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TOWARDS ADAPTIVE LEARNING: AI CHATBOT FOR USERS PROFILING AND LEARNING STYLES

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Abstract- Nowadays, education strongly depends on IT. Several applications have been created to support and enhance the education system. In this context, Artificial Intelligence technology offers new personalized services through the integration of multiple features such as Chatbots into various aspects of education. Exploring the application of chatbots in the education sector enables multiples functions as service assistants or educational agents with the purpose of enhancing the student learning experience. The present paper aims to create /generate a Model of chatbot functionality and design an adaptive e-learning system for identifying students' digital profile and learning style. The process of identification is founded on the student's profile and includes the evaluation of perception as one of the aspects of the Filder-Silverman Learning Style Model which encompasses processing, input, and understanding. This model was selected for its validity and suitability to the purpose of the study. The generated model will provide a distribution of different profiles which will help in drawing a better idea of students' learning requirements and propose adaptive learning for each distinguished profile.

Keywords: Artificial Intelligence, Chatbot, Education, Student's Digital Profile, Styles of Learning, Filder-Silverman Learning Style Model.

1. INTRODUCTION

Learning with digital technology currently represents the trend in educational systems, thanks to the numerous advanced functionalities it offers. These functionalities include communication, accessibility, flexibility, and interaction, which allow for a diverse range of learning and teaching approaches [1]. In this sense, Artificial Intelligence (AI) has increasingly become involved in the education field through various applications. These applications aim to upgrade the transition of the educational system from a traditional, tutor-centered approach to a learner-centered system which allows the development of learner's autonomy [2].

AI can provide learning flexibility and adaptation of the process to the special needs of students. Chatbots are regarded as highly popular AI technologies for supporting the teaching and learning process nowadays [3]. The education system Is taking advantages from the AI technologies since they are representing innovative solutions for the challenges currently facing it [4]. It is affording the personalization of learning content and learning resources depending on the student's profile and style of learning [5].

While the term "student profile" is used to indicate the representation of information about the student, it provides data about the student's knowledge, skills, and/or conceptions. This information is identified at the end of a pedagogical activity, whether it involves Information Communication Technology (ICT) or not. The student profile can be generated by a system, such as computer learning environments with a student model unit or designed and used manually in paper-and-pencil form by a teacher. The concept of a student profile has been used multiple times [6-8]. In this regard, several dimensions are involved in the definition of the concept of a student profile. These dimensions include personal information, preferences, educational expectations, information about possible disabilities, information about motivation and emotions, and finally, learning style.

Learning style, in contrast indicates the process to acquire information and knowledge [9]. It speaks about learns preferences regarding there learning process. Identifying a learner's learning style is crucial for deterring the way to transmit effectively the learning content and enhance the efficacy of learning process. To describe the learning styles which exist nowadays, scholars have proposed different models for that purpose. These models are classified into different categories based on external conditions or personality. In this project, the Filder-Silverman Learning Style Model (FSLSM) has been chosen as a model for guiding, as it is considered the most appropriate for a digital learning system depending on technology. Index of learning styles (ILS) represent the questionnaire instrument that will be integrated into the chatbot for the purpose to classify the student's profile.

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This paper explores the utilization of AI technology in the design of an educational-oriented chatbot model that serves as an investigative tool for identifying students' digital profiles and learning styles. A literature review examines the present status of AI and chatbot technology within the education industry, in addition, the understanding of students' digital learning profiles and learning styles depending on the FSLSM.

The task of manually identifying students' profiles and learning styles, and providing individual feedback to each student, is considered challenging for teachers and administrative staff due to the time and availability required. To address this issue, technology can be relied upon, specifically through the use of a conversational chatbot. The proposed model is based on a key component to define a Chatbot as an investigation instrument serving all the personnel involved in the educative process. Chatbot offers various potential functionalities beyond just classifying different student profiles. It also complements and provides useful information for teachers, administrative staff, and decision-makers about students, which can be utilized in future adaptive learning processes. Additionally, it outlines different roles for interacting with the Chatbot, depending on the tasks accomplished within the process of learning.

The next sections of the present paper are following this order: section 2 will offer a general comprehensive overview of the pervious theoretical foundations. for both the design architecture and the implementation of our Chatbot model. Third Section explains the development process of the proposed model. Section 4 contains a discussion of the model's results, and lastly, Section 5 is dedicated to the conclusion of the paper and future research directions.

2. THEORETICAL FOUNDATION

2.1. Student Profile

First, the education sector is currently facing several challenges, particularly in the post-Covid period. It is through the interactions between learners and the education system, as well as the teaching-learning process, that a massive amount of data is generated. Therefore, educational institutions have a vested interest in harnessing this data to generate knowledge that can shed light on learners' choices, interests, and orientations within the educational system. This data can also be used to assess learners' performance and, subsequently, create learner profiles that align with their individual learning models Second, the knowledge-building process varies among learners. However, the classroom learning experience provides an opportunity to observe the factors that influence this process. Learners demonstrate different reactions based on their learning styles, which can be observed through their selection, assimilation, and utilization of information, as well as their engagement in social interactions [10].

The student profile is the structure that encompasses both direct and indirect information about the learner, including their interests, preferences, personal data, abilities, etc., The composition of a student's profile is heavily influenced by the learning context, and in digital learning environments, it reflects interactions between the student and the system. By collecting and analyzing the data generated from these interactions, it becomes possible to describe the behavior and learning mechanisms of these students.

AI technologies and its application in education has resulted in a massive transformation in the field. This transformation includes significant improvements in the learning experience, time flexibility, and optimization of learners' education management, leading to rapid progress Additionally, it has created a learning ecosystem that fosters the development of skills used for problem-solving, promotes collaboration, and instills a sense of responsibility among learners. Cultivating critical thinking, which is an essential skill for university students, poses a major challenge in e-learning.

2.2. Learning Styles Concept

Teaching and learning are inclusive processes influenced by a variety of behavioral, social, and cognitive factors, such as interests, motivations, aptitudes, environment, teacher personality, intelligence, memory, and individual differences. Today, research on learning performance, memory, intelligence, and classroom climate is exploring new factors, including metacognition, reflective thinking, and adaptive technology. One significant factor among these is learning style. According to the literature, learning styles imply processes of acquiring information. The learning styles and variations in courses may have an impact on course outcomes, such as satisfaction and performance. Consequently, the new generation may exhibit different tendencies. When students' preferred learning styles do not align with teachers' teaching methods, they encounter barriers [11].

Identifying students' learning styles and using instructional resources according to their individual level and competencies ensures excellent results. Studies [12] have shown that students who face inconsistencies between their curriculum and learning styles tend to underperform. Similarly, research in references [13] and [14] has emphasized the criticality of identifying students' learning styles for effective learning and teaching. For that reason, learning style has been integrated into adaptive learning systems as a parameter for personalized learning [15, 16]. The literature describes a variety of learning style models, some of which are employed by different adaptive learning systems for the classification of learners into distinct groups.

2.3. Learning Styles Models

Various theories regarding learning styles are discussed in the literature, such as Kolb's model from 1984, the Visual-Auditory-Kinesthetic (VAK) model from 1995, Honey and Mumford' model from 1982, and Felder and Silverman's model from 1988. Most of these theories categorize individuals into distinct groups based on their styles of learning. However, the Felder-Silverman Model (1988) takes a different approach by dividing people into

four continuums instead of separate classifications. This unique characteristic makes the model distinctive, comprehensive, and encompassing a wide range of learning styles [17].

The two scientific Felder and Silverman (1988) introduced the Felder-Silverman model, also known as the Felder-Silverman Learning Style Model (FSLSM). They claim that it is a way for students to acquire and implement new ideas, concepts, and theorems to use is referred to as their learning style. The cognitive responses, connections, and learning outcomes of the learners are shown [18]. The FSLSM has advantages in terms of its ability to describe learning styles in more detail by characterizing learners according to four dimensions [19]. Additionally, the work referenced in [20] highlights that the FSLSM regards learning styles as tendencies rather than required types, in contrast to other models. For these reasons, the FSLSM was selected as a reference to direct the course of this investigation. The previous model uses four distinct dimensions to defined learning style as: Active/Reflective, Sensing/Intuiting, Visual/Verbal, and Sequential/Global.

While the Active and Reflective side of the FSLSM relates to how information is processed. Students that scored higher on the Active scale are more likely to learn through active experimentation, conversation, or teaching others. On the other hand, students who belong to the Reflective scale are more likely to observe critically. the Visual and Verbal dimension is about how the information is perceived by the students. The ones on the Sensing scale prefer to use their senses to take in information, while students on the Intuiting scale rely more on their memories and insights. The third dimension focuses on how information is received. Verbal learners prefer written words as their primary mode of learning, while learners with visual preferences like that the information to be presented through pictures, flow charts, diagrams, or videos. The final dimension is related to how the students understand information. Sequential learners tend to learn in logically linear phases, building one concept upon another. On the other hand, global learners need to develop a comprehensive understanding of a subject before delving into its specific details.

2.4. Chatbot as an Artificial Intelligence Educational Tool

The use of AI chatbots has grown in popularity recently. they are now widely used in various industries such as medicine and healthcare, online banking, e-commerce. The utilization of chatbots is becoming increasingly common across different sectors [21]. A chatbot is considered as software application using artificial intelligence (AI), natural language processing (NLP), and/or other technologies in order to establish an interaction process with humans through text or voice. Eliza was the first chatbot, was developed in 1966 with the goal of exploring natural language and human-machine communication. Since then, there has been a significant rise in the usage of chatbots, and experts predict even greater adoption in the upcoming years [22].

Currently, in education, through the process of digital transformation, chatbots are being introduced and are being utilized to either create new services or enhance those that already exist [23]. There are different types of educational chatbots depending on their implementation: service-oriented, and teaching-oriented chatbots. The service-oriented category includes chatbots that are helpful for academic institutions. They answer frequently asked questions and provide general information for internal and external users, such as educational offers, fees, admission process, and schedules.

On the other hand, the student/teacher-oriented category refers to chatbots that assist both students and teachers in order to generate knowledge. These chatbots have the following features, as illustrated in Table 1. There are many chatbots that fall into only one category, but for others, they have more than one feature in common. As an academic solution, chatbots must consider multiple functions in order to accomplish their mission. Based on technological development, chatbots are frameworks or libraries with many elements implemented to provide multiple functionalities and different features. However, sometimes not all these features work well.

Table 1. Features of different chatbot categories [35]

Service-Oriented	Information	It refers to information, as educational Prospective students require information on educational offers, staff contacts, and study plans when considering becoming a student of the institution
	FAQ	It is about questions and answers commonly asked by the students
	Procedures	It refers to a guide for students to maintain administrative policies such as: conditions for the class access, requirements for certification, and admission steps process
	Schedule	It refers for Examples of activities that students engage in include homework assignments, quizzes, exams, essays, and practice sessions
Student/Teacher-Oriented	Evaluation	The system offers students feedback regarding their performance and progress in the classroom
	Feedback	Chatbot users have the ability to ask precise questions, and in response, the chatbot can provide relevant and context-specific answers
	Q and A	The system furnishes educators with comprehensive information regarding the academic advancement of their students
	Reports	The system has the capability to engage with students regarding the courses they have enrolled in
	Subjects	It refers to the student's assistance, such as how to manipulate laboratory equipment
	Support	It involves addressing uncertainties related to specific subjects by offering students some form of guidance
	Tutorships	It pertains to assessment tools employed for students, such as assignments, quizzes, exams, essays, and practical exercises

Students value the positive influence of educational chatbots [24], such as enhancing the self-motivation and organization, and autonomous learning, which are generally successful. In order to evaluate an educational chatbot, they use typically their self-perceived learning experiences while using a chatbot for learning a specific subject during a specific time period compared to students not using this technology for the previous subject during the same time period.

For that purpose, many studies on educational chatbots, however, studies have demonstrated that students' assessments of using chatbots as teaching aids have shown improvements. Additionally, chatbots have the ability to track students' searches, providing valuable information that can be used to update course content [25].

3. A PROPOSED LEARNING STYLE MODEL

The experiment on which the suggested model is based on is a chatbot which is designed specifically for classifying learners depending on their learning style, preferences, and habits. As a result, learners can be classified into four categories using the FSLSM. The ILS is then integrated into an educational chatbot to fulfill the learner classification task.

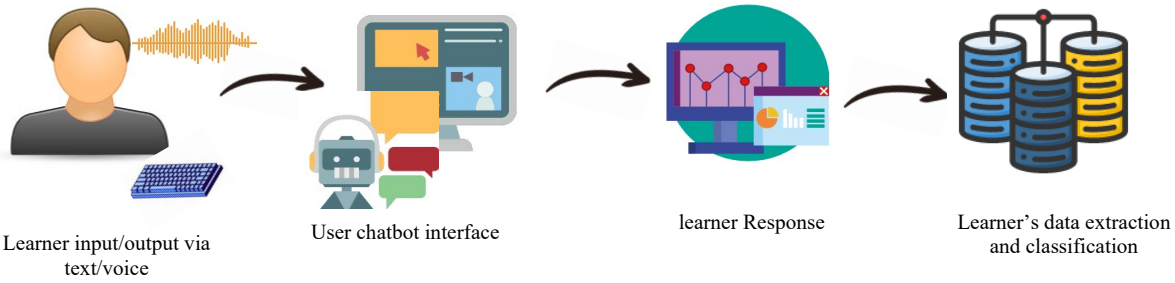

Figure 1. Schematic representation of the current chatbot project

The chatbot's purpose is to gather information about the learner's preferences through manual conversation with the bot. Basic information such as age group, level of studies, subject of studies, and learning preferences are collected during this process.

3.1. A Schematic Representation Design of the Educational Chatbot

Finding two chatbots with identical architectures is challenging, as different chatbots often have unique design structures. However, this study aims to simplify the architecture to provide an understanding and demonstration of what a "standard" chatbot architecture entails and the common components involved in its construction. Typically, a chatbot design is based on three main components: graphical user interface (GUI), backend, and the kernel.

The backend and kernel are responsible for handling natural language processing (NLP) tasks, while the database stores relevant information. Conversational bots powered by artificial intelligence or decision trees are an alternative. Chatbots' user interfaces are built on NLP results of human conversational structure. Algorithms can understand, interpret, and manipulate human language thanks to the NLP. Additionally, more sophisticated chatbots can use machine or deep learning to learn from discussions [26].

In the flowing section, we provide a model for developing the educational chatbot, as shown in Figure 1, learners have access to the user interface and interact with the chatbot through their preferred mode text or voice. The chatbot starts asking questions already mentioned in "The index of learning styles" it is a psychometrical tool introduced by The Filder-Silverman and provided free of cost for research and academic purposes [27]. The ILS is a 44-item questionnaire in which there are eleven questions designated for each of the four FSLSM dimensions [28].

Once the responses and actions are executed, they are then analyzed using coding and statistical programs. All the information and data are recorded in order to determine learner's learning style and provide learner classification. This classification includes recommendations and personalized feedback for different education actors, such as teachers and administrative staff [29].

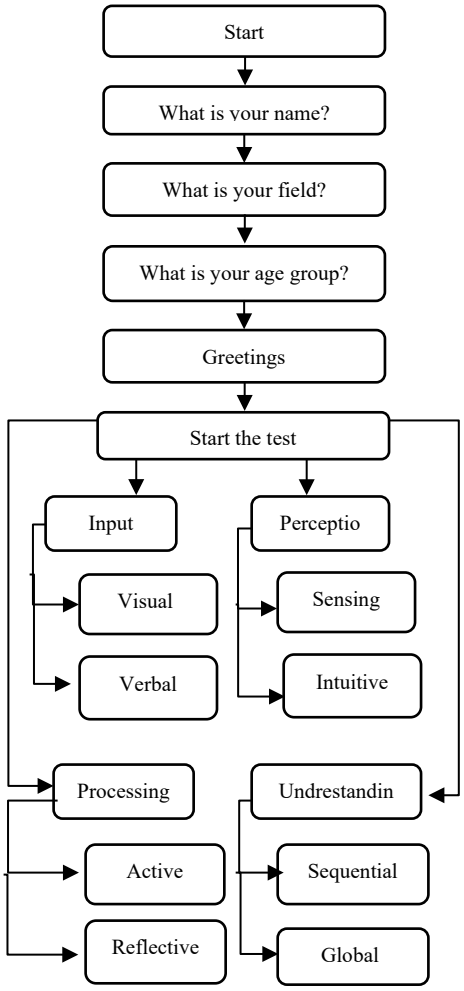

Figure 2. A model for a chatbot assisting the identification of student's learning style

3.2. A Chatbot Functionality Model

The proposed Chatbot has a data flow of simple and direct questions. a relation is established between the options provided by the Bot and the potential learner's responses, the question loop of is divided into two parts which are General questions and Learning preferences. The questions and answers provided by these learners are used to classify them into the four categories of the FSLSM, the chatbot is used for the classification at the end of the chat based on the age group of learners, studies, or the level. The Chatbot design consists of NLP as mentioned before, for generating answers, the NLU (Natural Language Understanding) for the extraction of data with a meaning from the learner's input. The DMG (Decision Making Engine) for deciding, to responding, or to waiting. At the backend, the database is storing all the conversations and information mentioned during the chat maintained between both the Bot and the learner using it, the data is secured by Blockchain technology which allows also the enhancement of the educational model [30].

The data flow diagram of our Chatbot proposition is illustrates in Figure 2. The development of the present Chatbot is based on previous research on integrating AI into education and enhancing student learning and educational services. The Chatbot engages with learners, allowing them to complete the interaction using his/her own time. This is because the interaction and responses to the 44 questions in the ILS are relative, depending on the individual student's understanding and perception of the questions. Additionally, the proposed Chatbot is compatible with both mobile and desktop browsers.

3.3. A Designing an Adaptive E-Learning Model Based on Student Learning Styles

The Chatbot design system for identifying student learning styles was created to provide content that follows their learning preferences. Figure 3 illustrates the activity diagram of our model design. Once the learner logs into the Learning Management System (LMS) interface using their personnel login and password, once the system validates the authentication. the learner proceeds to the next step. Otherwise, the system prompts the learner to re-enter their authentication details. If the authentication process is successful and the learning style has already been identified, the learner is guided towards customized content and resources, including videos, PowerPoint presentations, PDF files, etc., that align with their unique learning preferences and style. If the learning style has not been identified yet, the learner is automatically directed to the Chatbot to initiate a conversation. The Chatbot starts with a welcome dialogue. Once the test is ended, the Chatbot provides the learner with a detailed report that includes their profile and learning preferences. All learner accounts, profiles, learning styles, and courses are stored in the database. Learners are then classified into specific groups for further recommendations of appropriate learning content.

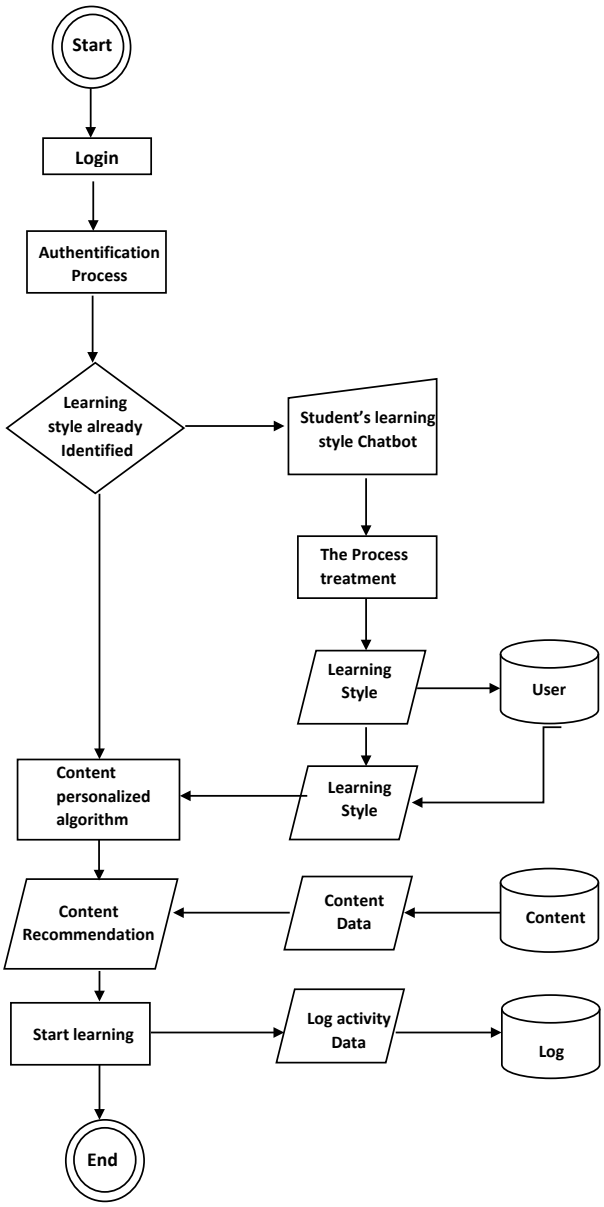

Figure 3. A Proposed Design for an adaptive E-Learning System

The Chatbot will be integrated into a LMS where learning content such as: Documents, storyboards, learning activity, activity logs are mapped into several types based on FSLSM as follows:

- Introduction content for all types of users
- Sensory-Verbal content to accommodate learners which are comfortable with facts and observations through real situation written materials or oral words.
- Sensory-Visual content to accommodate learners which are comfortable with information from visual images such as pictures, graphs, charts and demonstrations shown.
- Intuitive -Verbal content to accommodate learners which prefer abstract form of lessons and concept.
- Intuitive-Visual content to accommodate learners that cab show information through memory, reflection and imagination.
- Active content to accommodate learners which learn by doing and are more comfortable in group learning.

- Reflective content to accommodate learners which need to think before trying and have tendency to learn individually.
- Outline-sequential content to accommodate learners that obtain information to reach understanding according to regular order.
- Outline-global content to accommodate learners that tend to have a holistic view and receive information separately but can reach understanding after correlate the information.

4. DISCUSSION

The incorporation of AI techniques and technology-driven models in learning are often meant to be an intrusion of technology into pedagogical and educational matters. Educational models require technology for solving problems. Through the transition process from traditional in-person education to the online system, the new educational model must necessarily include ICT to afford the best assistance to teachers and academic staff. In online educational models, where face-to-face contact is absent, students and teachers do not have the opportunity to personally get to know each other. In such situations, the student makes their best effort to understand, while teachers do their best to understand student's styles of learning and difficulties. The Chatbot's design proposed in this paper, is useful for any educational model, in order to enhance learning performance by optimizing the student interaction with the online educational system. Moreover, the meaningful data derived from the learner's historical needs and learning experiences can help identify and facilitate better solutions.

The paper proposes a model that integrates several items that are responsible for the improvement of the learning experience. These items range from the profiling and learning preferences to the integration of Al and its functions within the LMS environment. By involving the entire procedure in a process where learning is focused on special needs of the learner, a system with these features enables enhancing learning. Nevertheless, the suggested architecture enables the collection and analysis of data from various sources, which can provide valuable insights into student performance. This architecture allows the extraction of data from diverse channels, as an example assessment, quizzes, assignments, and even student interactions with the chatbot itself. By gathering data from these different sources, it becomes possible to obtain comprehensive information about student performance and make informed decisions based on the analysis of this data.

An adaptive digital learning interface allows study materials, such as PowerPoint presentations, videos, PDF files, and interactive activities, to learners once they log in. The interface identifies their learning style through a conversation with the integrated chatbot, and the resources are then made available based on learner's profile. Additionally, the interface adapts than proceed for changes according to each learner's learning style. Many algorithms can be inferred from the choice of materials that matches the learning style of the user. For the purpose to make the understanding easier for the learners, for each learning style there is specific learning component. Many technologies are used Norde to manta and secure this engineering process:

- The SCORM (Sharable Content Object Reference Model) is used to display the packages. The different learning styles are represented as clusters. The users access the portal according to their preferences.
- A clustering algorithm used to classify learners according to generated data collected from learner's age, curriculum, discipline, type of files accessed, and time spent. Any changes in learner preferences will result in modifications to the profile to incorporate the changes accordingly.
- Enhancing the functionality and security of our model inside the educational platform using security programs such as the Blockchain technology Integration with Learning Management Systems (LMS) which can enable the secure storage of educational records.

Since every learner has both strong in addition to weak learning preferences, a special learning style is identified for each learner to help them use their time and effort efficiently and productively. The clustering based on the chatbot conversation including the ILS allows the identification of natural groupings of data from a large dataset. This process generates knowledge that can be used for the prediction of learner's learning style.

5. CONCLUSION

The current trend in the teaching and learning field is technology-based education as compared to traditional classroom education. As a result, digital learning interfaces are being developed for various LMS frameworks. These interfaces aim to enhance the student learning experience. One significant factor that influences this experience is the learning style category. The chatbot model designed in the present paper aims to identify student's learning style throughout a conversation with a chatbot. This identification is predicated on the ILS used in the identification of the learning styles according to FS model. Once the learning style is identified, chatbot can provide tailored learning content and customize the user interface to align with the specific learning style of the student. This adaptative learning experience will improve the learning capacity of students by providing them with specific materials and learning content tailored to their individual learning style.

By doing so, it improves the overall learning experience and optimizes the time and effort invested in the learning process. For a future work, we look for to continue developing and implementing the chatbot and integrating it into an LMS environment for the students of university. This experience will involve classifying students based on their learning styles, which will in-crease their self-awareness about how they learn best. Additionally, it will enable teachers and administrative staff to adjust learning process and content according to different learning styles of students. This personalized approach will further enhance the learning experience and outcomes for the students.

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