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► To cite this version:

Wijdane Kaiss, Khalifa Mansouri, Franck Poirier. Towards a Chatbot-based Learning Object Recommendation: A Comparative Experiment. Intelligent Tutoring Systems2023 (ITS 2023), Institute of Intelligent Systems, Jun 2023, Cofu, Greece. hal-04081079

HAL Id: hal-04081079


<https://hal.science/hal-04081079>

Submitted on 27 Apr 2023

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Towards a Chatbot-based Learning Object Recommendation: A Comparative Experiment

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Abstract. An adaptive learning system aims to provide learning that is adapted to a learner's current status, different from the traditional classroom experience. A key element of an adaptive learning system is the recommendation system, which provides the most suitable resources based on learner profiles. Recommending the most appropriate learning resources to learners has always been a challenge in the field of e-learning. Thus, learners may have difficulties in choosing the appropriate material when faced with a large volume of recommended material during their learning process. This challenge led us to implement a chatbot 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). The use of our chatbot integrated in Moodle, named *LearningPartnerBot*, provides learners a personalized recommendation of learning objects according to two strategies, one based on their knowledge level (KL) and the other based on their learning style (LS). The objective of this article is to compare the learning outcomes obtained after the realization of the two experiments based on these two approaches centered mainly on the use of the *LearningPartnerBot*. Consequently, the approach of recommending learning objects based on the knowledge level gave promising results by guaranteeing a more adapted learning to the learners.

Keywords: E-learning, Learning Object Recommendation, Experimental Design, Adaptive Learning, Chatbot.

1 Introduction

In recent years, educational technology has increased at a rapid rate. Once learning experiences are personalized, e-learning content is getting richer and more diversified [1], [2]. E-learning provides constructive learning outcomes as it allows learners to actively participate in learning at any time and place [3], [4]. Recently, adaptive e-learning has become a commonly implemented approach by higher education institutions. Adaptive e-learning is a learning process in which content is adapted based on student profiles [5], [6].

An adaptive learning system is a recommendation strategy that sequentially makes decisions about what to learn based on currently available information. According to [7], a recommender system in an e-learning environment has the potential to help learners discover relevant learning actions that match an individual learner's profile, and thus, provide learners with personalized content "at the right time, in the right context, and in the right way."

By providing personalized content, adaptive e-learning environments enhance the quality of e-learning. Adaptive e-learning dynamically changes the level of instruction based on students' knowledge levels and learning styles and personalizes instruction to increase or accelerate a student's success.

However, in e-learning environments, learners may have difficulty in choosing appropriate materials when faced with a large volume of materials during their learning process [8]. Although, the teacher is not able to provide personalized recommendations in real time, either due to availability or due to the number of learners, the more number of learners and resources, the more difficult and complicated it becomes. This is the reason for building our chatbot, named *LearningPartnerBot* that we integrated into Moodle, to have an adaptive learning capable of handling complicated queries and providing relevant learning objects to learners in need. It has been shown in [9] that a chatbot can assist learning with the same benefits as those obtained from a "real" interview. In addition to making the learning process helpful, the conversational chatbot could make students more likely to improve their level because they do not feel judged.

We conducted our experimentation on the C programming techniques module and 71 learners used the *LearningPartnerBot*. At the beginning, we programmed our chatbot to recommend learning objects according to the learners' knowledge level (approach 1: chatbot-based LO recommendation based KL). After the learners used it and obtained their learning outcomes, we reprogrammed it to provide learning object recommendations based on learning style (approach 2: chatbot-based LO recommendation based LS), in order to determine which approach helps to improve the learning experience. This paper presents the comparison between these two approaches, answering our research question: "Which approach has an impact on learners' learning outcomes?"

The rest of this article is organized as follows: In Section 2, discusses previous research related to our topic. In section 3 describes the methodology (the participants of our experimentation, the experimental setup, and the procedure). The experimental results are discussed in section 4, and section 5 concludes this comparative experiment.

2 Theoretical Background

2.1 Adaptive E-Learning Environments

Adaptive systems are defined as systems that modify their output and behavior based on different characteristics of the user, such as preferences, skills, and personality. Adaptive systems can be described as "the technological component of joint human-machine systems that can modify their behavior to meet the changing needs of their users, often without explicit user instructions" [10].

In the field of human-computer interaction (HCI), adaptability involves adjusting a system, graphical user interface, or content to meet the needs of a user [11]–[13]. Learning strategies can be matched and adapted to learners' profiles (their learning styles, knowledge level). The term personalization is also relevant to adaptability; personalizing means designing an object following the needs of a specific user.

Adaptive technologies can be applied to a wide variety of different domains such as e-health, e-commerce, and e-learning. For instance, AEADS provides adverts based on a user's preferences and behavior in the e-commerce field [14]. The CHAIN approach helps users accomplish tasks by incorporating adaptive help and assistance within a user interface [15].

Adaptivity is an essential component of modern e-learning systems [16]. It facilitates student learning by recommending appropriate learning strategies, providing relevant learning materials, and guiding navigation through the material [17]. Adaptive and personalized learning based on knowledge level, preferences, and learning style is still an important educational consideration [18].

Student modeling represents a more focused stream that involves the storage, representation, and maintenance of student attributes such as motivation, knowledge level, and learning style [5], [19].

The authors in [20], proposed an approach for automatic domain modeling in a way that allows the system to take into account different modes of adaptation that provide personalized and adaptive learning material.

Many attempts have been made to build and evaluate adaptive e-learning systems (AESs). However, there is a dearth of studies that consider detailed, carefully designed and controlled experimental evaluations that assess learning effectiveness [5], [16], [18], [21]–[23]

Many models of learning style exist, the Felder-Silverman learning style model is commonly used, especially in online learning research [21], [24]. The dimensions of the model are comprehensively detailed, and each dimension is associated with one or more learning strategies [25]. The model includes four dimensions, including Processing, Reception, Understanding, and Perception. The Index of Learning Style (ILS) tool that can be used to identify learning styles is also based on this model [26], which consists of 44 questions that have been shown to be effective in identifying the learning style of each learner.

According to the Felder-Silverman model, the Processing dimension (active-reflective) details the technique students use to process information. Active students learn by interacting with and manipulating something and by communicating with their peers. Reflective students think deeply about something before they act.

The Reception dimension (visual-verbal) is concerned with the presentation of information. For example, visual students' learning can be enhanced by using pictures, videos, graphs, and diagrams. Verbal students can be supported by offering oral information and written details. In the article [27], the authors examined the effect of learning with this dimension in mind.

The Understanding dimension (sequential-global) addresses the desired structure of information. Sequential students understand learning material better if it is presented in a linear and logical manner, with each step of the learning process described in detail.

Global students learn best when they are provided with an overview of the information before being given details.

The Perception dimension (sensory-intuitive) concerns the types of information preferred. Concrete learning resources are more likely to benefit sensory students, while abstract resources help intuitive students develop their understanding of the concept being studied. Examples of concrete information include facts, examples, simulations, and interactive lessons. Examples of abstract information include mathematical notations, definitions, and theories.

2.2 Recommendation Through Chatbot in E-Learning

According to [28], academic advising in China is an essential support service for students in higher education, but it is not always accessible to learners due to the lack of sensitive information, availability of the advisor, or other financial constraints. To overcome these problems, the authors proposed an interactive chatbot called "EASElective", dedicated to serve many learners at the same time and at any time of the day and to complement existing academic advising. The implemented chatbot provides the same expected advising service for all students.

Other research has confirmed that chatbots can be virtual companions for users intended to resolve availability issues, provide support and customer assistance [29], [30] powered by artificial intelligence.

In this field of education, chatbot as a learning tool for teaching is still in its infancy [31]. However, to our knowledge, there is no chatbot that has been used in the recommendation of educational resources on the Moodle platform. Recommending appropriate educational resources has become a current challenge for educators and researchers to develop new ideas to help learners improve their learning process.

This is the reason for building our chatbot that we named *LearningPartnerBot*, and integrated it into the Moodle platform. The chatbot we have implemented is dedicated to recommending learning objects to learners according to two approaches, one based on their knowledge level (KL) and the other based on their learning style (LS). This is the objective of this article, which is to compare the learning outcomes obtained after the realization of the experiments based on these two approaches.

The following section describes the methodology such as the participants of our experiment, the experimental setup, and the research experimental design.

3 Methodology

3.1 Experimental Setup

The e-learning platform we used for our experiment is Moodle. It is a flexible and secure platform that can be adapted and extended for a variety of possibilities to create personalized learning environments. It can even run on mobile devices.

We implemented the *LearningPartnerBot* chatbot and integrated it into Moodle, which aims to provide recommendations of learning objects adapted to learners' profiles. The tool we used to implement it is Google DialogFlow, which allows users to

develop human-computer interaction technologies capable of handling natural language understanding (NLU).

3.2 Research participants

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

3.3 Procedure

As shown in Fig. 1, our experiment is divided into two. The first one is the approach of recommending learning objects according to the knowledge level (KL) of the learners, and the second is the one based on their learning style, in order to compare the results obtained from each approach.

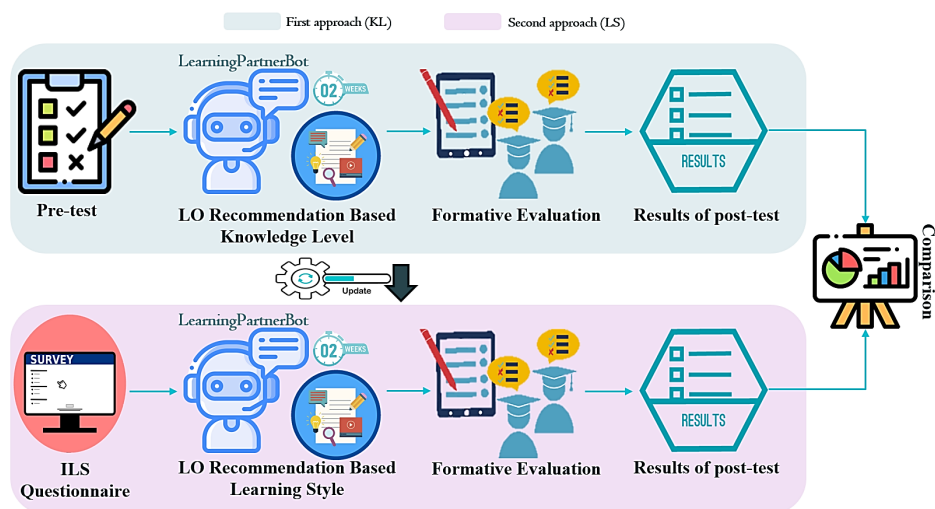


Fig. 1. Research Experimental design.

Participants will pass a pre-test in C programming to determine their knowledge level and identify the concepts they have not mastered and on which the *LearningPartnerBot* chatbot will rely to provide personalized learning object recommendations based on their level. The use of our chatbot will be for two weeks for the first approach (the one based on KL).

After this first experience, participants will have to answer the ILS questionnaire [32] to determine their preferred learning style. Thus, we reprogram our chatbot to be based on the learners' learning style characteristics in order to provide them learning object recommendations. After two weeks of participants learning, using our chatbot, they will pass a formative evaluation as a second post-test.

The learning results from these two post-tests will be compared to determine in which approach the learners have progressed the most.

4 Results and discussion

4.1 Recommendations based on the learners' knowledge level

As presented in the previous section, at the beginning, we programmed our chatbot to provide personalized recommendations of learning objects based on the learners' knowledge level. In their initial login into Moodle, they passed a pre-test in C programming using *QuizCbot* [33] to determine their knowledge level in all C concepts. Fig. 2 shows the results obtained in this pre-test. Out of 71 learners, 72% of learners (51 learners) are at the low beginner level, 25% of learners (18 learners) are at the medium beginner level, and 3% of learners (2 learners) are at the high beginner level.

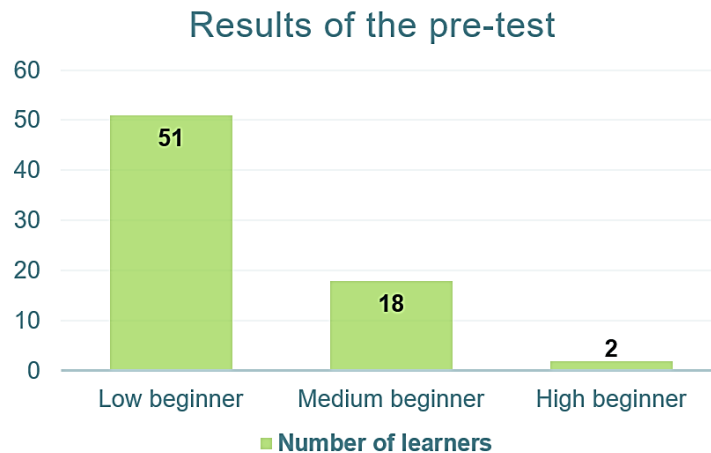


Fig. 2. Results of the pre-test.

Following the pre-test, *LearningPartnerBot* provided learning objects to the learners according to the level they belong to (on the concepts they did not master). During the two weeks of the first experiment, that of the approach chatbot-based Learning Object recommendation-based Knowledge Level, the learners were given to use the learning resources on the different concepts of C programming techniques that were added in Moodle, such as exercises, lessons, quizzes.

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. The result obtained is shown in Fig. 3.

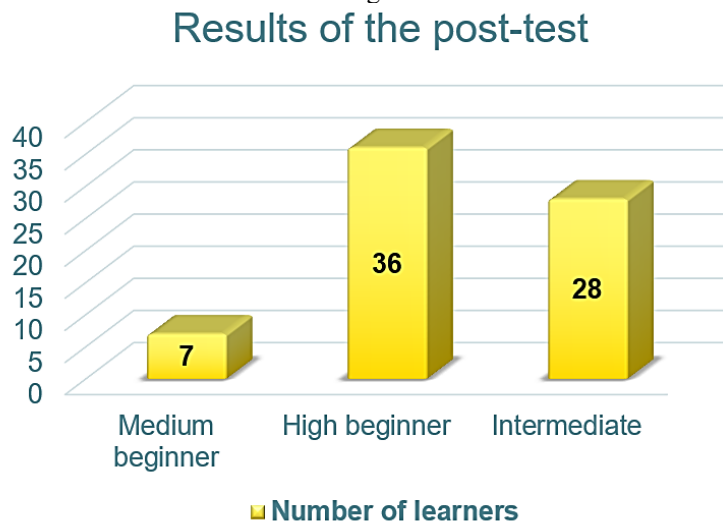


Fig. 3. Results of the post-test (approach 1).

It shows that there is an improvement in the results, the low beginner level became inexistent and the medium beginner level decreased from 25% (18 learners) in the pre-test to 10% (7 learners) in the post-test. For the high beginner level, there was an improvement from 3% (2 learners) to 51% (36 learners). For the intermediate level, there is an increase from 0% (no learners) to 39% (28 learners).

4.2 Recommendations based on the learning style

Then, in the third week, we moved on to the second experiment. To determine the preferred learning style of the learners, we used the ILS questionnaire because it is the most widely used in educational systems and in technology-enhanced learning and some researchers even argue that it is the most appropriate learning style model for use in adaptive learning systems such as [34], [35], as well as being easy to implement [36], [37].

After the participants answered this questionnaire, we found that the learning style to which most of the learners belong is the "visual learning style", followed by the "verbal learning style", those of the Reception dimension (explanations of different dimensions and learning styles are presented in section 2.1). The learning objects are provided in different formats and media to suit 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.

Our chatbot relies on these questionnaire results to provide recommendations of learning objects according to the preferred learning style for each learner. The pre-test for this second approach (chatbot-based LO recommendation-based LS) is the result of the last formative evaluation done which is the result of the post-test (Fig. 3) of the first approach (chatbot-based LO recommendation-based KL).

After using the chatbot for two weeks, the learners are submitted to another post-test to evaluate their learning result. The results are shown in Fig. 4.

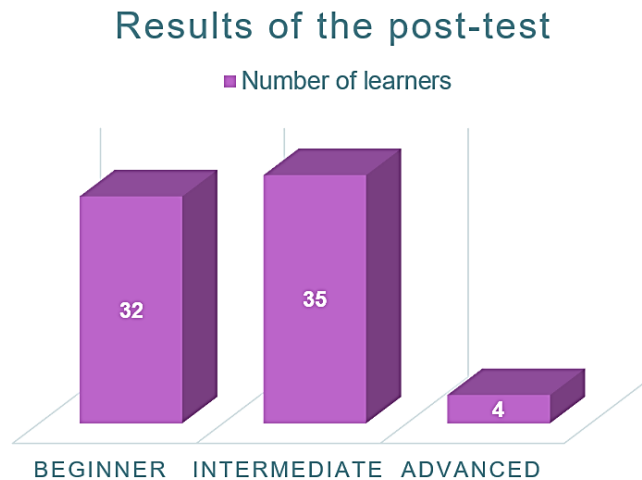


Fig. 4. Results of the post-test (approach 2).

Out of 71 learners, there are no more learners classified at the medium beginner level, so the number of learners who were classified at both levels (medium beginner, high beginner) in the pre-test became only classified at the high level in the post-test, which is why I renamed the high beginner class to beginner class. The beginner level decreased from 61% in the pre-test (10% medium beginner and 51% high beginner) to 45% (32 learners) in the post-test. For the intermediate level, there was an improvement from 39% (28 learners) to 49% (35 learners). For the advanced level, there is an increase from 0% (no learners) to 6% (4 learners).

Fig. 5 shows a comparison of the learners who improved in learning outcomes after using our chatbot in the two approaches, 72% of the learners (28 learners) improved in the first approach, while just 28% of the learners (15 learners) improved in the second approach, which indicates that the chatbot-based LO recommendation based KL approach improved the learners' learning outcomes compared to the learning style-based approach.

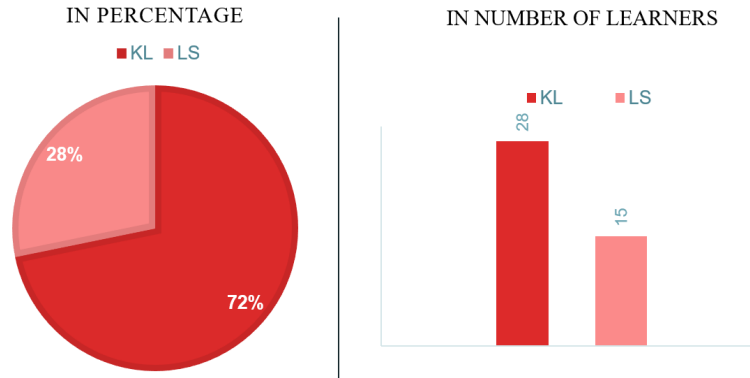


Fig. 5. Comparison of learners who progressed in learning outcomes between KL and LS.

We asked learners after each post-test the following questions: "Q1: Were the recommendations provided by our *LearningPartnerBot* chatbot useful in your learning process?"; "Q 2: How would you rate the overall experience with *LearningPartnerBot*?", to find out their satisfaction towards the recommendations and their satisfaction towards the chatbot for each of the two approaches. Table 1 shows the distribution of responses to each question.

Table 1. Evaluation questions.

	Recommendation satisfaction		Chatbot satisfaction	
	Approach 1 (based on KL)	Approach 2 (based on LS)	Approach 1 (based on KL)	Approach 2 (based on LS)
Very interesting	92%	73%	94%	91%
Interesting	8%	25%	6%	9%
Not at all interesting	0%	2%	0%	0%

It is shown that learners were satisfied with recommendation in the first case (chatbot-based LO recommendation-based KL) more than in the second case (chatbot-based LO recommendation-based LS). Thus, based on these results, we conclude that our *LearningPartnerBot* chatbot was perceived as interesting and helpful in providing learners personalized recommendations of learning objects.

5 Conclusion

In this paper, we compared the learning outcomes obtained after the realization of two experiments based on two approaches, one concerns the use of the chatbot-based learning object recommendation according to the knowledge level (KL) of the learners, and the other concerns the use of the chatbot-based learning object recommendation

according to their learning style (LS). The experimentation was conducted on 71 learners, on the C programming techniques module, and the results obtained show that the one based on the knowledge level (KL) improved the learning outcomes of the learners compared to the one based on the learning style (LS). Based on the results obtained from questions asked to the learners after each post-test, which were conducted to assess their satisfaction towards the recommendations and the chatbot, we concluded that our *LearningPartnerBot* chatbot is perceived as interesting and useful and shows a positive attitude of the learners. Future work will focus on personalizing learning path recommendations by combining these two approaches together (KL&LS), also based on the use of the chatbot integrated in Moodle, in order to improve the learning experience of learners.

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