Survey on Pedagogical Resources Recommendation using Cognitive Computing Systems

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***Abstract*—Taking into account that education supported by technology is a basic need for the citizen of a world in which the demand for computation and the access to information grow exponentially, this paper highlights the creation of cognitive computing systems that help people to acquire knowledge and to learn effectively within digital education environments. With this goal in mind, this paper summarizes the outcomes of a Systematic Mapping of Literature where the main aim was to identify what pedagogical approaches, methods, techniques, tools, and education activities have been used to recommend learning objects in the context of cognitive computing systems. We analyzed 348 papers from Scopus and Engineering Village digital libraries from which we selected 19 papers for data extraction. In order to increase the confidence of the proposed systematic review we calculated the Kappa Coefficient obtaining that the agreement was substantial (79.47%). From the data extracted we did several analysis. Concerning to pedagogical theories, 47.37% of papers presents a humanist approach and 26.32% a cognitivist approach, which shows one coherence with proposal of cognitive computing based on emotional and language processing. Most papers use natural-language, image or audio processing to detect emotion, attention and interactions to generate a user profile and, thus, to perform educational resource recommendation. Despite almost half papers do not indicate exactly the educational resources recommended, around 36% are textual materials and 45% are related to personalized exercises or interactive/games activities. Furthermore, we identified the spread use of analytical learning and cognitive computing for pedagogical activities recommendation. This paper ends up proposing new approaches and methods to educational recommendation for improving the students performance from interaction data in educational environments.**

***Index Terms*—cognitive computing, recommendations, systematic mapping of literature, education supported by technology**

I. Introduction

In the last years, the cognitive systems have made possible to generate more accurate recommendations in several areas of human activity. Beyond that, the popularization of education supported by technology have provided the emerging of new approaches to meet the needs of students and teachers, specially to enable the personalized learning and to allow exchanging and acquiring educational information. Thereby, cognitive systems is naturally being used to recommend educational resources, based on data from students interaction, to improve the teaching-learning process.

We have implemented a basic platform to support the teacher at the processes of compositing, executing and evaluating of the classes based on students interaction data [1]. In order to improve our platform, we want to add an user support for recommendation of pedagogical resources. Thus, both the teacher and student can use learning objects more appropriate to their needs, reducing the level of effort and, at the same time, increasing both performance.

Therefore, we perform a secondary study based on Systematic Mapping of Literature [2] to survey the mechanisms currently employed in the development of digital educational environments, identifying paradigms and pedagogical approaches, techniques, tools and learning objects with respect to the recommendation of pedagogical activities using cognitive computing. The main gains of this research is the state of the art of using of cognitive systems to pedagogical recommendation and the discovery of gaps that appointed ways to evolution of the actual educational systems.

The rest of this work is organized as follows. Section 2 overviews the main concepts needed to understand this paper, such as cognitive computing systems and educational recommendation systems. Section 3 describes the research method, which is composed by three subsections, namely, aims and research questions, string of search and screening of papers. Section 4 explains the results and discussion, where it answers all research questions. Finally, Section 5 concludes this paper and depicts future works.

II. Background

This section shows the summary of main concepts or aspects related the use of cognitive computing and educational recommender systems.

A. Cognitive Computing Systems

Over the centuries, several people (especially philosophers, psychologists and scientists) have tried to understand as we acquire knowledge, learn a language or solve puzzles. Thus, from the research related to philosophy, psychology, artificial intelligence, linguistics, anthropology and neuroscience, the

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Cognitive Science emerged in the 1950s [3]. However, only after the Internet and the personal computing devices popularization, has led to new problems based on interpretation of a large volume of unstructured data, whose traditional systems could not solve. Thus, the Cognitive Systems has appeared [4].

Although there is not a closed concept, we can define cognitive computing systems as systems that - inspired from the human mind's capabilities, aim to find coherent and unified solutions based on the extraction and interpretation of meanings from the data, primarily unstructured [4] [5]. Thus, it is worth noting that when we talk about human mind, we are referring to the process of sensation, perception, action, emotion, and cognition (abstraction, searching, learning, decision making, inference, analysis, and synthesis) [5] [6].

B. Educational Recommendation Systems

The development of educational environments supported by technology has enabled new approaches to teaching-learning processes, where perhaps the first effect is the great availability of educational data and resources. Thus, [7] notice that this is the starting point for dealing with the problem of information filtering and personalized distribution of learning materials.

An educational recommender system is a tool to help users in decision making process in educational environments with information overload, providing an adapted or personalized experience and facilitating the learning processes [8].

In general, there are four main recommendation techniques [7], [9]:

(i) Collaborative: it recommends items from the ratings based on choices and preferences commons to the users;
(ii) Content-based: recommendations are based on the self users, in case, items previously preferred by them are compared to the content of items that can be recommended;
(iii) Knowledge-based: recommendations are based on functional knowledge, i.e., how much an certain item of recommendation be useful to user; and
(iv) Hybrid: recommendations are performed combining some of the techniques shown above.

In this research, we are looking for the most used strategies to educational resources recommendation and how these techniques are associated with the emerging area of cognitive computing.

III. Research Method

In this section, we detail the steps performed in this research following the methodology proposed by [2], [10] and [11], where we carried out three main steps: (i) Planning of the Mapping: definition of aims, research questions, inclusion and exclusion criteria and string of search; (ii) Conducting the Mapping: screening of papers through the reading of abstract and keywords and, then, reading of full papers; (iii) Analysis and publishing: extraction, analysis and resume of data from papers.

A. Aims and Research Questions

The aims of this research was performed from GQM paradigm, proposed by [12]. Thus, we *analyze* papers that shows cognitive systems *with the purpose of* identifying paradigms and pedagogical approaches, techniques, tools and learning objects *with respect to* the recommendation of pedagogical activities using cognitive computing.

To achieve the goals of this research, we established the following *Main Question*: "How to recommend pedagogical activities using cognitive systems during the teaching-learning process?" and the following secondary questions:

- **RQ1:** What pedagogical approaches have been used in the implementation of recommendation systems in the educational context?
- **RQ2:** What techniques and tools have been used in recommendation of learning objects or pedagogical activities?
- **RQ3:** What pedagogical activities or learning objects have been recommended?
- **RQ4:** Which works make recommendations from the context of face-to-face and distance education?

RQ1 aims to describe the pedagogical theories that are most used to support educational contents recommendation. RQ2 reports how the recommendations of educational resources are implemented. The answer of the RQ3 indicates the learning activities and objects more recommended, beyond their relation with the used techniques, and, finally, RQ4 specifies the educational context of recommendation.

B. String of Search

The string of search of this mapping was defined based on [11], being: (i) Population: Cognitive Systems; (ii) Intervention: Recommendation Systems; (iii) Outcomes: pedagogical paradigms, techniques, models, tools and learning objects. Thus, after calibrating, we established the following string to be used on search engines:

(cognit* OR attention OR emoti* OR affecti* OR perception OR "Natural Language" OR "Sentiment analysis" OR conversat* OR consciousness) AND **("recommen* system")** AND **("learning object" OR pedagogi* OR "learning enviro*" OR teaching OR "learning activity" OR "learning context" OR educatio* OR tutoring)**

We selected the Scopus [13] and Engineering Village [14] digital libraries because they give best access to reference retrieval, and have best mechanisms to do automatic search. Besides that, those libraries are considered very significant to the computing area since they index works of others publishers. This step was performed between October and November, 2017 and a total of 348 papers was found, where 153 were from Scopus and 195 were from Engineering Village, however, 47 duplicated papers were excluded resulting in 301 papers.

C. Screening of Papers

We have been used inclusion and exclusion criteria to perform the screening. In this research, we created seven criteria, one for inclusion and five for exclusion. To be accepted in the mapping, a paper must either to propose or to describe the use of:

- **IC1:** Recommendation of pedagogical activity or resource using cognitive system.

Should not be included papers that:

- **EC1:** Does not apply to the inclusion criteria, in this case, the work has no relation with recommendation in digital education;
- **EC2:** The work is not a paper, but a Proceeding of Conferences or Journals;
- **EC3:** It does not use cognitive system to recommend pedagogical activity or resource;
- **EC4:** It uses cognitive system, but does not recommend pedagogical activity or resource;
- **EC5:** It does not recommend pedagogical activity or resource, nor uses cognitive system.

After the screening, 261 papers were rejected and 40 papers were accepted. Besides that, we calculated the Cohen's Kappa, where another researcher did the screening from a random sample of 10% of total papers and had gotten a concordance of 79.47% that means "substantial agreement" [15]. Thus, we have done other filtering from the complete reading of 41 papers accepted previously, that resulted 21 rejected papers and 19 accepted to extraction.

The data extraction consists of reading each paper for filtering and storing the relevant information according to our extraction form. Thus, we get basic data like title, keywords, own abstract, author's name, source (conference proceedings), publication year, subareas, and specific data that help us to answer the Research Questions as: (RQ1) - pedagogical approaches, pedagogical paradigms; (RQ2) - techniques, tools; (RQ3) - learning objects or activities and data used to recommendation; (RQ4) - educational context. Therefore, with such information, we can answer the research questions more accurately.

IV. Results and Discussion

This section presents the outcomes from the data extraction according to methodology showed in Section III. In order to facilitate the analysis, we divided into two parts. The first one shows an overview about the analyzed papers; the second part answer the research questions.

A. General Outcomes

In this section, we present some data about the analyzed papers, such as, publication year, subareas and sources. This information is important to find common points and to contextualize the papers.

In Table I, we can observe that the interest to implement recommendation systems using cognitive computing has started from 2012 and remained almost constant, though the year with most published papers is 2012 with five papers, except, of course, the 2013 where there are no paper. Additionally, we found that the papers [22] and [25], [27] and [33], [29] and [32] have the same authors. As this Systematic Mapping was finished at November 2017, it is possible that more papers have been published in 2017 and are not indexed yet, but this do not jeopardize the conclusions about the constance of interest in this theme.

TABLE I
Year of Publication

Year	Papers
2012	[30], [31], [32], [33], [34]
2013	no papers found
2014	[19], [20], [28], [29]
2015	[18], [24], [26], [27]
2016	[16], [17], [23], [25]
2017	[21], [22]

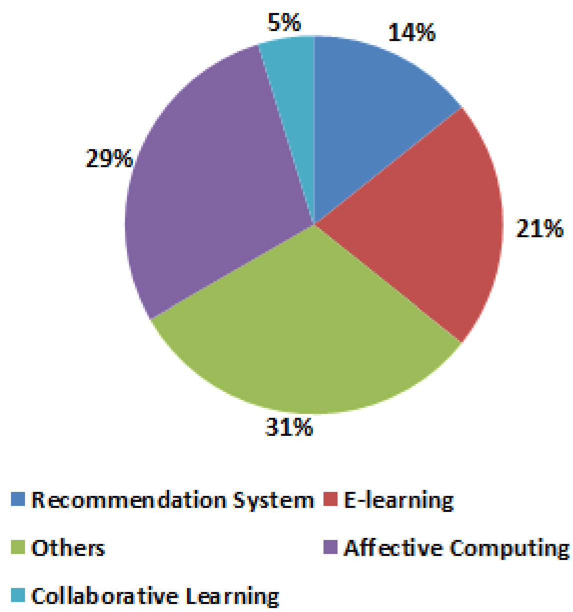


Fig. 1. Subareas of Papers

Fig. 1 shows the main subareas extracted from the papers, where one paper can have more of one subarea. Thereby, we can observe that the more cited subareas are:

- Affective Computing (29% - 12 papers);
- E-Learning (21% - 9 papers);
- Recommendation System (14% - 6 papers);
- Collaborative Systems (5% - 2 papers); and
- Others (31% - 13 papers).

The label "Others" includes subareas cited only once, such as, Technology Enhanced Learning, Learning Environments, Cloud Computing, Special Education, Self-regulated Learning, Inclusive Education, and Robotic Education.

Most papers (63.16% - 12 papers) were published in conference proceedings, while only 7 (36.84%) were journal papers ([20], [22], [23], [25], [27], [33], [34]).

B. Answering the Research Questions

This section presents the outcomes from the research questions.

RQ1: What pedagogical approaches have been used in implementing the recommendation systems in the educational context?

The main goal of this question is to identify the pedagogical approach that ground the implementation of the educational recommendation cognitive systems. However, many times, the papers do not show clearly this basis, being necessary to identify elements of the proposed theory from the analysis of architecture and description of the procedures performed on each work.

Fig. 2 presents the pedagogical approaches found on extracted papers, where the majority of papers is represented by the humanist (47.37% - 9 papers) and cognitivist (26.32% - 5 papers) approaches.

This perception is consistent with the aim of this research that are papers that implement cognitive systems, i.e., that consider emotions and languages used by students and teachers during the teaching-learning process.

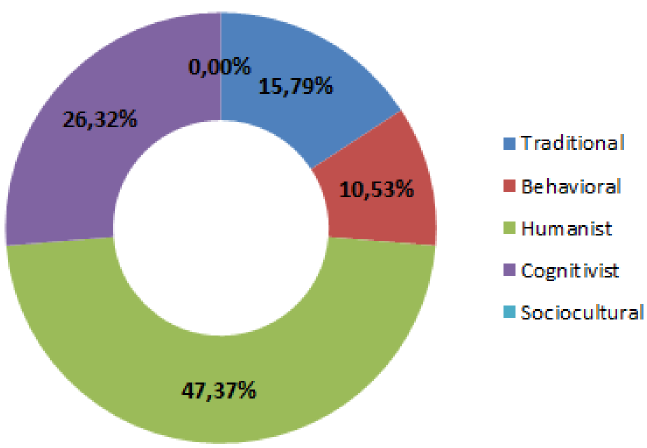


Fig. 2. Pedagogical Approaches

The main gap found here is related to the full absence of papers from sociocultural approach.

This means that the majority of papers have preferred aspects of cognitive computing related to emotion recognition and the implementation systems that make decision from there, but have not given importance to mechanisms that understand how the students organize the knowledge, process information and how the behavior influences their decision-making. In addition, it is needed to emphasize that, besides emotion detection, [24] uses learning styles and [31] uses the emotion data as element from student personality.

RQ2: What techniques and tools have been used in recommendation of learning objects or pedagogical activities?

We divided into two parts to better answer this question. In the first part, we discuss the techniques that are used and, after, we talk about tools for recommendation.

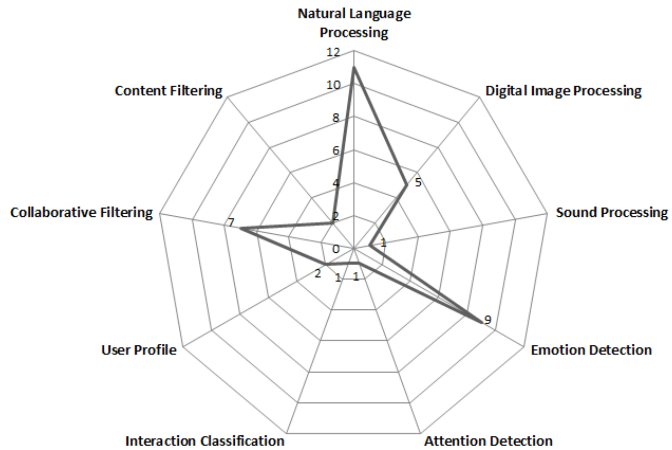


Fig. 3. Processing, Detections and Filtering

Fig. 3 presents an overview of the main techniques have been used to implement cognitive systems that recommends educational resources. We can observe that the approaches more used are Natural Language Processing (11 papers), Emotion Detection (9 papers), Collaborative Filtering (7 papers), and Digital Image Processing (5 papers). Some papers do not have used just one technique, but a combination of them, e.g, Table IV shows that [26] uses Digital Image Processing to detect emotion combined with user profile to recommend the educational resource, while [20], [22], [31] and [32] used Natural Language Processing to detect emotion, but only [22] and [32] have used collaborative filtering as an approach to recommendation.

Fig. 4 is a summary of the data from Table II. It shows that the most commonly used approaches are based on techniques of similarity/correlation (15 papers - 48.39%) and machine learning (9 papers - 29.03%).

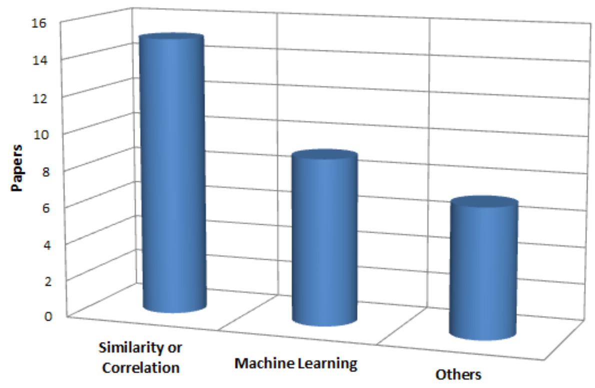
In addition, the techniques of similarity/correlation used are:

(i) TF-IDF [16] [21] [32];
(ii) Euclidean Distance [20] [25];
(iii) Cosine [21] [24] [25] [27] [33]; and
(iv) Pearson's Correlation [25] [27] [29] [33] [34].

The machine learning techniques used are:

(i) Decision Tree [18] [20];
(ii) Naive-Bayes [20] [22] [23];
(iii) Support Vector Machine (SVM) [20] [22]; and
(IV) k-Nearest Neighborhood (kNN) [25].

Those techniques are related to approaches shown in Fig. 3. It is worth noting that some papers adopt more than one technique to perform the recommendation. Besides that, one important gap discovered is that most approaches to emotion



	Similarity or Correlation	Machine Learning	Others
Paper	15	9	7

Fig. 4. Summary of Approaches to Recommendation

detection have used natural language processing, i.e., this approaches are based in sentiment analysis from textual elements (6 papers - [20], [22], [25], [29], [30], [31], [32]), while only 3 papers ([22], [24], [25]) have detected emotion through facial images. However, [22] uses both natural language and digital image processing. This means that recommendation approaches based on emotion detection from images or user interaction (clicks, likes or unlikes) and performance evaluation still can be explored.

TABLE II
TECHNIQUES PER PAPER

Technique	Paper
TF-IDF	[16], [21], [32]
Euclidean Distance	[20]
Cosine	[21], [24], [27], [33]
Pearson's Correlation	[25], [27], [29], [33], [34]
Map / Reduce	[30]
Weights	[16]
Ontology	[16]
Decision Tree	[18], [20]
Naive-Bayes	[20], [22], [23]
Support Vector Machine	[20], [22]
k-Nearest Neighborhood	[25]
Vector Space Model	[19]
Subject Identity Measure	[28]
Ranking of Educational Resource	[19]
MQI Protocol	[23]

Taking into account the tools adopted, each work have used a very diverse set of tools, which makes it difficult to put together them easily.

Despite this, the use of specific tools related to implementing cognitive computing systems can be observed. Therefore, we found out papers that adopts IBM Watson [17], Facebook API [20] [22], Apache Hadoop from EC2 - Amazon AWS [30], Apache Mahout [25] [30] and Kinect Sensor/Framework [18] [31].

Besides the use of learning objects repositories like MERLOT [21] [29] [32] and FROAC [24], it has also been reported the use of Languages as Fuzzy Control Language (FCL) [22], Behavior Markup Language [23], Emotion Markup Language [30] [31] and Web Ontology Language (OWL) [16]. Some papers have used web programming to implement user interfaces (HTML5, CSS, JavaScript, MySQL, JSON API, RESTful Web Services) [22] [25] [30]. [28] was book recommendation through the Freeling (Natural Language Processing Tool) using BookCrossing Dataset. Finally, only four papers do not specified their tools.

RQ3: What pedagogical activities or learning objects have been recommended?

Considering the educational resources recommended, several works (42.11% - 8 papers) do not have detailed the activities or recommended objects, but have just presented the strategies for recommendation. However, some learning activities and objects were observed among the works. These resources are presented in Table III, where we can observe that the majority of recommendations reported is related to interactive activities and games (45.45% - 5 papers) and textual resources (36.36% - 4 papers).

TABLE III
LEARNING RESOURCES RECOMMENDED

Resource	Papers
Personalized helps, lessons and exercises	[22]
Text Material (.doc, .txt. or PDF files, HTML pages, books,...)	[16], [19], [28], [30]
Games and interactive activities	[20], [23], [31], [33], [34]
Video	[17]

The strong recommendation of interactive activities shows that there is interest on the improvement of the efficiency and quality of learning, although students have demonstrated increased attention to the quality of the pedagogical material [17] [18] [31]. In addition, the focus on textual resources is important too and it is in accordance to the tendency in use natural language processing, in this case, to implement cognitive systems that, firstly established patterns from the data repositories and, then, performed recommendations based on the student behaviors [28] [30] [32].

RQ4: Which works make recommendations from the context of face-to-face and distance education?

The increasing in e-learning is related to the popularization of personal computing, where each person has several devices available for use at any time [35]. Thus, it is understandable that the implementation of educational environments is focused on e-learning. In addition, the construction of adaptive systems based on e-learning allows to reduce the cost of new systems, which facilitates their acceptance.

Fig. 5 confirms this trend of implementing e-learning-based educational environments. Despite 42.11% of papers (8 papers) does not specify their context, 52.63% of works (10

TABLE IV
TECHNIQUES USED TO EDUCATIONAL RECOMMENDATION

Paper	Natural Language Processing	Digital Image Processing	Sound Processing	Emotion Detection	Attention Detection	Interaction Classification	User Profile	Collaborative Filtering	Content Filtering
[16]	+							+	+
[17]	+	+	+						
[18]									
[19]	+								+
[20]	+			+					
[21]									
[22]	+	+		+				+	
[23]				+		+			
[24]		+		+				+	
[25]		+		+				+	
[26]		+			+		+		
[27]									
[28]	+								
[29]	+			+				+	
[30]	+			+				+	
[31]	+			+					
[32]	+			+				+	
[33]	+						+		
[34]									

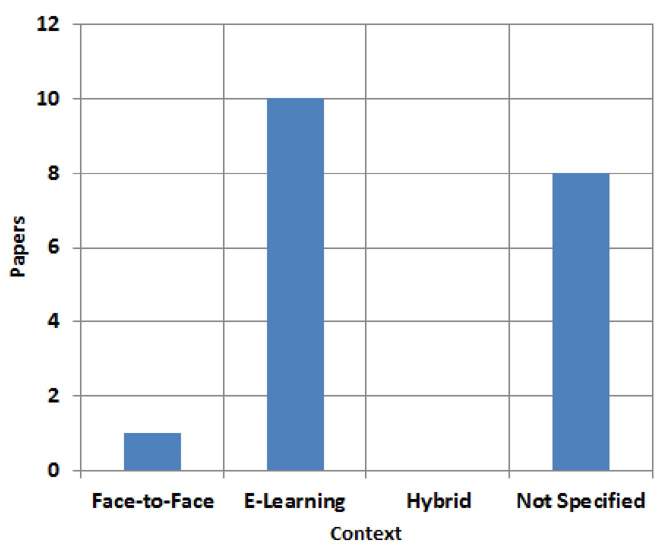


Fig. 5. Educational Contexts

papers) have used e-learning, while only 5.26% (one paper - [23]) specify explicitly that uses face-to-face education.

The main gap identified is the need to implement systems that support face-to-face education, which leads us to another still open question: How to build systems that integrate the advantages of physical classrooms in schools and enable learning of social interactions, in addition to the advantages of adaptive systems of cognitive computing?

One possible way to answer this new question is through the implementation of cyber-physical systems, which mix the signals of the physical sensors and the ability to trigger virtual elements. Integrating these systems into current educational systems would open up new possibilities for teaching-learning strategies.

V. CONCLUSIONS AND FUTURE WORKS

This paper summarizes the outcomes of a Systematic Literature Mapping, with the main aim of pointing out which pedagogical approaches, methods, techniques, tools and educational resources were used to recommend learning objects or activities in the context of cognitive computational systems.

We analyzed 348 papers from relevant digital libraries, where we selected 19 papers for data extraction, and, in order to increase the confidence of the proposed systematic review we calculated the Kappa Coefficient obtaining an agreement of 79.47% that means “substantial”, according to [15]. Furthermore, the initial analysis of papers revealed that the majority of works implement recommender systems based on affective computing in context of e-learning environments.

We identified that, in spite of the majority of papers (73.69%) has presented a humanist or cognitivist approach (consistent with the emotional and natural language processing reported), there is a important gap related to the full absence of papers from sociocultural approach. This means that strategies that emphasize mechanisms to understand (i) how students organize the knowledge and process information; and (ii) how their behavior influence the decision-making based on data from student interaction, this certainly can contribute with better recommendations than the current.

In relation to the techniques and tools found, the main gap is related to emotion detection, where there are few papers using facial recognition or user interaction to detect sentiments. Techniques based on student performance still can be explored. Taking into account the most commonly recommended pedagogical activities and learning objects, the majority of papers focus on interactive activities and textual material, but only around 9% of papers perform recommendation of personalized helps, lessons and exercises.

Finally, the last research question shows that most papers are applied to e-learning environments, which open opportunities to work with face-to-face education. Thus, we can suggest the association between cognitive and cyber-physical systems to perform recommendations based on physical sensors that allow discover and analyze different student behaviors.

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