

Chatbot-Based Learning Platform for SQL Training

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ABSTRACT

Learning the SQL language for working with relational databases is a fundamental subject for future computer engineers. However, in distance learning contexts or unexpected situations like the COVID-19 pandemic, where students had to follow lectures remotely, they may find it hard to learn. Chatbots are software applications that aim to have conversations with people to help them solve problems or provide support in a specific domain. This paper proposes a chatbot-based learning platform to assist students in learning SQL. A case study has been conducted to evaluate the proposal, with undergraduate computer engineering students using the learning platform to perform SQL queries while being assisted by the chatbot. The results show evidence that students who used the chatbot performed better on the final SQL exam than those who did not. In addition, the research shows positive evidence of the benefits of using such learning platforms to support SQL teaching and learning for both students and lecturers: students use a platform that helps them self-regulate their learning process, while lecturers get interesting metrics on student performance.

KEYWORDS

Chatbot, E-Learning, Interactive Learning Environments, SQL, Technology-Enhanced Learning.

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I. INTRODUCTION

THE application of computer technologies supports lectures to design more engaging and effective learning experiences for their students to help them achieve learning goals [1]. Furthermore, in contexts where lecturers are not always available, as may be the case in distance education or under conditions of confinement as experienced in the recent pandemic caused by COVID-19, education becomes more dependent on technology, and its availability [2], [3].

After being successfully used in other fields, a technological artefact that is beginning to be incorporated into e-learning platforms is the conversational agent, also known as chatbot [4],[5]. Chatbots interact with users using natural language, answer users' questions, provide them with personalised answers [6], and even manage emotions in the dialogue [7]. There are two kinds of chatbots: task-oriented chatbots designed to support a specific task or context and non-task-oriented chatbots designed to emulate casual conversations with the human user [8]. Leading companies have developed several chatbots for industry and research: Apple Siri, Microsoft Cortana, Facebook M, Google Assistant and IBM Watson Assistant.

This research study has its origin in the learning of the Structured Query Language (SQL). SQL is a specific domain language designed to manage and retrieve information from Relational Database Management Systems (RDBMS) [9]. Within the SQL, there is a set of instructions for managing tables and views known as Data Manipulation Language (DML). DML is based on relational algebra and relational tuple calculation. Consequently, not having a consolidated knowledge of these principles can severely disadvantage students when learning SQL in-depth [10].

This study proposes the use of a task-oriented chatbot to support students in learning SQL. The chatbot guides students in solving various SQL queries through natural language interactions, motivated by their questions and attempts. Besides, the chatbot provides different levels of difficulty, adapting to each learner's specific needs and pace and being available at any moment. Finally, we made it available to students enrolled in a university course on Databases to evaluate the chatbot.

The rest of the paper is organised as follows. The second section reviews various software systems supporting the learning of SQL. In the third section, the developed chatbot is described. The fourth section presents the experience carried out with students. The fifth section presents and discusses the results. Finally, conclusions and future work are shown.

II. STATE OF THE ART

Databases are one of the fundamental subjects for all computer engineering students. In a 2018 report on the 54 Database courses in Computer Engineering degrees at Spanish universities [11], it is shown that conceptual design is taught in 86% of them, the relational model in 81%, relational algebra and calculus in 55% and finally, logical design in 74%. In addition, students learn and practice SQL through a RDBMS such as Oracle, MySQL and SQLServer.

Although the most straightforward SQL queries are usually easy to learn for students, learning SQL in depth is often not an easy task for them if they do not have a good foundation in algebra and relational computing. The academy has tried to improve the situation by using interactive tools to help students learn SQL [12]. To this end, in the following subsection, several tools that have been recommended by the teaching staff and used by students are described. In the second subsection, different uses of chatbots in learning contexts are presented.

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A. Tools For Learning SQL

The first learning tool analysed is SQL Course¹. SQL Course is an interactive online tool that provides a theoretical and practical course in SQL, including the basic theory of the different clauses, and an online interpreter to write solutions to the proposed exercises. Although it uses a friendly approach, students' experience with this website is highly improvable in two respects. Firstly, each query produces a reload on the page when doing the exercises, creating unnecessary waiting times. Secondly, there is no interaction with the tool when solving the exercises: if a query is correct, the results are displayed, and if it is wrong, a generic error message is thrown.

SQLzoo is another interactive web tool for learning SQL [13]. This tool is similar to SQL Course, although it partially improves the feedback the student receives. Once the student proposes a solution to an exercise, the application returns the result of the execution of the query and indicates whether or not the result is as expected.

In line with the tools mentioned above, SQL easy² is another web tool that provides feedback on the accuracy of the queries provided to the proposed exercises. However, unlike the previous ones, it offers a more friendly design, although it does not guide and support students in the development of the queries beyond informing them if the query result is correct or not.

Khanacademy³ is a more up-to-date and comprehensive platform than those previously presented. It provides similar functionality and a follow-up through interactive videos that guide students in trying out the different queries. Although the video feature is interesting, it uses a generic approach that is not adapted to the needs of each student. On the other hand, it does not provide more help than checking whether the proposed query's result is expected when solving exercises.

The customisation of learning tools to enable self-regulation of student learning is of interest to lecturers [14]. In this vein, SQL-Knot was integrated with WebEx system and SQL-Lab to build a user model for each student, which was used to adapt some of its components based on individual progress [15]. SQL-KnoT is a tool that generates problems that students must solve through SQL queries. SQL-Lab is a tool that supports the formulation of SQL queries and the testing of their results.

B. Chatbots in Education

Chatbots, also known as conversational agents, are computer programs designed to converse with human persons, employing Natural Language Processing (NLP) and sentiment analysis techniques [16].

The evolution of chatbots can be differentiated into three phases [17]. The first phase took place during the 1970s and 1980s when the study of natural language interfaces commenced [18]. The first chatbot ELIZA is created in this phase based on pattern matching and a template-based response selection scheme [19]. However, it is limited by the inability to save a record of the conversation [20].

The second phase happened when the internet became increasingly popular, allowing users to have online conversations with many people. One of the most significant advances was the creation of ALICE in 1995, developed with a new Artificial Intelligence Mark-up Language (AIML), which allows a stimulus-response template to be defined [21].

The third and current phase is when significant advances in NLP and Automatic Speech Recognition (ASR) technologies have been achieved. As a result, a large number of new alternatives are created,

such as Apple Siri [22], IBM Watson Assistant [23] or Google Assistant [24], among many others. They stand out for providing a degree of naturalness and speed in their responses that sometimes lead the user to doubt if the interlocutor is a human person [25].

Due to the level of sophistication reached, chatbots are increasingly adopted in different fields such as commerce [26], entertainment [27], health [28] or the public sector [29]. In the educational field, chatbots have an essential potential due to two factors; their capacity to communicate through natural language and the possibility of offering support to students at any moment. These two factors allow the human teacher to delegate mechanical or repetitive tasks to the chatbot and assume other tasks with a higher cognitive level [17]. The use of chatbots by students helps to improve the learning process and teaching due to the information they gather during their use [30]. Although chatbots can be confused with Intelligent Tutoring Systems (ITS), these systems are different. ITS are domain-specific, and their interaction is strongly conditioned by following a series of steps, while chatbots base their interaction on natural language conversation.

Education-focused chatbots can be classified into two types [17]: tutors who support the learning process and exercise and practice chatbots for skill acquisition. Tutors are teaching agents who work as learning partners, providing dialogue, collaboration and reflection. In contrast, exercise and practice chatbots are based on the presence of stimulus-cognition-response and reinforcement.

Within the first of these types of chatbots, there is Genie [31]. Designed by Deakin University using IBM Watson, this chatbot is part of a strategic plan for the digitalisation of the university, and it aims to resolve any doubts students may have regarding the campus. Another chatbot is Jill Watson [32]. Also developed with IBM Watson, this chatbot answers students' questions and can raise doubts during the conversation. A study of 300 students did not detect that it was a chatbot, and it was even nominated as the best teacher of the year. Furthermore, Prof. Watson is a conversational agent for primary school students learning to program [33]. The students who used it stated that thanks to this tool, they learned in a dynamic and fun way while consolidating aspects of programming.

Concerning the second type of these education-oriented chatbots, those oriented towards language learning stand out. Duolingo [34] is a popular tool for language learning, supporting 34 different languages to choose from. This tool presents a learning mechanism where a series of questions are formulated, and users must answer them in writing or using their voice.

III. CHATBOT FOR LEARNING SQL

This section describes a chatbot for learning SQL and is divided into five subsections. The first subsection presents the platform architecture. The second one details its development, the third one describes the chatbot implementation, the fourth its functionality, and the fifth one explains how the interaction between the student and the chatbot is performed.

A. Architecture

Fig. 1 shows the platform's architecture as a container diagram as proposed in the C4 model [35].

The SQL learning platform is presented as a web application to which both students (1) and lecturers (2) connect using a username and a password. The web application is based on the Laravel framework. It was chosen due to its extensive documentation, clarity and performance in database queries thanks to Eloquent Object-Relational Mapping (ORM) [36].

¹ <https://www.sqlcourse.com/>

² <https://www.sql-easy.com/>

³ <https://es.khanacademy.org/computing/computer-programming/sql>

The web application is connected to two databases. Firstly, the web application is connected (3) with a database that stores the platform's configuration: users, SQL statements for the exercises and levels of difficulty.

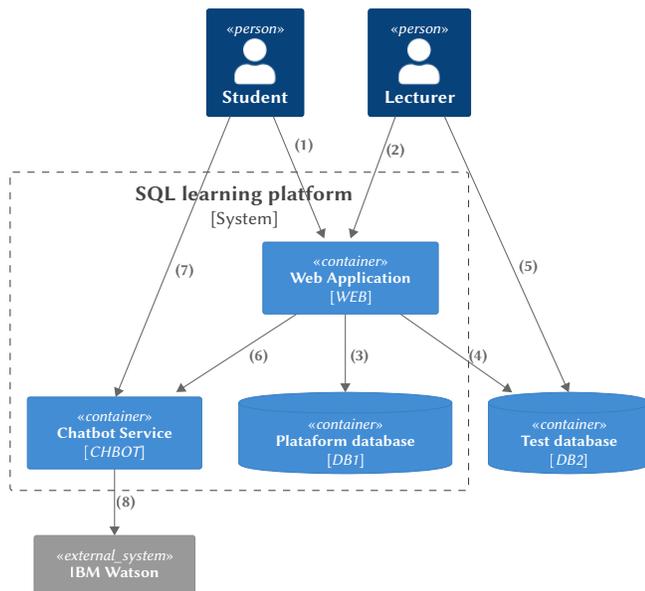


Fig. 1. SQL learning platform architecture.

Secondly, the web application is connected with a database (4) that contains the tables on which the queries issued by the students to solve the proposed exercises will be run. Lecturers can connect to this database (5) to insert or delete data records or incorporate new data structures.

These databases are currently hosted by Amazon Web Services (AWS). The choice of AWS was based on the reliability provided by this platform, its ease of administering the services contracted, and the non-functional aspects it offers, such as security [37].

Finally, to implement the chatbot functionality, the web application connects to IBM Watson (8) via a service API (6). It was decided to use a Node.js server, which allows concurrent queries, to connect users with IBM Watson artificial intelligence [38]. Students will interact with the chatbot for support in resolving queries (7).

B. Chatbot Development

An NLP platform is required to design the artificial intelligence responsible for providing the chatbot with the ability to interpret natural language. IBM Watson was chosen because of its monitoring functions and integration with Big Data tools and its widespread use in education research [33]. The conversation flow between the user and the chatbot is defined using a series of nodes interconnected. These nodes indicate to the chatbot how it should operate when a particular event occurs during the conversation. These events, known as intents, are defined by a series of phrases instructing the chatbot about what text input is expected from the user. Within these nodes, intents are sometimes accompanied by entities used to identify specific content in the users' phrases.

Fig. 2 shows how the nodes have been grouped according to their function in the conversation. The group of nodes called "Exercise" determines the steps of the exercise and the corresponding help for each step. These nodes are nested among themselves to follow a consecutive order in the execution of the exercise.

The group of nodes called "Jumps" leads the flow of the conversation according to the achievement of the exercise by the user.

This achievement level ranges from a wrong exercise to a partially or correct one. In order to resolve any doubts about the SQL syntax, the "Information" node group has been created. Thanks to this group, the user obtains an extensive description of the concepts presented in the exercises and examples of their use.

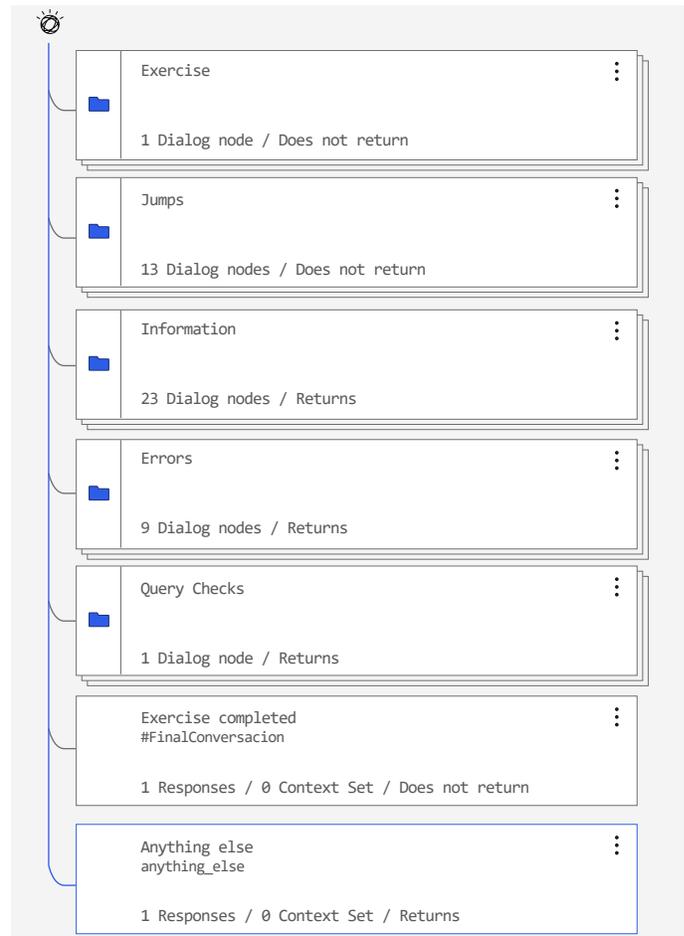


Fig. 2. IBM Watson Dialog Nodes.

The last two of these groups, "Errors" and "Query Checks", express the interactions with the server. "Query Checks" conveys to the server the SQL queries issued by the user, while "Errors" optionally sends to the user explanations of the results obtained during the exercises. Finally, the second to last node informs users that the current exercise has ended, while the last one indicates that the conversational agent has not understood their question.

C. Chatbot Dialogue Implementation

This subsection describes how the conversation is implemented in the IBM Watson Assistant.

To identify which of the different dialogue nodes a conversation should be directed to, the assistant will try to correspond the message received with one of the nodes through the conditions. Fig. 3 shows how the dialogue nodes work. For defining the conditions, the intentions and context variables are used. The list of intents defined in the implementation of this assistant is as follows:

- #Acknowledgements
- #Help
- #Goodbye
- #Start

- #End_Conversation
- #Get_Information
- #Go_Next
- #What_you_can_do
- #Regular
- #Hello
- #Syntax_error
- #Start_exercise
- #Finished

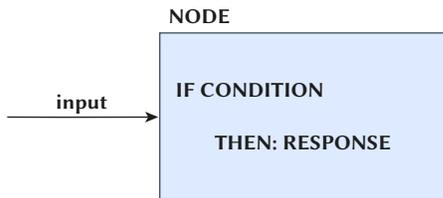


Fig. 3. Operation of IBM Watson nodes.

Below, we describe the intention #Start_exercise. In order for the assistant to identify that the student wants to start the exercise, training sentences must be given in advance. In this case, the following sentences were used for this intent:

- I want to start the exercise
- I want to start
- Let's start the exercise

Thus, if the assistant identifies a sentence similar to one of these, it will perform the actions specified in this node. You can see this example in Fig. 4. The assistant will reply with the specified message if it recognises the intent to start the exercise (#Start_exercise) and receives an exercise entity (@Exercise) of the basic type, provided through a context variable.

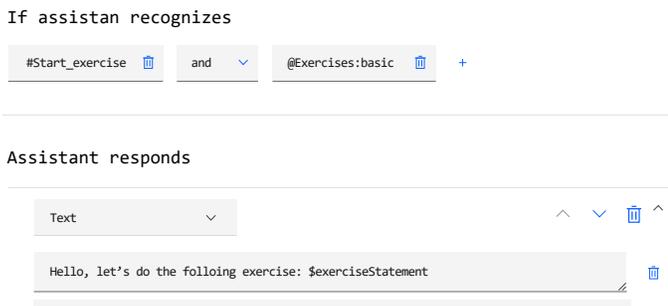


Fig. 4. Response exercise configuration.

A context variable is a variable that is defined at a given moment in the conversation, which is always available to the assistant and whose value can be changed throughout the conversation. In this way the conversation can be personalised. In addition, the assistant can collect information that can then be referred to or reused later in the conversation. For example, in the SQL chatbot, the context variables used are two:

- Context variable to store the exercise statement. This is defined at the start of the exercise and is not modified, being available in case the student asks the assistant for it at a given moment in the conversation.
- Context variable to know in which step the student is. As the student progresses through a query, this context variable is updated. For example, if the student asks for help right at the

start, the chatbot tells him to start by identifying which table he needs (with the "show tables" query). On the other hand, if the student has almost completed the query but is failing to implement "HAVING", he/she will receive help with the HAVING clause.

In the example shown in Fig. 4, the statement is in the context variable \$exerciseStatement, which is used to indicate the statement to the student.

Fig. 5 shows the whole process of integration and communication of the learning platform and the chatbot with the IBM Watson Assistant. When a student proceeds to initiate an exercise on the platform, the exercise data is requested from the view through its identifier (1). This request is processed by the controller, which consults the exercise data from the exercise database (2) and returns the exercise information (3) so that the view can show it to the student on the screen (4). The controller also sends a conversation start message to the chatbot (5), which establishes communication and initiates a session with the IBM Watson Assistant (6), defining the context variable and returning a message (7) to display a welcome message and a message with the statement on the chat dialog box.

Now the student will be able to interact with the platform by typing a SQL query in the console or asking the chatbot for help through the chatbot dialogue box.

- If the student types a SQL query in the console (8), the controller submits the query (9) to the DB server and collects the results (10). The controller returns these results to the view (11) to be displayed to the student and sends them to the chatbot (12). The chatbot sends a message to IBM Watson with context variable and the result of the query (13), and IBM Watson returns an appropriate response to the result received by the query (14).
- If the student asks for help directly to the chatbot through the dialogue box (15). The chatbot sends the message and the context variable to the assistant (16). The IBM Watson assistant returns a response appropriate to the help requested and the point of the exercise the student is going through (17).

D. Functionality Description

The SQL learning platform that integrates the chatbot offers two different user profiles: lecturer and student. As a student, the platform allows performing SQL exercises, classified into three levels of difficulty, which will be enabled as they complete them. There is positive evidence of the benefits of offering flexibility to students in managing their learning [39]. Thanks to the levels of difficulty, each learner can learn at his or her own pace.

For each exercise, the SQL learning platform displays the problem statement (see Fig. 6, top centre box). On a text entry box just below the statement box, the student can write and issue the queries and observe the results. On the right side of the platform, a panel is displayed from which the user will interact with the chatbot. This chatbot will provide clues on how to solve the exercises and clear and concise instructions on the syntax and semantics of the SQL language.

The learning platform also includes a ranking page showing the users who have completed the exercises, providing a gamified experience. Gamification of learning activities increases higher motivation, thus, positively affecting student academic performance [40].

The SQL learning platform enables lecturers to include new exercises by adding their problem statements, an SQL query to generate the correct solution, and additional clues to help them. In addition, the platform provides a screen from which to access the set of exercises and conversations held between students and the chatbot, which can be used to conduct further learning analytics.

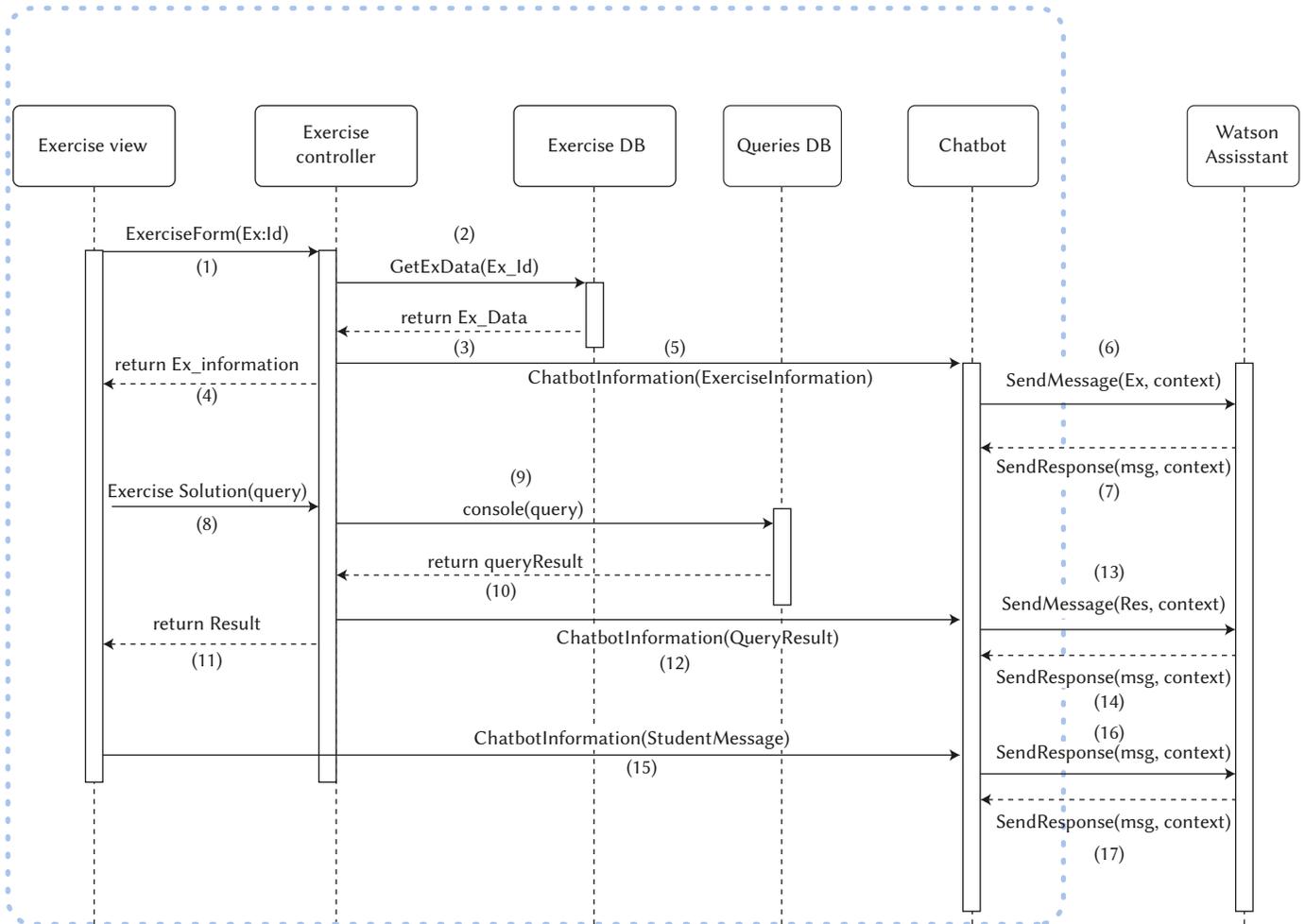


Fig. 5. Design and integration diagram of components that are part of the learning platform.

Task to solve: Display the information in the columns of the table Clients.

```
1 SELECT * FROM clients
```

Query result

ID	SURNAME	NAME	COUNTRY	CITY
1	Borras	Margarita	S	Madrid
2	Nike	Michael	S	Madrid
3	Dupont	Jean	F	Paris
4	Dupret	Michel	U	Manchester
5	Llopis	Antoni	S	Barcelona
6	Souris	Marcel	F	Paris
7	Smith	Pablo	U	London
8	Courbon	Gerad	U	Manchester

Chatbot Available

Next step: now that we know the tables of which our database is composed, you have to see how the table we are looking for is composed.

Next step: now that we know the fields our table is composed of, we have to choose the ones we need.

What should I do now?

To select the fields, you must use the SELECT clause. And remember that you are only being asked for two columns, not all of them.

Next step: now that we know the fields our table is composed of, we have to choose the ones we need.

You should review the selected columns. Remember to indicate only those requested by the task, so as not to consume unnecessary resources.

Next step: now that we know the fields our table is composed of, we have to choose the ones we need.

I need help with the SELECT clause

The SELECT clause is one of the most important SQL statements, as it allows queries to be performed on data stored in the database.

Syntax:
SELECT [column1, column2, ... | *]
FROM table_name;

Fig. 6. The main screen of the SQL learning platform where the student performs the exercises while interacting with the chatbot.

E. Student-Chatbot Interaction

Student interaction with the chatbot involves a series of steps that are described below:

1. Exercise: the SQL learning platform provides the student with the statement of the exercise to be solved.
2. Hint: the chatbot provides a hint for the student to take the next step in the exercise.
3. Propose a solution or ask for help: the student can introduce a query to solve the exercise or ask for help from the chatbot (in case of asking for help, the student would go back to step 2).
4. Feedback: after entering the SQL query, it is evaluated by the RDBMS, and the result returned is displayed on the screen.
 - If the query result is correct, the exercise is considered solved, and the student proceeds to the next exercise.
 - Otherwise, the chatbot informs the student that the query defined is incorrect, provides a new hint and goes back to step 3.

IV. EVALUATION

The SQL learning platform has been evaluated in a case study conducted with students of the subject Databases, compulsory in the second year of the Degree in Computer Engineering at the University of Cadiz (Spain) during part of the 2019/2020 academic year. The objective of this preliminary evaluation, in which 59 students participated, was to inspect the chatbot's behaviour with real students to assess the quality and effectiveness of their responses. In addition, the SQL learning platform served as reinforcement material for preparing the SQL final examination of the course, especially suitable for this course due to the suspension of face-to-face classes because of the COVID-19 pandemic.

The Database course consists of 3 components: theory, practice and assignments. The assignment component is 15% of the course's final grade and is only considered if the practice component has been passed. The chatbot was available to students for two weeks before the SQL final examination. Students did not receive specific instructions on how to work with the chatbot. Although the use of the chatbot was not mandatory, students were encouraged with a 10% increase of their grade in the assignment component if they used it and passed at least the first level.

A. Use Descriptive Scenario

The following is a detailed description of a sample user interaction. In Fig. 7, the conversation held by one of the students with the chatbot during the completion of one of the exercises available on the SQL learning platform is shown.

1. Chatbot proposes exercise: the statement of the exercise asks the student to find all the clients who live in Northampton.
2. Chatbot provides a hint: the chatbot suggests that the student type the necessary query to show the different tables in the database.
3. Student follows hint: the student types in the query box to visualise the different tables in the database.
4. Chatbot provides a hint: the chatbot suggests that the student type the necessary query to see the customer table.
5. Student follows hint: the student types in the query box to visualise the customer table.
6. Chatbot provides a hint: the chatbot tells the student that he/she has now all the information to solve the exercise.
7. The student proposes a solution: the student issues a query trying to solve the proposed exercise.
8. RDBMS provides feedback: the RDBMS evaluates the query and provides the console error code.
9. Chatbot provides feedback: then, the error is processed by the chatbot to display a more friendly message. In this case, the student has used a column that does not exist in the table queried in the database. As a result, the chatbot informs the student that the query is incorrect, indicating that the column to which the filter should be applied cannot be found.
10. Chatbot provides a hint: the previous hint is repeated.
11. Student proposes a solution: The student proposes another solution to the exercise.
12. Chatbot provides feedback: the RDBMS evaluates the query, and the instances of existing customers in the database who live in Northampton are listed. As a result, the chatbot informs the student that the query is correct, the exercise is considered solved, and the student proceeds to the next exercise.

B. Student Results in the Chatbot Environment

After monitoring the students' interactions with the chatbot, it can be seen that the SQL learning platform guides the students

Queries	Conversation
(3) SHOW tables	(1) Hello! Let's do the following exercise: List all the customers who live in Northampton.
(5) DESCRIBE Customers	(2) Write the query needed to show the different tables in the database and identify the one you need.
(7) SELECT * FROM Customers WHERE city = 'Northampton';	(4) Now that you know the tables that compose the database, you need to know the structure of the one we need.
(11) SELECT * FROM Customers WHERE town = 'Northampton';	(6) Now that you know the fields in the table, use the ones you need to solve the query.
	(9) The column you are trying to apply the filter to is not found.
	(10) Now that you know the fields in the table, use the ones you need to solve the query.
	(12) Correct! You are done with this exercise.
Errors	
(8) SQLSTATE[42522]: Column not found: 1054 Unknown column 'city' in 'where clause' (SELECT * FROM Customers WHERE city = 'Northampton');	

Fig. 7. Example of a student's conversation with the chatbot during an exercise (the numbers in parentheses have been included in the image editing to coincide with the numbering in the scenario description, but these numbers do not appear in the application).

to solve the errors contained in their proposed solutions, allowing them to try again to define their solution on an unlimited number of opportunities. This approach can benefit students during the independent study of the Database subject since they cannot interact directly with the lecturer in such an easy and quick way. In Table I, some of the statistics automatically obtained from the application are collected. The first column corresponds to the exercise identifier. The second column shows the level of difficulty of the exercise: Beginner (A), Intermediate (B) and Advanced (C). The column 'Solved' shows the number of students who solved it successfully. The fourth column, 'Dropouts', shows the number of students who dropped out of the exercise without solving it. The column 'Errors' shows how many wrong queries a student makes on average before successfully solving the exercise. Finally, the column 'Queries' indicates how many queries on average the students use before finding the solution.

TABLE I. STATISTICS ON STUDENTS' ATTEMPTS AT EACH EXERCISE

Ex.	Level	Solved	Dropouts	Error	Queries
E1	A	49	7	0,73	3,17
E2	A	54	2	0,34	2,37
E3	B	51	2	0,57	2,83
E4	B	51	2	0,09	1,53
E5	B	52	1	0,34	1,82
E6	B	42	11	1,09	5,00
E7	B	50	3	0,45	3,06
E8	C	36	15	1,52	4,21
E9	C	36	15	1,99	5,74
E10	C	47	4	0,49	2,73

For all the exercises, the number of students who managed to solve each one was much higher than those who dropped out. Similarly, the data helps identify which type of exercises are most difficult for the student. For example, exercise number 9 is the one with the least number of students who managed to solve (36), the one with the most dropouts (15), the one with the highest average number of errors (1.99) and the one that required the most attempts for those students who successfully solved it.

C. Impact on Students' Performance

To study the impact of chatbot use on students' performance, we considered student marks in the SQL final examination. 103 students took this examination, 54 of whom used the chatbot. Table II shows the correlation between the students' use or non-use of the chatbot and whether or not they passed the SQL final examination.

TABLE II. USE OF THE CHATBOT CONCERNING PASSING THE COURSE

Chat box use	Passed the exam	Failed the exam	Total
Yes	23	31	54
No	9	40	49
Total	32	71	

We can see how of the 54 students who trained with the chatbot, 23 passed the SQL final examination (43%). Meanwhile, of the 49 who did not train with the chatbot, only 9 passed (18%). In other words, if a student trains with the chatbot, he/she is 25% more likely to pass the SQL final examination than if he/she does not train with the chatbot.

To verify whether the difference shown by the data is significant, we use the Chi-squared test and define the following null hypothesis:

- H_0 : The fact that a student has trained with the chatbot is independent of passing the SQL final examination.

Therefore, the alternative hypothesis would be stated as follows:

- H_1 : The fact that a student has trained with the chatbot is related to passing the SQL final examination.

To determine the dependency between passing the SQL final examination after training with the chatbot, we used the Chi-square test with a significance level of 0.05. As a result, we obtained a p-value of 8.2047 in the Chi-square test. This value is above the significance threshold of 0.05 ($X^2 > 3.8414$). Thus, we cannot accept the null hypothesis, and we assume that there is a relationship between training with the chatbot and passing the SQL final examination.

Below, we show the students' marks concerning whether they have used the chatbot or not. In Table III, it can be seen that the 5 students with the highest marks in the exam did use the chatbot. Similarly, the only ranges in which the students who did not use the chatbot outnumber those who did use it are in the three lowest mark ranges, especially in the last two.

TABLE III. NUMBER OF STUDENTS IN EACH MARK RANGE

Mark range	Chatbot use Yes	Chatbot use No
0.0-0.9	7 (13%)	14 (29%)
1.0-1.9	7 (13%)	11 (22%)
2.0-2.9	6 (11%)	7 (14%)
3.0-3.9	7 (13%)	5 (10%)
4.0-4.9	4 (7%)	3 (6%)
5.0-5.9	5 (9%)	3 (6%)
6.0-6.9	9 (17%)	4 (8%)
7.0-7.9	4 (7%)	2 (4%)
8.0-8.9	1 (2%)	0 (0%)
9.0-9.9	3 (7%)	0 (0%)
10.0	1 (2%)	0 (0%)

Although there is evidence that students who have used the chatbot have better marks than those who have not, it could be that the students who are more motivated and perform better in the subject are those who have used the chatbot.

To shed light on this issue, we will compare the marks of the students that worked with the chatbot with those of the previous year (Table IV). It can be seen that the marks, in general, have gone up one step regarding the previous year.

TABLE IV. NUMBER AND PERCENTAGE OF STUDENTS IN EACH MARK RANGE COMPARED WITH PREVIOUS YEAR

Mark range	Chatbot students	Previous year students
0.0-0.9	7 (13%)	41 (30%)
1.0-1.9	7 (13%)	23 (17%)
2.0-2.9	6 (11%)	5 (4%)
3.0-3.9	7 (13%)	9 (7%)
4.0-4.9	4 (7%)	4 (3%)
5.0-5.9	5 (9%)	24 (18%)
6.0-6.9	9 (17%)	10 (7%)
7.0-7.9	4 (7%)	8 (6%)
8.0-8.9	1 (2%)	7 (5%)
9.0-9.9	3 (7%)	4 (3%)
10.0	1 (2%)	0 (0%)

While in the previous year, 47% of the students had the lowest marks (between 0.0 and 1.9), Among the students who used the chatbot in this year this indicator dropped to 26%. So, the students with the lowest marks are fewer.

In the three mark ranges between 2.0 and 4.9 we find a higher number of students in the chatbot group than in the previous year

(31% vs. 14%). Although these are students who did not pass the exam, we see that the marks of failed students increased compared to the previous year.

Something similar happens with students who pass with the minimum mark (between 5 and 5.9). We can see that in the previous academic year, 18% of the students narrowly passed the exam. This percentage is somewhat lower in the chatbot course (9%), shifting part of this percentage to the next range (between 6 and 6.9) with 17% against 7% in the previous course.

Fig. 8 graphically shows this difference between the two cohorts. It can be seen how the red stripe (previous course) is higher in the 0.0-0.9 and 1.0-1.9 range column, while the blue stripe is higher in the 2.0-2.9, 3.0-3.9 and 4.0-4.9. Although these are still low marks, they do denote an improvement with respect to the students who obtain the lowest marks. In addition, the red stripe (previous course) is higher in the 5.0-5.9 range column, while the blue stripe (students who used the chatbot) is higher in the 6.0-6.9 than the red stripe, i. e. there is evidence that the tool has also helped to improve the level of students who passed the subject with the minimum mark. Finally, there is hardly any difference in the highest marks.

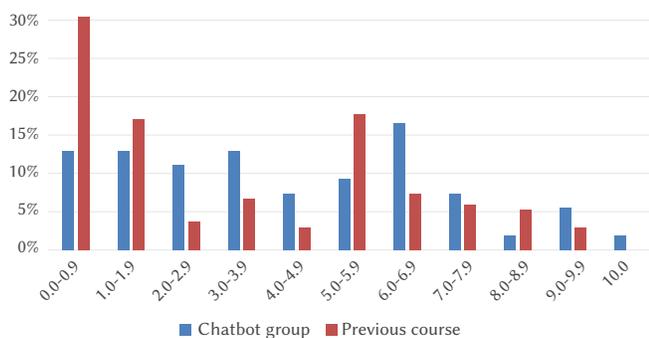


Fig. 8. Year comparison.

The analysis that follows from these results is the following:

- There is evidence that within the same academic year, students who practised with the chatbot get better marks than those who did not.
- Compared to the previous academic year, there is evidence that the improvements are more significant among students with lower and average marks.
- There is no evidence that students with medium-high marks move up in level and get the highest mark.
- This is consistent with comments from some students who, while enjoying the use of the chatbot, suggested the implementation of more complex queries.
- Therefore, there is evidence that the chatbot has helped students who were low performers in SQL language to improve their level and helped medium-high performers to brush up on their SQL skills.

D. User Acceptance Evaluation

A study to evaluate the user acceptance of the chatbot was conducted. Its design and its results are described below.

1. Survey Design

A survey to evaluate the user acceptance of the chatbot was designed with Google Forms to collect the users' opinions. The survey includes 15 questions to score several attributes according to the Technology Acceptance Model (TAM). The attributes analysed are Perceived Usefulness (PU), Perceived Ease-Of-Use (PEOU), Perceived

Enjoyment (PE), Attitude (A) and Behavioural intention (BI). In addition, a question to assess the students' motivation for learning the theoretical concepts of the database course (LDBM) was included. These questions allow values in a Likert scale from 1–5, representing the user's dissatisfaction with value 1 and total compliance with value 5. Below are the questions included in the survey and their correspondence to each of the attributes mentioned above:

- Perceived ease-of-use (PEOU): Two questions were included to find out if the chatbot is easy to learn (Q1) and use (Q2).
- Perceived usefulness (PU): To measure this attribute, six questions have been included to find out if the chatbot enables users to learn the SQL syntax (Q3); assists in identifying the different errors that happen when running SQL queries (Q4); enables to learn how to issue simple SQL queries on a single table (Q5), queries that include SQL functions (e.g. min, max and others) (Q6), nested queries (Q7) and queries on multiple tables (Q8).
- Perceived enjoyment (PE): This attribute is measured through one question regarding whether the users had a positive experience using the chatbot (Q14).
- Attitude (A): Three questions have been included to find out if the users think that chatbots are useful learning platforms to help users solve problems, learn new things or be more productive (Q9), grasp computer engineering concepts from the academic curriculum (Q10), and learn how to manage databases (Q11).
- Behavioural intention (BI): For this attribute, two questions ask if the users would recommend using the chatbot to people interested in learning about databases (Q12) and if the users will use the chatbot to prepare themselves for further course assessments (Q13).
- Learning database motivation (LDBM): Lastly, students are asked whether if the chatbot encourages them to keep learning database concepts (Q15).

Five questions were also included to collect students' alias, age, gender, the latest exercise level they achieved to complete, and the number of calls they have been previously evaluated. These items enable us to classify user responses. Finally, their comments after using the chatbot are collected through a free text field. The survey is included as supplementary material to this manuscript.

2. Survey-Data Analysis

Firstly, 56 survey results were collected from the students. The results obtained and the analysis performed is available in a spreadsheet included as supplementary material. To check the validity of the data, an Alpha Cronbach test was conducted, obtaining very high confidence (0.98). The results obtained after the analysis of the measured attributes were significantly positive. The average values of the scores of the attributes are: PEOU 4.39, PU 3.98, PE 4.07, A 4.51, BI 4.36 and LDBM 4.1.

On the other hand, the answers collected have been classified according to the user's age and gender, the latest exercise level achieved and the number of calls the user has been evaluated. The results of the analysed data are included in Table V.

Although there are no significant differences, we can draw some interesting insights. First, the average data for the measured attributes are quite positive. Regarding gender, men score the PE attribute slightly lower (4) than women (4.57). Moreover, the analysis shows that the students who have previously taken one or more examinations score the PE attribute lower (3.69) than those who have taken no previous exam (4.19). The PE attribute also decreases to 3.75 for users above 20 years old, which may be related to the above insight. Furthermore, users who have not completed all the levels have scored lower on the PEOU (3.6), and PE (3.8) attributes. Finally,

concerning the feedback provided by students, some ask for making clear several of the messages generated by the bot, others propose to increase the difficulty of the exercises, and others ask for allowing multi-line answer entries, among other improvements.

TABLE V. RESULTS OF THE SURVEY WITH STUDENTS: THE MEASURED ATTRIBUTES (THE ITALIC FONT SHOWS THE CHI-SQUARED VALUES)

User Profile	PEOU	PU	PE	A	BI	LDBM
<i>Gender</i>						
Man	4.26	4.28	4	4.45	4.43	4.10
Woman	4.43	4.43	4.57	4.86	4.86	4.71
<i>Chi-squared</i>	<i>0.63</i>	<i>0.63</i>	<i>0.59</i>	<i>0.65</i>	<i>0.65</i>	<i>0.61</i>
<i>Number of examinations taken</i>						
0	4.28	4.42	4.19	4.56	4.51	4.19
1 or more	4.31	4	3.69	4.31	4.38	4.15
<i>Chi-squared</i>	<i>0.63</i>	<i>0.65</i>	<i>0.76</i>	<i>0.66</i>	<i>0.66</i>	<i>0.62</i>
<i>Age</i>						
<=20	4.36	4.42	4.25	4.64	4.58	4.19
>20	4.15	4.15	3.75	4.25	4.30	4.15
<i>Chi-squared</i>	<i>0.64</i>	<i>0.65</i>	<i>0.76</i>	<i>0.67</i>	<i>0.67</i>	<i>0.62</i>
<i>Exercise levels completed</i>						
A & B levels	3.60	4.40	3.80	4.60	5	4
All levels	4.35	4.31	4.10	4.49	4.43	4.20
<i>Chi-squared</i>	<i>0.54</i>	<i>0.65</i>	<i>0.57</i>	<i>0.67</i>	<i>0.71</i>	<i>0.59</i>
<i>Students</i>						
All	4.39	3.98	4.07	4.51	4.36	4.1

V. DISCUSSION

This research is aimed at supporting students in learning and training with SQL. From the results collected, we can report positive evidence using the chatbot for both students and lecturers.

Previous work in the literature related to using chatbots and learning a programming language focuses on analysing chatbot usability and acceptance. However, it does not analyse the impact of chatbot use on learner outcomes [30], [33], [34]. In this paper, we could analyse the impact of the chatbot on student performance. We observed that a student who passes the exam is much more likely to have trained with the chatbot than one who has not. In other words, the students who use the chatbot obtain better results than those who did not use it. Of course, that does not necessarily mean that training with the chatbot is the only variable involved in this increase in passing. However, there are likely other characteristics of the students that have pushed them to use the chatbot. Nevertheless, we do consider these numbers to be positive evidence of the benefit of the chatbot.

The positive impact of the chatbot can also be confirmed with the students' evaluation carried out through the TAM. All the TAM attributes analysed were in the upper range (between 4 and 5), except for perceived usefulness at 3.98. It is worth noting that students also had a high motivation to learn databases (4.1 out of 5). Student motivation is fundamental to their academic success [41]. That could also point to the significant difference found in passing the final SQL examination between the students who used the chatbot and those who did not. The students who used the chatbot are the most motivated to learn databases and therefore used the chatbot. Besides, some of their survey responses indicated that the chatbot could be enriched with more complex queries, suggesting that they were eager to further work with the chatbot. This conclusion is in line with the findings of Munday [34], who reported that, after finishing the course, 10% of her students continued to use the chatbot to improve their language skills. Future work along these lines could aim to engage less motivated students.

From the lecturers' point of view, the learning platform assists in monitoring students' progress. The analysis of learning logs can be very relevant for lecturers when assessing computer programming tasks [42]. From the records of the students' attempts at the different exercises, the lecturer involved in the study was able to draw beneficial conclusions:

- The contents of the course that students mastered, based on the queries they solved successfully and with fewer attempts.
- The learning aspects that must be reinforced, according to the queries that were more difficult for the students and had a lower success rate.
- It allows us to know which errors were repeated more frequently when trying to solve the exercises.
- It has allowed us to know the results of the advice provided by the chatbot that has been more or less useful for the students to solve the problems.

Therefore, we encourage lecturers to implement learning platforms based on chatbots to support students learning programming languages.

VI. CONCLUSIONS

Learning SQL is one of the critical activities for any computer engineer, but it often presents difficulties for students. For this reason, this paper presents a chatbot embedded in a learning platform to help students in databases to perform SQL queries correctly. The chatbot was implemented and made available to the students of a university course on Databases in the second year of the degree in Computer Engineering. The students use it for two weeks before the final SQL examination. The results, so far, are promising because:

- The chatbot helps students learn SQL when the lecturer is not present by adapting to the needs of individual students based on their errors.
- Our data analysis revealed a high acceptance of the chatbot by the students.
- There is evidence that the chatbot helped students to achieve better results, specially to students with both average and low marks.
- The SQL learning platform provides detailed information to lecturers about their students' learning process that they can use to improve it.

As future work, we plan to conduct further studies with more students to collect more data that will enable us to apply Machine Learning (ML) algorithms to improve various aspects of the SQL learning platform. Thanks to the automatic ML algorithms that IBM Watson incorporates and the lecturers' adjustments, the precision of the answers and advice offered by the chatbot will be progressively improved. Also, implement higher levels of difficulty that also motivate students with higher marks.

APPENDIX

A. Survey to Evaluate Chatbot Acceptance

Students must answer all questions by assigning a value according to the following 5-point Likert scale: (1) Strongly Disagree (2) Disagree (3) Neither Agree nor Disagree (4) Agree (5) Strongly Agree

1. Perceived Ease-Of-Use (PEOU)

- I consider the SQL chatbot to be easy to learn (Q1)
- I consider the SQL chatbot to be easy to use (Q2)

2. Perceived Usefulness (PU)

- I consider that the SQL chatbot allows me to learn the syntax of the SQL language (Q3)
- I consider that the SQL chatbot helps me to distinguish the different types of errors that occur when launching queries (Q4)
- I consider that the SQL chatbot allows me to learn how to launch simple SQL queries on a single table (Q5)
- I consider that the SQL chatbot allows me to learn how to launch SQL queries that include functions (e.g. min, max, etc.)(Q6)
- I consider that the SQL chatbot allows me to learn how to launch nested SQL queries (Q7)
- I consider that the SQL chatbot allows me to learn how to launch SQL queries involving several tables with joins, etc (Q8)

3. Attitude (A)

- I consider chatbots to be useful tools that can help us to solve problems, learn new things or be more productive (Q9)
- I consider it interesting to use chatbots for the acquisition of Computer Engineering concepts that are studied at the University (Q10)
- I like the idea of using chatbots to learn how to manage databases (Q11)

4. Behavioural Intention (BI)

- I would recommend this tool to anyone interested in learning how to use databases (Q12)
- I will use this application to prepare myself for the Database subject assessments (Q13)

5. Perceived Enjoyment (PE)

- When I use the SQL chatbot I have a good time (Q14)

6. Learning Database Motivation (LDBM)

- Using the SQL chatbot makes me more interested in learning databases (Q15)

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