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PAPER

SMART Chatbots in the E-learning Domain: A Systematic Literature Review

Khadija EL Azhari[1](✉), Imane Hilal[2], Najima Daoudi[2], Rachida Ajhoun[1]

[1]ENSIAS, Mohammed V University, Rabat, Morocco

[2]School of Information Sciences (ESI), Rabat, Morocco

khadja_elazhari@um5.ac.ma

ABSTRACT

Integrating Artificial Intelligence (AI) technologies implied significant growth in various domains. Furthermore, many companies integrate AI technologies into their products to enhance the quality of their services. Chatbots are among the AI technologies widely used in several areas, especially E-learning. Chatbots support learners in their learning processes by helping them to find the appropriate answers to their questions. We aim to conduct a systematic literature review (SLR) to uncover the use of AI chatbots to offload teachers from repetitive and massive tasks. This article surveys the literature over the period 2016–2022 on the use of AI chatbots in the E-learning domain as they automatically answer learners' questions. Thus, we identify, collect, and synthesize multiple research studies on the application of AI chatbots in the E-learning field. Based on the renowned frameworks, PRISMA and PICO, we have succeeded in (1) Developing our research questions and (2) Automatically implementing a solution based on Python language to analyze selected papers, highlighting research gaps, and opening new windows to guide our future works. Our study shows that chatbots effectively interact with learners. However, there are some drawbacks: (1) Educational chatbots are still limited in their local Knowledge Base (KB), which makes them unable to answer students' questions correctly. Thus, Chatbot's KB needs to be extended through external sources, enabling the chatbot to update its KB over time, making it rich and saving time. (2) Lack of reliable external sources to enrich the chatbot's KB and make it up to date. (3) Lack of educational chatbots with smart services such as speech recognition and sentiment analysis to boost the user experience and make learning easier. In our SLR, we discuss these limitations and propose some solutions to fill the gap.

KEYWORDS

Artificial Intelligence, AI, natural language processing, chatbots, E-learning, Knowledge Base, NLP

1 INTRODUCTION

Artificial intelligence (AI) has recently attracted international attention [1]. It has emerged as a creative and revolutionary assistant in various areas [2]. It becomes a

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trend domain, because of the variety of its technologies that can be applied to add innovative value to various services. Among the AI technologies widely used: (1) Natural language processing to understand human language and handle it appropriately [3]. (2) A neural network is a collection of algorithms that aims to identify underlying links in a given dataset using an AI approach that imitates how the human brain functions [4]. (3) Chatbots are AI-based computer programs that mimic natural language conversations with users through messaging services, mobile apps, and websites [5].

In the last couple of years, AI technologies have been implemented in several fields including E-learning platforms. More specifically, the use of AI in education is expanding and has attracted significant interest [6]. The use of AI in the education field aims to advance the reform of educational practices and enhance both the training personal model and the learning environment [7]. In addition to that, the rapid advancement of AI technologies in the education field gave birth to a new concept called "Smart Education" [8]. It adopts smart technologies for improved value orientation, greater conduct ability, and wisdom-enhancing abilities [9]. Nevertheless, despite integrating such recent and innovative technologies in the educational field, during the pandemic COVID 19, many teachers and students have had some difficulties in learning through online sessions and virtual classes. They suffer from ineffective time management, lack of interaction, and technical issues. Hence, the educational field needs additional efforts to help teachers and students in their learning processes. Especially, there is a wide range of issues that the educational field could face, namely: (1) Teachers cannot answer all repetitive and massive students' questions in the course. (2) Students feel lost in many available information sources. (3) Students fear being misjudged if they ask repetitive questions. (4) Teachers and students suffer from a lack of interaction in online courses.

To deal with these issues and challenges, several universities and institutions integrate AI chatbots into their platforms to support their students, encourage them to ask questions, and give them answers rapidly without wasting time searching in other different sources, or waiting for tutors and teachers to give responses. In this paper, we conduct a systematic literature review to deeply analyze papers over the period 2016–2022 on the use of AI chatbots to offload teachers by answering repetitive and massive learners' questions. In our SLR, we developed a Python script to automate the process of retrieving relevant papers related to our research questions. Thus, we succeed in saving time and energy. Thanks to the solution, we could focus our energy on synthesizing relevant papers and retrieving some perspectives of improvements that can guide our future works rather than wasting time manually filtering extracted papers.

The existing SLRs on educational chatbots focus their analysis on the application of chatbots in E-Learning without deeply presenting technical details such as datasets employed to train the chatbot and the process carried out to create the chatbot's local KB. For that reason, we decided to conduct this current SLR to include an exhaustive list of (1) methods and techniques proposed to build the knowledge base of educational chatbots and (2) external sources to support the chatbots' knowledge base to feed, enrich, and update it. (3) AI technologies adopted to improve and enhance educational chatbots. Results can serve as a comprehensive manual for researchers working on intelligent educational chatbots. The study's findings can guide universities and other organizations looking to use AI chatbots as online tutors to improve learners' skills and comprehension of subjects.

The remainder of this paper is structured as follows: The next section details the context and problem statement. The third section explains the methodological strategy adopted to conduct this SLR. The fourth section presents the results of the study. The fifth section discusses the findings. The sixth section presents the implication of the study. The seventh section provides the conclusion and future work, and the last section presents declarations.

2 CONTEXT AND PROBLEM STATEMENT

As mentioned in the introduction section, the education domain suffers from a variety of issues that can be presented in three types, namely, issues related to the: (1) Availability of tutors. (2) Information sources. (3) Student behavior. (4) Lack of interaction.

2.1 Availability of tutors

Tutors and professors are responsible for a variety of tasks including preparing course materials, presenting, and explaining the course content to students, and evaluating assignments etc. [10] These tasks consume tutors' energy and time [11],[9]. Thus, they won't have enough time to answer repetitive and massive students' questions and give them the information they need to better master the course [12],[10].

2.2 Information sources

Currently, a variety of information sources are available to students: books, online links, encyclopedias, and search engines etc. [13],[11]. They are an opportunity for students. Effectively, they can use them to search for information, find answers to their questions, and make their search richer. However, there are some challenges related to such information sources. In effect, it's hard to evaluate information, recognize the correct one, and satisfy the real need of students [14],[12]. Therefore, students feel lost, can't find information rapidly, and waste time filtering the information found, which can negatively impact their learning engagement [15].

2.3 Student behavior

Often, students can't ask all their questions to the tutor or share their thoughts in public. They fear being the object of others' attention, being evaluated, and being misjudged[6], which can negatively impact their engagement. Even when students ask questions, it is hard for the professor to give detailed answers to them, because of the limited time allocated to course sessions [7].

2.4 Lack of interaction

In the last couple of years, more especially in the era of the pandemic Covid 19, universities and institutions adopt online courses and distance learning [8]. Thus, students and teachers only interact during the online sessions, which is not sufficient neither for students who have massive questions nor for professors who can't interact deeply with learners because of the limited time of the online sessions [13]. Hence, a new challenge has emerged related to the lack of interaction between students and teachers [14], which can negatively impact students' retention and learning [15].

To overcome these issues, a large number of AI technologies have been proposed and implemented. In the next section, we will present an overview of AI technologies that could enhance learning processes, especially AI chatbots, since they are the focus of our SLR.

3 OVERVIEW OF AI TECHNOLOGIES IN LEARNING

AI technologies have shown increasing use in the learning domain [16]. According to [17] many AI technologies are applied in the educational domain to overcome many issues and improve the learning processes. In Figure 1 we present an overview of AI technologies that are used in various e-learning use cases [18].

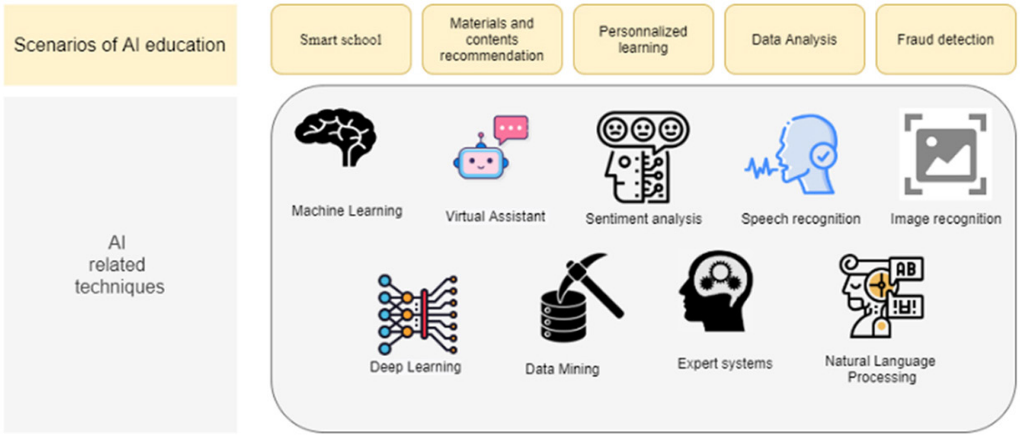

Fig. 1. AI Applications in the education domain

As shown in Figure 1 AI technologies are integrated into education to satisfy multiple needs and scenarios. Machine Learning, Deep Virtual Assistants, etc. are applied to automate tasks and perform processes in the learning domain. In our SLR, we will focus on the use of AI chatbots to automate learning tasks, especially answering repetitive and massive students' questions. In Figure 2 we present Scopus search results related to the development of AI chatbots [25].

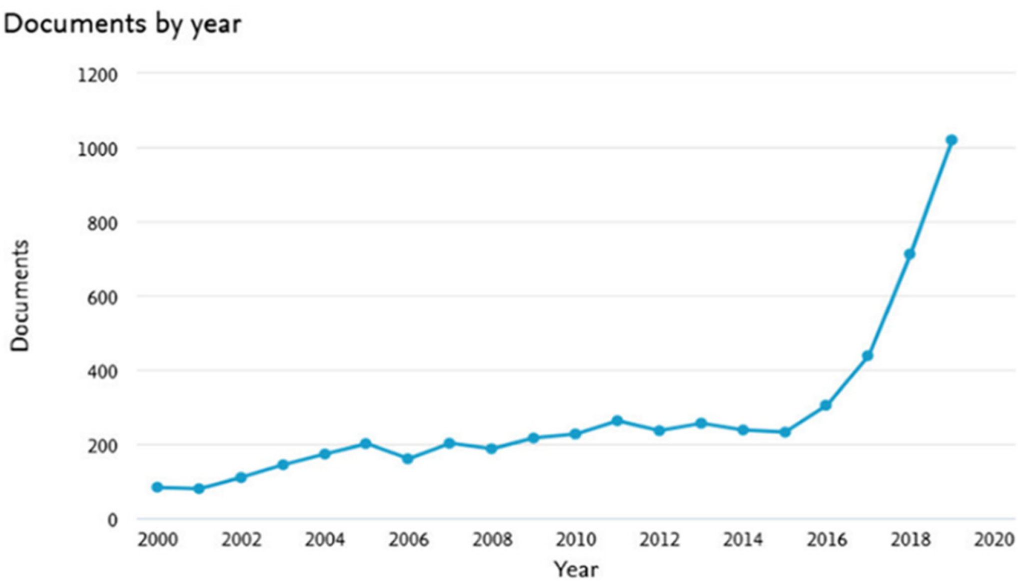

Fig. 2. Search results in scopus for documents focusing on AI chatbot from 2000 to 2020

As shown in Figure 2, there is an increasing interest in AI chatbots, more significantly, the exponential growth of the development of chatbots from 2016 until 2020. For that reason, we decided to focus our SLR on educational chatbots implemented from 2016 to 2022 to guarantee the diversity and wealth of included papers.

Educational chatbot is an intelligent program that can mimic human behavior by understanding natural language and responding correctly to the students' requests. According to the chatbot's domain, we can differentiate between (1) Open domain chatbots that are able to answer questions related to general topics. (2) Closed domain chatbots that can only discuss topics about a specific domain and can't correctly answer questions that concern other domains [26]. Generally, chatbots can be divided into two general types depending on how the chatbot is programmed: (1) Rule-based chatbot, which means that chatbot is programmed to do a predefined command or rules [27]. (2) Chatbot that uses AI technologies to answer students' questions [28]. AI chatbots are based on Natural Language Processing, which is an AI technology that aims to explore the use of natural language text or speech by computers. It provides some techniques that enable chatbots to understand human expressions to perform the desired tasks [29]. The core technique of every NLP task is called Natural Language Understanding. It aims to analyze human language to extract context and meanings. Its principal goal is to understand the student's intention based on the unstructured input received [29]. For this purpose, it identifies two elements: (1) Intent, which means what the student says and what is the intention behind his sentence. (2) Entity is a tool to extract values of parameters based on the student's input, for example, the sentence: What does Machine Learning mean? The student's intent is to learn the explanation of a specific topic and the entity value is Machine Learning, which is the topic needed by the student. Thanks to the NLP techniques, more significantly, NLU, the system understands that the student asks for the definition of AI. After understanding student input, another technique is applied to generate the appropriate answer, called Natural Language Generation (NLG). It aims to prepare a human-like response based on the intent and entity extracted by the NLU technique [30]. In Figure 3 we present the process adopted by NLU and NLG to answer a student's question.

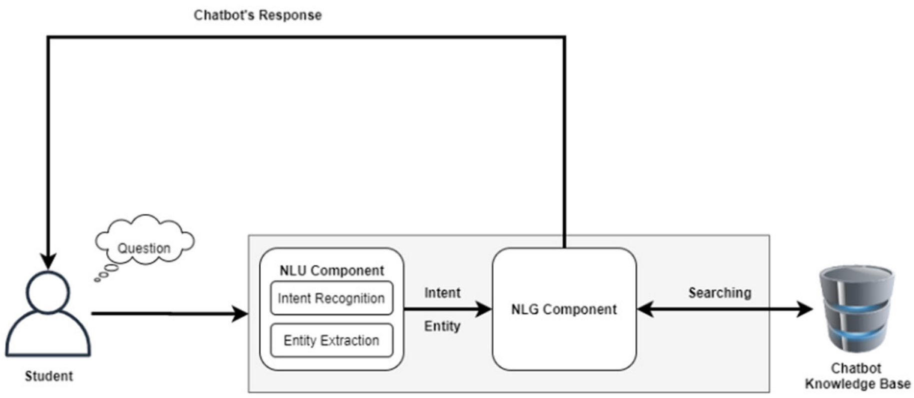

Fig. 3. The process adopted by NLG and NLU to answer questions asked by students

In Figure 3, we present the chatbot Knowledge Base which is the central component of an AI chatbot. It can be defined as a database that contains technical knowledge related to a specific field. The knowledge is modularized and structured based on technical knowledge and expression rules [31]. Thus, adding new knowledge or modifying an existing one is possible. The knowledge base is the principal component of AI chatbots. It stores all chatbot's knowledge and enables it to generate the appropriate response related to the student's message. It stores a set of pairs of questions and answers (Q&A) related to the chatbot's domain. Based on how AI chatbots generate the response, they can be categorized into two main categories, namely, (1) Generative chatbots [32] and (2) Information Retrieval Chatbots [33].

Generative Chatbot aims to adapt itself to any type of situation or student, especially in non-programmed situations. It can generate answers by itself without referring to its knowledge base every time it receives a student question. Generative chatbots are trained through deep learning algorithms such as Neural Networks (NNs), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), etc. [34]. Thus, these algorithms allow the chatbots to be autonomous and respond to students' questions themselves. However, current models can lead to incoherent answers or produce invalid sentences in the case of using small or bad-quality datasets to train the chatbot [35]. In Figure 4 we resume how generative chatbots work to answer students' questions.

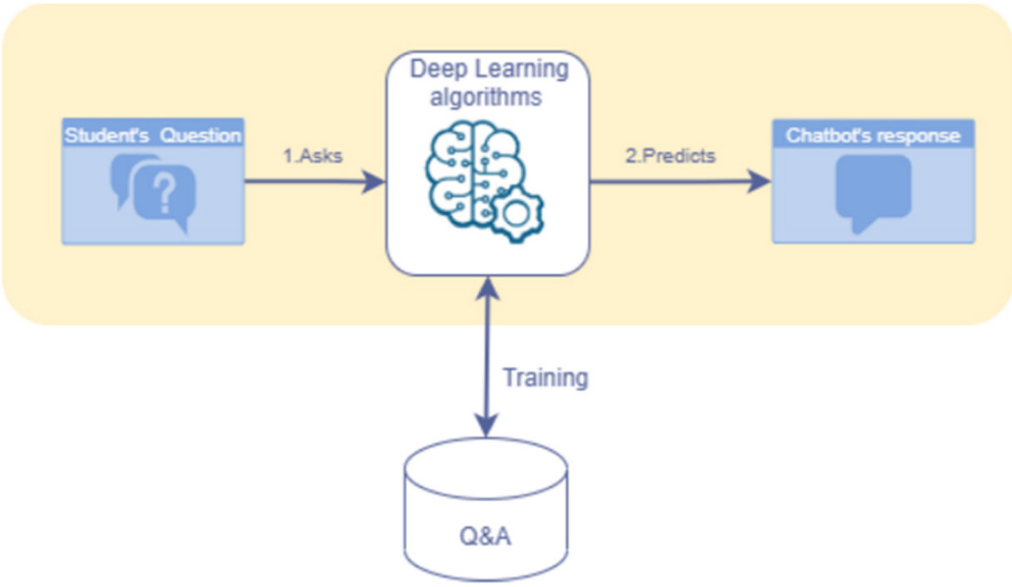

Fig. 4. Process of generating responses through generative chatbots

The information retrieval chatbots answer the students' requests based on a collection of sentences that have been given to them in advance. Unlike generative chatbots, information retrieval chatbots work by retrieving information from the student's question and searching for the appropriate answer through NLP and local KB [33]. In Figure 5 we resume the process of answering students' questions through information retrieval chatbots. Compared to generative chatbots, information retrieval chatbots ensure the quality of the chatbot's answers, they give answers that are grammatically correct because the response is generated based on its local KB. Furthermore, the information retrieval Chatbots don't require a large amount of data to answer users' questions compared to the volume of data needed in generative chatbots [36].

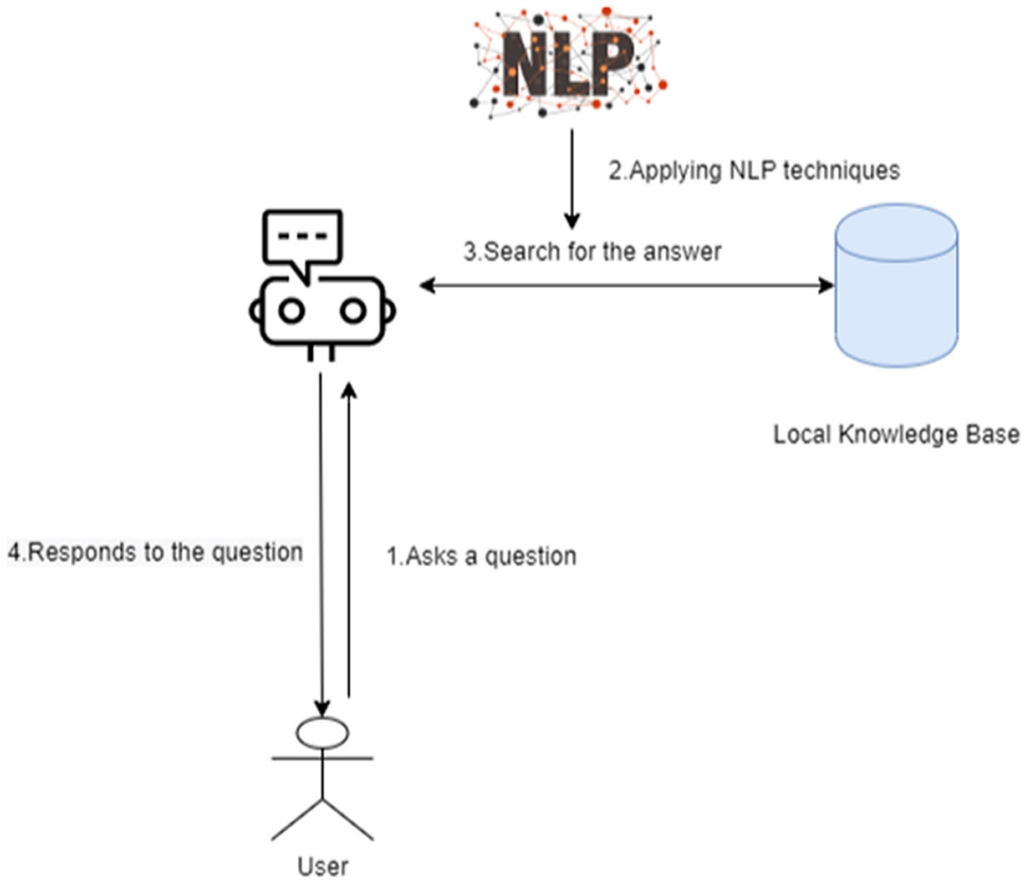

Fig. 5. Process of generating responses through information retrieval chatbots

In our SLR, we aim to conduct a deep analysis of works carried out on the use of AI chatbots in the e-learning field. We will synthesize and analyze the recent implementations of educational chatbots with AI technologies to discover the process adopted to create the chatbot and identify areas for improvement. The idea behind conducting such SLR is due to the lack of SLRs presenting the approaches adopted to construct educational chatbots and their knowledge base. The existing SLRs on educational chatbots focus their analysis on the use of chatbots in education without deepening technical details such as datasets used to train the chatbot and the process or algorithms adopted to create the chatbot's local KB.

4 METHODOLOGY STRATEGY

According to [37], there are seven main steps to systematically conduct an SLR, namely: (1) Developing and validating the review protocol/publication standard and reporting standard/guidance, which are manuals of systematic plans that guide researchers on things they want to consider in the review. (2) Formulating research questions (RQ) that drive the entire process. (3) Systematic searching strategies to systematically conduct the process of searching in databases for articles that will be included in the review. (4) Quality appraisal to assess the quality of articles. (5) Data extraction to extract any data that assists researchers in answering research questions. (6) Data synthesis to analyze data extracted earlier in step 5. (7) Data demonstration to illustrate review findings.

4.1 Developing and validating the review protocol/publication standard and reporting standard/guidance

In our SLR, we decided to adopt two frameworks that are most popular in guiding SLRs. (1) The first one is preferred reporting items for systematic reviews and meta-analyses (PRISMA) [20], it consists of a checklist of 27 items and a four-phase flowchart, which aims to help researchers improve the reporting of systematic reviews and meta-analyses by increasing clarity and transparency, without claiming to be a quality assessment tool. We have used the PRISMA framework to conduct the data screening and the identification of relevant articles to include in the study. (2) The second one is PICO criteria [21] (Population/Problem, intervention, comparison, and outcome), used to identify the study context, develop the research questions, and elaborate research strategies.

4.2 Formulating research questions

According to [21], [22], the research questions are determined by identifying four elements in the PICO model: (1) Population/Problem to identify the population of interest, its characteristics, and the Problem that interests the study. (2) Intervention to determine the intervention that will be tested in the study. (3) Comparison to determine if the study investigates making a comparison between different elements. It is not applicable in each study, it can be excluded if the study doesn't aim to make a comparison. (4) Outcome to determine the desired outcomes. In our study, we identified the following three elements:

Population: E-learning users.
Intervention: AI Chatbots.
Outcome: Answering students' questions.
Based on these three elements, we formulated our research questions:

RQ1: How can chatbots offload teachers by answering all students' questions (repetitive, massive, unpredictable, misspelled, poorly worded?)
RQ2: What are the existing implementations to construct and feed the chatbot's KB?
RQ3: What are the existing external sources that enrich the chatbot's KB?
RQ4: How can AI technologies improve the chatbot's inclusivity and its ability to socially interact with students?

4.3 Systematic searching strategies

After developing our research questions, we elaborate a systematic searching strategy that has three sub-processes, namely: (1) Identification, which consists of selecting keywords, enriching them, and selecting the most appropriate databases to use while searching. (2) Screening is the process of determining the inclusion and exclusion criteria that will be applied to the articles to select suitable articles for the review. (3) Eligibility is an evaluation process that helps researchers minimize deficiencies made by databases and exclude irrelevant articles.

Identification: Selection and enriching the selected keywords. According to [23], keywords can be obtained by using the research questions. Keywords should not be too general to avoid producing more articles that will include many irrelevant articles. Also, too-specific keywords will get more relevant articles but also brings the risk of missing some records [24]. The PICO model proposes to carefully select synonyms and related terms of selected keywords to make the search process richer. Based on the research questions presented in step 2, we determined the list of keywords and synonyms to use in the review. They can be presented as follows: (1) Chatbots: Chatterbot, conversational agent, talkbot, interactive agent, artificial conversation entity, virtual assistants, interactive system, answering system, FAQ system. Learning: E-learning, smart learning, learning, education, training. (2) Artificial Intelligence: Deep Learning, Natural Language Processing, Natural Language Generation, Expert Systems, Machine Learning, Knowledge Base.

To enrich the identification process, we used the selected keywords, their synonyms, and related terms to find suitable articles for our review. Thus, we made a combination of advanced search functions and symbols to use in databases' search engines to enrich the identification process. The search strategy used in our SLR can be presented as follows:

(AI OR Artificial Intelligence OR Natural Language processing OR Machine Learning) AND (Chatbot OR chatterbot OR conversational agent OR talkbot OR interactive agent OR artificial conversation entity OR virtual assistants OR interactive system OR answering system OR conversational agent OR Educational chatbot OR "Chatbot's Knowledge Base" OR "chatbot construction" OR "update of Knowledge base") AND (learning OR education OR teaching OR E-learning OR studying OR schooling OR tuition OR training) AND (Students' questions OR learning process).

Identification: Selection of databases. According to the PICO Model [39], it is recommended to integrate five databases to conduct an SLR and retrieve the high-quality articles for the review. We decided to use the five well-known databases, namely: (1) ScienceDirect. (2) Scopus. (3) IEEE Xplore, (4) Web of science, and (5) ACM Digital libraries. To properly conduct our SLR, we decided to focus our search on some types of studies and publications: journal publications, conference articles, and book chapters.

Screening. It is the process of selecting suitable and related articles for the review based on the inclusion and exclusion criteria that should be comprehensive and clear [43]. As mentioned by [41], criteria applied to articles should help researchers to answer the research questions. Thus, we developed the following inclusion (IC) and exclusion criteria (EC) to retrieve the most relevant articles related to our SLR:

- IC 1: Articles that focused on the use of chatbots in the education field.
- IC 2: Articles timeline between 2016-mars 2022.
- IC 3: Articles written in English.
- IC 4: Articles that are scientifically sound.

Regarding the exclusion criteria, the aim was to remove papers that are not related to the review. Then, the paper is removed if it conforms to at least one of the following exclusion criteria:

- EC1: Articles that focused on the use of chatbots in other domains besides education.
- EC2: Duplicate articles.
- EC3: Full text of the article is not available.
- EC4: Articles that did not present methods used, results found, and conclusions.

Eligibility. In our SLR, we succeeded in retrieving 10969 papers divided as follows: (1) 5398 papers from ScienceDirect. (2) 249 papers from Scopus. (3) 3000 papers from IEEE Xplore, (4) 1772 papers from web of science, and (5) 550 papers from ACM digital libraries. The eligibility process is time-consuming. Analyzing these articles takes a lot of time and needs effort and energy. For that reason, we developed a Python script that automates the eligibility process. Thus, we saved time and focused our energy on synthesizing included papers rather than manually filtering 10969 papers. First, we tried to use some existing software that proposes the automatization of the eligibility process such as Asreview[1], Rayyan[2], RobortReviwer[3], and Swift screener[4]. However, these programs offer a semi-automatic way to conduct the eligibility process. The researcher should manually indicate some papers that are related to the study, then, the program runs a machine learning algorithm to predict articles to include in the SLR. While testing these programs, we discovered some drawbacks, namely: (1) As Machine Learning algorithms need a large amount of data for making good predictions, researchers should spend a lot of time labeling training data. (2) Software is not able to handle a large amount of data; thus, they can't make predictions for all articles. (3) Algorithms integrated into such software cannot be modified or changed, thus, when we use them, we risk limiting our study. To alleviate these issues, we developed our Python script to analyze our data and conduct the eligibility process based on inclusion/exclusion criteria. In Figure 6, we resume the process handled by the Python language in six typical steps.

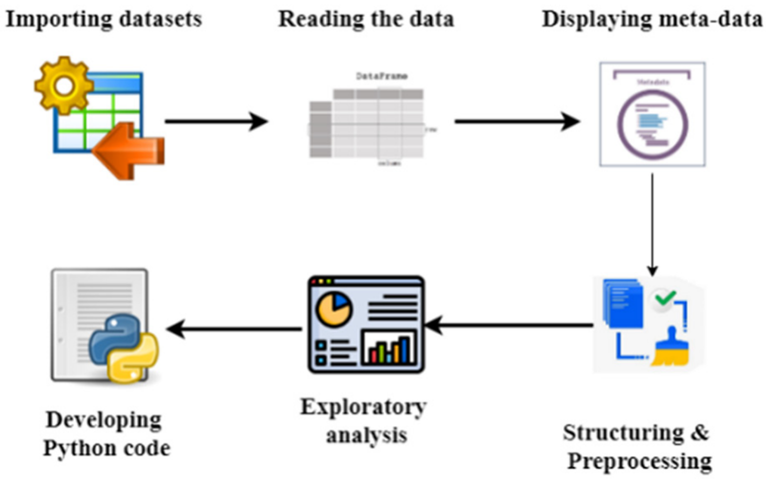

Fig. 6. Process adopted to analyze the data of extracted papers

Importing datasets. In this step, we import datasets that contain information related to extracted papers from the databases mentioned in the identification process.

Reading the data. Reading datasets and merging their content into one file. In Figure 7, we present an overview of the dataset, including some attributes and rows.

Displaying meta-data. Meta-data describes and gives information about the extracted papers. It provides many details that help in filtering papers and keeping only relevant ones. In this step, we display the metadata of our datasets. Figure 8 presents information related to the extracted articles in the SLR.

Structuring and Preprocessing. Structuring the data by removing missing values, dropping duplicate rows based on the article Digital Object Identifier (DOI), selecting

[1] https://asreview.nl/
[2] https://www.rayyan.ai/
[3] https://www.robotreviewer.net/about
[4] https://www.sciome.com/swift-activescreener/

the most important columns such as publication year, publication type, title, abstract, and tags that will help us to decide whether to include or exclude an article.

	Key	Item Type	Publication Year	Author	Title	Publication Title	ISBN	ISSN	DOI	
0	8BKGQY6W	conferencePaper	2021.0	Ceha, Jessy; Lee, Ken Jen; Nilsen, Elizabeth; ...	Can a Humorous Conversational Agent Enhance Le...	Proceedings of the 2021 CHI Conference on Huma...	978-1-4503-8096-6	NaN	10.1145/3411764.3445068	https://doi.org/10.1145/3411764.3445(
1	UVWRWZIN	conferencePaper	2020.0	Wambsganss, Thiemo; Winkler, Rainer; Söllner, ...	A Conversational Agent to Improve Response Qua...	Extended Abstracts of the 2020 CHI Conference ...	978-1-4503-6819-3	NaN	10.1145/3334480.3382805	https://doi.org/10.1145/3334480.3382ᐤ
2	29CI7YYI	conferencePaper	2019.0	Paschoal, Leo Natan; Turci, Lucas Fernandes; C...	Towards a Conversational Agent to Support the ...	Proceedings of the XXXIII Brazilian Symposium ...	978-1-4503-7651-8	NaN	10.1145/3350768.3352456	https://doi.org/10.1145/3350768.33524
3	CZRGWL6R	conferencePaper	2019.0	Göschlberger, Bernhard; Brandstetter, Christoph	Conversational AI for Corporate E-Learning	Proceedings of the 21st International Conferen...	978-1-4503-7179-7	NaN	10.1145/3366030.3366115	https://doi.org/10.1145/3366030.3366'
4	VLLVLNS5	conferencePaper	2021.0	A. Gonzalez, Luis	Investigating the Benefits of Applying Artific...	Proceedings of the 17th ACM Conference on Inte...	978-1-4503-8326-4	NaN	10.1145/3446871.3469770	https://doi.org/10.1145/3446871.34697

5 rows × 23 columns

Fig. 7. Dataset of extracted articles in the SLR

```
Entrée [32]: df.columns

   Out[32]: Index(['Key', 'Item Type', 'Publication Year', 'Author', 'Title',
                   'Publication Title', 'ISBN', 'ISSN', 'DOI', 'Url', 'Abstract Note',
                   'Date', 'Date Added', 'Date Modified', 'Pages', 'Issue', 'Volume',
                   'Series', 'Publisher', 'Place', 'Extra', 'Manual Tags'],
                  dtype='object')

Entrée [33]: df.info()

             <class 'pandas.core.frame.DataFrame'>
             Int64Index: 10969 entries, 0 to 999
             Data columns (total 22 columns):
              #   Column             Non-Null Count  Dtype
             ---  ------             --------------  -----
              0   Key                10969 non-null  object
              1   Item Type          10969 non-null  object
              2   Publication Year   10917 non-null  float64
              3   Author             10802 non-null  object
              4   Title              10958 non-null  object
              5   Publication Title  10035 non-null  object
              6   ISBN               2957 non-null   object
              7   ISSN               6507 non-null   object
              8   DOI                9667 non-null   object
              9   Url                6133 non-null   object
              10  Abstract Note      9483 non-null   object
              11  Date               10917 non-null  object
              12  Date Added         10969 non-null  object
              13  Date Modified      10969 non-null  object
              14  Pages              10054 non-null  object
              15  Issue              2549 non-null   object
              16  Volume             6659 non-null   object
              17  Series             242 non-null    object
              18  Publisher          991 non-null    object
              19  Place              560 non-null    object
              20  Extra              3653 non-null   object
              21  Manual Tags        8947 non-null   object
             dtypes: float64(1), object(21)
             memory usage: 1.9+ MB
```

Fig. 8. Information related to the extracted articles in the SLR

Exploratory analysis. In this step, we visualized our dataset based on Python language to get a comprehensive idea of the extracted papers. In Figure 9 we plotted histograms to present the number of articles retrieved by publication year and article type. After analyzing the histograms, we conclude that our data need to be standardized and preprocessed. In fact, histograms contain two paper types, "Book Section" and "Book", which refer to the same thing. Moreover, in the histograms, we identify some papers published before 2016. Thus, we should apply inclusion and exclusion criteria to keep papers published from 2016 until mars 2022. In addition to that, Figure 9 demonstrates the exponential growth of educational chatbots from

2016 and a significant decrease in the number of conference papers in 2022 because of the lack of conferences due to the pandemic Covid 19 and its impact.

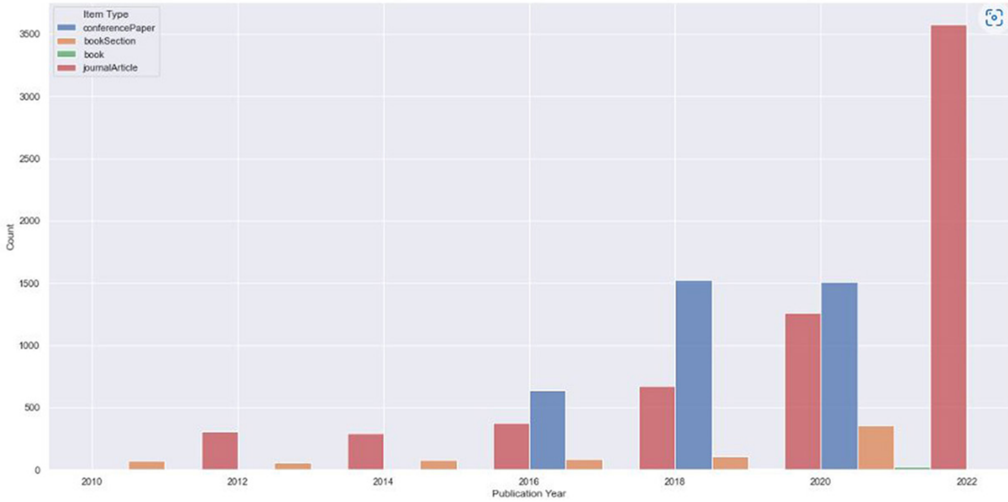

Fig. 9. Number of extracted papers by types and publication years

After creating histograms, we present word clouds or tag clouds that give us an idea about word frequency in the text. The bigger and bolder the word is in the word cloud, the more often it appears in the text.

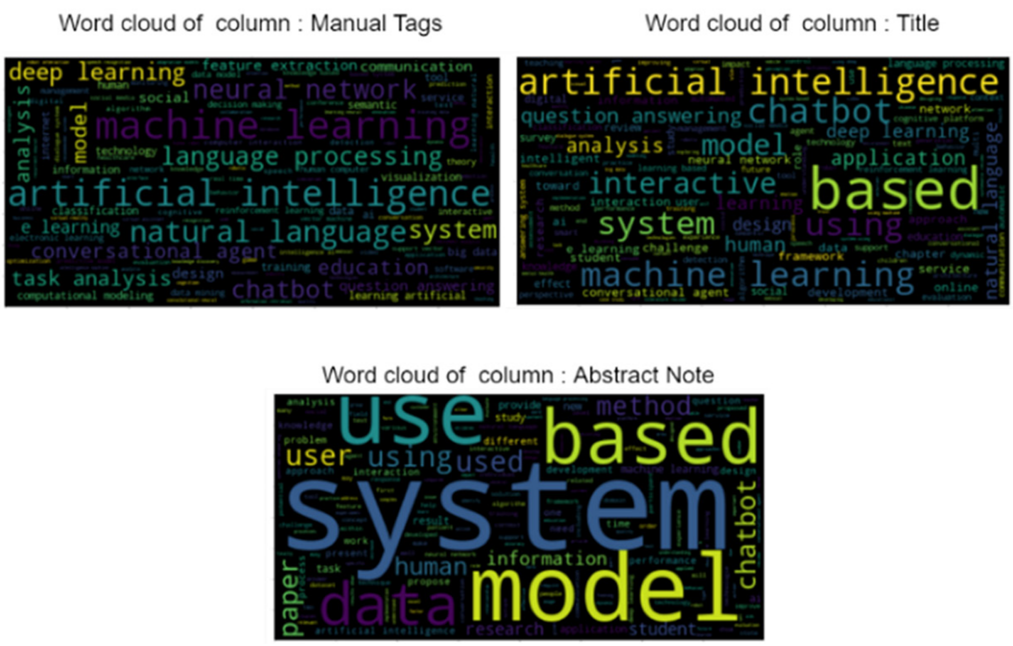

Fig. 10. Word cloud of papers' keywords before applying the inclusion and exclusion criteria

In Figure 10, we present the word cloud of several textual data namely: manual tags, titles, and abstract notes. We can conclude that the word cloud contains terms related to several domains such as Artificial Intelligence, natural language, language processing, and deep learning whereas we don't recognize easily terms related to chatbot, education, learning, and training.

Despite adopting a detailed search strategy to retrieve relevant papers for our study, there are some deficiencies in databases' search engines. Thus, we retrieve some papers that don't meet our keywords and requirements. As shown in Figure 10, there are few words related to educational chatbots, which means that our data needs to be preprocessed to apply the inclusion/exclusion criteria and get the articles that meet our requirements. For that reason, we developed our Python script to filter papers.

Developing Python code. In this step, we create a Python script to exclude papers that don't meet the inclusion criteria by automatically verifying each article's metadata, including publication year, publication type, keywords in abstracts, title, tags, and paper language. The Python script verifies whether keywords related to our study exist in each paper or not in two main steps namely: (1) Verifying the chatbot's keywords presented in the identification process to detect papers related to chatbots and (2) Using the output of step one to detect learning keywords to select articles that address educational chatbots and keep them in a new data. In the beginning, we included the keyword "learning" in our Python. However, we found some included papers that focus on the use of machine learning or deep learning in the education domain rather than a chatbot. For that reason, we decided to replace the keyword "learning" with "smart learning" and "E-learning". In Figure 11, we present the word cloud after applying the Python code. In fact, there is a difference between the two word clouds. In Figure 10, it was difficult to recognize terms related to educational chatbots. Whereas, in Figure 11, words related to education and chatbots appear. Hence, the keywords used in the Python script helped us to filter out papers that do not contain at least one keyword for education and chatbot.

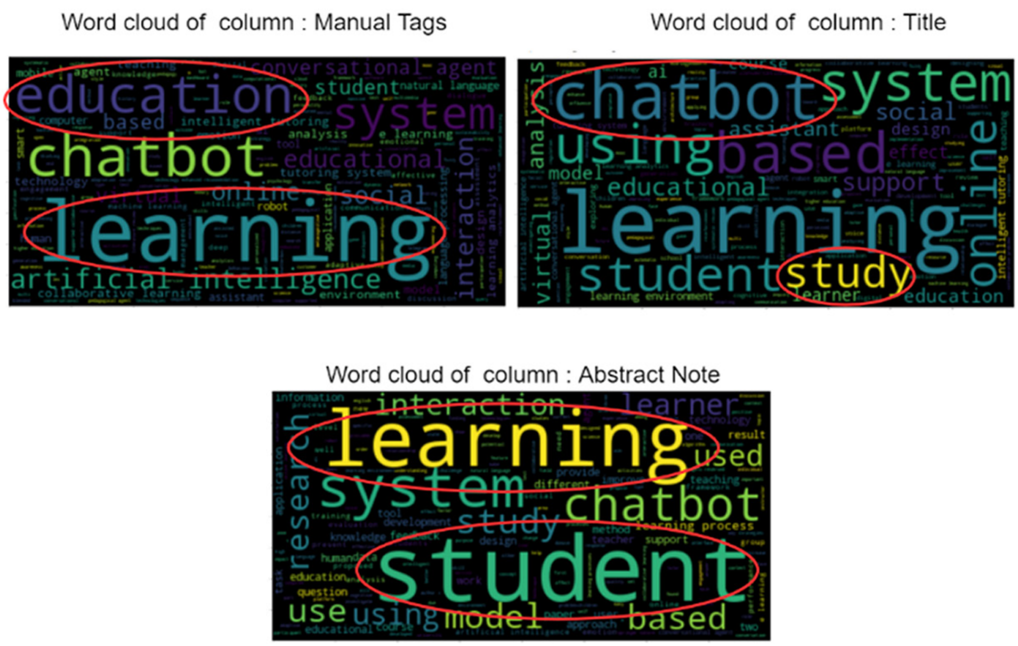

Fig. 11. Word cloud of papers' keywords after applying the inclusion and exclusion criteria

In the same context of filtering out irrelevant papers. Figure 12 presents histograms of included papers after applying inclusion/exclusion criteria based on our Python script. These histograms aim to ensure that the papers meet the inclusion criteria detailed previously.

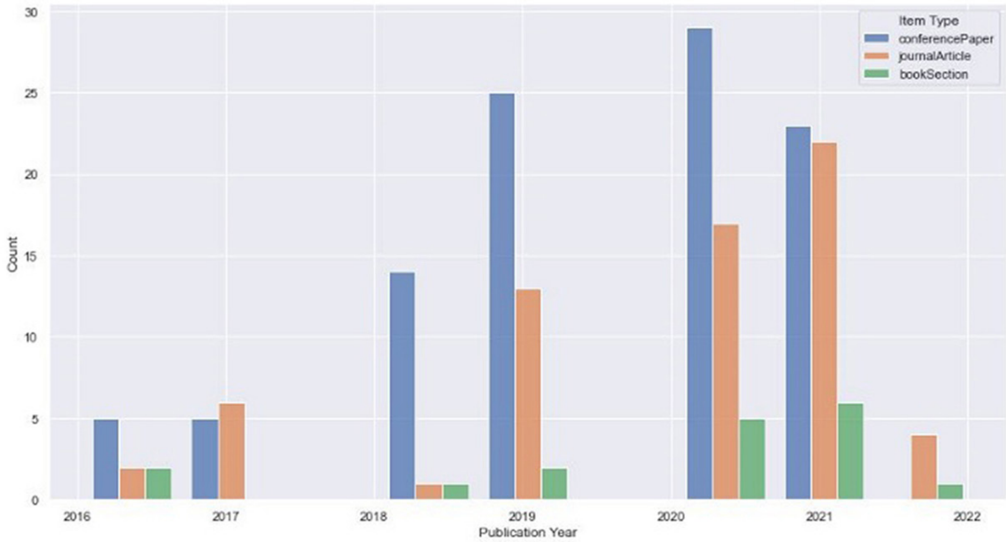

Fig. 12. Histograms of included papers after applying inclusion/exclusion criteria

Effectively, Figure 12 presents three types of included papers in the SLR: journal publications, conference articles, and book chapters from 2016 to mars 2022. More especially, the number of conference papers is higher than other paper types due to the increasing number of conferences.

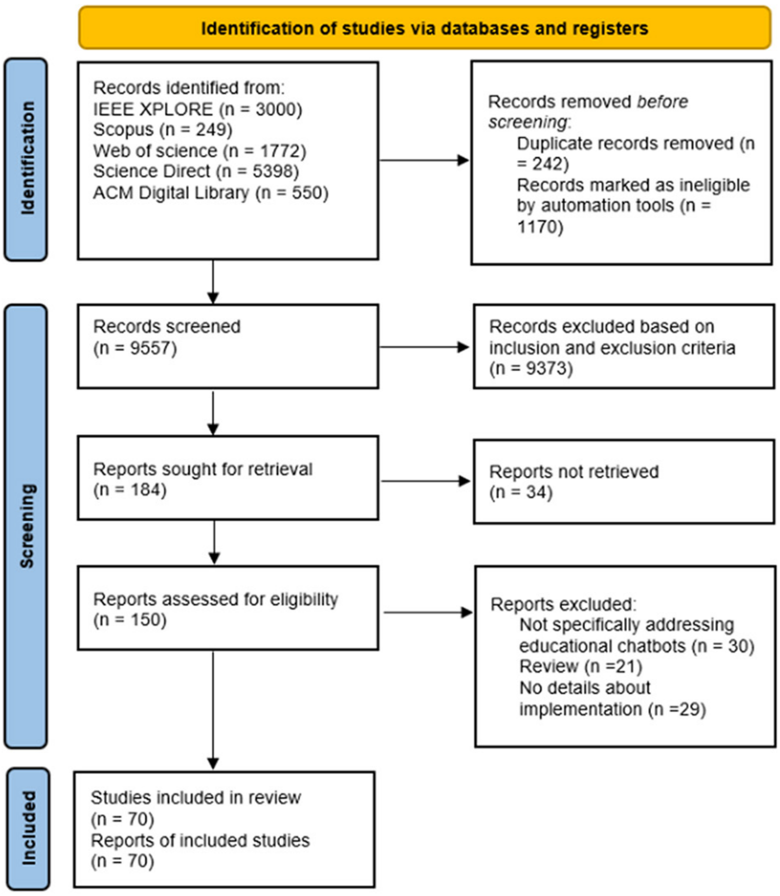

Fig. 13. PRISMA flowchart of the SLR

After completing the three sub-processes of systematic searching strategies, namely: (1) identification, (2) screening, and (3) eligibility, we present the information flow of the searching process by specifying the number of articles found in each step in the PRISMA flowchart (Figure 13). Firstly, we started with 10969 papers, and we used our Python script to retrieve 9557 articles after removing duplicated articles. Secondly, we reduced the number of papers to 184 papers after applying the inclusion and exclusion criteria based on our Python script. Thirdly, we retrieved the available full text of the papers. We succeeded in retrieving 150 full papers. Finally, the last number of included papers was 90 papers after excluding papers without implementations, papers that don't present their proposed method, and review papers.

4.4 Quality appraisal

According to [25], included articles should be examined and evaluated to ensure that they are free from any bias. Thus, there are several tools, scales, checklists, and standard forms that can be used. Authors in [45] mentioned that the Critical Appraisal Skills Programme (CASP) is one of the most used tools to assess the quality of included articles. It contains ten questions that help reviewers to detect methodological deficiencies. In our SLR, three independent experts have been chosen to examine and evaluate the quality of included papers based on the CASP checklist. After reviewing the different steps adopted to conduct the SLR, the reviewers confirm that our process meets all the requirements of the CASP checklist to guarantee that the included articles are free from any bias.

4.5 Data extraction

In the data extraction process, we extracted any data from the included papers that can assist in answering research questions [26], [27] and any disagreement on the extracted data was discussed by the team's members [23]. We conducted a reading sheet to summarize information and details related to the included papers. For each paper, we extracted eight main elements, namely: title of the paper, authors, related concepts, context, problem statement, proposed solutions, methodology and techniques adopted to construct the local chatbot's KB, and finally, the advantages and limitations of the proposed system. This method helped us to organize our work and build a comprehensive idea about the data presented in the included papers.

4.6 Data synthesis

After completing the data extraction step, we used the information presented in our included articles to synthesize existing findings and answer the research questions of the study. Basically, for each research question, we grouped all data extracted that can help us to respond to that question and we used the reading sheet information to synthesize knowledge and, more specifically, to use it to respond to the research question.

4.7 Data demonstration

All results and findings presented in our SLR are demonstrated through models (PICO and PRISMA), PRISMA flowchart, findings tables, and graphics with explanations to ensure that the process adopted to conduct the SLR is clear and comprehensive.

5 RESULTS AND FINDINGS

In this section, we will present the different results obtained after analyzing the selected papers. To be more organized and facilitate the presentation of the results, we will subdivide this section into four parts, each part focusing on a research question.

5.1 RQ1: Offloading teachers

Educational Chatbots automate several tasks in different manners. They offload teachers from repetitive tasks, support students in universities, institutions, and schools, and assist them in mastering the course knowledge. In fact, they offer an interesting opportunity for students to find the information they are seeking without wasting time waiting for the teachers' answers and explanations. Moreover, educational chatbots automate exercises by helping students practice theoretical knowledge through exercises and giving them hints, questions, and tips to assist them in solving exercises. Furthermore, chatbots evaluate students' knowledge and automate the assessment task. Hence, Chatbots automate many tasks, thus offloading teachers, professors, and administration officers. In Table 1, we resume the different ways to adopt AI chatbots in the educational field.

Table 1. Educational chatbots presented in the included papers

Papers	Tasks	Chatbot Interface	Language	AI Platforms or from Scratch?
[28]	Provide information about institutional courses.	Moodle Facebook Messenger	Portuguese	IBM Watson
[29]	Recommend learning materials and resources	Moodle	Not specified	Not specified
[30]	Access Learning materials Practice questions, discuss and get exercises corrections	Line	Italian	From scratch
[31]	Provide administrative and learning support.	FB Messenger	Vietnamese	Dialog Flow
[32]	Provide administrative and learning support.	FB Messenger Line Telegram	English	Dialog Flow
[33]	Answer questions about Open Campus courses	Telegram Twitter FB Messenger	English	Not specified
[34]	Respond to students' questions about international Economic Relations.	Facebook Messenger	Bulgarian	Wit.ai
[35]	Give students the meaning and the explanation of Japanese grammar. Share exercises about the basics of Japanese knowledge.	Line	Japanese, Indonesian, and English.	Dialog flow
[36]	Answer questions about human anatomy.	Specific interface	English	From scratch

(*Continued*)

Table 1. Educational chatbots presented in the included papers (*Continued*)

Papers	Tasks	Chatbot Interface	Language	AI Platforms or from Scratch?
[37]	Answer questions related to the Python course.	Chinese-based MOOC platform: ShareCourse	Chinese	From scratch
[38]	Answer questions related to an Introductory Programming Course.	Canvas LMS	English	Microsoft QnA Maker
[39], [40]	Answer questions related to open domain.	Specific interface	English	From scratch
[41]	Answer questions related to math problems.	Specific interface	Chinese	From scratch
[42]	Give students mathematical tips, guide them to solve exercises	Specific interface	Vietnamese	From scratch
[43]	Ask questions to students and give them hints to answer questions related to the basics of electrical force.	Specific interface	English	From scratch
[44]	Ask a series of questions to train the students' scientific inquiry and develop the student's analytical skills.	Specific interface	English	IBM Watson
[45]	Ask questions about the JAVA programming language to help students master the course.	MOOC platform	English	Google Assistant
[46]	Answer students' questions about an uploaded document. Assess and evaluate students' knowledge related to a specific document.	Not specified	Not specified	Not specified
[47]	Students practice the exercises given by the chatbot and evaluate their peers' responses.	Telegram	English	From scratch
[48]	Assist students and help them in the exam preparation.	Communication PLatform	Spanish	From scratch
[49]	Feedbot offers a series of writing tasks about the literature and generates responses in the form of graphs or FAQs style. Litbot asks questions to support students in their reading and help them enhance their reading skills.	Rocket. Chat.	Dutch	Social Bot Framework (SBF)
[50]	Recommend learning resources. Answer students' questions related to the knowledge shared in the chatbot's collaborative learning groups.	Specific Interface	English	Dialog Flow
[51]	Recommend materials and learning resources according to students' inputs.	Slack	English	Messenger Bot API
[52]	Provide administrative information.	Specific interface	English	RASA framework
[53]	Provide administrative information.	Dialog Flow testing interface	Spanish	Dialog Flow
[54]	Help students to solve technical errors in C programming language.	Specific Interface	English	RASA
[55]	Answer questions related to the JAVA programming language.	Specific Interface	English	From scratch
[56]	Students check, at any time, how many concepts have been studied in the current and previous sessions, and how many concepts remain to be studied.	specific interface	Portuguese	From scratch
[57]	Provide information about diabetes education.	Specific Interface	English	From scratch
[58]	Provide information about Bulgarian history.	Specific Interface	Bulgarian	From scratch
[59]	Answer students' questions about the biology domain.	Not specified	Not specified	From scratch
[60]	Deliver learning resources.	Not specified	German language	Dialog flow
[61]	Support students in the cultural Heritage learning	Specific Interface	English	From scratch
[62]	Answer students' questions about Agile Scrum learning.	Specific Interface	English	IBM Watson

(*Continued*)

Table 1. Educational chatbots presented in the included papers (*Continued*)

Papers	Tasks	Chatbot Interface	Language	AI Platforms or from Scratch?
[63]	Answer FAQs by software engineering students.	Not specified	Portuguese	From scratch
[64]	Answer questions related to vaccination knowledge.	Specific Interface	Chinese	From scratch
[65]	Respond to educational questions asked by the visually impaired people	Specific Interface	English	From scratch
[66]	Answer students' questions related to a specific domain.	IBM Watson testing interface	English	IBM Watson
[15]	Promote learners' interaction about an online course.	Specific Interface	English	From scratch
[67]	Provide administrative information about the university.	Specific interface	Indonesian	Dialog flow
[68]	Provide official information about the institution	Specific interface	English	IBM Watson
[69]	Answer parents' questions related to students' performance.	Specific interface	Tamil	Dialog Flow
[70]	Provide exam regulations and instructions	University application	Not specified	From scratch
[71]	Provide administrative information about the university.	Not specified	Myanmar Language	From scratch
[14]	Answer students' questions related to trajectories in Physics.	Telegram	English	Botfather
[72]	Answer administrative questions asked by students.	Specific interface	English	from scratch
[73]	Answer students' questions related to the course knowledge.	e-learning platform	English	from scratch
[74]	Answer administrative questions asked by students.	specific interface	English	from scratch
[75]	Answer general questions asked by students.	Not specified	Bengali	from scratch
[76]	Answer questions related to the content of a document.	Not specified	English	From scratch
[77], [78]	Answer FAQs related to the Manipal University.	specific interface	English	From scratch
[79]	Answer questions related to Object Oriented Programming languages domain	Specific interface	English	from scratch
[80]	Provide information about the department, its staff, and their offices.	department web page Amazon echo devices	Slovak	Dialog flow
	Manage exercises related to "databases" subject.	Not specified		
[81]	Answer questions related to Data Science Question	Specific Interface	English	Dialogflow
[82]	Answer questions related to MATLAB dataset	Not specified	English	from scratch
[83]	Provide course information, recommendations and ask for students' opinions about the course.	Telegram	English	IBM Watson
[84]	Provide support for the Graduate Teaching Assistants (GTAs).	Dialog Flow testing interface	English	Dialogflow
[85]	Answer students' questions related to the AI domain.	Telegram	Malay	Dialogflow
[86]	Answer administrative information.	Specific interface	English	from scratch
[87]	Help students to find and access learning resources	specific interface	English	Rasa
[13]	Provide definitions related to specific commands.	Discord	English	From scratch
[88]	Answer students' questions in the field of Bioprocess Systems Engineering.	specific interface	English	From scratch
[89]	Provide schedule classes and exams.	Specific interface	English	From scratch
[90]	Teach punctuation in the Spanish Language.	Specific Interface	Spanish	Collect. chat
[91]	Provide administrative need for Disabled Students	Specific Interface	English	From scratch

Based on Table 1, we conclude that educational chatbots are used in different manners to offload teachers. They respond to students' questions related to specific knowledge, provide administrative information, evaluate students' knowledge, and help students solve exercises. In addition to that, Table 1 demonstrates that the majority of included chatbots provide information related to the course knowledge and answer repetitive questions asked by students. On the other hand, few papers propose educational chatbots to provide administrative information, recommend materials and evaluate students' knowledge. As shown in Table 1, chatbots are capable to communicate with students using various languages, especially English. It is widely used by educational chatbots in comparison to other languages. More than 50% of included papers propose English as the language of the chatbot. AI chatbots are integrated into different communication channels to support students. In Figure 14, we present channels adopted to integrate educational chatbots. There are various channels for educational chatbots such as Learning Management Systems, MOOCs, and social media. They facilitate the use of educational chatbots and make them more inclusive. Figure 14 demonstrates that Telegram and Facebook messenger are widely used compared to other communications channels. However, 59.7% of included papers propose a chatbot-specific interface for its use. Thus, they are free to design the chatbot's interface depending on their needs without any technical requirements.

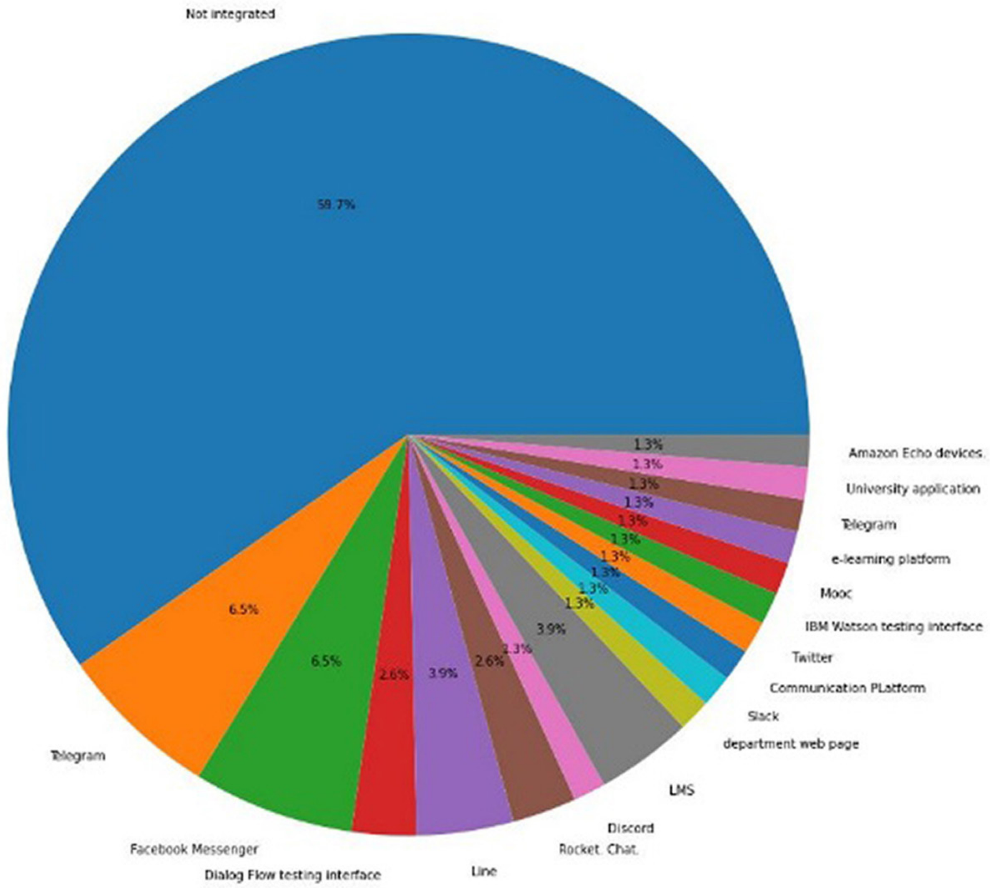

Fig. 14. Platforms and channels to integrate educational chatbots

Regarding the chatbot's implementation, there are two main ways to construct a chatbot, either through AI platforms that boost the developing process or from scratch. As shown in Figure 15, 47.5% of researchers avoid technical requirements related to AI platforms and prefer developing their chatbots from scratch. Thus, they are free from any technical limitations, and they focus their energy on proposing more advanced chatbot architecture. There are a variety of AI platforms to create chatbots: Dialog Flow, IBM WATSON, RASA, etc. They help non-programmer people to construct chatbots rapidly. Figure 15 demonstrates that 20% of papers use Dialog Flow because it's simple and easy to use.

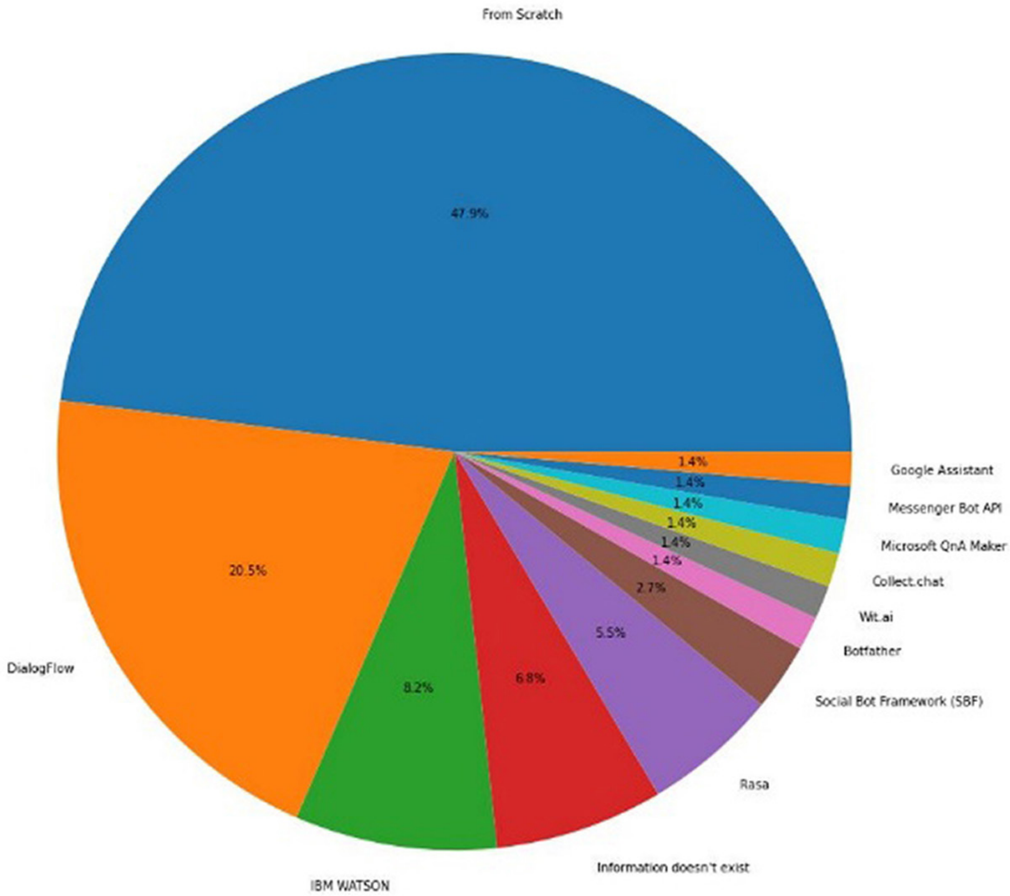

Fig. 15. AI platforms to create chatbots

5.2 RQ2: Constructing the chatbot's KB

A chatbot's KB is the brain behind the chatbot. It is the central component that allows chatbots to respond to users' questions and interact with them correctly. Among the simplest ways to construct a chatbot's KB is to create a list of pairs of questions and answers that allow a chatbot to respond to predefined questions based on its KB. Various works have been proposed to successfully construct the chatbot's KB and feed it either (1) manually or (2) automatically. In Table 2, we present the different methods proposed in the included papers to construct the chatbot's KB.

Table 2. Methods adopted to construct the chatbot's KB

Papers	Automatically or Manually?	Details
[65]	Exited KB	AB Library that contains predefined Q&A.
[55]	Automatically	Extracting knowledge from several sources such as PDF, scanned documents, digital photos, images of typed, handwritten, or printed text and generating pairs of questions and answers through Overgenerating Transformations.
[44]	Manually	Collect knowledge from several sources such as lecture videos, documents, and records.
[68]	Manually	Collect official information about the institution available on SICA web Portal.
[45]	Manually	Collect quiz questions available on the MOOC.
[92]	Manually	Collect resources from the Moodle database and store them in a recommendation database.
[93]	Manually	Extract the discussion threads in the forum of the course that contains questions asked by students about the course and their answers.
[42]	Manually	Collect knowledge from several sources such as lecture videos and the available resources.
[30]	Manually	Collect definitions, concepts, theorems, hint questions, some samples, and a various number of exercises.
[35]	Manually	Collect the data shared by professors in a Content Management System to extract learning materials, questions, answers, corrections, and discussion on National Examination exercises.
[94]	Manually	Collect Grammar topics that exist in several proficiency tests and store them in the MySql database.
[14]	Manually	Extract knowledge from course materials and store it in a firebase.
[95]	Manually	Use existing data from Kherson State Maritime Academy.
[96]	Manually	Collect data from the online learning platforms.
[72]	Manually	Collect the content of the holy Quran and store it for further use by the chatbot.
[97]	Manually	Collect relevant data (Q&A) and store it in a hybrid KB model which involves AIML and a database.
[98]	Automatically	Collect data from a junior high school subject library through a spider robot
[60]	Automatically	Collect relevant documents, index them through Elasticsearch, and store them in a relational database as Postgres database
[99]	Automatically	Extract knowledge from uploaded documents by users using techniques such as Apache PDFBox and an over-generating system
[100]	Automatically	Use an FAQs dataset that contains pairs of questions and answers to train the chatbot, then, it can predict the answer from the users' question
[83]	Manually	Use existing data available on the internet.
[93]	Automatically	Extract chatbot's KB from a discussion forum that contains a large amount of pairs Questions and Answers
[81]	Automatically	Scrap and extract knowledge from glossaries and FAQs of the topic
[76]	Semi-automatically	Collect data from text corpora.

After analyzing the information presented in Table 2, we can conclude that most methods proposed to feed the chatbot's KB are based on the manual collection of knowledge [20], [50], [54], [60], [62], [63], [83], [87], [97]. Figure 16 demonstrates that 71.5% of knowledge bases are collected manually, which consumes energy and time. Whereas there are a few papers (25%) that propose autonomous processes to feed the chatbot knowledge base through recent technologies such as scraping, OCR, and so on.

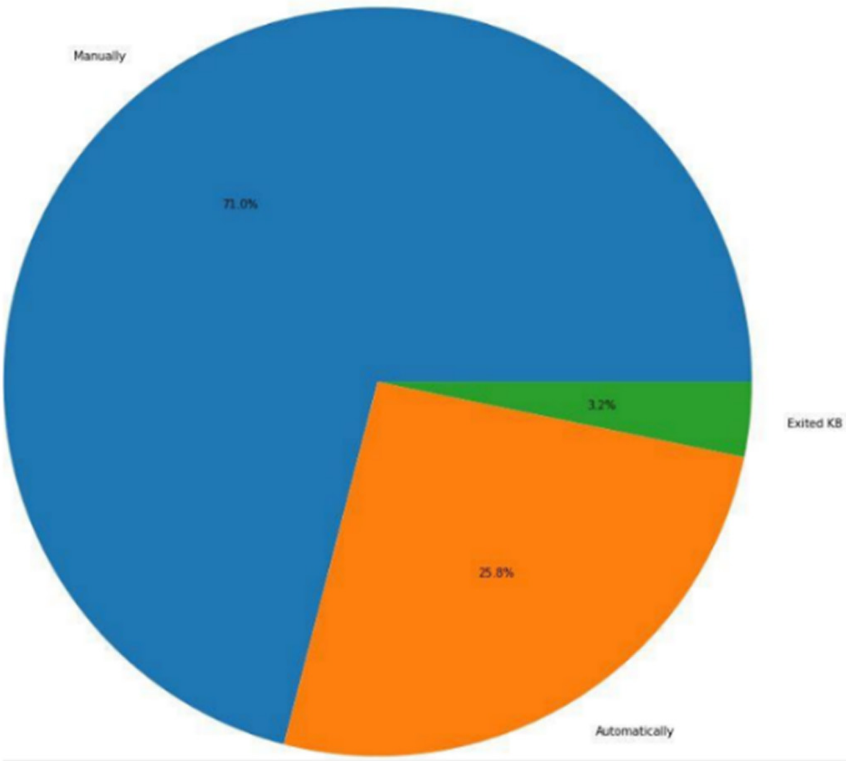

Fig. 16. Methods adopted to feed the KB

5.3 RQ3: External sources

As mentioned previously, the local KB is the central component of the chatbot that allows it to respond correctly to users' requests. Various propositions and works have been carried out to support the chatbot's local KB through external sources and services that allow the chatbot to answer many users' questions. In Table 3, we present the different sources used for enriching the chatbot's KB.

Table 3. External sources to enrich the chatbot's KB

Papers	Sources	Details
[65],[40],[57]	MediWIKI API.	The chatbot can answer questions that have no answers in the KB.
[41]	Chinese Wikipedia & textbooks.	Benefit from a large amount of knowledge and answer users' questions.
[61]	Rest services.	Europeana and DatabencArt are used to answer users' requests related to cultural heritage.
[101]	External databases.	The use of an external database to construct the local KB of a chatbot.
[65]	Students' knowledge.	Integrate students' knowledge to enrich the local KB
[40]	Open Weather MAP API	It gives users weather information
[39],[58]	Search Engine KB.	Use the World Wide Web to satisfy users' needs.

5.4 RQ4: Advanced AI technologies

AI technologies improve the chatbot's inclusivity by enhancing its capacity to interact with users and act humanly with them. Hence, chatbots with smart services are capable to boost the user experience, encourage students and make them more engaged in their learning processes. There are two main AI technologies presented in the included papers: (1) NLP techniques to understand users' messages written in natural language, manage the general conversation, and imitate human behavior by responding socially to users' requests. (2) Speech recognition techniques to understand the users' questions through voice and respond correctly.

Natural Language Processing. NLP allows the chatbot to understand users' messages written in natural language and imitate human behavior by responding socially to users' requests. Moreover, NLP techniques are proposed in some works to benefit from SMALL TALK [56], which is a dataset that groups a sample of conversations in human language. It helps in understanding general messages apart from educational requests. Hence, the chatbot enhances its capacity to act friendly to users [40], [41], [56], [81].

Speech Recognition. Speech recognition techniques positively impact the sociability and intelligence of the chatbot [102], allowing it to understand the human voice. The chatbot becomes friendlier and more social, it can understand a user's question through voice and respond correctly. The proposed work by [65] aims to construct an educational chatbot for impaired people. Thus, Google voice was used to detect human voice and understand it. In addition to that, the proposed approach investigates the use of Deep Learning techniques to enable the chatbot to understand voice. Based on speech recognition, students ask their questions through voice and get the information they need rapidly [41], [45], [69], [103].

Regarding the RQ4, we conclude that included papers in our SLR focus their energy on creating educational chatbot that can understand students' requests and respond correctly, rather than adopting more advanced tools, services, and AI technologies to boost the inclusivity of the chatbots. Few papers investigate integrating such smart services in their educational chatbots.

6 DISCUSSION

The purpose of this paper was to conduct an SLR on the use of chatbots in the educational field, especially (1) Identifying tasks they can automate to offload teachers and respond to repetitive and massive users' questions, (2) Understanding the different implementations to construct the chatbot's KB, (3) Determining the external sources used to enrich and support the local KB, (4) Identifying AI technologies that can enhance the chatbot's intelligence and sociability. In this section, we will synthesize and discuss the reviewed papers based on each research question.

6.1 RQ1: Offloading teacher

AI chatbots offload teachers by answering repetitive questions asked by students, through different communication channels and languages, according to their needs. Several works propose AI chatbots to offload teachers in different and multiple manners. However, some limitations should be covered: (1) Lack of multi-language educational chatbots. Most of them use the English language to interact with students. For that reason, some improvements related to the chatbots' languages are needed to ensure the use of chatbots by many students in different countries. (2) Lack of educational chatbots that are integrated into existing communication channels. Most of the proposed chatbots propose their specific interface. For that reason, educational chatbots need efforts to integrate the most-used communication channels by students to encourage students to use the AI chatbot easily. (3) Lack of chatbots that support students in solving exercises and technical problems. The majority of proposed chatbots answer students' questions related to the course knowledge. Thus, some efforts are needed in implementing more chatbots that manage exercises, help students master technical knowledge, and develop analytical skills. In addition to that, some works adopt AI platforms to construct the chatbot. They help build all chatbot components without any technical prerequisites. However, they have drawbacks: (1) The chatbot is limited to the few questions and answers included in the training sentences. (2) AI platforms are costly, and their free versions offer a limited number of requests. (3) AI platforms limit the possible channels to integrate the chatbot.

6.2 RQ2: Constructing the chatbot's KB

There are various ways to construct and feed the local chatbot's KB either manually or automatically. The majority of current implementations focus on manually creating a pair of questions and answers that can be used as the local KB of the chatbot, which is time and cost consuming. In addition to that, there are some works carried out to automate the construction of the chatbot's KB to save time and energy. However, results are still insufficient, because the local KB is still fixed and limited on the knowledge previously stored. Thus, the chatbot KB does not evolve over time and the chatbot's responses risk being out of date. For that reason, educational chatbots are considered limited and need some improvements by designing more comprehensive KB.

6.3 RQ3: External sources

The process of feeding a chatbot's KB needs some improvements to make it richer in information and knowledge. Hence, additional efforts are needed to integrate external sources that support the local KB and update it with recent knowledge. A few papers include external sources such as Wikipedia, search engines, and rest services. However, some limitations are covered: Wrong knowledge among the APIs largely used is MediaWiki [65], [40], [57], or Chinese Wikipedia [59] to retrieve information from Wikipedia since it can help students to get a general idea about several topics. Wikipedia is easy to use and contains a wide range of information. However, its content can be edited by anyone, whether an expert or not, and the knowledge shared is not verified by professionals. Thus, it cannot be considered credible or reliable. In the same context of enriching the chatbot KB, [80] use students' knowledge as an external source to support the chatbot's KB. However, they don't propose any validation process to ensure the quality of new knowledge. Thus, it can lead to feeding the KB with the wrong knowledge. For that reason, more efforts are needed to deal with wrong knowledge and ensure the high quality of the chatbot's responses. System Workload Some works propose the use of the World Wide Web knowledge to extract chatbot responses [13], [58] and benefit from the unlimited knowledge and information available on the web. However, it needs to be preprocessed and cleaned, which requires a considerable time because of the huge volume of extracted data. Thus, some additional efforts are needed to improve and enhance the system's performance and enable it to handle that data volume. In addition to that, more efforts are needed to integrate external sources to successfully support the local knowledge base and keep chatbot responses up to date. Therefore, a KB that evolves over time encourages students and makes them more engaged to interact with the chatbot. Otherwise, when the chatbot's KB is limited, students lose interest and prefer to seek information they need using other tools.

6.4 RQ4: Advanced AI technologies

Recent AI technologies and applications enhance the chatbot's inclusivity and sociability by integrating additional functionalities and services. However, there are few papers that adopt AI technologies to improve AI chatbots in education. Thus, some improvements are needed to fill this gap: (1) Investigate more advanced NLP techniques and AI algorithms to enable chatbots to act like a human, socially interact with users, and respond correctly apart from messages related to educational topics. Thus, students learn while having fun, which makes them more engaged and encourages them to use the chatbot. (2) Adding emotion recognition or sentiment analysis helps in understanding students' emotions to build a strong human relationship between the student and the chatbot. Hence, the chatbot enhances its ability to act humanely and socially according to the students' emotional state and builds a strong relationship between the bot and the user. As a result, students become more engaged and motivated to use the chatbot. It will be their friendly E-tutor that understands their sentiments and encourages them if they are frustrated or depressed. (3) Increase the chatbot's inclusivity by integrating voice responses to help disabled students benefit from the chatbot's knowledge and use them easily.

7 IMPLICATION

The present SLR provides an exhaustive list of (1) Techniques used to construct the chatbots' KB. (2) Sources that can be used as a support to chatbots KB to feed, enrich and update the Chatbot KB. (3) AI technologies to enhance chatbots' sociability and enhance the students' experience of learning. The present study can be a complete guide for researchers that focus on educational chatbots and enhance their intelligence and capability to answer students' questions. It offers a comprehensive explanation of recent studies and their proposed approaches. The findings of the study help (1) Universities and institutions that aim to adopt AI chatbots as E-tutors to develop students' skills and enhance their comprehension of specific topics. (2) Passionate researchers about AI chatbots to boost the implementation of educational chatbots. (3) Students who are interested in developing educational chatbots but have no idea about the implementation process and the sources that can be used.

8 CONCLUSION

Chatbots are an AI technology that can imitate human behavior by answering users' questions in natural language based on natural language processing and text mining techniques. In this paper, we conduct a systematic literature review to analyze and synthesize recent works and implementations on the use of AI chatbots to improve learning processes and offload teachers from doing repetitive tasks, especially, answering students' questions and helping them solve technical problems in exercises. Our SLR aims to understand recent implementations carried out to create educational chatbots based on AI technologies. First, we followed the requirements of the well-known standards PRISMA and PICO to systematically conduct our SLR. Then, we adopted well-known databases to conduct our SLR. After that, we developed a Python script to carefully find a series of high-quality papers conducted in the field of educational chatbots. Finally, we analyzed our included papers to answer our research questions. Despite including such kinds of papers, however, some limitations can be covered by other researchers, namely: (1) Limiting the SLR on papers that focus on the use of chatbots in education except in other domains. (2) Excluding papers that are not written in the English language since it is the universal form of communication in science in the most known databases. (3) Limiting our SLR on journal publications, conference papers, and book chapters since they are well-recognized formats in databases, except for other formats of publications such as gray literature or others. In future works, we can contribute to enhancing the central component of AI chatbots which is the knowledge base that stores all chatbots' knowledge. Thus, we can propose an architecture of an intelligent system that can alleviate the following issues: (1) The manual process of constructing a chatbot's KB by proposing some techniques that can automate the process. (2) The lack of reliable and credible knowledge sources that can support local KB by searching for sources that contain knowledge validated by experts and professionals. (3) The workload of the educational chatbots by providing an architecture that enables accelerating the system performance and enhancing the user experience. (4) The lack of advanced AI technologies in educational chatbots to improve their inclusivity.

9 DECLARATION

9.1 Funding

The authors did not receive support from any organization for the submitted work.

9.2 Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

9.3 Conflict of interest

There is no potential conflict of interest disclosed by the author.

9.4 Ethical approval

We officially state that this material was independently written by us and submitted for reviewers' remarks. There are no research findings in this document that have been previously published or written by other people or organizations. This manuscript's only authors are us. We will be held accountable for this statement legally.

10 REFERENCES

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11 AUTHORS

Khadija EL Azhari is a Data Engineer from the School of Information Sciences (ESI) and is currently a Ph.D. student at the Smart Systems Laboratory from the National Superior School of Computer Science and Systems Analysis (ENSIAS), Mohammed Vth University, Rabat, Morocco.

Imane Hilal is an Associate Professor at the School of Information Sciences, Rabat, Morocco. She got an engineering degree from the National Superior School of Computer Science and Systems Analysis (ENSIAS) and has a Ph.D. in Computer Science from Hassan II University, Casablanca, Morocco.

Najima Daoudi is a Full Professor at the School of Information Sciences, Rabat, Morocco. She has an engineering degree from the National Institute of Statistics and Applied Economics (INSEA) and a Ph.D. in Computer Science from ENSIAS.

Rachida Ajhoun is a Full Professor of Higher Education at the Mohammed V University of Rabat, Morocco, specifically at the ENSIAS. She has an engineering and a Ph.D. degree in Computer Science and E-learning from the Mohammadia School of Engineers, Rabat, Morocco.