

One of the first systematic reviews of the effectiveness of chatbots during COVID-19 was conducted by Biplav Srivastava, AI Institute, University of South Carolina [30]. Srivastava observed minimal chatbot use during COVID-19 and asked if chatbots missed their "Apollo Moment". Massively using technology at a scale provides people in general life-saving contextual, personalized and reliable decision support.

The report observes that most chatbots worked in simple scenarios and raised questions about usability, effectiveness, and handling of user privacy. The critical value recognised on developing a chatbot was that its success is not just of the specific technology developers but rather the ecosystem that makes them safely available to people [21].

In the sociology of the application users, a vital distinction given the input, is expert users and novice users. The last one requires a more user-friendly virtual interface assistance that meets certain specifications to fulfil novice users' questions. Accordingly, Sansonnet, Leray and Martin [31] identify a basic framework in which the virtual assistant can meet the requirements. In the first step, the system should understand the user thinking process; the understanding function is "The Dialogical Agent". The second step is to answer user questions by accessing the knowledge base known as "The Rational Agent". Lastly, being able to earn the user's trust through the presence, "The Embodied Agent". [31].

An inspiring framework evaluation method was proposed by Kuligowska [32] to acknowledge diverse aspects of chatbots functioning, that contains a “Visual Look”, “Knowledge Base” (the chatbot should contain general and specialised information, for the reason that a dialogical agent must be able to answer a set of general knowledge questions; also the topic they specialize in, as part of the chatbot personality, “Language Skills and Context Sensitiveness”, “Conversational Abilities” the context of the conversation, giving feedback, to maintain a harmonious conversation), “Personality Traits” (presenting a distinct personality, different aspects of personality, emotions and physiology), “Having answers in adverse situations” (overcoming the user’s writing errors or others, diplomatically answer the provocative questions), “Possibility of Rating Chatbot” (asking for feedback on communication is a critical value-add for determining the chatbot’s efficacy) [32].

Later chatbot proposed systems emphasise the prerequisite to developing the chatbot with psychosocial factors and adding the users’ cognitive and social behaviour. The classic machine usability definition is not enough to build a successful chatbot application. Chatbots should build a connection with users, in a way that is both practical and enjoyable. It should be Flexible (chatbot’s adaptivity for personalisation of the user), Affective (attention to the relationship quality), Communicative (interaction simplicity or minimum effort required) and finally, Autonomous (take initiatives on the conversation). Therefore, to be successful and believable the chatbot requires a body, a personality and a mind. The mind should be developed with cognitive abilities, problem-solving, social capabilities and affective sensitivity (reply with an assertive emotional state). The chatbot personality defines the interaction style of the human-machine. The mix of these three aspects creates the chatbot’s behaviour [33]. In order to build the chatbot knowledge database it will be necessary to process the knowledge discovery.

When someone develops a chatbot, a key question is why is it needed over any other alternative available? This paper proposes the proactive chatbot framework to improve the students’ learning experience, which creates a scalable and cost-effective solution to assist students.

The proposed framework chatbot belongs to the “virtual assistant” category. The goal is to assist students in their academic subject and controllable academic factors (PS2CLH model) that affect their performance, such as time management, setting and achieving goals, stress, sleep problems, and more.

3 The proposed Proactive Chatbot Framework for Students based on PS2CLH’s model

In order to build a framework to help students during their academic year by effectively assisting them with controllable factors such as time management, setting and achieving goals, stress, and sleep problems, using the PS2CLH’s model, we propose the following proactive chatbot framework.

The proactive chatbot framework is divided into two parts. The first part of the framework is the wide-ranging extended chatbot. It was inspired by Extending language representation BERT (Bidirectional Encoder Representations from Transformers) model based on machine learning technique for natural language processing. This first part has the initial interaction with students' input/question. The second part is the Educational Chatbot Ecosystem, which is an educational ecosystem that supports and enhances the AI ability of the chatbot, facilitating and improving the student-lecturer/assistant interaction.

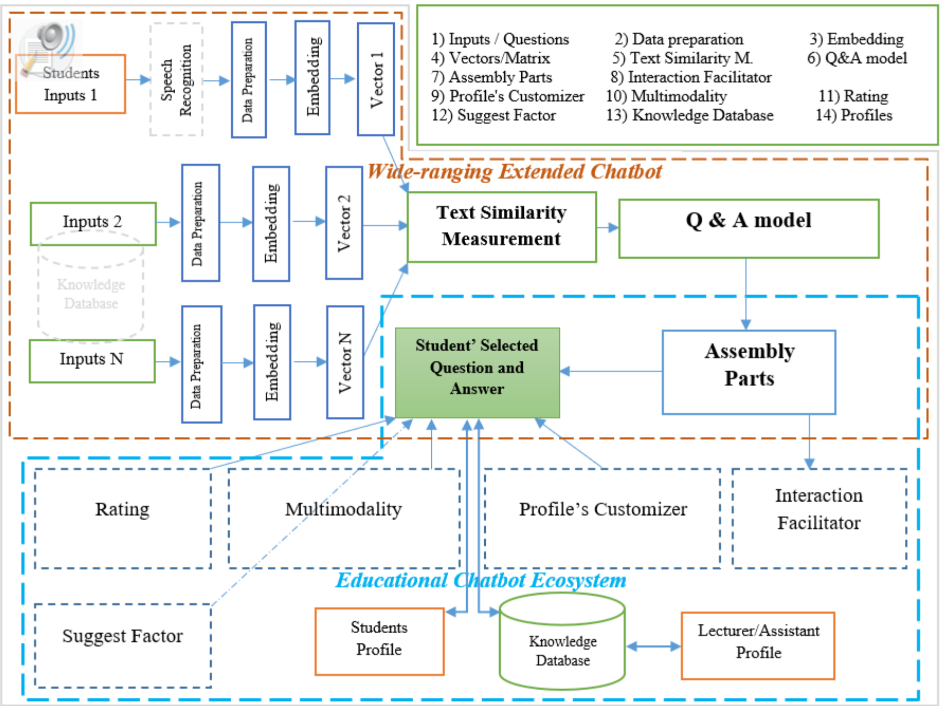

Fig. 1. Proactive Chatbot Framework

3.1 Wide-ranging Extended Chatbot

The typical BERT based Question and Answer system works well for a limited number of words summary. However, it does not understand more than ten paragraphs or 512 tokens well. The limitation will affect obtaining good results with a large corpus. It is trained on the Stanford Question Answering Dataset SQuAD (a reading comprehension dataset consisting of questions posed by crowdworkers on a set of Wikipedia articles) [34].

The extending BERT has overcome this limitation of ten paragraphs, likewise the wide-ranging extended chatbot, giving the flexibility to our framework to deal with a significant number of different subjects. Below we start by presenting the Inputs component.

Inputs/Questions, Data Preparation. The Inputs component is the connection point between the framework and students. The Inputs starts by receiving students' questions via writing or voice. The students' writing Inputs is the expected regular Inputs from keyboards. Then speech recognition captures the voice input. First, we used an API, which has all the necessary functions to convert text to voice and voice to text, then we went to data preparation.

*Data preparation***.** This component is essential to the clean data process. The Framework implements syntax and semantics. Syntax and Semantics, the broad categories under which Natural Language Processing techniques fall. It starts by tokenising the students' questions. Next, we reduce a word to its root or stem using the Stemming process. Then we use Lemmatisation, which reduces a word to its root form by analysing the word morphologically [35]. After this cleaning process, we are using word embeddings.

Embedding, Vector/Matrix. Embedding was one of the essential breakthroughs for the current fantastic performance of Deep Learning methods. Generally speaking, word embeddings are vector representations of a specific word. There are different ways to represent a word; In our framework, we used ***TF-IDF*** (Term Frequency-Inverse Document Frequency) *is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus*. Word embeddings enable representing words with similar meanings to have an equal representation [36].

Discussion: The use of text and speech to detect the student's questions are strengths of the application. However, the Inputs writing and speech were designed only for regular students. The reality is that there are many universities worldwide with students with learning difficulties/disabilities who will not be able to use the application. Furthermore, data preparation goes through many processes, such as sentence tokenisation, word tokenisation, stemming and lemmatisation. These multiple processes can increase the time for the chatbot to respond to the student.

In contrast, the data cleaning phase decreases the number of words in the question, which helps in processing the following stages. Finally, during the process, word embeddings run the risk of the word not being contextualised and the question losing its meaning; despite this limitation, the machine needs to understand the student's question.

Embeddings generate vectors from text, and the combination of these vectors can generate a matrix. These steps transform human language into computer language.

Below is presented the text similarity measurement.

Text Similarity Measurement. This component measures the text similarity. Measuring the semantic similarity between two text fragments has been one of the most challenging tasks in Natural Language Processing. As a result, various methods have been proposed to measure semantic similarity over the years. Because of its simplicity, we chose the Cosine Similarity as the text similarity measurement in this framework, which establishes the similarity between student questions and dataset questions [37]. Then, the cosine Similarity takes on the matrix with the student question and the existent questions on the knowledge database. Using term frequency to obtain the top 10 most similar student's question is selected from the knowledge database. Let A and B be two vectors for comparison.

A practical example we have: Cosine similarity between two term-frequency vectors, we have **x = (***the vector of:* **How much sleep do I really need?)** and **y = (***the vector of:* **What is the amount of sleep do I require?)** are the first two term-frequency vectors, where converted into machine language become **x = (5, 0, 3, 0, 2, 0, 0, 2, 0, 0)** and **y = (3, 0, 2, 0, 1, 1, 0, 1, 0, 1)**. How similar are x and y? The cosine similarity between the two vectors we have below:

$$\begin{aligned} \boldsymbol{x}^t \cdot \boldsymbol{y} &= 5 \times 3 + 0 \times 0 + 3 \times 2 + 0 \times 0 + 2 \times 1 + 0 \times 1 + 0 \times 0 + 2 \times 1 \\ &\quad + 0 \times 0 + 0 \times 1 = 25 \\ ||\boldsymbol{x}|| &= \sqrt{5^2 + 0^2 + 3^2 + 0^2 + 2^2 + 0^2 + 0^2 + 2^2 + 0^2 + 0^2} = 6.48 \\ ||\boldsymbol{y}|| &= \sqrt{3^2 + 0^2 + 2^2 + 0^2 + 1^2 + 1^2 + 0^2 + 1^2 + 0^2 + 1^2} = 4.12 \\ sim(\boldsymbol{x}, \boldsymbol{y}) &= 0.94 \end{aligned}$$

The similarity measurement is connected with the Q&A model used in the framework; it is presented below.

Q&A model, Transformer model. For the component Q&A model, we used the BERT model, which stands for BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. The Transformer model: is a Deep Learning technique model introduced in 2017 at the time of the innovative paper "Attention is all you need" [38] that utilizes the mechanism of attention. The attention mechanism allows the chatbot to understand the context of the students' questions.

The Transformer model is applied to the top 10 most similar questions selected.

Discussion: In summary, the transformer model overcomes the long-term dependency problem. It also deals with vanish and explosion problems found by previous models. Another advantage is that it also solves the context problem. However, it still has the vanilla transformer model problem. The transformer model is still facing the computational cost problem.

Assembly parts. This component is the linking component between the Wide-ranging Extended Chatbot and the Educational Chatbot Ecosystem, resulting from the student's question. We have three possible questions as chatbot answers and one optional choice, "None". Even though adding more than one possible answer to the conversation breaks the natural flow, it increases the chances of the chatbot giving a correct answer and lessens the possibility of the student saying that it was not the question he/she would like to see answered. This approach is appropriate for universities that want to provide more assertive assistance to their students.

Discussion: The weakness of this component is that it breaks the natural and fluent conversation between the student and the proactive chatbot because when a question is asked, one answer is expected, not four options. In contrast, this component gives more chances for the proactive chatbot to correctly answer the student's question.

3.2 Educational Chatbot Ecosystem

The second part of the framework is the educational ecosystem that allows the student to have more personalized assistance and interact more with the proactive chatbot. In the following sections, we present the components of the educational chatbot ecosystem of the proposed framework.

Interaction Facilitator. This component facilitates the interaction between the student and the lecturer or human assistant. One of the most glaring problems of the current chatbot is usability. When the user does not find the answer to his question, he may stop using the chatbot, impacting the chatbot's usability. This issue becomes more accentuated when dealing with students who lack patience.

When the student selects the option "None", the chatbot sends this question to the lecturer or the human assistant. When they answer the question, it is saved in the knowledge database to be available for all the students and improve it. Besides, lecturers and human assistants can also add new questions-answers and new subjects from their profiles.

Discussion: The weakness of this component is that the lecturer often does not have time to answer the questions. If the lecturer has too many questions, he/she will likely leave the student unanswered, or he/she might answer it too late when the student has already investigated and found the answer. The strength is that it creates an indirect interaction where the student can feel more comfortable asking the lecturer or the human assistant. The following section presents the chatbot acting according to students' profiles.

Profile's Customizer. This framework component customizes the student profile, making the proactive chatbot work according to each student's profile. Defined by the PS2CLH model and the selected proactive chatbot persona, thus organizing the controllable factors that affect student performance in the order of importance and making the proactive chatbot act accordingly to student's profile.

It is known that students pay attention and engage more in their preferable personality to assist or teach them. However, it is a fact that there are preferences in the style and attitude of the lecturer in class. For this reason, we have implemented this component in the framework. In addition, the student profile is developed based on filling the PS2CLH questionnaire, which will make the student focus on the controllable factors that present their problems.

The chatbot has the persona chosen by students based on four pairs (Introversion vs Extraversion, Sensing vs Intuition, Thinking vs Feeling and Judging vs Perceiving). The chatbot will act according to the student chosen persona. However, this approach still has many representational limitations on the application.

Discussion: One of the weaknesses is the complexity in representing the 16 different personality types in programming. The other fact is that the human being generally likes variance in the deal. For example, an assistant need to know when to be more logical than emotional or vice versa; this way, the proactive chatbot will not have the flexibility to have more extroverted procedures after being programmed to have introverted attitudes (or responses). The vital point is that the human being has habitual behaviour. Therefore, customizing the student profile can give the student more control and comfort because he will expect interaction with the proactive chatbot. Next, we have the component responsible for the presentation in multimodality of the content of the chatbot responses.

Multimodality. In this component, we present the diversity of chatbot responses presentation. It displays the answer according to the student's learning style: text, image\graphic \diagram, video or voice. A university has several faculties with different courses. Course contents vary. In this variance, we find several disciplines such as history, geography, marketing, computing, music, archaeology, graphics, images, and more. In addition, there are things that we naturally learn by listening, seeing or reading.

Therefore, by adding this component to the chatbot, we hope to bring curiosity in teaching and the same involvement in students dealing with the chatbot. We hope to facilitate assistance in the various subjects and factors that affect student performance.

The multimodality personalisation of the answer works in the Knowledge database. When human assistants and lecturers save the question and answer, the image or graphic is saved, as well as the video link if applicable.

Discussion: Research [39] proves the efficacy of multimodality in education, enhancing the students' learning process. However, sometimes, not all content can be represented in the best or expected way. For example, multimedia content can distract the student. In contrast, there are contents more easily represented using multimedia resources. Next, we present the Rating component.

Rating. This component is the student's performance evaluation component of the proactive chatbot, the feedback of the interaction between the proactive chatbot and the student. The primary purpose of getting feedback from students is to understand how helpful chatbot responses are so that the course lecturer can improve the responses and the human assistant can improve the PS2CLH responses, aiming at the qualitative improvement of the chatbot responses. The other motivation, getting the rating of the answers, will make the algorithm developed in the proactive chatbot give more weight to the most relevant questions. Furthermore, there will be less attention to the questions with a lower rating in such a way that it automatically improves the performance of future answers given by the proactive chatbot.

When the student receives the answer to their question, the chatbot also sends a rating on a scale of 1 to 5, where one is the student is not satisfied with the answer and five the student is satisfied and gives the answer five stars. The chatbot sends student feedback to the knowledge base so that the chatbot will know the best and worst answers. This way, in the future, lecturers and assistants will be able to delete or improve the worst answers in their profiles. After the proactive chatbot has many interactions with students, all the conversations are saved, and the chatbot Transformer model is improved by retraining the model with that new data.

Discussion: Usually, people do not give the rating, making for a less natural conversation. However, the vital point is that the proactive chatbot will improve the Q&A using the structure of the knowledge database. The following session is the suggest factor component.

Suggest Factor. This component is the one that makes the proactive chatbot have a more proactive approach. Generally, universities, student assistants and even a typical student are often unaware of the existence and impact of controllable student factors that affect their academic achievement. It is almost humanly impossible for a regular assistant to know the correlated factors for each student in a university of ten or twenty thousand students. The number of controllable factors is high and complex as it varies between countries and universities. Often the student can ask about a factor. The average chatbot would respond, having only a reactive attitude, unlike the proactive chatbot, which proactively suggests factors that may have a more significant impact on the student's result. It may redirect the student to look at the root (what generated the problem the student is facing) of the problem and not just the consequence of the problem.

If the student's question is related to the PS2CLH model, proactively, the chatbot suggests students work on the correlated areas affecting student performance. Correlating the variables or factors that affect students' results will allow the chatbot to make individual suggestions, giving a specific question. For instance, if a particular student has a problem with stress and wants to know more about dealing with it during the interaction between chatbot and student. In the example below, first, we ask about sleep problems. Then, the suggestion was about stress and anxiety, time management, and establishing and achieving personal goals.

It Uses weights to quantify the correlation among the factors. The system will know which factors impact the most in the other factor. Therefore, the suggestion will be according to the correlation among the factors. Thus, it leads to building clusters of correlated factors.

Discussion: The weak point is that this can distract the student from working on the factor they asked for. However, on the other hand, the student will have more assistance and more knowledge related to the factor he is looking for, thus opening the possibility for the student to find the root or actual cause of the problem he is facing.

Knowledge Database. The file JSON has the proactive chatbot's knowledge database of each subject; this is the questions and answers from PS2CLH's model and lecturer's subjects. The structure of the file is presented in the figure below.

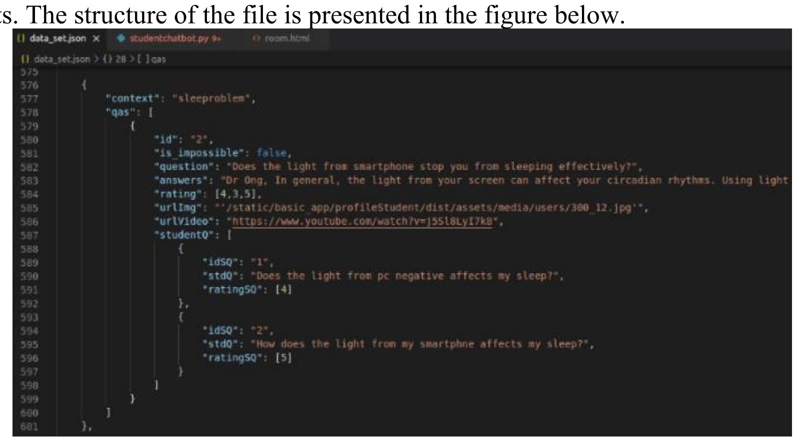

Fig. 2. Chatbot's JSON file structure

The "context" represents the student subject, "qas" has the reference of questions and the answers. Often students may ask a question in different ways; therefore, as we can see in the figure above, one answer can have many questions, giving the proactive chatbot the flexibility to improve the accuracy of the answer. However, by increasing the number of questions associated with an answer, we will have a more extensive knowledge base, which increases processing time, so we limit the number of questions associated with an answer to just three. In addition, we seek to make the proactive chatbot as efficient and human-like as possible. The aim was to minimise the chatbot time response and, at the same time, improve the accuracy of the answers. The current proactive chatbot assists students in their subjects via an interaction between the proactive chatbot and students.

Discussion: The weak point is the growing number of questions associated with an answer. This situation will negatively affect the response time in a large data set, affecting the proactive chatbot's efficiency, causing the student to wait longer for the chatbot's response. The vital point is that it will enable machine learning of the students' terms and language, making algorithm similarity work better after several interactions with students, thus improving the effectiveness of the proactive chatbot.

Below is presented the students' profile, lecturers' profile and assistants' profile.

Profiles. This component is the profile component, where we present the students, lecturer and assistant profiles.

We created two applications. The first one is the social network, where we have the students' profiles, assistants' profiles and lecturers' profiles. The second application has the chatbot app.

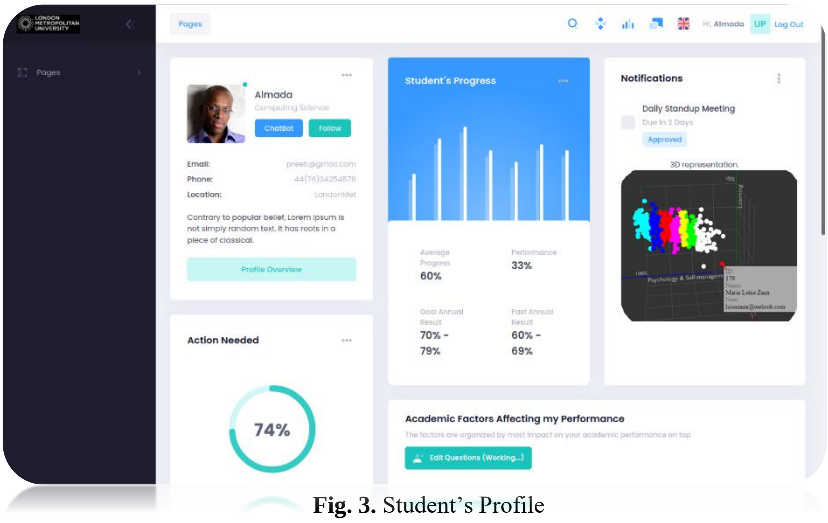

Fig. 3. Student's Profile

The profile of the students has the questions he or she selected from the PS2CLH questionnaire. In addition, the student's profile has a proactive chatbot that helps him in the factors and the material given by the lecturer and the assistant. In the human assistant's and lecturer's profiles, we have the form to add questions and answers students ask, which are not found in the knowledge base.

4 Test the proactive chatbot framework and extending BERT chatbot, Results

We test the proposed proactive chatbot framework in this application's test phase. We do not aim to test which word embeddings such as word2vec, TF-IDF, or MV-LSTM works better. Neither test the combination among embeddings and text similarity measurement (cosine similarity, Euclidean distance, Manhattan distance, Hamming distance, distribution distance or semantic distance). It is not our purpose to test different Q&A models. Our test goals are to test the chatbot answer's accuracy and then compare the approach of an extending chatbot with the proactive chatbot framework. Below we start the test phase by presenting the test setup.

Test Setup. We created two applications to perform the test. The first is the proactive chatbot framework which we will call "proactive chatbot" the second application is an implementation of the Extending Bidirectional Encoder Representations from Transformers, and we will call it "extending chatbot".

Results: "***proactive chatbot*** ***vs*** ***extending chatbot***".

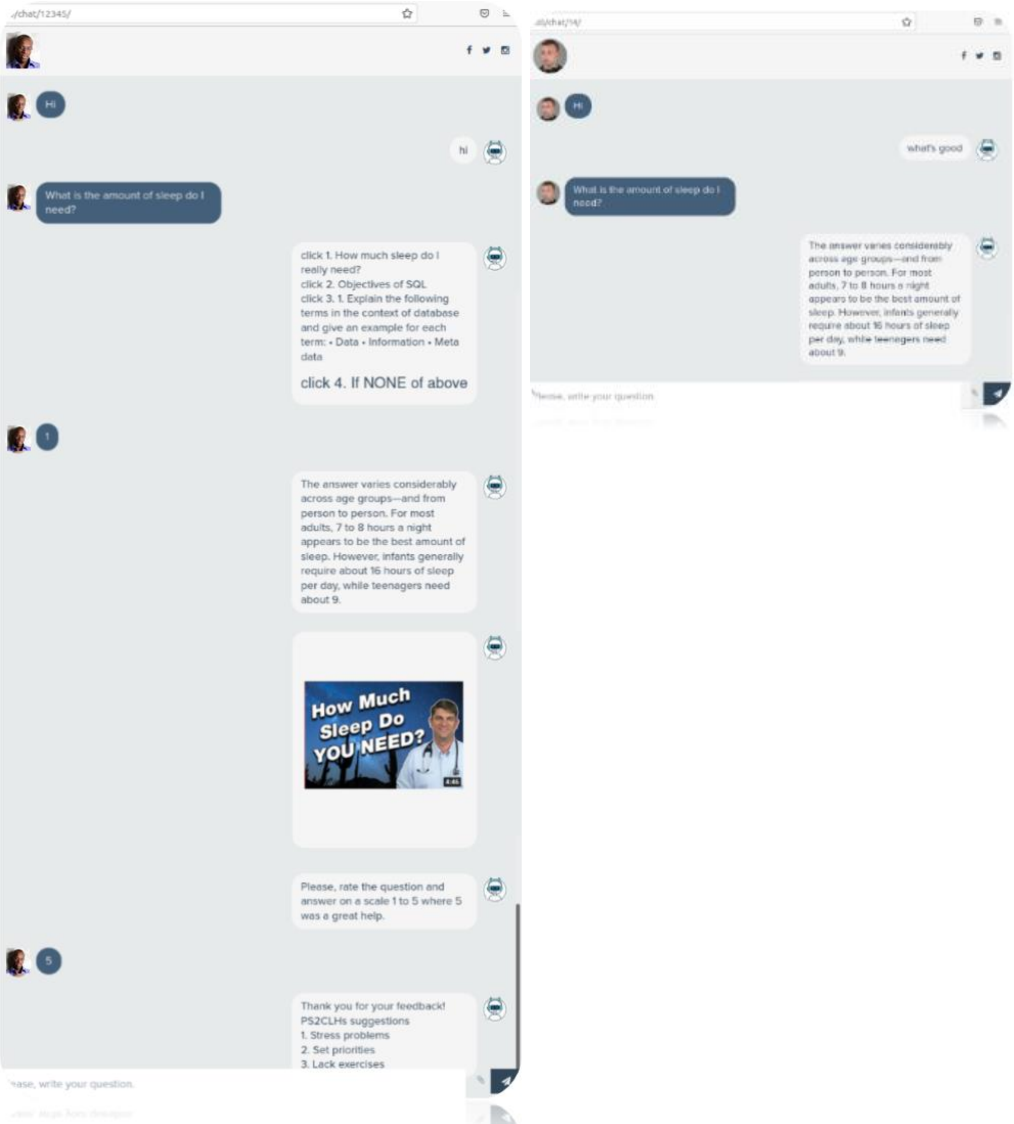

Fig. 4. Proactive chatbot vs Extending chatbot

For the test to be fair and realistic, the two applications were programmed with the exact word embeddings, the same text similarity measurement and the same Q&A

model. The difference lies in the components added by the proactive chatbot, i.e., the methodology for presenting the answer to the student's question. Below is a small sample of the questions used in the test.

Both applications used the same dataset of 100 questions and answers. The test consists of two types of questions. The first is a simple question; the simple questions are questions that use some keywords from the question in the knowledge database, the second type of question is the complex question. We try to ask the same question using different words in this type of question.

Table 1. Small sample of the questions used in the test

	Question *(Knowledge D.)*	***Simply*** *(Student's question)*	***Complex*** *(Student's question)*
1.	What is database?	Could you define database?	What is a data repository?
2.	How can I manage better my time?	Prioritise better my time?	How can I prioritise well my time?
3.	What are the objectives of SQL?	Tell me the objectives of SQL.	Objectives of the Structured Query Language?
4.	What are the symptoms caused by stress?	What are the stress side effects?	Stress side effects?
…	…	…	…
100.	How much sleep do I really need?	What is the amount of sleep do I require?	What is the sum of rest do I require?

In this example, the proactive chatbot takes longer to interact with the student, four interactions per step. In contrast, the extending chatbot has two interactions. However, the last two student interactions are minimal. In this example, the two chatbots give the correct answer to the student, where students who only wanted a simple answer would be more satisfied. However, with the proactive chatbot, most students would have a better idea of the problem, where they will have more information about it through the video and of PS2CLH suggestions. Below are the test results performed with the proactive chatbot and the extending chatbot. The total number of questions was 100, and the number of correct question options given for the Chatbots was:

Table 2. Results of the small sample of the questions used in the test

Question	***Proactive Chatbot***		***Extending Chatbot***	
Type of Question:	Simply	Complex	*Simply*	*Complex*
What is database?	Right	Wrong	Right	Wrong
How can I manage better my time?	Right	Right	Right	Right
What are the objectives of SQL?	Right	Wrong	Right	Wrong
What are the symptoms caused by stress?	Right	Right	Wrong	Wrong
…	…	…	…	…
How much sleep do I really need?	Right	Right	Right	Wrong

The formula for calculating Accuracy is found below:

$$Accuracy = \frac{Correct\ \#\ of\ questions\ answered}{Total\ \#\ of\ questions\ made} = 94/100 = 0.94 \approx 94\%$$

Accuracy is the ratio of the number of answers correctly answered to the number of questions asked, and the chatbot test results indicated % accuracy.

Table 3. Accuracy results

		Proactive Chatbot		*Extending Chatbot*	
Type of Question:		*Simply*	*Complex*	*Simply*	*Complex*
Answer's Accuracy	≈	94%	77%	91%	59%

On the test results, the proactive chatbot showed better results for both simple and complex questions: a higher number of correct answers than the extending chatbot. The difference was four more correct questions for simple questions and eighteen more for complex questions. Below we establish the comparison in practical terms between the proactive chatbot and the extending chatbot.

Comparison between proactive chatbot and extending chatbot: We have a practical overview of what one chatbot does better than another in the table below.

Table 4. Comparison between proactive chatbot and extending chatbot

	Proactive Chatbot	*Extending Chatbot*
Answer's accuracy	☑	
Execution time, chatbot's response		☑
Instant learn from previous questions	☑	
Most Human-like conversation		☑
Dealing with question that is not in knowledge database	☑	
Multiple ways of content display	☑	
Proactivity	☑	
Receive students' feedback	☑	
Q&A in relatively large data set	☑	☑
Students' assistance	☑	☑

As we can see, the two chatbots assist the student, both using a decent number of questions in their data set. However, the proactive chatbot has higher accuracy. In contrast, the extending chatbot responds faster to the student's questions. Nevertheless, one of the causes of the delay in the proactive chatbot's response is the approach. Its procedures make the proactive chatbot learn from past questions and deal with unexpected situations where the questions asked by the student are not found in the knowledge database.

Furthermore, it uses multimodality in its responses, receives feedback from students, and proactively acts by suggesting other factors correlated with the question asked by the student. This interaction makes the conversation less natural between the proactive chatbot and the student. The key observation was that, despite the limited real-world test (test with students) simulation, the proactive chatbot learned and used more information to give a response for each interaction. For example, it created a cluster of similar questions related to a particular answer, suggesting that it was the cause of improved accuracy whilst students interacted with the chatbot.

The proposed proactive chatbot needs to be further monitored and tested in different universities and countries despite encouraging results.

5 Conclusion and Future Works

This paper proposed an AI-Deep Learning chatbot using the state-of-the-art model Transformer combined with text similarity measurement and some components, resulting in a proactive chatbot framework to assist students on the PS2CLH factors and their academic subject individually. This approach improved the proactive chatbot accuracy. Moreover, it could instantly learn with student' interaction. The components assembly parts, interaction facilitator, profile's customizer, multimodality, rating, and suggest factor. Effectively created the educational chatbot ecosystem, the innovation proposed by this paper. However, the proposed framework still has limitations. For instance, there is no image or video for every question-answer on our knowledge database to fully display a multimodality environment. In our case, we just represented the pair Introverted – Extroverted on the chatbot persona due to complexity. In addition, future framework testing is required. The best test environment could be conducted during a semester at different universities.

Future work would be in individualising and personifying the proactive chatbot based on the 16 types of personalities in ways that can involve students and captivate them in the interaction with the chatbot. In addition, works need to be done to find a more efficient integration of text similarity measurement and questions and answers model and pay more attention to the knowledge database's structure.

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