Online-Journals.org

iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 13 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i13.39329

PAPER

Effectiveness of an Adaptive Learning Chatbot on Students' Learning Outcomes Based on Learning Styles

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ABSTRACT

Intelligent learning systems provide relevant learning materials to students based on their individual pedagogical needs and preferences. However, providing personalized learning objects based on learners' preferences, such as learning styles which are particularly important for the recommendation of learning objects, re-mains a challenge. Recommending the most appropriate learning objects for learners has always been a challenge in the field of e-learning. This challenge has driven educators and researchers to implement new ideas to help learners improve their learning experience and knowledge. New solutions use artificial intelligence (AI) techniques such as machine learning (ML) and natural language processing (NLP). In this paper, we propose and develop a new personalization approach for recommendation that implements the adaptation of learning objects according to the learners' learning style mainly focused on the use of a chatbot, named *LearningPartnerBot*, which will be integrated into the Moodle platform. We use the Felder-Silverman Learning Styles Model to determine learners' learning styles in order to recommend learning objects, and also to overcome the cold start problem. A chatbot is an automated communication tool that attempts to imitate a conversation by detecting the intentions of its user. The proposed *LearningPartnerBot* should be able to answer learners' questions in real time and provide a relevant set of suggestions according to their needs.

KEYWORDS

e-learning, conversational agent, recommendation, personalization, learning object recommendation, learning style, chatbot, Moodle

1 INTRODUCTION

Intelligent learning systems offer new ways of acquiring knowledge and have increased in popularity and influence over the past few decades. Popular e-learning websites, such as Moodle, are constantly digitizing materials for learners with

Kaiss, W., Mansouri, K., Poirier, F. (2023). Effectiveness of an Adaptive Learning Chatbot on Students' Learning Outcomes Based on Learning Styles. *International Journal of Emerging Technologies in Learning (iJET)*, 18(13), pp. 250–261. https://doi.org/10.3991/ijet.v18i13.39329

Article submitted 2023-03-03. Resubmitted 2023-04-17. Final acceptance 2023-04-17. Final version published as submitted by the authors.

different backgrounds and educational needs. However, without proper guidance, learners may find it difficult to choose appropriate materials when faced with a mass of information during their learning process [1]. Thus, for an educator, as the number of resources and learners increases, it becomes more difficult and complicated. This is the reason for building an adaptive learning system that can handle complicated queries and provide relevant resources to learners needing help. To automate this help, an intelligent conversational tool is a solution to explore.

The development of adaptive learning systems, which provide instructions and recommendations of learning resources based on different levels of expertise, interests, goals, training, and personal characteristics of learners, has become an important area of research. To represent learners' characteristics and traits on the Web, the most popular research direction is the integration of learning styles [2]. Learning styles are unique ways in which learners begin to focus, process, absorb, and retain new and difficult information [3]. Having insight into different learning styles can offer ways to design and provide recommendations adapted to individual needs.

Selecting an appropriate model is a key to incorporating learning styles into adaptive learning systems. However, this is challenging because at least 70 theories or models of learning styles have been proposed by experts in various fields [4]. The Felder-Silverman theory is the most widely used [5], [6] because it compromises other traditional theories and is simple to incorporate into computer applications because to its data gathering instrument, called Index of Learning Styles.

In this paper, we aim to introduce a chatbot that can solve the tutor availability problem, named *LearningPartnerBot*, which will be integrated in Moodle and can provide recommendations of learning objects, in real time, considering the learning style of the learners as a prior knowledge on which the chatbot will rely when they first log in Moodle to solve the known problem in recommendation systems called cold start.

A chatbot is a new form of automated contextual communication between users and machines or systems, which exploits a conversational approach based on natural language. In [7] stated that the term "chatbot" refers to a software system, also called a conversational agent, as it interacts in turn with the user, through written messages. It is a technology that simulates human conversation by providing feedback and can interact intelligently through machine learning and artificial intelligence [8].

The rest of this article is organized as follows: In Section 2, discusses previous research related to our topic. The proposed approach will be discussed in section 3. The experimental results are discussed in section 4, and section 5 concludes this work.

2 BACKGROUND

2.1 Learning style

Learning style theories have proven their impact on optimizing learners' performance [9]. However, given the subversive changes and freedom of knowledge acquisition brought by online learning, classical theories based on traditional, systematic, and linear learning environments may no longer be appropriate.

Studies have also been conducted to analyze the behavioral patterns of online learners. In [10], proposed a hybrid model, which combines literature-based detection and automatic detection to identify the learning style of a learner. In [11], extracted preferences and learning styles by analyzing the content of web pages. In the article [12], the authors used a learning progress bar for measuring learning styles in MOOCs. In [13], used a literature-based method and a support vector machine (SVM) to predict learning styles.

A growing number of researchers are using learning style models in e-learning activities. However, many people ignore that learners' behaviors and their learning styles differ in traditional and online learning. Only a few studies have been devoted to online learning style, and the models are mainly at the design level.

2.2 Description of the felder-silverman learning style model

The term "learning style" refers to the preferential way in which the student perceives, processes, understands, and retains information [14]. Different models of learning style have been presented in the past by researchers, such as those of Felder and Silverman [5], Honey and Mumford [15], Dunn [16], and Pask [17]. In our case, we will use Felder and Silverman's model (FSLSM) [5] to represent learners' learning styles for the following reasons. First, it is the most widely used model in educational systems due to its ability to quantify learners' learning styles. Second, it is very often used in technology-enhanced learning and some researchers have even argued that it is the most adequate learning style model for use in adaptive learning systems such as [18], [19], while being easy to implement [20], [21].

The FSLSM describes learning styles by characterizing each learner along four dimensions, each defined as follows. The Processing dimension (Active/Reflective) indicates how the learner prefers to process information. An active learner wants to try things out, working with others in a group, while a reflective learner chooses to reflect, working alone or with a familiar partner. The Reception dimension (Visual/Verbal) determines how the learner prefers information to be presented. A visual learner likes visual presentations, pictures, diagrams and flow charts. A verbal learner prefers written and oral explanations. The Understanding dimension (Sequential/Global) determines how the learner prefers to organize and progress in understanding information. A sequential learner prefers linear thinking and learning in small incremental steps. In contrast, a global learner prefers holistic thinking, systems thinking, and learning in large leaps. The Perception dimension (Sensing/Intuitive) indicates how a learner prefers to perceive or assimilate information. A sensing learner is attracted to concrete thinking, is practical and is concerned with facts and procedures. While the intuitive learner opts for conceptual thinking, innovation and interest in theories and meanings.

Felder and Silverman [5] developed an Indexing of Learning Styles (ILS) questionnaire, which consists of 44 questions that have been shown to be effective in identifying the learning style of each learner. The ILS provides a method for calculating percentage values of learning style attributes from the learner's responses on the questionnaire [5], [22].

2.3 Chatbots in education

The employment of chatbots in the education has the potential to greatly enhance student satisfaction and learning outcomes [23]. Chatbots have been successfully used in educational settings, according to studies [24], [25]. The educational system has been viewed to profit from these chatbots in a number of ways, including content integration, which is the capacity of teachers to upload all relevant knowledge about a particular topic to an online platform for authorized students to easily access. The topics addressed as well as the assignment, test, and exam schedule are all included in this content.

Students can receive individualized information from chatbots. You can inform students about upcoming school activities like sports, workshops, and other events that may be interesting to them. According to several studies, using chatbots in education makes it easier to integrate subject material so that students may easily access it whenever and wherever they want [26], [27] .Thus, chatbots in the education serve to boost student engagement [28]–[30].

The capacity to allow several users to access the system at one time is a crucial benefit of employing chatbots in education. This indicates that many students from various locations can engage in uninterrupted conversation with a specific chatbot and obtain the necessary information. One of the key benefits of employing a chatbot for educational purposes is that it allows many users to access it at once [27]. According to [31] who also concurred, a chatbot can answer several queries at once, saving the user time in order to complete other tasks.

However, to our knowledge, there is no chatbot that has been used in recommending learning objects on the Moodle platform. Recommending appropriate learning objects has become a current challenge for educators and researchers, who are developing new ideas to help learners improve their learning process.

In the next section, we will present our proposed approach to introduce a chatbot that will be integrated into Moodle and that can provide adaptive learning via realtime recommendations based on learners' learning styles.

3 ARCHITECTURE OF PROPOSED APPROACH

Of all the learning management systems (LMS) available on the Internet, Moodle is the most widely used. Moodle is a flexible and secure online learning platform that can be adapted and extended for a variety of possibilities to create personalized learning environments. It has a library of plugins that can be used to implement specific features. In addition, Moodle can even work on mobile devices.

The goal of our approach is to implement an interactive chatbot into Moodle that can communicate with learners and provide recommendations of learning objects suitable for their learning styles. There are many chatbot building tools that can be used to achieve this goal. Since they are designed for better customer service, they can support different platforms such as Facebook, Skype, Slack and others. The main frameworks listed are Microsoft Bot Framework, Wit.ai, Google DialogFlow and BotPress. Our chatbot is based on the open source version of Google's Dialogflow machine learning framework that allows users to develop human-computer interaction technologies that can handle natural language understanding (NLU). Basically, this allows us to create digital programs that interact with end users via natural languages.

Figure 1 shows the architecture of the proposed approach, adaptive learning chatbot based on learners' learning styles. Using the DialogFlow Framework to build our chatbot which will be integrated into the Moodle platform as a widget in an HTML block. During a conversation with the chatbot, the adaptive learning based on learners' learning styles engine is launched on demand, which has access to the Moodle database and the learners' database to generate a personalized list of learning objects recommended to the target learner according to his/her preferred learning style.

As mentioned before, to solve the cold start problem i.e. in the case of a new user of Moodle, an Index of Learning Styles Questionnaire will be given to learners to determine their preferred learning styles and classify them to the appropriate style (visual, verbal, active, reflective,...) and the result obtained will be stored in the learner's database which will be used by the Adaptive Learning Engine based Learning Style module to recommend learning objects appropriate to the style he/she prefers.

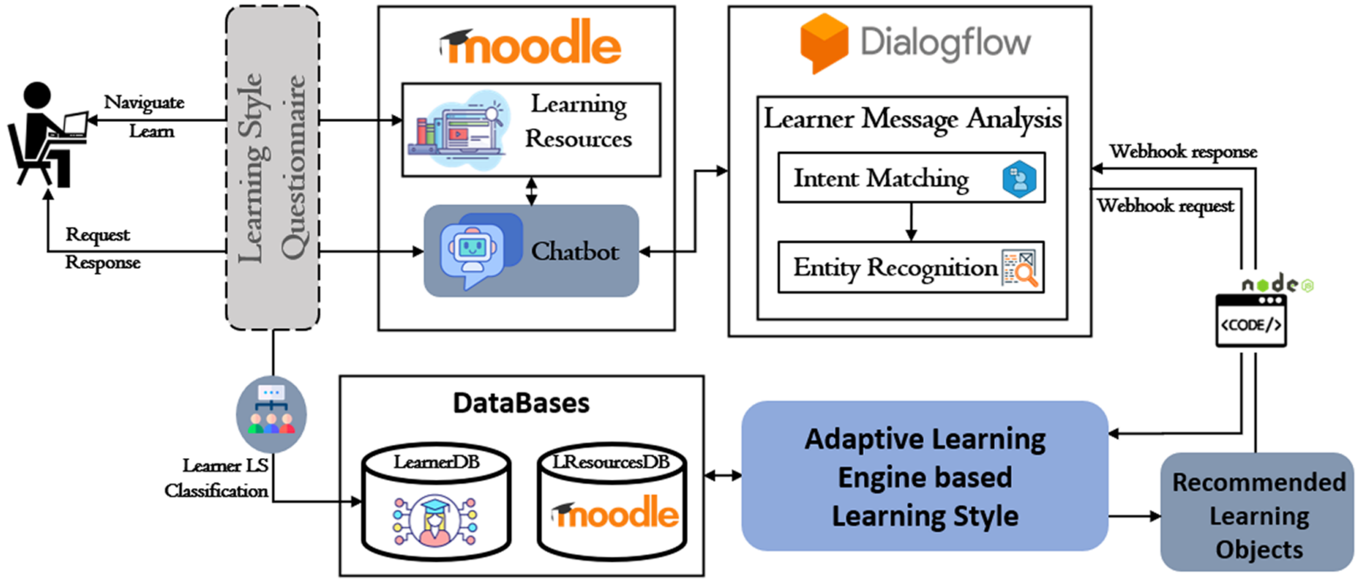

Fig. 1. The general architecture of the proposed approach

Once the chatbot is started, the learner in the current session is already known via their email which is used for access and extraction of data. The chatbot offers a variety of services, which include greetings, receiving requests, interactions with learners, sharing files and personalized recommendations.

When the student sends a message to the chatbot in Moodle, the chatbot transmits it to Dialogflow, which attempts to understand the received text by associating it to an intent using Natural Language Understanding (NLU). All chatbots have the same basic functionality, they work as follows: Read incoming messages, Identify intents and corresponding entities, Execute functions accordingly, and Send responses.

The learner message analysis component consists of learner intent matching and entity recognition. Once the learner's intent is determined, the chatbot approach proceeds to extract context information about the learner's message. In the field of natural language processing, researchers have done this very effectively, known as Named Entity Recognition (NER) systems [32].

Once the intent is detected by Dialogflow, an action to execute is chosen, the Webhook sends a formatted response corresponding to the intent. All actions are coded in Node.js and hosted by the Webhook Fulfillment. The latter is a service that allows a dynamic response by searching for response elements in an external database. It is at the Webhook level that the questions and answers are processed, the Adaptive Learning engine is launched and it generates a personalized list of learning object recommendations that will be provided to the learner. At this stage, Adaptive Learning engine based on the learner's learning style, the comparison will be made between the learner's data and the learning objects' data to extract only those learning objects that have similar learning styles to the target learner.

4 EFFECTIVENESS OF ADAPTIVE LEARNING CHATBOT BASED LEARNING STYLE

In our implementation of the chatbot, we used Dialogflow is a development platform from Google for creating human-computer interaction technologies based on natural language processing. We integrated our chatbot named *LearningPartnerBot* into the Moodle platform.

For the experimentation, we implemented our chatbot on the C programming module to provide the recommendation of learning objects. We chose the Ecole Normale Supérieure de l'Enseignement Technique de Mohammedia (ENSET), an engineering school in Morocco to conduct our experiment. The sample included 71 learners (52 males and 19 females), who participated in this study. The participants are first year engineering students in the Software Engineering and Distributed Computing Systems (GLSID) and Big Data and Cloud Computing Engineering (BDCC) fields, and are between 20 and 21 years old. Participants were allowed to use our chatbot *LearningPartnerBot* on any device of their choice.

Figure 2 shows the learning styles of the participants obtained after they answered the Index of Learning Styles Questionnaire [33] to determine their learning styles. In our experimentation, the learning styles that most participants belong to is the "visual learning style" at 51%, followed by the "verbal learning style" at 27%. Therefore, I have taken into account these two learning styles of the Reception dimension in the representation of the learning contents which are structured into learning objects for each part. Both styles define how students prefer information to be presented. The learning objects are provided in different formats and media in order to meet the learning styles of each learner. These can be text documents (e.g. pdfs), presentations (e.g. powerpoint slides), videos, etc. For example, a visual learner will prefer to watch a video rather than read a pdf document, while a verbal learner will choose the opposite.

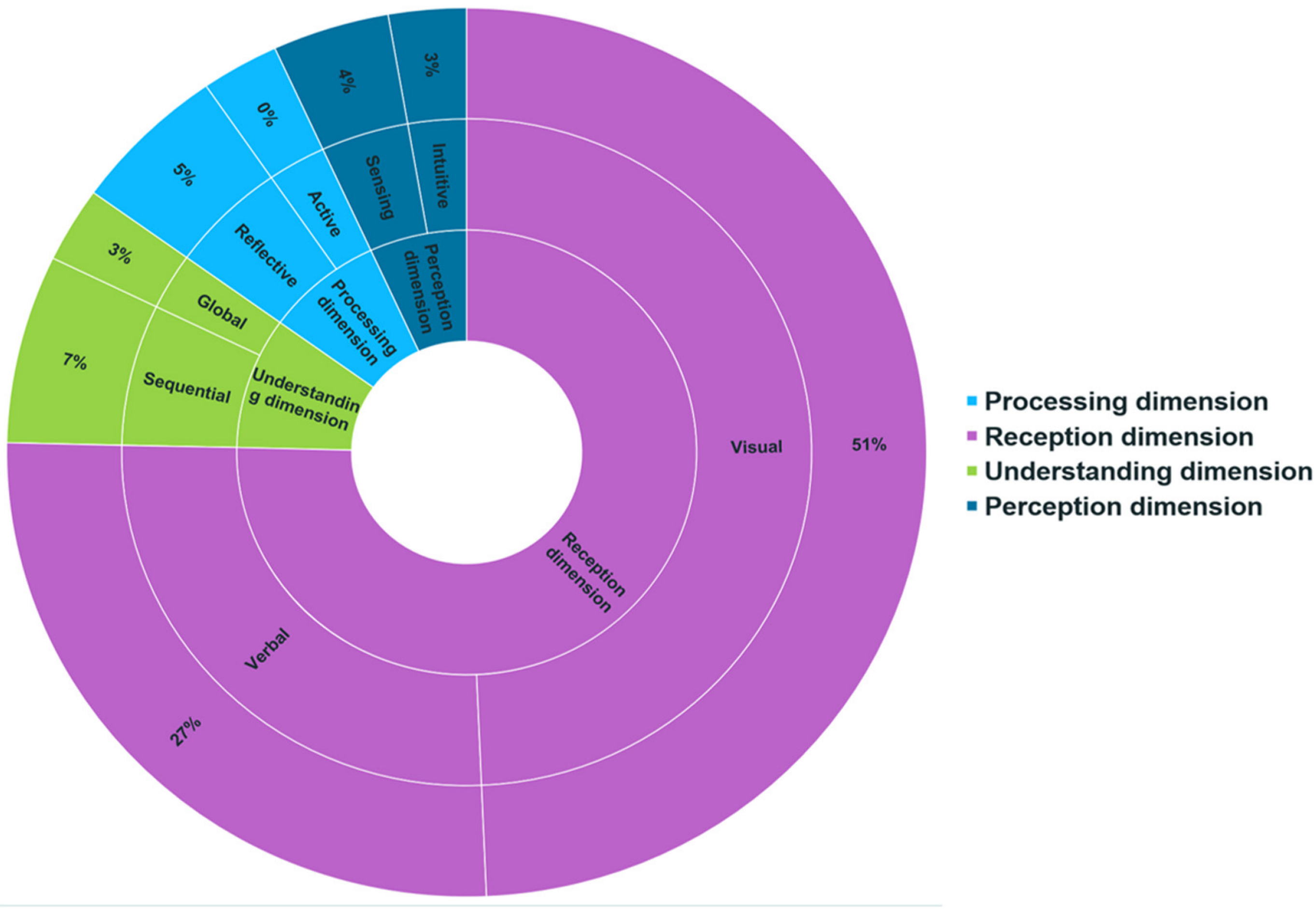

Fig. 2. Learning style of the class

The final objective of our chatbot is to allow it to identify and generate adaptive learning objects (from Moodle) according to the learner's learning style. Figure 3 shows an example of learning object recommendation for the case where the learner is in visual learning style, for example, if he clicks on one of the provided recommendations, it will redirect him/her to the content in video format. Whereas for a learner with a verbal learning style, our chatbot recommends, for example as shown in Figure 4, learning objects in text format, PDF document, Powerpoint presentation. The list recommended by our chatbot *LearningPartnerBot* are clickable to facilitate redirection and search in Moodle.

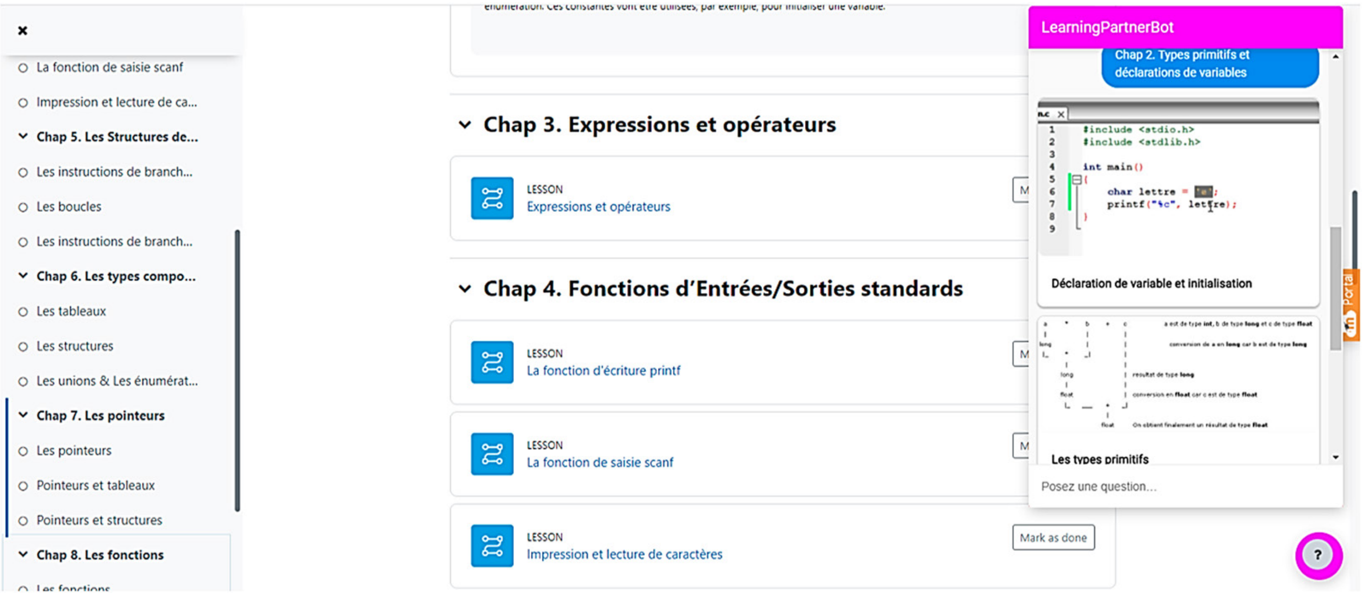

Fig. 3. Example of recommending learning objects in visual learning style

Fig. 4. Example of recommending learning objects in verbal learning style

Figure 5 shows the percentage of learners' knowledge level after passing the pre-test. Out of 71 learners, 10% of learners are at the medium beginner level, 51% of learners are at the high beginner level, and 39% of learners are at the intermediate level. This classification is due to the large number of participants classified at the beginner level, so we decided to divide this beginning level into supplementary levels.

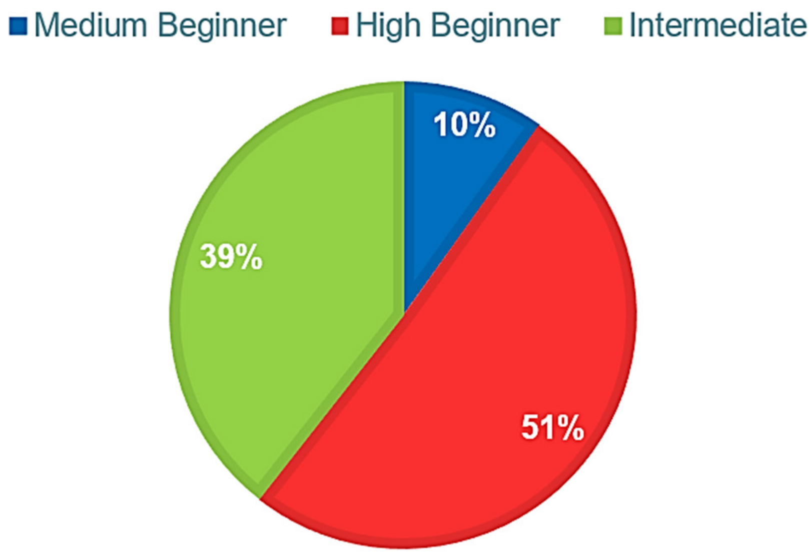

Fig. 5. Results of the pre-test

After completing the pre-test, the participants used our chatbot whenever they wanted during two weeks, recommendations are provided to them according to their learning style (examples of learning object recommendations are shown in Figures 3 and 4). After these two weeks of learning with support of our chatbot (using the recommendations it provides to them), they were given a formative evaluation considered as a post-test to see the learning outcome after using our chatbot. The results obtained are shown in Figure 6.

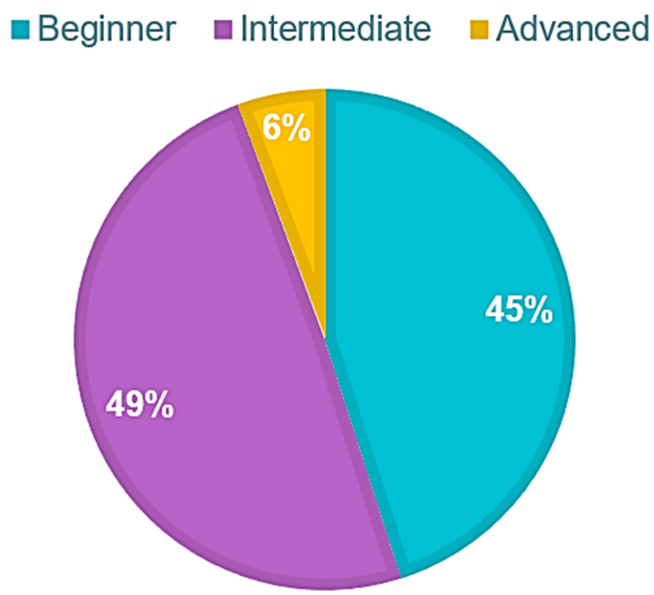

Fig. 6. Results of the post-test

Out of 71 learners, 45% of learners became at the beginner level, 49% of learners at the intermediate level, and 6% of learners became at the advanced level. There are no more students classified at the medium beginner level, so the number of students who were classified at both levels (medium beginner, high beginner) at the pre-test became only classified at the high beginner level at the post-test, which is why I renamed the high beginner class to beginner class.

This post-test evaluation shows that our proposed approach improved the learners' learning outcomes compared to the pre-test results. Figure 7 shows the difference in learning outcomes between the pre-test and post-test. The beginner level decreased from 61% in the pre-test (10% medium beginner and 51% high beginner) to 45% in the post-test. For the intermediate level, there was an improvement from 39% to 49%. For the advanced level, there is an increase from 0% to 6%.

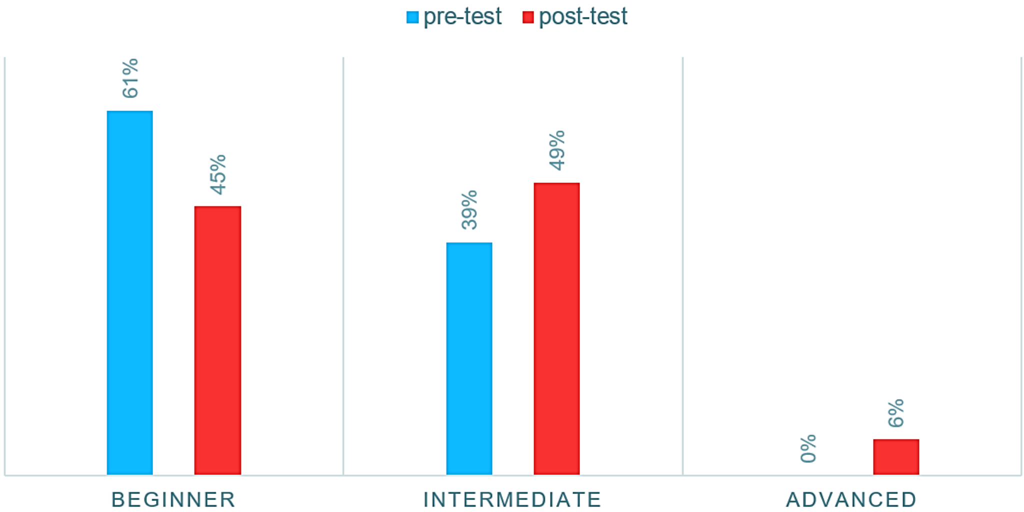

Fig. 7. Comparison of learning outcomes between pre-test and post-test

After taking the post-test, learners are asked the following questions: "Q1: Were the recommendations provided by our chatbot *LearningPartnerBot* helpful in your learning process?"; "Q2: How would you rate the overall experience with *LearningPartnerBot*?", to find out their satisfaction towards the recommendations based on their learning style and their satisfaction towards the chatbot. Table 1 shows the distribution of responses to each question.

Table 1. Evaluation questions

	Very Interesting	Not at All Interesting	Interesting
Recommendation satisfaction	73%	2%	25%
Chatbot satisfaction	91%	0%	9%

Based on these results, we conclude that our chatbot *LearningPartnerBot* was perceived as interesting and helpful, by providing learners with personalized recommendations of learning objects according to each learner's learning style.

5 CONCLUSION

In this paper, we presented our new adaptive learning approach according to learners' learning styles, based mainly on the use of the chatbot integrated in Moodle. The Index of Learning Styles Questionnaire is used to determine the preferred learning style of learners in order for our chatbot to rely on it to personalize the recommendations of learning objects and overcome the cold start problem in the case of a new user of Moodle. For the implementation of our chatbot, which we named *LearningPartnerBot*, we used Dialogflow. The experimentation was conducted on 71 students, on the C programming techniques module, and the results obtained show that our proposed approach improved the learning outcomes of the learners. Based on the results obtained from questions asked to the learners, after the post-test, which were conducted to assess their satisfaction towards the recommendations and the chatbot, we concluded that our chatbot *LearningPartnerBot* is perceived as interesting and useful and shows a positive attitude from the learners. Future work will focus on personalizing the learning path recommendation based on learners' knowledge level and preferences to improve their learning experience also based on the use of the chatbot integrated in Moodle.

6 ACKNOWLEDGMENT

This work is supported by the University Hassan II of Casablanca-Morocco, and we thank the students who participated in this study.

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