Proposal for the Design and Implementation of Miranda: A Chatbot-Type Recommender for Supporting Self-Regulated Learning in Online Environments

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Abstract

The use of virtual platforms as a new space where online learning occurs has experienced a progressive increase in recent years. These platforms, also known as learning management systems (LMS), bring many benefits, not only the intrinsic ones due to their virtual modality: the ease of access and availability, but also due to the large amount of data that they store with respect to student interactions. At present, these data have not yet been processed or exploited in their entirety and if they do so they could provide various indicators that would be oriented to understand the way in which knowledge is acquired, the behavior of students in order to further improve the experience of student learning on online platforms. Fortunately, platforms like Moodle are characterized by storing a large amount of data, for that reason several plugins are developed, which add extra functionalities to the platform and use learning analytics (LA) to monitor and describe the learning process. However, most plugins do not reach a prescription level, that is, they do not delve into specific actions to improve the learning process. Thus, this study proposes the design and implementation of a chatbot-type recommendation system, the proposed tool will help students in self-regulation of their learning, providing recommendations for time and sessions, resources and actions within the platform to obtain better results.

Keywords [1]

Learning Analytics, Self-Regulated Learning, Chatbot, Recommender System, Moodle

1. Introduction

Free and robust Learning Management Systems (LMS) such as Moodle have a high degree of acceptance in the academic community and in several Higher Education Institutions (HEIs). LMSs offer support for deploying a wide variety of courses available in different languages and on different topics [1]. The acceptance of the Moodle LMS by HEIs is mainly due to its open source code, ease of installation, ease of use and customization [2]. On the other hand, from the developers' point of view, Moodle and its modular development philosophy and interoperable design, allows the creation of extensions or plugins that add new functionalities to those already existing in the LMS [3]. Currently, Moodle has an extension catalog of about 1,800 plugins. These are distributed by functionality and can be classified into at least 50 different types, with the most important being activity module plugins, blocks, themes, course formats, enrollment plugins, authentication plugins, repository plugins and

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filters. Table 1 details this classification in more detail. There is a special type of plugin called "local plugins" that function as generic add-ons for local customizations or in cases where the functionality to be added does not fit into the types mentioned above. Traditionally, LMSs have been used by teachers as large repositories of educational material, limited to receive assignments and take evaluations, leaving aside delicate and important tasks such as feedback, monitoring, tracking and measurement of the academic load, allowing the optimization of learning paths. For this reason, local plugins allow the development of complements that support teachers in the aforementioned tasks, redefining the LMS as a tool for the mediation of teaching and learning processes.

In the current context of the COVID-19 pandemic, new challenges have arisen in attempting to translate the face-to-face learning context to virtual teaching and learning environments (VLEEs). In different studies compiled by [4] point out that the completion rate of online courses is less than 50 percent, where among the main causes for dropout or abandonment, lack of motivation and lack of support for self-regulation strategies for learning have been identified [5],[6].

Table 1

Plugin Type Classifications by Moodle

Plugin Type	Description
Activity module	Provide activities in the courses, for example: forums, tests, homework, etc.
Bloc	Information screens or tools that can be moved through the pages.
Themes	Change the appearance of Moodle, through the manipulation of HTML and CSS.
Course formats	The activities and blocks of a course allow different forms.
Inscription	Allow control who is enrolled in the courses.
Authentication	Allow connection to external sources of authentication.
Repository	Allow connect to external sources of files to use in Moodle.

Self-regulation of learning, according to several authors, can be understood as the capacity of students to manage their own learning process [7]. However, in online environments, LMSs have been found to lack mechanisms to support self-regulation strategies for learning; and which have been found to be related to student retention and academic success. These strategies are goal setting, time management, self-monitoring, and self-efficacy [8]. In this sense, supporting the teacher in making decisions about supporting students' self-regulation strategies, anticipating those students at risk of dropping out and, above all, taking actions to avoid it, is a topic of great interest and current research.

Disciplines such as learning analytics are being used to measure, collect and analyze learners' traces (product of their interactions with resources on a technological platform) in order to understand and improve the contexts where learning processes take place [9]. An example of this is the recent work carried out by [10], [11], where a tool was developed to support self-regulated learning strategies called FlipMyLearning and NoteMyProgress. These tools allow the teacher to monitor and track the learning process of students to make informed decisions by means of visualization panels that the tools present. Although these tools are designed for teachers and students, teacher intervention actions are limited to the use and knowledge of how to exploit these tools as support inside and outside the classroom. This means that if the teacher does not take actions based on the visualizations offered by the tools, no recommendation will be made to the students that will allow them to support their learning process. On the other hand, students need to receive constant feedback not only on their academic performance, but also on the actions that other peers may have taken and that would be helpful for them to know. For this reason, this article proposes the design and implementation of a system for recommending educational resources and self-regulation strategies for learning.

Specifically, the recommender system will make suggestions on session time and interactions in chatbot format based on student behavior and developed for the Moodle platform. This with the purpose of allowing students to better organize their study sessions, know their performance in relation to other students in the course and achieve successful completion of online courses. The chatbot is a complement to the FlipMyLearning plugin, as it will use several of the visualizations and indicators developed in that plugin to generate recommendations. In addition, it will integrate with the FlipMyLearning visualization dashboards in order to provide more information. The chatbot will also be oriented to give general course information to the learner, inform them about new resources, pending activities and provide additional information from the graphs presented by the FlipMyLearning plugin. This article has the following structure: Section 2 describes the related work, Section 3 discusses the methodology used, Section 4 details the design proposal, functionalities of the artifact, Section 5 presents the conclusions and recommendations and Section 6 contains the acknowledgements.

2. Related Works

2.1. Learning analytics plugins in Moodle

The purpose of Learning Analytics (LA) is to understand and optimize the learning process and the environments in which it occurs [12]. LA offers new ways for teachers to understand the behavior of their students, and promote the use of effective strategies to achieve the proposed objectives [13]. According to Gartner different levels of LA can be developed [14]. The first level of LA is the descriptive level (see Table 2), which tries to answer the question "What happened? For this, statistical data are obtained, which seek to explain what is happening in a given context. The second level of LA is the diagnostic level, which tries to answer the question Why did it happen? For this, statistical methods are used to explain the reasons why a phenomenon occurs in a given context. The third level of LA is predictive, it is about answering the question "What will happen? And finally, the fourth level of LA is prescriptive, which tries to answer the question "What should be done to make it happen? This is one of the levels of LA that has a greater effort and difficulty in its implementation, but it is the level that adds the most value to an organization [14].

Table 2

Levels in Learning Analytics

Level	Analytics	Description
1	Descriptive	What happened?
2	Diagnosis	Why did it happen?
3	Predictive	What will happen?
4	Prescriptive	What must be done to make it happen?

In the bibliography it is possible to find several works that have developed different studies applying the 4 levels of LA on the Moodle platform. For example, in a study conducted by [15], the authors propose a new discrete method that uses Bayesian networks to automatically model student personalities in order to build adaptive learning environments on the Moodle platform. For example, in [16], the authors developed the GISMO plugin, which aims to present a visualization dashboard for monitoring and tracking students at the diagnostic level. In another work [17], the authors developed a plugin called "Course dedication", whose objective was to estimate the time of participation of a student in the course at a descriptive level, calculates this statistic based on the clicks made in a study session. In the work [18], the author develops the plugin called "Kopere Dashboard", whose objective is to use the data to generate reports, know the online users, backups, manage notifications at diagnostic level through the use of a dashboard panel. In the work [19], the authors present the "Moodle Engagement Analytics Plugin" which aims to find indicators of student engagement and performance at the diagnostic level. In another paper [20], the author proposes the plugin called "Students at risk of missing assignment due dates", which presents a predictive model to identify students who are likely to miss assignment due dates, this plugin reaches a predictive level of learning analytics. In the paper [21], the authors propose the "SmartKlass" plugin, which aims to measure and analyze the learning process during a Moodle course at a diagnostic level, by detecting students who are behind, the least challenging content for the students, and the most challenging content for the students.

Table 3 presents some of the plugins that were developed between 2010 and 2021, which employ learning analytics and data collection in Moodle. These are the most relevant plugins presented by the platform when searching with the phrase "Learning Analytics". Although the described plugins show great contributions and application of LA levels at different scales, the application levels remain predictive, leaving aside the prescriptive. There is no plugin that can provide recommendations based on student behavior and that can prescribe recommendations related to self-regulation strategies for Moodle.

Table 3
Plugins for Moodle using learning analytics (2010 -2021).

Name	Type	Version	Target	Analytics	Description
Gismo	block	2.3 – 2.8	Docents	Diagnostic	Interactive graphical tool for monitoring and tracking students
Course dedication	block	1.9 – 3.11	Docents	Descript	It allows to calculate the estimated time of dedication of the participants within a course.
Flip My Learning	local	3.9 – 3.11	Docents / Students	Diagnostic	Allows the instructor to monitor the students' learning process for informed decision making.
MEAP	report, mod, block	2.2 – 2.7	Docents	Diagnostic	Provides feedback on a student's level of participation in a Moodle course.
Students at risk of missing assignment due dates	local	3.4 – 3.7	Docents	Predict	Adds a predictive model to identify students who are likely to miss assignment or homework due dates.
SmartKlass	local	2.4 – 3.0	Docents	Diagnostic	Measure and analyze the learning process at any time throughout Moodle courses.

2.2. Chatbots to support self-regulation of learning

Chatbots are machine agents that serve as natural language user interfaces to provide data and services. [22]. In recent years this technology has been employed for multiple purposes mainly in messaging applications. Chatbots can also serve various purposes such as customer care, emotional or social support, information providers, entertainment, etc.[23]. However, to our knowledge, there are no chatbots that have been used in the educational context to support self-regulated learning strategies and/or the recommendation of educational resources on the Moodle platform. Recommending appropriate educational resources has become a current challenge for educators and researchers, who are developing new ideas to support students to improve their learning process. In different works developed, it is explained that chatbots perform in contexts where answers have to be given based on a bank of pre-defined questions. For example, in [24], the use of a chatbot in an educational context for the automation of higher education student care is presented. The chatbot interacts with students through text messages on topics in a closed context answering doubts about the "Higher Institution Course". Chatbots have also been used as recommender systems. For example, a study developed by [25] proposes a recommendation approach centered on the use of a chatbot that responds to student queries and also provides relevant suggestions according to their academic management needs. These recommendations are content-based and knowledge-based.

The approach proposed by the authors turns out to be quite general and does not conclude with the development of an artifact that employs this approach. As can be seen, chatbots as recommender systems have not been fully exploited, in the studies explored no chatbot approach has been found that makes recommendations based on student behavior for Moodle. No study has explored this possibility, so this work is of great interest and a first contribution in this area.

3. Methodology

The methodology used in this study is based on Design Based Research (DBR), which has shown great potential over the years, being especially suitable for research and design of learning environments [26]. This methodology mixes empirical research in education with theories oriented to the design of learning environments. Five key characteristics can be identified in this methodology: 1) pragmatic (both design and intervention oriented), 2) theory and research based, 3) interactive, flexible and iterative, 3) integrative and 4) contextual.

This methodological approach will: involve classroom participants (teachers and students) more actively, it is often argued that most research on learning is conducted in "laboratory" settings by research educators, psychologists and cognitive scientists. Guiding research with RBD requires differentiating 4 iterative phases: analysis and exploration, design and construction, evaluation and reflection, and redesign and dissemination as shown in Figure 1.

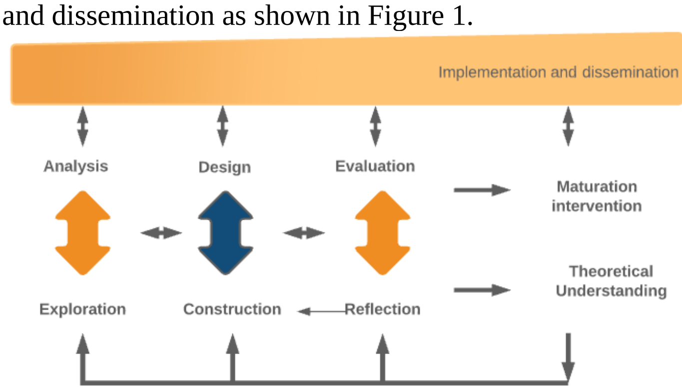

Figure 1: Stages of the DBR methodology

4. Chatbot architecture design and implementation proposal.
4.1.1. Chatbot architecture

The proposed chatbot is named Miranda, in honor of Juana Miranda (1842-1914) who was the first university professor in Ecuador. Its architecture is divided into two modules: the Backend and the Frontend, as shown in Figure 2. The two modules communicate synchronously and bidirectionally, which allows greater flexibility when interacting with the chatbot.

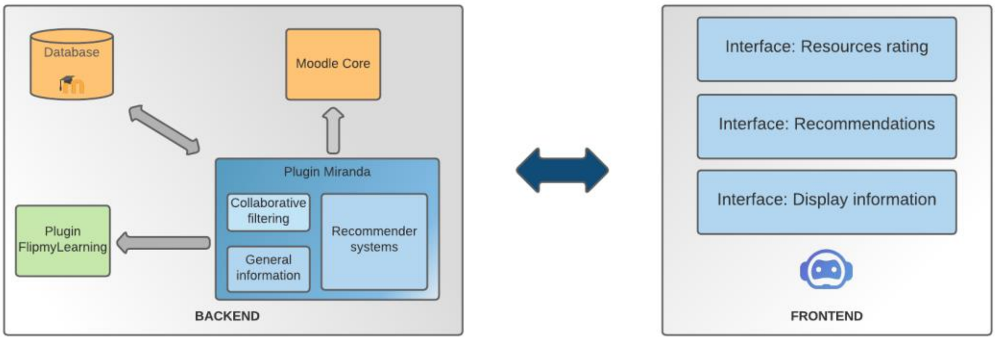

Figure 2: Miranda plugin architecture

The Backend will be in charge of collecting and analyzing the data in order to provide general information or recommendations. The data sources are both the Moodle database and the FlipMyLearning plugin. As for Miranda, it is divided into three sub-modules:

- Recommendation system: it provides recommendations on session time and student behavior within the course.
- Collaborative filtering system: provides recommendations of resources rated by other student members of the course, and
- General information system: which gives general information about the student and the platform.

On the other hand, the Frontend is intended to be the user's point of interaction with the whole system. The Miranda icon will be displayed on each page of the courses in which the student is enrolled and will allow the student to receive and request recommendations, rate resources and display FlipMyLearning viewing information.

4.1.2. Miranda's characteristics

Table 4 shows in a general way the options that the chatbot will have, the option "Courses and events" is related to level 1 of LA, since in this option the student gets a general idea of the events on the platform, can review their courses, check upcoming events or tasks or review new resources of the course, the option "Tasks and recommendations" is related to level 4 of LA, because in this option are all the recommendations provided by the system, these can be based on indicators of cognitive depth and social breadth, based on the most viewed resources by course members, based on weekly session times set by the teacher and resource recommendations based on student ratings, and the "View visualizations" option is related to LA level 2, because it is directly related to the FlipMyLearning plugin, which reached the diagnostic level of LA.

Table 4
Chatbot options menu

Main options	Sub options
Courses and events	View Courses Upcoming events New Resources
Tasks and recommendations	View recommendations Most viewed resources Weekly recommendations Recommended resources
View Visualizations	General indicators Study sessions
Remove Bot	-

In Moodle the interaction with the student is fundamental for learning support. Figure 3a shows the process followed to find the recommendations. The interaction flow starts by providing data of the student's engagement with the platform, this data is in turn processed using data mining techniques and procedures through exploratory analysis and the use of collaborative filtering algorithms based on elements such as SlopOne [27], clustering methods such as k-means, which is widely used in important data mining processes. [28], In addition, the use of an algorithm developed for the identification and analysis of groups. Together with certain indicators provided by the "FlipMyLearning" plugin, it results in the different recommendations, which are displayed through a chatbot-like interface, as shown in Figure 3b.

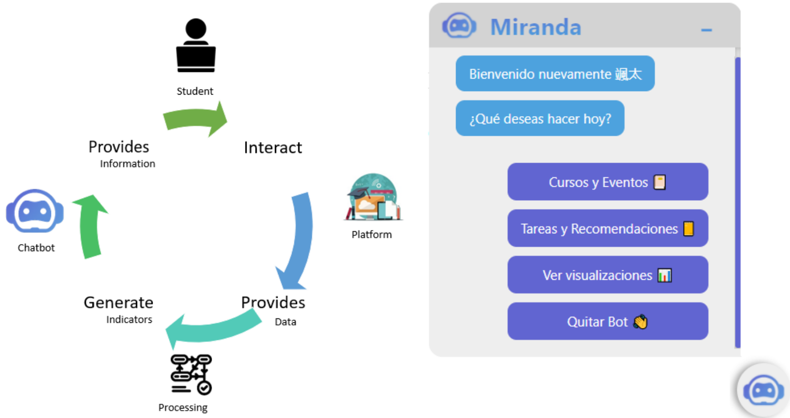

Figure 3: Interaction and Interface: (a) Flow of interactions. (b) Chatbot interface.

Regarding the recommendations provided by the chatbot, it is possible to differentiate several types according to their purpose. Thus, the first type of recommendations are suggestions of actions within the platform, these recommendations are the result of a process that consists of:

- Identify two groups of students, for this purpose K-means will be used whose input will be a set of characteristics mainly, study session time, grades obtained, number of resources visited, average of Moodle LA indicators: Cognitive Depth (5 levels), and Social Breadth (2 levels). Cognitive Depth is defined as "The extent to which participants in any particular configuration of a research community are able to construct meaning through sustained communication." [29] While

Social Breadth is defined as "The ability of participants to identify with the group or course of study." [30], among others.

- To categorize these two groups, once the students have been divided, we will proceed to categorize them into students who need help and those who do not need help, for this purpose we will compare the means of the input characteristics of the K-means algorithm.

Thanks to this process, if a student is in the group of those who need help, it is possible to make a comparison of the interactions of this student versus the group of students who do not need help. By analyzing the level of cognitive depth and social breadth of an activity, it is possible to generate recommendations for a user, based on what level he/she is at and what level he/she should be at according to the other students, thus generating recommendations such as: "There are Forums that your classmates usually check, you should check them", taking into account that the student has not interacted with Forum-type resources, but his/her classmates have, as shown in Figure 4.

Figure 4: Personalized recommendations.

Another type of recommendation that can be provided relates to resources. One of these will employ collaborative filters, which use user ratings on certain items in the total set to predict ratings on the remaining items and recommend those with the highest predicted rating. [31] The rating information can be obtained by generating an extra interface in the chatbot, which asks the rating that a student would propose for a specific resource once the student enters the chatbot, as shown in Figure 5a. In this way, when another student with similar ratings to the student who rated the first resource accesses the resource type recommendations, the student will be able to obtain the resources rated higher by the first student, as shown in Figure 5b. Another resource recommendation can be made based on the most visited resources by the other students.

Another type of recommendation is related to the study session time, for this recommendation it will be necessary the teacher's participation, who will be able to define the study time and resources for each week. In this way, the chatbot will analyze the student's participation with that defined by the teacher and will recommend both the time that should be invested and the resources that have not been seen in the current week.

Additionally, another functionality that the recommendation system will use is the possibility of interaction with the "FlipMyLearning" plugin, this can be seen in the "View visualizations" option, where it will redirect to the views generated by this plugin, this is done with the purpose of showing the student information that may be useful for him/her along with the personalized recommendations, as shown in Figure 6.

Figure 5: Rating and Recommendation Interface: (a) Rating interface. (b) Resource recommendation interface.

Figure 6: Options to view visualizations.

5. Conclusions and future work

This paper proposes the design and implementation of a Moodle plugin that supports self-regulated learning that reaches the prescriptive level of learning analytics, through the use of recommendations through a chatbot-like agent. The result of this work will be the design and implementation of a chatbot type recommendation system, coded as a plugin for Moodle, this recommendation system will be able to offer time and session recommendations, it will also be able to recommend the most visited resources of the course, make time suggestions on the platform based on the time defined by the teacher in the plugin "FlipMyLearning" and will provide additional information of the plugin visualizations mentioned above. This recommendation system is mainly focused on the students and will not depend on the intervention of a teacher, beyond the necessary to generate new resources and the specification of the study time, that is why the recommendations are generated from the participation of the students with the platform.

The scope of the study is limited by the data analysis capacity of the Php programming language used by Moodle, which is why a possible line of future research could be developed based on the use of a more suitable environment for data analysis and the use of more robust artificial intelligence algorithms. Another line of future research could address the replication of the proposed approach to other online education platforms.

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