Metaheuristic-based adaptive curriculum sequencing approaches: a systematic review and mapping of the literature

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Metaheuristic-based adaptive curriculum sequencing approaches: a systematic review and mapping of the literature

Marcelo de Oliveira Costa Machado[1] · **Natalie Ferraz Silva Bravo**[2] · **André Ferreira Martins**[2] · **Heder Soares Bernardino**[2] · **Eduardo Barrere**[2] · **Jairo Francisco de Souza**[2]

Abstract

The presentation of learning materials in a sequence, which considers the association of students' individual characteristics with those of the knowledge domain of interest, is an effective learning strategy in online learning systems, especially if related to traditional approaches. However, this sequencing, called Adaptive Curriculum Sequencing (ACS), represents a problem that falls in the NP-Hard class of problems given the diversity of sequences that could be chosen from ever-larger repositories of learning materials. Thus, metaheuristics are usually employed to tackle this problem. This study aims to present a systematic review and mapping of the literature to identify, analyze, and classify the published solutions related to the ACS problem addressed by metaheuristics. We considered 61 studies in the mapping and 58 studies in the review from 2005 to 2018. Even though the problem is longstanding, it is still discussed, especially considering new modeling and used metaheuristics. In this sense, we emphasize the use of Swarm Intelligence and Genetic Algorithm. Moreover, we have identified that various parameters were considered for students and knowledge domain modeling, however, few student's intrinsic parameters have been explored in ACS literature.

Keywords Adaptive learning · Evolutionary computing · Learning path · Student modeling · Knowledge domain modeling · Intelligent tutoring systems · Artificial intelligence in education

✉ Marcelo de Oliveira Costa Machado
marcelo.machado@edu.unirio.br

1 Federal University of the State of Rio de Janeiro, Rio de Janeiro, Rio de Janeiro, Brazil

2 Federal University of Juiz de Fora, Juiz de Fora, Minas Gerais, Brazil

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1 Introduction

Technological advancements in recent years have allowed several applications to become real. Nowadays, it is not hard to find robust applications running on a small mobile device. In this sense, people are developing a proactive paradigm of Internet use through provision and consumption of products, services and knowledge. Online learning is developing from this new paradigm, offering courses with different teaching-learning strategies in web-based learning systems that offer flexibility as the educational content may be accessed anytime and anywhere (Karpova et al. 2015).

Conventional teaching strategies provide static courses with the same set of learning materials to be delivered to all students regardless of their background, interest and goals, that is, "one size fits all" (Kardan et al. 2015). These strategies follow the instructivism learning paradigm in which teachers take on a central role in the learning process (Khosravi et al. 2020). On the other hand, the student may access the learning environment to learn on their own. However, due to the explosion of learning materials in repositories, it is very difficult for students to find relevant content in accordance with their model (Birjali et al. 2018), and this may cause disorientation and cognitive load as well (Al-Azawei and Badii 2014).

Online learning still has disadvantages that open the way to challenges to be overcome. For example, transitional distance, inappropriate infrastructure, student distractions and general faculty acceptance of online learning (Choudhury and Pattnaik 2020). The effectiveness of this approach depends on solutions that guarantee student's satisfaction as distance learning modality suffers from high rates of dropouts and failures (Davis et al. 2016). This study focuses on the lack of appropriate content delivery according to students' individualities (e.g., background, needs, profile, intention, preferences) as this is also one of the main obstacles in online learning adoption (Choudhury and Pattnaik 2020; Dwivedi et al. 2018; Muhammad et al. 2016). Hence, the correct management of learning materials, according to the student model, is an important issue to be considered when designing strategies and systems in that niche (Holstein et al. 2019; Johnston et al. 2018; Mohamed et al. 2018; Mavroudi et al. 2018).

The research and development of Intelligent Tutoring Systems (ITS) seek to combine techniques of Artificial Intelligence, Cognitive Psychology and Learning Theories towards learning systems capable of knowing what to teach, to whom to teach and how to teach (Silva et al. 2018; Nwana 1990). Learning material recommendation is a widely researched topic in ITS and adaptive learning fields (Dwivedi et al. 2018; Erdt et al. 2015). However, only the recommendation does not guarantee overall understanding as the ordering of learning materials is disregarded in the solution (Dwivedi et al. 2018). Adaptive Curriculum Sequencing (ACS) considers this arrangement an important concern for personalization as it refers to the sequence of recommended learning materials that have to match a particular learning process related to student model (Sentance and Csizmadia 2017; Premlatha and Geetha 2015; Muhammad et al. 2016).

According to Brusilovsky (2003), the sequencing goal is to provide the most suitable ordering of knowledge units and learning tasks (examples, questions, problems, etc.) to the student. Kardan et al. (2015) argue that a sequence must take into account the student characteristics and goal and the learning materials information. Thus, the ACS problem can be seen as a function $f : U \times L \times C \rightarrow S$ that receives as parameters the user model $u \in U$, the learning material information $l \in L$ and the concepts to be learned $c \in C$ (Machado et al. 2019). This function returns a sequence $s \in S$ that best approximates the student model among the various sequence possibilities contained in S. According to De Marcos et al. (2008), in a course with various constraints like prerequisite relations, fixed-order sequence for some itinerary concepts, etc., a feasible sequence consists of C concepts arranged in a way that satisfies all constraints, and the total number of possible (valid and invalid) sequences (permutations) approaches $C!$.

The automatic selection of a proper sequence of learning materials is a problem (from now on, the ACS problem) as unsuitable selection can bring unexpected results, increasing the dropout and failure rates (Xie et al. 2017). The selection must deal with solution spaces that are much larger and rather expansive in a realistic e-learning situation in which the variety of learning materials and student model features are considered as constraints. Finding an optimal curriculum sequence is a combinatorial problem falling in the NP-Hard class of problems (Pushpa 2012; Acampora et al. 2011). Thus, several researchers were motivated to use artificial intelligence techniques, especially metaheuristics, to deal with the problem, after all, in a classical manner, they are employed to solve similar problems (Khamparia and Pandey 2015; Pushpa 2012; Al-Muhaideb and Menai 2011).

Given the importance of ACS in the adaptive learning and the increasing use of metaheuristics to find solutions to this kind of problem, we present here a systematic review and mapping of the literature to reduce biases and provide a reliable picture of the current state of the art. We identified 61 papers dealing with the ACS problem based on metaheuristic solutions. Therefore, we first present an overview of the area highlighting the number of publications by year, the most active authors, the publication venues that are the main targets for research publication and the commonly used metaheuristics. Further, we identified and analyzed the main elements used to infer the student model and the knowledge domain. We also analyze how the metaheuristics were used regarding different formulations of the problem. This study guides researchers and developers to understand the state-of-the-art solutions and their possibilities for solving the ACS problem leading them to foster the resolution of the challenges and to build more robust proposals. The main contributions of this paper are:

- The use of a systematic method to provide an overview of the state of the art in metaheuristic-based ACS approaches;
- A “map” of the use of metaheuristics covering 13 years of published researches;
- A review of how researchers modeled this problem and how features are extracted;
- An analysis of technological and pedagogical issues related to different ACS solutions;
- A discussion on the more frequent choices made by researchers and unsolved problems that can be useful for guiding new researchers in this field;

The remaining of this paper is organized as follows. Section 2 reviews the related works, Sect. 3 presents the methodology applied in this study, Sections 4 and 5 presents the systematic mapping and review, respectively. Section 6 presents some threats to the validity of our study. Finally, Sect. 7 presents the concluding remarks.

2 Related works

Several studies have been developed in recent years due to the importance of sequencing learning materials, the increasing use of online learning platforms and the technological advances in Artificial Intelligence. To assist and encourage new studies in this research field, some studies were developed as an attempt to address the state-of-the-art in some aspect of the ACS problem—similarly to the intent of this paper. This section presents those surveys that discuss the use of metaheuristics to tackle the ACS problem.

Firstly, Wong and Looi (2010) used the term Learning Pathway Planning to refer to ACS. The authors presented a survey whose main goal is to highlight new trends and key research achievements that have been carried out in the years before the survey. The research focus was on Swarm Intelligence—called by the authors “a new paradigm”. In short, the authors presented papers with solutions based on Particle Swarm Optimization (PSO) or Ant Colony Optimization (ACO). In the following year, Al-Muhaideb and Menai (2011) reviewed publications from year 2002 to 2009 which used evolutionary computation approaches to the ACS problem. The authors provided a classification of these approaches with emphasis on the required tools for facilitating learning content reusability and automated sequencing. The selected studies were divided according to the type of sequencing: individual sequencing or social sequencing. Similarly, Pushpa (2012) focused on Swarm Intelligence but only ACO-based solutions have been discussed. That paper described solutions and showed the student’s context taken into consideration in the existing ACO-based approaches for the provision of ACS.

Kardan et al. (2015) explored research trends in adaptive learning. That study provided classifications of research papers from two different points of view: the adaptive technologies used in research papers to provide services for adaptive e-learning system (AES) and the application fields of research papers in AESs as research goals. That paper also presented open problems and prospective directions of researches. Khamparia and Pandey (2015) also reviewed problems related to AESs. That study classified research papers according to the methods used, such as knowledge-based, computational intelligence and these two conjointly. Those works showed that the ACS is one of the most discussed problems in the adaptive learning field. Likewise, Muhammad et al. (2016) also presented a survey of adaptive e-learning efforts with studies from 2008 to 2015, highlighting the importance of adopting ACS solutions.

Although some authors stated that the ACS problem is a crucial issue in adaptive learning field, ACS is not the main subject in the following reviews: (Khamparia and Pandey 2015; Kardan et al. 2015; Muhammad et al. 2016). Even though Wong and Looi (2010) and Pushpa (2012) discussed on using evolutionary computation to treat the ACS problem, the authors solely cater studies that used PSO and ACO.

To the best of our knowledge, there is no systematic review and/or mapping that presents an overview of this research field. Unlike other works, this paper presents a detailed review of student modeling, knowledge domain modeling and the characteristics of the metaheuristics used to tackle the ACS problem. The study presents the similarities and differences between different evolutionary approaches, and highlights the more frequent modeling choices by researchers. Finally, the paper discusses the technological and pedagogical issues related to the different ACS solutions.

3 Systematic review and mapping methodology

Evidence-based research considers that the accumulation of results from scientific experiments is more reliable than those based on experts opinion. Evidence-based research and practice were initially developed in medicine and since then other domains have adopted this approach, e.g., Software Engineering (Kitchenham et al. 2009). In evidence-based

Table 1 Scope of the current research defined using PICOC

	Terms
Population	e-Learning
Intervention	Curriculum Sequencing
Comparison	–
Outcome	Metaheuristics
Context	Education

Software Engineering, evidence is defined as a synthesis of best quality scientific studies on a specific topic or research question. The main method of synthesis is a systematic review and mapping of the literature.

The purpose of a systematic review and mapping of the literature is to identity, evaluate and report the available studies considering research questions. Thus, it is possible to gather evidence to identify gaps and research opportunities. Systematic mapping, in particular, aims to provide an overview by identifying and categorizing the available research on a broad topic. This review was organized based on the main activities proposed by Petersen et al. (2015): planning, conducting and reporting the study.

3.1 Review and mapping planning

During the planning activity we identified the objectives and defined a protocol. The protocol specifies the method to be used in the systematic review and mapping to reduce researcher bias (Steinmacher et al. 2013) and make the process reproducible. This section summarizes the protocol.

3.1.1 Research questions

The systematic mapping aims to answer the questions below:

MQ1: How many studies were published over the years?
MQ2: Who are the most active authors in the area?
MQ3: Which publication venues are the main targets for research production in the area?
MQ4: What are the most commonly used metaheuristics for this problem?

The systematic review aims to answer the questions below:

RQ1: How is the student model inferred?
RQ2: How is the knowledge domain inferred?
RQ3: How are the metaheuristics used to address the ACS problem?

The search string was defined based on the research questions and the scope defined using the PICOC method (Petticrew and Roberts 2008) (Table 1).

Table 2 Electronic databases used here

Source	URL
Scopus	http://www.scopus.com
Science@Direct	https://www.sciencedirect.com
ISI Web of Science	http://www.isiknowledge.com
IEEE Digital Library	http://ieeexplore.ieee.org
ACM Digital Library	https://dl.acm.org/dl.cfm
El Compendex	http://www.engineeringvillage.com

3.1.2 Inclusion and exclusion criteria

Our goal was to include only relevant studies on the ACS problem addressed by metaheuristics. The process used to exclude a paper was organized in four exclusion criteria (EC):

EC1: The study is not about Adaptive Curriculum Sequencing OR
EC2: The paper was not written in English OR
EC3: The proposed solution for Adaptive Curriculum Sequencing is not addressed by a metaheuristic OR
EC4: The paper is grey literature.[1]

After the definition of the research questions and the paper inclusion and exclusion criteria, the following steps were (1) to define the sources of papers and (2) the search string. The sources of papers were chosen according to the following requirements, based on (Costa and Murta 2013):

- Capacity of using logical expressions or a similar mechanism.
- Availability in the researcher's institution.
- Covering computer science and education area.
- Acceptance of full-length searches or searches only in specific fields of the works.

Next, the search was done in six electronic databases (Table 2).

3.1.3 Query formulation

Initially, the terms of the search string were identified from the major terms in the research questions, PICOC, and their alternate spelling and synonyms. Based on the identified terms, an initial search string was formed using Boolean OR/AND operators. Synonyms

[1] Artifacts outside of the traditional commercial or academic publishing, and distribution channels are known as grey literature. Usually, they are not exposed to a peer-review process. Examples of grey literature include: conference presentations; regulatory data; unpublished trial data; government publications; reports (such as white papers, working papers, internal documentation); dissertation/thesis; patents; and policies and procedures.

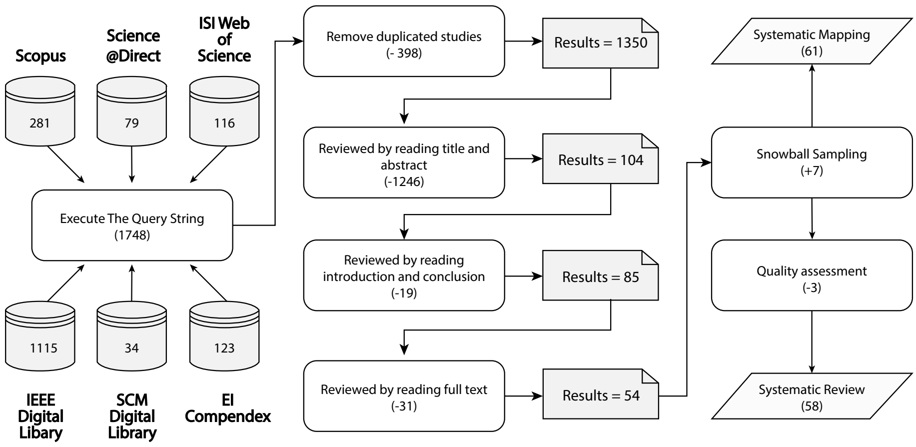

Fig. 1 Systematic review and mapping conduction

and alternate spellings were concatenated using Boolean OR and then these terms were concatenated using Boolean AND to form one string. A set of 23 potential primary studies[2] were defined to validate the search string accuracy and the results relevance. The keywords from the primary studies and from newly fetched ones were analyzed to find new relevant terms to be included as part of the search string. The final search string was described as follows:

("e-learning" OR "web-based learning" OR "learning system" OR "educational environment" OR "learning environment" OR course OR mooc OR "Massive Open Online Course" OR "intelligent tutoring system" OR "course composition system") AND ("pedagogical sequence" OR "learning path" OR "sequencing" OR "learning sequence" OR "learning itineraries" OR "content delivery" OR "course composition" OR "course generation" OR "pathway planning") AND ("metaheuristic" OR "meta-heuristic" OR "evolutionary computation" OR "ant colony" OR "evolutionary algorithm" OR "evolutionary computing" OR "genetic algorithm" OR "optimization" OR "particle swarm" OR "swarm intelligence" OR "evolutionary approach")

3.2 Review and mapping conduction

After the definition of the databases and the search string, the following selection process of the papers was applied:

1. Execution of the search string in the selected databases and removal of duplicates after merging the returned results.
2. Analysis process of the papers by reading (1) title and abstract, (2) introduction and conclusion, (3) full text and data extraction.
3. Application of backward snowballing and quality assessment checklist (Petersen et al. 2015).

[2] https://github.com/marcelomachado/acs-slrm/blob/master/potencial_primary_studies.csv.

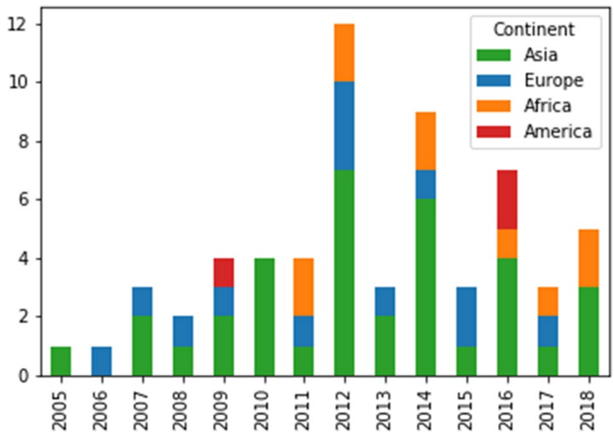

Fig. 2 Number of published papers by year

Figure 1 presents the results obtained based on the steps described above. The process described in step 2 was based on both inclusion and exclusion criteria. Steps (1) and (2) were each applied by the second and third authors, and step (3) was further subdivided among all the authors, who extracted data[3] from the read papers, such as publication year, authors, country, publication type (i.e., journal, proceedings, book), publication venue, used metaheuristics, student parameters, learning material parameters, experiment characteristics, etc. Divergences, doubting publications and excluded ones during step (3) were analyzed by the first and last authors to avoid research biases. In step 3, the backward snowballing technique was applied to find some papers that were not covered by the search string. Therefore, 7 papers were added in our dataset, totaling 61 publications. The quality assessment checklist presented below was applied to evaluate their quality and ensure the rigor and relevance of the studies analyzed in the next phase. The studies that fall into any of the checklist items were excluded from the systematic review (but not from the mapping).

- It does not use any of the analyzed parameters.
- It does not satisfactorily explain how the approach works.

The outcome obtained from the mapping conduction is an inventory of publications, with a set of mapped characteristics, on the topic area. Hence, a mapping study provides a good overview of the area, the possibility to visualize research trends, and identify research gaps, and provides a valuable baseline for the systematic review as well (Petersen et al. 2015). In the next two sections, the systematic mapping and review reports are described.

4 Systematic mapping report

The 61 selected papers were fully analyzed and the information to answer the mapping questions (MQ) was extracted.

[3] https://github.com/marcelomachado/acs-slrm.

Table 3 Most active authors and their respective number of publications

Authors	Total
Luis de Marcos	4
Chih-Ping Chu, Jos Antonio Gutirrez, Jos Javier Martnez, Roberto Barchino, Yi-Chun Chang	3
Carlos Delgado Kloos, Yueh-Min Huang, Eugenijus Kurilovas, Inga Zilinskiene, Valentina Dagiene, Cheng-Chang Tsai, Jos Mara Gutirrez, Melvin Ballera, Shanshan Wan, Tzone I. Wang, Sergio Gutirrez, Susan Elias, Deepak V., Dheeban S.G	2

4.1 MQ1: How many studies were published over the years?

We considered search-based approaches to the ACS problem published from 2005 onward (Fig. 2). The first study was published by Seki et al. (2005), the only published study in that year. A significant increase could be seen in 2012, which was also the year with the largest number of publications, 12 papers coming from different places, mostly from Asia, where has the most publications overall, indicating that although there is research elsewhere, there is some centralization of the research area.

4.2 MQ2: Who are the most active authors in the area?

Mapping the main authors of the area may contribute to find people and places of interest to guide researchers to find the best forums and partnerships, being able to unite researchers with different backgrounds working on the same topic. We analyzed the authors who published more than once on the subject. Only nineteen distinct authors were identified. Table 3 presents the authors' names and the number of publications associated with each one of them.

To analyze the contributions among the authors, we investigate two kinds of collaboration: (1) co-authorship, an active form of collaboration in which the authors interact during a common research, and (2) citations, a passive form of contribution.

The co-authorship graph presented in Fig. 3 can be interpreted as follows: the nodes are the authors and the edges represent the co-authorship among the authors. The thicker the edge, the more works published together they have. The highlighted subgraphs correspond to papers that have at least one author who published in distinct work groups. Those authors have a larger node. For example, nodes 2 and 3 publish together in two different papers, in which they work in distinct working groups.

By observing the co-authorship graph, it is noticeable that there is no tight interaction between the authors: only 11 of the 158 authors contributed in more than one paper with different authors. The lack of interaction indicates the isolation of the research groups, which, as a consequence, generates isolated efforts on common problems and publications with very similar approaches. Reproducibility is a problem in this area, as we further discuss in Sect. 5.3.3. The lack of interaction between research groups can be one of the causes of a few researchers sharing their data and, consequently, there are few existing

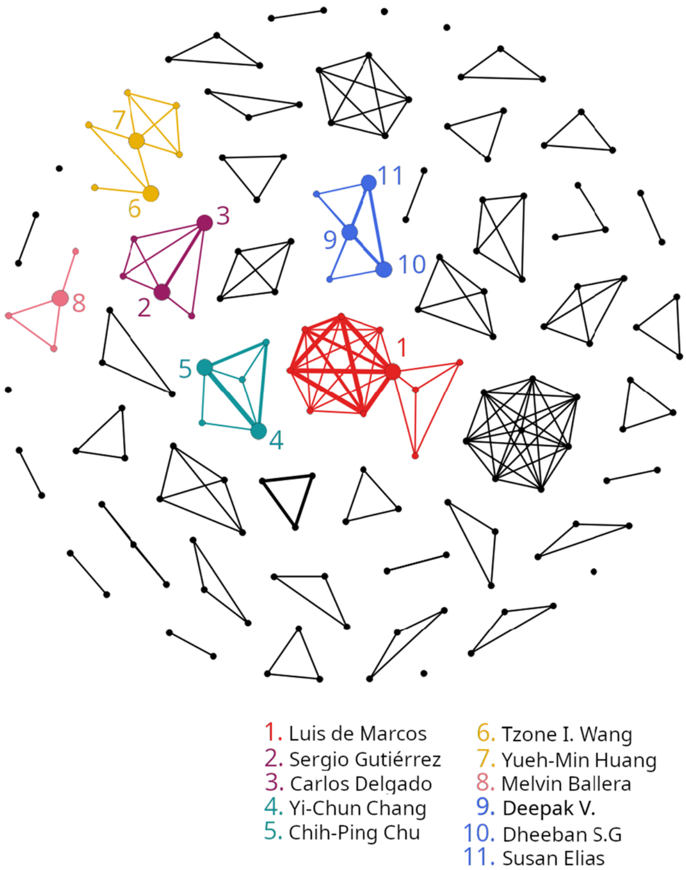

Fig. 3 Co-authorship graph

Fig. 4 Information contained in the citation graph

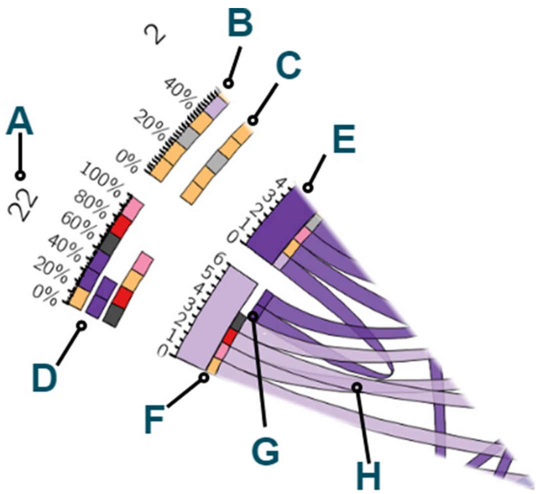

Table 4 Most common countries and their respective number of publications

Countries	Total
Spain	5
Taiwan	4
Lithuania	3

Table 5 Number of papers and distinct venues (journal, event, and book) for each publication type

Publication type	Number of papers	Distinct venues
Journals	35	26
Proceedings	24	22
Book	2	2

Table 6 Journals with more publications regarding ACS

Journals	Total	H-index
Expert Systems with Applications	6	162
Journal of Educational Technology and Society	2	40
Education and Information Technologies	2	31
International Journal of Engineering Education	2	44

open-access datasets to evaluate ACS approaches. Therefore, the results presented in those studies are poorly reproducible.

The citation graph[4] (Fig. 5) represents the citations among the studies mapped in this work. After filtering only citations to the mapped studies, 46 papers were found. According to Fig. 4, the citation graph can be read as follows: each sector (E) of the graph represents a specific paper identified by a number (A) in the range [1, 46] (Table 12 in the "Appendix" maps each identifier to its respective paper). The colors used in each sector indicate the year that the paper was published. Between each distinct paper (sector), there is a set of rows. Each line starts on an inner circle (F) and ends on an outer circle (G). The outer circle represents the paper being cited and the inner circle represents the paper that cited it. The colorful edges represent the publishing year of the paper in which the citation was made. Around the sectors are two to three arcs, each with an array of colors. They represent, from the inside out, the outbound citations (C), the inbound citations (D), and the sum of them all (B). The more distinct the colors, the more the specific study interacted with others. The graph is better viewed with larger size.[5]

Upon careful observation of the graph presented above, it is possible to determine that the citations are well distributed and none of the papers, when juxtaposed with each other, presents a concentration of them. That is, there are indications of a variety of scopes in the field of research under consideration or that communication between the papers is scarce.

4 Generated using Circos (http://circos.ca/software/download/).

5 A high-resolution version is available at https://github.com/marcelomachado/acs-slrm/blob/master/Figures/Citation_Graph.png.

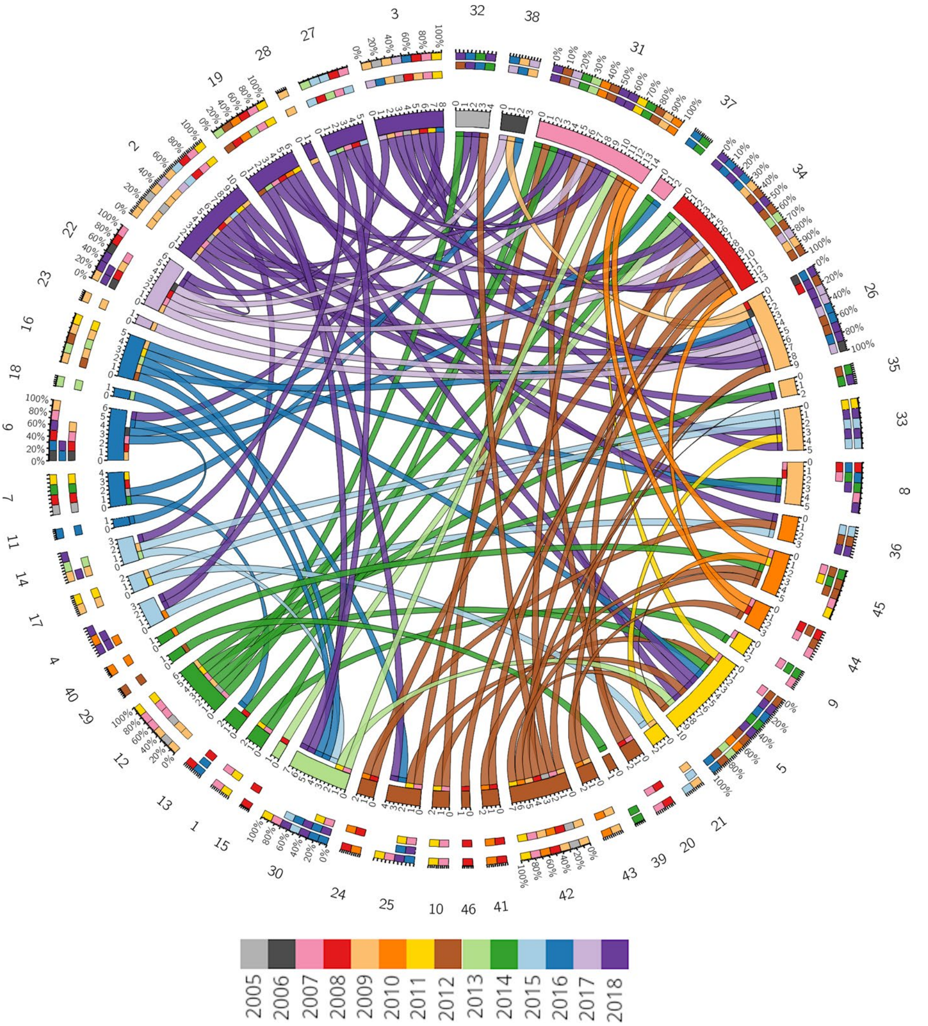

Fig. 5 Citation graph

Despite the number of authors that we obtained, the number of countries with the most active authors is restricted to three, as can be seen in Table 4. With this result, we can conclude that the most active authors publish together when they are from the same country.

4.3 MQ3: Which publication venues are the main targets for research production in the area?

Table 5 shows where the selected papers were published. Most papers, 57.4%, were published in journals, followed by 39.3% in proceedings and only 3.3% in books.

To better know the most popular publication venue, Table 6 shows the journals where more than one mapped paper was published.

Conferences are valued as a destination for reporting research on Computer Science (CS) (Meyer et al. 2009; Patterson et al. 1999) (Fig. 5). Unlike other academic fields, the length of conference papers in CS enables sufficient detail of the work to be reported and discussed. Although some researchers criticize the use of conferences as main dissemination route in CS (Fortnow et al. 2009; Vardi 2010), some authors discuss that high-quality conferences have a higher average citation rate compared to journals in the same stratum (Vrettas and Sanderson 2015), and seem to serve as a distinct channel of scholarly communication, not a mere preceding step to journal publications (Kim 2019). Results in Table 5 do follow this pattern and show that conference papers are important sources of information about ACS research. However, the number of conferences and journals in the final listing, 22 conferences and 26 journals (Table 5), shows that it can be challenging to keep up with ACS research advances due to the lack of specific discussion forums. Besides, the variety of venue knowledge areas shows that this problem has been of interest to researchers from different backgrounds, such as Computers in Education, Computational Intelligence, Computer Networks, Engineering Education, and Information Sciences.

4.4 MQ4: What are the most commonly used metaheuristics?

The following paragraphs briefly describe each of the metaheuristics found and their relationship to the ACS problem. We divided the subsections according to the main metaheuristics used, namely Ant Colony Optimization (ACO), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), and others used in a few studies. Table 7 summarizes this section relating the papers with their metaheuristics used.

4.4.1 Ant colony optimization

Ant Colony Optimization (ACO) is a metaheuristic for solving combinatorial optimization problems. It is the result of an effort to define a common framework that emerged from several versions of ant algorithms (Dorigo and Di Caro 1999). In ACO, the ants are agents able to construct networks forming spanning trees and find optimal paths from the colony to the sources of food by releasing special chemicals called pheromones. These agents are able to create candidate solutions for the optimization problems by moving through a graph, which is a representation of the problem. In this type of method, the pheromone and the heuristic information are combined to define the path of the ants and, consequently, the components of the solutions. This probabilistic model is used to bias the agents' choices and the pheromone information is updated to increase the chance of choosing components used in the best paths (Dorigo and Birattari 2010).

ACO has been successfully used to solve difficult optimization problems, including, for instance, traveling salesman, graph coloring, quadratic assignment, and vehicle routing (Dorigo and Di Caro 1999). That is the main reason given by adaptive learning researchers on the use of such a metaheuristic for the ACS problem. ACO acts in a knowledge domain modeled as graph in which learning materials are nodes and students are ants walking on the edges seeking to find the best path in accordance with their attributes.

4.4.2 Genetic algorithm

Genetic algorithm (GA) was proposed by Holland (1975) as a search technique inspired by the Darwin's Theory Of Evolution, in which "fitter individuals will have a higher

Table 7 Metaheuristics used in the ACS literature

Metaheuristic	Papers	Total
ACO	Kamsa et al. (2018), Birjali et al. (2018), El Lakkah et al. (2017), Rastegarmoghadam and Ziarati (2017), Lebedev et al. (2017), Agarwal et al. (2016), Lugo et al. (2016), Dharshini et al. (2015), Kurilovas et al. (2014), Ahmad et al. (2013), Kozierkiewicz and Zyśk (2013), Wang (2012), Vazquez et al. (2012), Allach et al. (2012), Zilinskiene et al. (2012), Riad et al. (2012), Sharma et al. (2012), Haghshenas et al. (2010), Wang et al. (2008), Wong and Looi (2009), Gutiérrez et al. (2007), Gutiérrez et al. (2006), Kardan et al. (2014)	23
GA	Christudas et al. (2018), Birjali et al. (2018), Dwivedi et al. (2018), Yin et al. (2016), Shmelev et al. (2015), Han (2014), Wu et al. (2014), Ballera et al. (2014) Wang et al. (2013), Anitha and Deisy (2013), Chang and Ke (2013), Li et al. (2012), De Marcos et al. (2011), Jebari et al. (2011), Bhaskar et al. (2010), da Silva Lopes and Fernandes (2009), De Marcos et al. (2008), Chen (2008), Huang et al. (2007), Seki et al. (2005), Lin et al. (2016)	21
PSO	Menai et al. (2018), Govindarajan et al. (2016), Gao et al. (2015), Li et al. (2012), Chu et al. (2011), Chandar et al. (2010), Wang and Tsai (2009), De Marcos et al. (2009), Wang et al. (2008), De Marcos et al. (2008)	10
Other	Hnida et al. (2016), Wan and Niu (2016), De Marcos et al. (2015), Debbah and Ali (2014), Gomez-Gonzalez and Jurado (2012), Wan and Lyu (2014)	6

probability to survive and pass their genes to the next generation through genetic operations". In GAs, a population of candidate solutions is evolved by (1) selecting the best individuals as parents, (2) generating new individuals by recombining the parents and mutating the created offspring, and (3) inserting these new individuals in the population. A replacement strategy is commonly adopted to keep the population size fixed during the search. Also, the candidate solutions are evaluated according to an objective function and this information can be used to represent the fitness of the individual.

Several variants of GA can be found in the literature. For instance, Dwivedi et al. (2018) presented a GA in which the chromosome length is variable to solve the ACS problem. Also, one can formulate the optimization problem involving multiples and conflicting objectives. In these situations, GA must be adapted to evolve the population considering all the objectives and a set of non-dominated solutions are obtained. An example of this type of modification is proposed by Seki et al. (2005), where the population is divided into groups, one for each objective function. This organization of the population in groups is important for maintaining the diversity of the individuals.

One of the techniques found in the literature for solving ACS problems is the Reversed Roulette Wheel Selection Algorithm (RRWSA) (Ballera et al. 2014). This search method was classified here as a GA, as this is a simplification of a GA without a crossover operator. The authors justify the use of this technique to perform the optimization for small populations without going through a rigorous GA process, since in the absence of large data, it becomes unreliable and the optimization process becomes biased.

4.4.3 Particle swarm optimization

The Particle Swarm Optimization (PSO) (Kennedy and Eberhart 1995) methods were inspired by the social behavior of bird flocks and fish schools. In this type of technique, a particle refers to a bird or fish and represents a candidate solution. Each particle keeps information regarding its best position reached so far (pbest) and the swarm records the global best solution (gbest). In PSO, a particle is represented by its position and velocity. The velocity components are updated using the current position of the particle, and the positions of its pbest and gbest. In the sequence, the new velocity is used to modify the position of the particle. Finally, the quality of the candidate solutions is also evaluated with respect to an objective function, and pbest and gbest are replaced when an improvement is observed with respect to each one of them.

Swarm Random Walk (SwarmRW) (Altwaijry and El Bachir Menai 2014) is a metaheuristic originally designed for solving optimization problems in continuous search spaces. In SwarmRW, there are no bests (particles and global), the new position is updated using the difference (scaled by an user defined parameter) of the position of each particle to another randomly selected one for a dimension also selected at random and the new position replaces the previous one when an improvement is observed. Menai et al. (2018) present a discrete version of SwarmRW to find curriculum sequences. Those authors claimed that ACO and PSO typically outperformed GA-based solutions for solving different variants of the ACS problem, however, there were other effective Swarm Intelligence methods which had not yet been examined. These include particularly SwarmRW which has demonstrated to outperform PSO in solving several continuous optimization test functions. Its discrete version has outperformed artificial bee colony in solving several instances of the standard cell placement problem (Altwaijry and Menai 2014). These results, consequently, motivate the investigation of SwarmRW for solving the ACS problem.

4.4.4 Others

Other metaheuristics can be found in the literature applied to the ACS problem. However, as only one paper was found for each one of these other techniques, we classified them in a common group consisting of: DNA Computing, Harmony Search Algorithm, Immune Algorithm and Shuffled Frog Leaping Algorithm.

Although DNA Computing was initially used for computation purposes, an optimization approach was proposed in Adleman (1998) for solving Hamiltonian Path Problems. In DNA computation, the candidate solutions are encoded using DNA sequences and the moving operators are based on combinations of primitive bio operations, such as melting/annealing, merging and extraction. Debbah and Ali (2014) adopted DNA approache to treat the ACS problem. The authors' choice indicates that the DNA computation has took place because it can perform millions of operations simultaneously, and generate a complete set of potential solutions, lead massive parallel searches and efficiently handle enormous amounts of working memory.

Harmony Search Algorithm (HSA) (Geem et al. 2001) is a music-based metaheuristic optimization algorithm which mimics the improvisation process of jazz musicians when producing a harmony. For instance, the music players who have never played together use their improvisation to cooperatively refine the tune and find better harmonies. HSA is a population-based algorithm and the new solutions are generated using all the current candidate solutions; in terms of the approach: all harmonies in the Harmony Memory are considered. The use of HSA for solving ACS problems was proposed in Hnida et al. (2016) based on the justification that this was applied to various optimization problems, e.g., project Scheduling, timetabling, Tour Planning, Text Summarization, Internet Routing, Image Segmentation, Water Network Design, Vehicle Routing. However, no computational experiment was performed to evaluate the performance of the method.

Artificial Immune Systems (Castro et al. 2002) are a class of techniques inspired by immunological principles. Wan and Niu (2016) defend the use of Immune Algorithm for ACS problem against the main metaheuristics approached in the literature: GA is easy to be implemented and it is effective to solve sequencing of learning materials. However, GA faces the problems of parameter setting and operator selection. For example, the inappropriate parameter designs of crossover, mutation and recombination often make the evolutionary process uncertain and even out of control; PSO has fewer parameters and it has been applied on ACS with more complexity levels of resources. Yet, compared with GA, PSO is easier to fall into local optimum and it lacks effective convergent analysis approach; ACO algorithm performs better in learning path regulation. Pheromone accumulation and evaporation mechanism influence the movement of ant colony. But it is hard to organize the large quantity of learning materials into a foraging graph, and pheromone is not convenient to represent the large number of constraints. The authors further argue that, in terms of the implementation of the above algorithms, their operators have fixed forms, therefore, they are difficult to reflect the inherent information in the unsolved problems. As for immune system, it is a highly evolved and complicated functional system of organisms. It can self-adaptively identify and eliminate the foreign antigens which intrude into antibodies. In addition, the immune system is capable of learning, memorizing and self-adaptive controlling. Immune Algorithm uses the clonal selection principle to guarantee the diversity and availability of antibodies. The immune strategy accelerates the search speed and also ensures the global search capacity. Wan and Niu (2016) proposed an Immune Algorithm with an integer encoding to represent permutations (or sequences) of learning materials. The proposed approach moves the candidate solutions using the antibody fitness (to improve the quality of the sequences) and concentration (to increase the diversity of the population). Also, two types of vaccines (local searches) are used to improve the algorithm performance.

Parliamentary Optimization Algorithm (POA) (Borji 2007) is inspired by the behavior of politicians trying to take control of the parliament. The process is divided into two steps: (1) an intra-group step where each individual of the group gets closer to the fittest individual of its group, and (2) an inter-group step where the stronger groups merge together and weaker groups are removed. To apply POA to the ACS problem, De Marcos et al. (2015) proposed replacing the original linear fitness-proportional weighting towards all candidates in the group to bias regular members by using a fitness proportional selection to stochastically permute each position in the tuple towards one candidate. De Marcos et al. (2015) chose POA because it has demonstrated to be competitive for numerical optimization, even outperforming other well-known and well-studied stochastic approaches such as GA and PSO.

Shuffled Frog Leaping Algorithm (SFLA) (Eusuff et al. 2006) is a metaheuristic similar to PSO that seeks the global optimal by moving its population towards the best-known individuals. In SFLA, the candidate solutions are divided into groups and, for each group, the worst individual moves toward the direction of the difference vector computed using the worst position and (1) the best position of the frogs from the group, or (2) the best global solution. If neither of the methods improves the results, then a random solution is generated. A Binary Shuffled Frog-Leaping Algorithm is proposed by Gomez-Gonzalez and Jurado (2012) to obtain a personalized curriculum introducing a binary PSO step into SFLA iteration. Their solution was compared and overcame some PSO and GA implementations.

The use of a Population-Based Incremental Learning (PBIL) is the prototype of probabilistic modeling evolutionary algorithm. Baluja (1997) put forward the idea that probability vector is used to represent chromosomes group structure. And probability can record the proportion of each gene to be set as 1 or 0 in the structure. The initial probability vector for each gene bit is 0.5 which means that the probability of 0 and 1 is equal. The probability will approach toward 0 or 1 step by step under searching process. With the gene probability vector new individuals are generated, and based on the value of these new individuals probability vector is updated, so finally the optimal solution is approaching under the direction of the evaluation. Wan and Lyu (2014) proposed PBIL for the ACS problem which a transition matrix among the learning materials is used. At each iteration, candidate solutions are created based on a roulette-wheel biased by the probabilities in the transition matrix. This population is evaluated and the transition matrix is updated according to the best feasible individual using an increment ϵ. The probability matrix is normalized after this modification. The authors argued that PBIL has a simple evolutionary mechanism, and it demonstrates strong robustness and stability in solving many permutation and combination problems. Their experiments indicated that PBIL performed better than GA concerning the fitness function and executing time.

4.5 Findings

In this systematic mapping study, we have identified and evaluated the existing published solutions related to the Adaptive Curriculum Sequencing problem approached with metaheuristics. The investigated topics were the frequency of publication over time, most active authors and countries in the searched area, publication vehicles and commonly used metaheuristics.

Luis de Marcos is the most active author in the area, addressing the problem with different metaheuristics. The authors tend to work on isolated workgroups. No paper concentrates a large number of citations, indicating a variability on the research or a lack of communication between researchers. Twelve metaheuristics (including variations) have been identified (Table 7) and 73.77% used ACO or GA. It may indicate a possible saturation of the research topic using these approaches and shows that there is an opportunity to explore other solutions.

5 Systematic review report

In e-learning platforms, different teaching approaches are offered, varying according to the learning strategy. The most commonly used approaches are teacher-centered, in which teachers choose learning materials to an audience, and free-walking, in which students can build their own learning path. In the 58 (3 papers were removed based on the quality assessment) reviewed studies, several parameters were involved in adapting content delivery, mainly, considering the different learning strategies. The following subsections present our findings based on the research questions that were formulated to understand the approaches and elements surrounding the ACS problem in literature.

5.1 RQ1: How is the student model inferred?

Student modeling is one of the major areas of adaptive learning field (Abyaa et al. 2019), after all, the student is the main character in this research field. The student model is a representation of the student within the educational context, in other words, it is a “picture” of the student that the computer system can assimilate. This representation is based on information that characterizes the student and it is built from different sources of information, which were divided into two parts: (1) intrinsic parameters and (2) extrinsic parameters.

5.1.1 Intrinsic parameters of student model

Intrinsic parameters represent unique characteristics that belong to a student and have no relation to external information. The following intrinsic parameters have been identified in the reviewed papers: preference, learning style (LS), intention, psychology profile, and attitude.

A commonly mentioned intrinsic parameter is student’s preference. Either directly or indirectly, this parameter indicates student’s manifestation of affection to characteristics of learning materials. Student’s preference may be obtained explicitly according to the learning strategy being offered by the proposed system. In Debbah and Ali (2014) and da Silva Lopes and Fernandes (2009), student's preference was represented with the following properties (based on IEEE-LOM standard): Learning Resource Type, Interactivity Type, Interactivity Level, Typical Learning Time, Difficulty, Language and Context. Each of these properties has its own value domain. In Bhaskar et al. (2010), a student may prefer to receive learning materials that present the content as follows: Concept, Detailed Concept, Example, Case study, Simulation and Demonstration. In addition, that study considers the media format preference based on the Internet bandwidth of the student's device at the moment in which the platform is accessed. Finally, Pushpa (2012) also used a predefined preference group: Conceptual, Example Oriented, Case Study, Problem Oriented, Demonstration and Simulation. Only one of them could be chosen to be the student's preference, however, this preference may vary during the course.

One of the most common approaches to gathering student's learning characteristics in ACS literature is based on LS theory (although being criticized by some studies (Husmann and O'Loughlin 2018; Kirschner 2017; An and Carr 2017; Dembo and Howard 2007)). In general, LS indicates that every student learns differently. Technically, an individual LS refers to the preferential way in which a student absorbs, processes, comprehends and retains information. Some studies created their own assessment tool to gather student's LS. For instance, in Wan and Niu (2016), a questionnaire[6] was designed containing 69 single-choice and true-false questions. That study considers preferences such as learning media—video, text, picture and audio in sequence—and learning resource type—theory, pretest, example, explanation and unit test in sequence. In addition, Wong and Looi (2009) created four preferences groups:

1. Concept-Task spectrum: Each student grades his/her preference, emphasis and competency in learning conceptual or practical knowledge (1–5)
2. Specialization-Generalization: Each student specifies whether he/she prefers to learn specialized before generalized knowledge (1), or vice versa (5)
3. Abstract-Concrete: Each student specifies whether he/she prefers to learn concrete before abstract knowledge (1), or vice versa (5)
4. Free-Guided navigation: Each student grades his/her willingness to comply to the system's recommendations of the subsequent nodes to visit, or to explore the course network at her own will, in the scale of 1 (guided navigation) to 5 (free navigation), with 3 as no preference or "not sure".

An Unified LS Model (ULSM) (Popescu et al. 2008) was used in Riad et al. (2012). The authors argue that this model integrates characteristics of several models relative to perception methods, treatment mode, information organization and also motivation and social aspects. However, most of the studies considered previously presented models, such as:

- **Felder and Silverman LS Model (FSLSM)** (Felder et al. 1988) This model is divided into four dimensions of learning style in which each dimension offers a dichotomy as an option—namely Active/Reflexive, Visual/Verbal, Sensing/Intuitive and Sequential/Global. Student LS based on FSLSM can be assessed by Index of LS (ILS) (Solomon and Felder 1999), which contains 44 questions and can be easily found in multiple languages on the web. Most of the studies have chosen this model (Christudas et al. 2018;

[6] https://www.wjx.cn/jq/7090233.aspx.

El Lakkah et al. 2017; Lugo et al. 2016; da Silva Lopes and Fernandes 2009; Kozierkiewicz and Zyśk 2013).

- **Kolb** (Kolb et al. 2001) David Kolb's LS model was developed from his experiential learning cycle theory. Kolb believes that effective learning occurs by a cyclic process of experiencing, reflecting, thinking and acting. David Kolb put forward four kinds of individual LS which are converging, diverging, assimilating and accommodating. In Kolb learning experiment, a questionnaire (Kolb 2005) based on Kolb LS is given to a student for evaluating his/her LS. Kolb model was used in Agarwal et al. (2016),Pushpa (2012) and Wang (2012)).
- **VARK model** In VARK (Visual, Aural, Reading/Writing and Kinesthetic) (Fleming 1995), identifying a student' style involves using an instrument to detect learning preference (Dunn and Griggs 2007). The instrument consists of 16 questions. There is only one answer for each question. Every answer corresponds to one of the four classes of LS. The responses are compiled by category and the maximum value is used to determine the respondent's LS (Fleming 1995). VARK was used in Rastegarmoghadam and Ziarati (2017) and Wang et al. (2008).
- **Honey and Mumford** This LS system was developed as a variation on the Kolb (Kolb 2005) by proposing a four stages cycle comprising of concrete experience, reflection on the experience, abstract conceptualization and active. The authors developed a questionnaire with 80 items that classify students according to their individual strength experimentation. This model was used in Kurilovas et al. (2014), Zilinskiene et al. (2012) and Musa and Ballera (2011)).
- **Myers-Briggs Type Indicator (MBTI)** (Myers et al. 1985): The MBTI model provides a basis for finding the relationship between personality traits and problem-solving styles. The MBTI questionnaire divides personality traits into four distinct spectrums: Extroverted/Introverted, Sensing/Intuitive, Thinking/Feeling and Judging/Perceiving. Rastegarmoghadam and Ziarati (2017) used this model .

Some studies used more than one LS (Rastegarmoghadam and Ziarati 2017; Lugo et al. 2016). For instance, Lugo et al. (2016) considered FSLSM, cerebral quadrants (Herrmann 1991) and the cerebral hemispheres (Despins 1985) to model and cluster students.

Although most of the studies explicitly obtained preferences and LS through questionnaires, some studies gather this information by student's activity log in e-Learning environment. In Wan and Lyu (2014), student's preference is automatically inferred from student activity log that is indicated according to the type of learning materials which the student usually visits by free and spontaneous choice.

Another parameter considered in some studies was the student's intention. In fact, this parameter is presented as an attempt to consider student motivation when accessing a particular learning strategy. In Hsu and Ho (2012), the student's intention is approached as a career plan. At first the student indicates which career plans he/she intends to follow, then this career plan is cross-checked with pretest results to verify what learning concepts the student should learn (learning goals). Besides, in Chakraverty et al. (2012), user chooses from among a list of learning aims (i.e., student's intention), indicating the purpose of his/her taking the course. For instance, the possible learning aims for a course can be gaining in-depth knowledge, preparing for an interview, apply associated practical skills, satisfy the cursory interest, professional training, preparing for an examination. Thus, ACS is presented prioritizing learning materials that address these intentions (these features must be mapped in advance). Likewise, in Bhaskar et al. (2010), the student's intention may be related to research, survey work, interview purpose, assignment work, project work or just

Table 8 Classification of papers according to students' intrinsic parameters

Paper	LS	Preference	Intention	Psychology Profile	Attitude
Wan and Niu (2016)	✓			✓	✓
Anitha and Deisy (2013)					✓
Bhaskar et al. (2010)			✓	✓	
Dharshini et al. (2015)			✓		
Chakraverty et al. (2012)			✓		
Hsu and Ho (2012)			✓		
Kamsa et al. (2018)		✓			
Lin et al. (2016)		✓			
Debbah and Ali (2014)		✓			
Wan and Lyu (2014)		✓			
Pushpa (2012)	✓	✓			
da Silva Lopes and Fernandes (2009)	✓	✓			
Christudas et al. (2018)	✓				
Dwivedi et al. (2018)	✓				
El Lakkah et al. (2017)	✓				
Rastegarmoghadam and Ziarati (2017)	✓				
Agarwal et al. (2016)	✓				
Lugo et al. (2016)	✓				
Kurilovas et al. (2014)	✓				
Kozierkiewicz and Zyśk (2013)	✓				
Zilinskiene et al. (2012)	✓				
Riad et al. (2012)	✓				
Wang (2012)	✓				
Musa and Ballera (2011)	✓				
Wong and Looi (2009)	✓				
Wang et al. (2008)	✓				

to obtain a general introduction of the subject of study. This intention is compared with learning material types.

Student's intention was also explored based on cognitive traits. For instance, in Dharshini et al. (2015), the user, when accessing the e-learning portal has to choose the cognitive level in which he/she wants to complete the course. This cognitive level is selected based on the cognitive domain of revised Bloom's Taxonomy (Krathwohl 2002). In short, Bloom's Taxonomy is a hierarchical ordering of cognitive skills that can, among other uses, help teachers teach and learner learn. The original sequence of cognitive skills was Knowledge, Comprehension, Application, Analysis, Synthesis and Evaluation (Bloom 1956). This framework was revised in 2001, yielding the revised Bloom's Taxonomy (Krathwohl 2002). The most significant change was the removal of "Synthesis" and the addition of "Creation" as the highest level of Bloom's Taxonomy. Being at the highest level, the implication is that it is the most complex or demanding cognitive skill.

We have identified the use of other parameters in some studies. In Bhaskar et al. (2010), the psychology profile of a person is related to his/her intents and preferences.

That study presents eight psychology profiles: Extrovert, Introvert, Sensate, Intuitive, Feeler, Thinker, Judger and Perceiver. For instance, if the psychology of a person is extrovert and he/she prefers to learn by demo and he/she has come with research intention, the abstractions of the chosen learning material and their sequencing are: Concept, Demonstration, Case Study, Simulation, Example, Detailed Concept. Besides, Wan and Niu (2016) consider the student's attitude during the learning process. They defined the learning attitude as a student's emotional experience during the learning process. A positive attitude is in favor of knowledge acquisition. Such attitude arouses the student's courage to overcome difficulties. A negative attitude is not conducive to knowledge acquisition. Students with such attitude are often afraid of difficulties and they lack the necessary patience. Medium attitude is between the above two attitudes. Different attitudes lead to different learning behaviors. Anitha and Deisy (2013) considered student's attitude based on the affective domain of Bloom's Taxonomy (Bloom 1956). Therefore, the study maps attitude factors such as receive, respond, valuing, conceptualizing and internalizing with learning methodologies such as: Theoretical Explanations and Examples, Interrogative Presentations, Assignment, Case study, Problem Solving.

Table 8 summarizes the papers according to the student intrinsic parameters that we identified in our analysis. It is important to note that only works that used at least one parameter were presented in this table. To better conclude, in Sect. 5.1.3 we discuss about these findings.

5.1.2 Extrinsic parameters of student model

Extrinsic parameters represent external characteristics of a student that are related to the information of the e-learning environment or knowledge domain. The following extrinsic parameters have been identified in the reviewed papers: knowledge level, competency and time availability.

According to Ausubel's subsumption theory for meaningful learning (Ausubel 1962), a human cognitive structure (i.e., individual's organization, stability and clarity of knowledge in a particular subject matter field) is the main factor that influences the learning and retention of new knowledge (Ausubel 1963). In addition, meaningful learning is inspired in constructivist theories of learning (supported, for instance, by Piaget (1976)) and knowledge formation in which knowledge acquisition goes beyond the absorption of isolated facts and, instead, is enabled, stimulated and supported by related existing knowledge and experiences (Weingart and Eickhoff 2016). Considering that, there is a clear need for understanding the student's knowledge level and, therefore, it is an important issue to be considered in ACS solutions.

The most common way to acquire student's knowledge level is through pre-tests (Hsu and Ho 2012; Li et al. 2012; Gao et al. 2015; Wan and Niu 2016; Agarwal et al. 2016; Chen 2008; Riad et al. 2012; Dheeban et al. 2010). The knowledge level is represented as a number or label related to the student's knowledge of an entire course or as being related to each of the concepts that will be presented in the course. For instance, Dwivedi et al. (2018) used pre-test and calculated student's the knowledge level from the average of scores related to each concept of a course. Other authors used the Maximum Likelihood Estimation (MLE) to analyze student's knowledge level according to each learning material (considering its difficulty) related to a concept of a course. In this case, student's final response is a binary value indicating whether he/she understood the learning material or not (Debbah and Ali 2014; Li et al. 2012; Chu et al. 2011). Agarwal et al. (2016) considered that the Knowledge level is divided into 4 stages related to pre-test score:

- Beginner: score $\in [0, 40]$
- Medium: score $\in (40, 70)$
- Expert: score $\in [70, 90)$
- Professional: score $\in [90, 100]$

Similarly, in Birjali et al. (2018), knowledge level is called as learning rhythms and classified as beginner, intermediate and advanced. In Dwivedi et al. (2018), student's knowledge level are collected in the following ways: (1) each student (active or alumni) is asked to provide his/her previous grades for analyzing his/her learning ability, (2) each student (active or alumni) provides his ratings on experienced learning resources and, (3) for analyzing learning activity information and performance of each alumni student after finishing the course, the system conducts a post-test and stores his overall grade as well as grades on various subjects of that course. Each student provides his grades in the selective learning path in various subjects on a five-point rating scale.

Knowledge level are mostly used in direct comparison with the difficulty level of a learning material, however, it was also used to indicate learning goal, that is, whether a concept should be delivered or not to a student. Assuming that a student has a good score in an item of pre-test assessment means that he/she perhaps does not need to study the concept related to that item. For instance, in Chen (2008), the ACS was built upon learning priority according to the incorrect testing responses of an individual student. Some approaches consider that knowledge should be tuned according to the learning material to be learned. Therefore, some studies used the MLE function to tune the student knowledge level using feedback from the student and from others (Christudas et al. 2018; Li et al. 2012).

The cognitive domain of Bloom's Taxonomy was also used to express student's knowledge level. In Anitha and Deisy (2013), initially, an entry behavioral test corresponding with the learning goals is given to students to assess their prior knowledge on the topic. The set of questions reflect the bloom's taxonomy of knowledge domain. The outcome of this test decides upon the knowledge level of the student and the appropriate difficulty of the learning material is selected with their proposed algorithm.

Student's competency is another parameter that appears in some analyzed studies. Broadly speaking, competency represents factors and skills, at different levels, that a student maintains regarding the knowledge domain. De Marcos et al. (2009) states that competencies are *"multidimensional, comprising knowledge, skills and psychological factors that are brought together in complex behavioral responses to environmental cues"*. This definition emphasizes that competencies are not only knowledge but a set of factors. However, in practical ways, we argue that competency can be used as a measure of knowledge level to select learning materials by relating to equivalent difficulty or, as an intention, linking a student cognitive level to an ability of the learning material to reach this cognitive level. Corroborating with our interpretation, in Wan and Niu (2016), competency is defined in two parts—cognitive competency and knowledge competency. The former part is the student's comprehensive self-evaluation of understanding, thinking, discovery and autonomous learning power, and it is obtained by a questionnaire. The second part is based on prior knowledge assessment. Some questionnaires are applied to build student model in Wan and Niu (2016), but the authors do not present the questions related to competency, and it is represented as a number between 1 and 5 used in comparison with the difficulty of learning material in their examples. Likewise, the term competency is mentioned in

Govindarajan et al. (2016). Based on Learning Analytics, the proposed system first classifies the students into four levels: beginner, intermediate, advanced and expert. These levels are calculated based on proficiency (competence and meta-competence) and these values are in [0, 1]. Hsu and Ho (2012) proposes a competency-based adaptive M-learning system that selects suitable learning materials based on pre-tests and career planning to achieve the goal of adaptive learning. Again, the term competency was used as knowledge level.

Another parameter that is commonly considered is student's time availability, since students ability and attention affect the individual learning time, then the expected learning time for each student is different. In general, this indicates how long the student intends to be available to take a course. Students often indicate this time from a form. For instance, in Menai et al. (2018), Wan and Niu (2016), Chakraverty et al. (2012) and Haghshenas et al. (2010), the student's time availability is a number (e.g. expressed in minutes). However, most of the studies work with a range between a lower and upper bounds (Hnida et al. 2016; Chang and Ke 2013; Li et al. 2012; Chakraverty et al. 2012; Gomez-Gonzalez and Jurado 2012; Chu et al. 2011; Dheeban et al. 2010). This information ensures that learning materials' total required time for learning is within the period of the lower and upper bounds of the expected learning time for individual students. In addition, retention time is another factor taken into consideration regarding time. It is based on a well-known process, the forgetting curve, first studied by Ebbinghaus (2013). The author illustrated the decline of memory retention over time as an exponential curve. In a typical schoolbook application (e.g. learning word pairs), most students show the retention of 90% after 3–6 days (depending on the material). Considering that, in Rastegarmoghadam and Ziarati (2017), Wang et al. (2008), the authors used the ratio of learning memory retention which relates a time (day/date) for the learning duration between two nodes of learning materials, a strength of memory which is proportional to the number of iterations of a concept and a learning constant. It is implied in the definition as the capability of a student required to achieve the next learning goal.

Table 9 summarizes the papers according to the student extrinsic parameters that were identified in our analysis. To better conclude, in Sect. 5.1.3 we discuss about these findings.

5.1.3 Discussion on student modeling

Student model is inferred from several information obtained about them and consumed as parameters for the sequencing process. A variety of these parameters were explored, and in most works these parameters were captured from questionnaires that students must completed manually before attending the course. We argue that the student modeling is based on two parameter groups, intrinsic parameters and extrinsic parameters.

Even though learning style is criticized in some studies it is the most commonly used parameter of the first group, followed by student's preference. Nevertheless, Table 8 shows that, in general, the works use few of the students' intrinsic parameters discussed in the literature. The maximum number of parameters used was three and it was contemplated by only one study (Wan and Niu 2016). Indeed, 21 studies considered only one parameter and about 52% of the works did not consider any of these. We ascribe this phenomenon to the difficulty of computationally representing human and dynamic aspects which are less quantifiable (e.g. psychological, emotional, cognitive) and the complexity of using them in comparison to the knowledge domain. This corroborates with the higher frequency of using parameters such as learning style and preference, as they are parameters that can be used in direct comparison to various formats and types of learning materials (parameters presented in the next section). A conceptual factor that may be related to this phenomenon is the lack of knowledge about

Table 9 Papers according to students' extrinsic parameters

Paper	Knowledge level	Competency	Time availability
Wan and Niu (2016)	✓	✓	✓
Menai et al. (2018)	✓		✓
Hnida et al. (2016)	✓		✓
Wang et al. (2008)	✓		✓
Chang and Ke (2013)	✓		✓
Gomez-Gonzalez and Jurado (2012)	✓		✓
Dheeban et al. (2010)	✓		✓
Chu et al. (2011)	✓		✓
Li et al. (2012)	✓		✓
Chandar et al. (2010)	✓		✓
Chakraverty et al. (2012)	✓		✓
Dharshini et al. (2015)	✓	✓	
Wang (2012)	✓	✓	
Hsu and Ho (2012)	✓	✓	
Wong and Looi (2009)	✓	✓	
Haghshenas et al. (2010)			✓
De Marcos et al. (2011)		✓	
Govindarajan et al. (2016)		✓	
De Marcos et al. (2015)		✓	
Birjali et al. (2018)	✓		
Christudas et al. (2018)	✓		
Dwivedi et al. (2018)	✓		
Kamsa et al. (2018)	✓		
El Lakkah et al. (2017)	✓		
Gao et al. (2015)	✓		
Agarwal et al. (2016)	✓		
Kardan et al. (2014)	✓		
Ahmad et al. (2013)	✓		
Han (2014)	✓		
Kurilovas et al. (2014)	✓		
Debbah and Ali (2014)	✓		
Anitha and Deisy (2013)	✓		
Pushpa (2012)	✓		
Sharma et al. (2012)	✓		
Riad et al. (2012)	✓		
Jebari et al. (2011)	✓		
Musa and Ballera (2011)	✓		
Bhaskar et al. (2010)	✓		
da Silva Lopes and Fernandes (2009)	✓		
Chen (2008)	✓		
Huang et al. (2007)	✓		

learning theories that support the association of such aspects with, not only the learning materials, but also the teaching-learning process, especially in online learning.

Student knowledge level is the most used extrinsic parameter in student's dimension, indicating that researches believe that understanding the student's current knowledge structure is critical to guiding them to new knowledge, which supports the Meaningful Learning Theory (Ausubel 1963). In addition, many studies considered student availability time as an important parameter. We agree with such importance when it comes to online learning as this approach shares space with several daily tasks and, therefore, adjusting the study time may increase satisfaction.

Although not included in the Table 9, some studies used some few usual parameters. For instance, Haghshenas et al. (2010) states that learning speed and performance is not equal for every student. Hence, they considered to use the student's speed in comprehension of learning materials. To achieve that information, the authors used available standard assessments (e.g. Stanford-Binet test). In Wu et al. (2014) proposal, extended from the methodology of situational language, it was developed an ubiquitous English reading learning system based on RFID-based location-aware technology and a portfolio-centric paper reading guide. Through RFID technology, the learning system can detect a student's location; then, it sends to the learner highly situational and relevant English papers to read and study. In Bhaskar et al. (2010); Anitha and Deisy (2013), the bandwidth of student device was a parameter responsible for assisting in selecting the format of the most appropriate learning material. Especially when it comes to online learning, we believe that infrastructure context parameters should be increasingly explored since many of the accesses come from mobile devices with varying configurations.

5.2 RQ2: How is the knowledge domain inferred?

Similar to the student model, the knowledge domain is built on different aspects, especially considering different learning strategies. We consider the knowledge domain as a representation of the educational content in the way that a computer system can assimilate. It is not only digital media by itself, but also about the information that is around and that can bring semantics in an application. In this section, first we briefly present some artifacts (i.e., models, frameworks) that were used to describe such information. Further, to compare the selected studies, we performed analyses on this information that are assimilated as parameters for the sequencing process.

5.2.1 Knowledge domain specification

In order to express a course from the sequencing of learning materials, some authors chose to use some existent specifications. The Shareable Content Object Reference Model (SCORM) (Dodds 2001) is a collection of standards and specifications for e-learning. It is commonly used to define courses (static ones) in learning management system, such as Moodle. SCORM specification permits, from an XML-based structure, to describe the learning materials (metadata) and to define relationships among these learning materials. In our set of selected studies, some mentioned the use of SCORM (Dharshini et al. 2015; Li et al. 2012; Chu et al. 2011; Dheeban et al. 2010; Chen 2008; Wang et al. 2008). For instance, Li et al. (2012) developed an Introduction to Computer course based on SCORM specification and imported in MOODLE to investigate the satisfaction of actual learners who participate in the course based on their proposed solution.

The data around the media, used as didactic content, is of fundamental importance for a certain type of application. It helps in the indexing, retrieving and, in our case, sequencing learning materials in accordance with the student model. The Learning Object Metadata (LOM), developed by the IEEE Learning Technology Standards Committee (LTSC) (RISK 2002), is one of the most referenced specification for metadata in the literature (e.g. (De Marcos et al. 2015; Debbah and Ali 2014; De Marcos et al. 2011; da Silva Lopes and Fernandes 2009; De Marcos et al. 2009; Seki et al. 2005)). It is structured in 60 elements that seeks to provide a means of developing more comprehensive descriptions of learning objects and providing support for user services. These elements are organized into nine categories:[7] General, Life Cycle, Meta-metadata, Technical, Educational, Rights, Relation, Annotation and Classification. The *Educational* is the most explored dimension of IEEE-LOM, in ACS literature. Moreover, SCORM metadata may be described with LOM specification, indeed some studies only considered SCORM as a metadata provider(e.g. (Chen 2008)).

The concept structure is an important attribute for the sequencing problem. It is a representation of the programmatic content containing interconnections between the concepts addressed in a course (De Marcos et al. 2011; Sharma et al. 2012). It is especially useful when the direct relationship between learning materials is not considered, and it is a common approach related to informal learning environment where the learning materials are not properly annotated as well. The concepts represented in this structure should be covered by the learning materials in repositories. Therefore, from specifications (such as those previously cited), various studies have used this association to ensure that delivered learning materials are in line with course concepts and student learning goals (Birjali et al. 2018; Menai et al. 2018; Gao et al. 2015; Chang and Ke 2013; Gomez-Gonzalez and Jurado 2012; Hsu and Ho 2012; Li et al. 2012; Chandar et al. 2010).

As pointed before by Al-Muhaideb and Menai (2011), three main approaches were used to construct the concept structures: (1) approximated from mathematical methods, (2) predefined by experts, and (3) ontology based (Al-Muhaideb and Menai 2011). Mathematical methods are used to approximate the concept structure automatically in a decentralized way (Seki et al. 2005; Chen 2008; Huang et al. 2007; Guo and Zhang 2009).These methods ignore the relationships between concepts, making it necessary to evaluate their use in the ACS problem since illogical sequences may be produced (Chen 2008). The construction of concept structure based on expert experience is common and well-accepted, but it still has some disadvantages since it is a costly labor which depends on the experience of those involved and it is not flexible for students. Finally, the ontology-based approach seeks to associate semantics in relationships between concepts, hence, it is possible to understand how concepts are interconnected and to how apply inferences (El Lakkah et al. 2017; Shmelev et al. 2015; Lebedev et al. 2017). This last approach is represented as a graph, favoring the use of some computational strategies, such as the use of algorithms based on ant systems. Automatic construction of the concept map is also a relevant issue in adaptive learning and related fields (Pereira et al. 2019; Wang et al. 2016; Pan et al. 2017; Liang et al. 2018; Manrique et al. 2019).

[7] http://edutechwiki.unige.ch/en/Learning_Object_Metadata_Standard.

Table 10 Student's knowledge level, and learning materials format and difficult level (Wang et al. 2008)

Knowledge level	Learning material format	Learning material difficult
Apprentice	Graphic	Easy
Beginner	Video	Intermediate
Intermediate	Text	Advanced
Expert	XML	Expert

5.2.2 Knowledge domain parameters

The difficulty level of learning materials is widely used in the knowledge domain. It is a quantitative measure that indicates how hard it is to work with or through this artifact for the typical intended target. It can be expert-adjusted and sometimes updated from continuous feedback. Difficulty level set by experts may not be always precise. Earlier approaches tune the complexity level based on general feedback from a random set of students (Li et al. 2012; Chen 2008). Later, Christudas et al. (2018) indicated that tuning of difficulty level of the learning material with respect to student's knowledge level helps to increase the understanding ability of the student. Hence, they proposed an approach that tunes the difficulty level of the learning materials based on similar students i.e. the students having similar learning styles.

The learning time represents an approximation or typical required time that a typical intended target audience takes to work with or through a learning material—it is matched to student availability time. For instance, Wan and Niu (2016) expressed the learning time in minutes as natural numbers. Learning time is set by both expert suggestions and previous students' average learning time. Chakraverty et al. (2012) used a concept graph in which each vertex has a weight that represents the total time taken by a student visiting that node if he/she were to learn all the learning materials contained within that node, this weight is assigned by experts. The total time allocated to a vertex of the graph is divided among its various learning materials as per the priorities pertaining to the learning intent of a student. Some papers aim to minimize the learning time taken to pass a course (Rastegarmoghadam and Ziarati 2017; Ballera et al. 2014).

To support the use of student preferences, intentions and competencies, learning material format and learning material type are other parameters commonly used in the knowledge domain. Learning material format represents technical datatype(s) such as audio, video and image. In Wan and Lyu (2014), video, image, audio and text were the learning material formats used for adaptation. Different learning materials type were considered in literature. Wan and Lyu (2014) used types such as pre-test, example, theory, explanation and quiz. Riad et al. (2012) defined the following types: graphic (image, graph, symbol), video (animation, audio), text (text, Word, Power Point) and XML (Web, SCORM, LOM). That study mapped these learning material formats with the student's knowledge level and learning material difficult, as depicted in Table 10.

The concept of competency was also used in knowledge domain to define both requisites and learning outcomes for each individual learning unit (De Marcos et al. 2015). Some studies (De Marcos et al. 2015; Dharshini et al. 2015; De Marcos et al. 2011, 2008, 2009) needed an universal way to define, identify and access competency definitions. Those studies state that the RDCEO specification (IMS 2002) fulfills these requirements. This specification describes a competency as a four-dimensional element: Definition,

Table 11 Papers according to learning material parameters

Paper	Difficulty	Type	Format	Competency	Learning Time
Wan and Niu (2016)	✓	✓	✓		✓
Dharshini et al. (2015)	✓	✓		✓	
Anitha and Deisy (2013)	✓	✓	✓		
Pushpa (2012)	✓	✓	✓		
Bhaskar et al. (2010)	✓	✓	✓		
Menai et al. (2018)	✓				✓
Lin et al. (2016)	✓				✓
Gao et al. (2015)	✓				✓
Han (2014)	✓				✓
Ballera et al. (2014)	✓				✓
Chang and Ke (2013)	✓				✓
Li et al. (2012)	✓				✓
Chakraverty et al. (2012)	✓				✓
Chu et al. (2011)	✓				✓
Dheeban et al. (2010)	✓				✓
Chandar et al. (2010)	✓				✓
Gomez-Gonzalez and Jurado (2012)	✓				✓
Riad et al. (2012)	✓		✓		
Musa and Ballera (2011)	✓		✓		
Wang et al. (2008)	✓		✓		
Haghshenas et al. (2010)		✓	✓		
Kamsa et al. (2018)	✓	✓			
Sharma et al. (2012)	✓	✓			
Seki et al. (2005)	✓	✓			
Wang et al. (2013)					✓
De Marcos et al. (2015)				✓	
De Marcos et al. (2011)				✓	
De Marcos et al. (2009)				✓	
De Marcos et al. (2008)				✓	
Agarwal et al. (2016)			✓		
Wan and Lyu (2014)		✓			
Christudas et al. (2018)	✓				
Dwivedi et al. (2018)	✓				
Hnida et al. (2016)	✓				
Debbah and Ali (2014)	✓				
Kardan et al. (2014)	✓				
Ahmad et al. (2013)	✓				
Kozierkiewicz and Zyśk (2013)	✓				
Hsu and Ho (2012)	✓				
Jebari et al. (2011)	✓				
da Silva Lopes and Fernandes (2009)	✓				
Wang and Tsai (2009)	✓				
Chen (2008)	✓				
Huang et al. (2007)	✓				

Context, Evidence and Dimensions. The competency *definition* records general information about the competency. Each competency can be exhibited in one or more different *contexts* and a set of factual data must be used to *evidence* if an individual has or has not acquired a particular competency. Finally, *dimensions* are used to relate each context to its particular evidence and to store information about this relation such as the knowledge level. According to RDCEO and IEEE nomenclature, a competency record is known as a "Reusable Competency Definition" (RCD). RCDs can be attached to a learning material to define its prerequisites and its learning outcomes. Those studies have used this approach to model sequences of learning materials by defining a competency (or a set of competencies) as a learning material outcome and identifying the same competency as the prerequisite for another learning material. To describe learning materials, they used IEEE LOM with fragments of competency information. A constraint between the two learning materials is established so the first must precede the second one in any valid sequence (those works modeled the ACS problem as a constraint satisfaction problem).

Table 11 summarizes the papers according to the most commons learning materials parameters that were previously presented.

5.2.3 Discussion on knowledge domain modeling

Our first perception about knowledge domain dimension is that there is no consensus about the most appropriate technologies to describe knowledge. Some studies, as proof-of-concept, used own representations, others relied on existing specifications of e-learning scenario and others applied ontology-based representation. In this sense, we argue that metadata alone provide only a low-level description with respect to multi-modal aspects of learning materials. That is, general multimedia applications, such as videos in which are made up of temporal and spatial anchors, are represented only by general terms. Nonetheless, even in ontology-based solutions, few fact representations were explored and, in most cases, only precedence and hierarchy facts were used. Therefore, it is still a challenge in adaptive learning literature to support richer semantic relations among different content and consider multi-modal aspects of learning materials in a diverse knowledge domain. We believe that conceptual models, such as *Hyperknowledge* (Maranhão et al. 2019; Moreno et al. 2017), should be explored.

Using standard specifications or not, metadata was largely used to describe the information around the learning materials. A variety of parameters to represent the learning materials were explored, and, in most works, these parameters are populated by experts. We strongly support the creation of automated content capture and semantic annotation solutions, for instance, using natural language processing, computer vision and optical character recognition. After all, many of the existent learning materials were built for informal learning in which exists negligence or lack of knowledge on the part of the media creator when filling the content metadata. Moreover, the manual annotation process is time and labor consuming.

Table 11 depicts the most traditional parameters that were used in literature. The difficulty parameter was largely used. This should be expected since in the student model the knowledge level was the most used parameter. That is, the authors consider a direct comparison between them. The same analogy can be made with respect to the learning material format, learning material type and learning competence with student learning style, student preference and others intrinsic parameters. The same happens with respect to the learning type of a learning material and the student availability time parameters.

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0	1	0	0	1	0	1	0	1	0	1	1	1	1	0	1

Fig. 6 Example of candidate solution represented by a vector of binary variables. According to this illustration, the learning materials 1, 4, 6, 8, 10, 11, 12, 13, and 15 are delivered to the student

Although not included in Table 11, some studies used some unusual parameters. For instance, Wan and Niu (2016) used the importance level of learning material, which is a number from 1 to 5 that are selected by the teacher. Higher value means that the learning materials has higher importance. Some authors have considered levels of Bloom's taxonomy to indicate the outcome that the student should achieve from that learning material.. For instance, a learning material labeled with *Comprehension level* aims to lead the student to understand the meanings of the facts. Besides, Shmelev et al. (2015) and Dharshini et al. (2015) considered the Bloom's taxonomy to represent learning material objective and outcome. Hence, the sequencing problem is based on constructivist theory considering the lower levels as the first to be taught.

5.3 RQ3: How the metaheuristics were used to address the ACS problem?

The choice of a metaheuristic varies according to some problem's characteristic. To answer this third research question, we first present common choices applied to classical problem formulations and modeling, then we present how the solutions are being evaluated and, finally, we discuss these findings.

5.3.1 Common formulations and modeling of the ACS problem

Different formulations of ACS can be found in the literature and they guide the modeling and the choice of the metaheuristic used to address the problem. Much of the studies has found that the ACS problem involves multiple and conflicting objectives. Thus, a common way of formulating the problem is based on a multi-objective optimization problem (Li et al. 2012; Chu et al. 2011; Gomez-Gonzalez and Jurado 2012; Chang and Ke 2013; Gao et al. 2015). In this sense, multiple objective functions are commonly combined into a single fitness function using a weighted sum. Equation 1 presents a fitness function F where O_i represents the i-th objective function, ω_i represents the weight of the i-th objective function, $\mathbf{x}$ represents a candidate solution, s represents the student model and n represents the number of objectives.

$$F(\mathbf{x}, s) = \sum_{i=1}^{n} \omega_i O_i(\mathbf{x}, s) \tag{1}$$

The candidate solution ($\mathbf{x}$) are usually represented by a binary vector in which size is equal to the number of learning materials for a particular topic that is available in the learning materials repository (Chang and Ke 2013; Li et al. 2012; Pushpa 2012; Gao et al. 2015; Gomez-Gonzalez and Jurado 2012; Chu et al. 2011). Each vector's position identifies a learning material that may be delivered to a student after a series of evaluations (using the fitness function). Thus, each position assumes 0 or 1, where 1 indicates that the learning material is delivered to the student in case that solution is selected at the end of the optimization process. Figure 6 illustrates a candidate solution for a problem with sixteen learning materials available, in which the learning materials 1, 4, 6, 8, 10, 11, 12, 13 and 15 are delivered.

The fitness function used to evaluate the solutions vary in each study according to the parameters chosen for customization. However, we identified a set of objective functions commonly used to compose the fitness function (Chang and Ke 2013; Li et al. 2012; Pushpa 2012; Gao et al. 2015; Gomez-Gonzalez and Jurado 2012; Chu et al. 2011). In these objective functions, $\mathbf{x}$ represents a candidate solution, M represents the set of learning materials, C represents the set of learning concepts of a course and x_i represents a binary value of the i-th position of the candidate solution:

- **Coverage**: This objective function evaluates if the learning concepts of a candidate sequence match those expected learning goals of a learner:

$$O_1(\mathbf{x}, s) = \frac{\sum_{i=1}^{|M|} \sum_{j=1}^{|C|} x_i \left| R_{c_j}^{m_i} - E_{c_j}^{s} \right|}{\sum_{i=1}^{|M|} x_i}, \tag{2}$$

  where $R_{c_j}^{m_i}$ indicates whether the learning material $m_i \in M$ cover a concept $c_j \in C$. Thus, $R_{c_j}^{m_i} = 1$ if the learning material cover the concept c_j and $R_{c_j}^{m_i} = 0$ otherwise. $E_{c_j}^{s}$ indicates whether a concept c_j is in accordance with a student's learning goals. Thus, $E_{c_j}^{s} = 1$ if the concept c_j is expected by the student s and $E_{c_j}^{s} = 0$ otherwise.
- **Difficulty**: This objective function evaluates whether or not the difficulty of the learning material matches the learner's knowledge level:

$$O_2(\mathbf{x}, s) = \frac{\sum_{i=1}^{|M|} x_i \left| D^{m_i} - K^{s} \right|}{\sum_{i=1}^{|M|} x_i}, \tag{3}$$

  where D^{m_i} represents the difficulty associated to a learning material $m_i \in M$ and K^s represents the knowledge level of a student s.
- **Learning Time**: This objective function evaluates the limitation of learning time for individuals:

$$O_3(\mathbf{x}, s) = \max\left(T_{\downarrow}^{s} - \sum_{i=1}^{|M|} T^{m_i} x_i, 0 \right) + \max\left(0, \sum_{i=1}^{|M|} T^{m_i} x_i - T_{\uparrow}^{s} \right), \tag{4}$$

  where $T_{\downarrow}^{s}$ represents the lower and $T_{\uparrow}^{s}$ the higher bounds times expected by a student s. Besides, T^{m_i} represents the estimated learning time of a learning material m_i.
- **Balance**: This objective function evaluates the balancing of covered learning concepts in a sequence to avoid the situation in which a concept is treated as more relevant than others:

$$O_4(\mathbf{x}, s) = \sum_{j=1}^{|C|} E_{c_j}^{s} \left| \sum_{i=1}^{|M|} x_i R_{c_j}^{m_i} - \frac{\sum_{i=1}^{|M|} \sum_{j'=1}^{|C|} x_i R_{c_{j'}}^{m_i}}{\sum_{j'=1}^{|C|} E_{c_{j'}}^{s}} \right|. \tag{5}$$

Genetic Algorithm and Particle Swarm Optimization were common options to tackle the ACS problem, considering multi-objective formulation and the modeling presented above. The candidate solution is related to binary chromosomes in GA and to particles in PSO. Considering the discrete (binary) search space, the moving operations of these metaheuristics flip some of these bits. Some papers used both metaheuristics to compare their performance concerning fitness value and execution time.

The ACS problem was also formulated as a classical Constraint Satisfaction Problem (CSP) (De Marcos et al. 2009, 2008; Wan and Niu 2016; De Marcos et al. 2011; Menai et al. 2018; Dharshini et al. 2015). According to Solnon (2002), a CSP is a triple (X, D, CT) where $X = \{x_0, x_1, \cdots, x_m\}$ is a finite set of variables, D is a function that maps each variable $x_i \in X$ to its corresponding domain $D(x_i)$, that is, the finite set of values that can be assigned to x_i, and CT is a set of constraints, i.e., relations between some variables that restrict the set of values that can be assigned simultaneously to these variables. A solution to a $CSP(X, D, CT)$ is a complete assignment for all the variables in X, which satisfies all the constraints in CT (Al-Muhaideb and Menai 2011). The standard penalty function, which returns the number of constraints violated, is a typical used fitness function when dealing with CSP problems (Dharshini et al. 2015; De Marcos et al. 2011, 2009; Wan and Niu 2016). When a solution returns a fitness value of 0, a sequence that satisfies all constraints has been found and the algorithm is finished. As a CSP, the ACS problem can be formulated as the triple (L, D, CT), where:

- $L = \{l_1, l_2, \ldots, l_m\}$ is the set of learners and its attributes (e.g., availability learning time, difficulty, learning goals);
- D is a function that maps each $l_i \in L$ to a finite set of learning materials that can be assigned to l
- CT is a set of constraints (e.g. learning time, prerequisite, learning difficulty).

Swarm Intelligence metaheuristics were a regular choice to tackle the ACS problem considering the CSP formulation. For instance, De Marcos et al. (2009) defined sequences in terms of competencies in such way that the ACS problem was modelled like a CSP using PSO. They labeled the learning materials with discrete numbers and the constraints were permutations associated to learners and knowledge domain parameters. Likewise, Dharshini et al. (2015) approached the ACS problem by formulating it as a CSP using ACO to handle constraints. In terms of fitness value, the authors compared their proposed solution by implementing it also with PSO and GA.

Al-Muhaideb and Menai (2011) presented two types of sequencing: the *individual sequencing*, which considers only the learner's own parameters for selecting the sequence of learning materials, that is, it focus on the individual learner rather than the collective performance of learners; and the *social sequencing*, which considers information provided by other learners in the process of selecting a sequence to an specific learner. We note that the different formulations of the problem show a certain pattern about these types of sequencing. Individual sequencing approaches base their decision on learner's attributes and tag it on a pedagogical structure (Al-Muhaideb and Menai 2011). The student model and the concept structure are, therefore, fundamental to these systems. Thus, most works that approach the problem following this type of sequencing choose to formulate the problem as multi-objective using metaheuristics such as PSO, GA, Harmony Search Algorithm and Immune Algorithm. On the other hand, social sequencing approaches seek to infer the best sequences according to the paths taken by other learners. In this case, the solutions disregard a previously established concept map and use other learner's traits and may associate the learners by model resemblance. Thus, most works that address the problem following this type of sequencing choose to formulate the problem as CSP largely using ACO, PSO and other Swarm Intelligence metaheuristics.

5.3.2 Evaluating ACS approaches

Different evaluation approaches were used according to research objectives. Some studies were concerned with intrinsic evaluations, seeking to demonstrate that the proposed approach is suitable for the ACS problem and performs better, in computational terms, than others. On the other hand, some were concerned with extrinsic evaluations, seeking to understand the pedagogical outcome.

Considering intrinsic evaluations, the simplest way to evaluate a proposed solution is to check if the chosen metaheuristic can converge to coherent solutions, observing fitness values (De Marcos et al. 2011; Chu et al. 2011; De Marcos et al. 2009; Seki et al. 2005; Huang et al. 2007). Other common approach was to compare the execution time according to the number of learning materials in a repository. For instance, Li et al. (2012) presented an experiment comparing PSO and GA in a multi-objective formulation of the ACS problem. They showed that fitness values of PSO are close to those of GA concerning the average fitness value of 100 independent runs, however, GA depends of more user-defined parameters than PSO. They also compared the number of generations and execution time according to the increasing amount of learning materials. When the number of learning materials is less than 300, the number of generations and execution time of PSO are less than those of GA. However, when the number of learning materials is greater than 300, the GA approach performs better than the PSO implementation. Christudas et al. (2018) also reported the same behavior when comparing GAs and PSO.

Three main extrinsic evaluations predominate in the literature. The first approach tries to certify if the solution actually implies learning, so it analyzes the same students using pre- and post-tests (Christudas et al. 2018; Lugo et al. 2016; Kurilovas et al. 2014; Anitha and Deisy 2013; Vazquez et al. 2012). The second approach considers a comparative analysis among a control group of learners and the one which receives the proposed adaptive sequencing. Although little reported, these approaches should apply statistical tests to validate the solution when the study is guided by a quantitative methodology. The control group can be formed by learners who will receive a fixed instruction simulating the choice of a fixed curriculum presented by a teacher (Dwivedi et al. 2018; Anitha and Deisy 2013; Jebari et al. 2011; Chu et al. 2011; Seki et al. 2005; Wan and Niu 2016; Kurilovas et al. 2014; Shmelev et al. 2015) or it can be formed by learners who navigate freely in the learning materials space (Chen 2008; Wang and Tsai 2009; Wan and Niu 2016). The third approach verifies qualitatively the learners' perception regarding the received content, that is, it uses satisfaction forms and interviews (Christudas et al. 2018; Chen 2008; Li et al. 2012; Wang and Tsai 2009; Wang et al. 2008; Anitha and Deisy 2013; Wan and Niu 2016).

Few studies indicate or make the data used in the evaluation process available. Menai et al. (2018) tested their solution performance in a real e-learning environment on real data from an information technology diploma program and 2,000 learners selected randomly at Buraydah College of Technology.[8] The data were gathered from the Learner Affairs System. Agarwal et al. (2016) used data of 10,000 learners from the anonymized Open University Learning Analytics Dataset (OULAD)[9] which contains data of courses, students and their interactions with Virtual Learning Environment for seven selected courses (Kuzilek et al. 2017). In many cases, studies have created their own dataset and provided information about them in the body of the paper. For instance, Shmelev et al. (2015) described a list of 6 learning materials and its prerequisites and outcomes. However, in most cases the studies do not provide sufficient data to reproduce its experiments.

5.3.3 Discussions on metaheuristics

Even though the ACS problem is longstanding, researchers still find it an interesting problem to be approached in different ways seeking to infer even better results. Therefore, different metaheuristics have been used in the past and new solutions have been proposed.

Considering the problem as a multi-objective, we found commonly used functions that are directly related to the main parameters of the learner and knowledge domain models. Therefore, we associate the solutions of this scenario to individual sequencing as they do not consider data from other learners in the adaptation process and they are dependent on the relationship among the concepts. This formulation allows for other objectives to be aggregated. However, it is necessary to define the weights of each function. Genetic Algorithm is the most used metaheuristic in this approach, where chromosomes can be directly associated with the modeling of learning material sequences as a binary vector.

Formulated as a CSP, we also found a commonly used fitness function in which penalty is assigned to unmet constraints in the process of attempting adaptation. Regarding the multi-objective approaches verified, this formulation gives more freedom in the choice of constraints, since it does not need a prior mapping of the concepts and does not make a direct association between the learning domain and the student model. Given this freedom, several solutions have used information from other students in the adaptation process and, therefore, we recognize the association of this formulation with social sequencing. Swarm Intelligence metaheuristics were widely used in this scenario, especially ACO which the agents (ants) were naturally associated with learners walking through a graph of learning materials and PSO.

Based on common formulations, several researches seek to compare their solution against others: PBIL vs GA (Wan and Lyu 2014), PSO vs GA (Li et al. 2012), PSO vs GA vs ACO vs Immune Algorithm (Wan and Niu 2016), and different implementations of PSO and/or ACO (Chandar et al. 2010; Menai et al. 2018). This is a good practice according to the *no-free-lunch theorem of optimization*, which states that a metaheuristic cannot be expected to perform well for all the class of optimization problems (Ho and Pepyne 2002). However, each study considered its own dataset for experimentation. Most studies use synthetic data without presenting implementation details, as well as not providing the datasets.

[8] www.tvtc.gov.sa.

[9] https://analyse.kmi.open.ac.uk/open_dataset.

This compromises the reproducibility of studies and makes it hard to compare different works. This behavior reveals the need of a benchmarking to facilitate the comparisons of the proposals. A public baseline, in addition to providing common input for comparison, should serve to select a metaheuristic for each deployment scenario.

There is no clear explanation about the use of a specific metaheuristic other than a choice based on the formulation and modeling of the problem, in most of the analyzed papers. In general, the authors argue that this type of search technique was successfully applied to similar optimization problems and, thus, they expect that the chosen search technique would also reach a good performance when solving the ACS problem.

Although many studies are concerned only with the computational approach of the problem, others have been interested in attesting, from experiments, the effectiveness of using ACS solutions in real scenarios of learning. The most commonly used evaluation method compares a control group of learners with an experimental group that receives the adaptation. However, the literature is still scarce with respect to this kind of analysis. The presented approaches does not consider application in diversified scenarios, such as classes of different courses, different modalities and different educational level.

We understand that the difficulties in the evaluation processes are related to the required variables for experimentation. Due to the number of adaptation parameters it is difficult to find complete dataset. Evaluations in real-world scenarios typically require a large (and diverse) number of learners and available learning materials. Besides, experiments involving people raise ethical issues that, while extremely important, increase operational complexity. Moreover, in most case, online learning platforms are not designed to use external solutions, making it difficult to evaluate the approaches in real-world situations. Thus, many of the studies consider only intrinsic evaluations, or use synthetic data to attest their proposed solutions. However, although challenging, we argue that while intrinsic evaluation is important, extrinsic one cannot be underestimated as this whole process is related to learning.

6 Threats to validity

This systematic literature mapping aimed to identify challenges in adaptive curriculum sequencing domain. However, there are threats to its validity and limitations. The results of this study may have been influenced by certain uncontrollable limitations. Although we have covered 61 papers, we have omitted papers not written in English, as well as grey literature, which could threaten conclusion validity. We may miss influential work in the area, but we focused on those publications which are more rigorously peer reviewed. Furthermore, we did not consider all the relevant electronic databases, i.e., Google Scholar,[10] so it is possible that relevant studies were not indexed by our selection. However, we believe that the selected electronic databases were enough to obtain a big picture of the research area.

There might be bias regarding the number of researchers selecting the papers. In spite of reviewing the overall process, and aiming to mitigate this threat to validity, more than one researcher (first, second and third authors) was able to reproduce this process to reduce the possibility of bias. The inclusion or exclusion of papers may be subjective or error prone.

[10] http://scholar.google.com/.

However, we mitigate this threat by having two people checking the inclusion/exclusion of papers and discussing borderline papers.

Our systematic search criteria may also be subject to critique, threatening construct validity. The search string may not contain all the relevant keywords, which causes loss of some studies and errors can be inserted in the protocol definition. To mitigate this, the search string was evaluated using papers to control the results. Papers appeared in the results generating evidence about the search string correctness.

Relating to external validity, with systematic literature mapping and review, it is important to demonstrate sufficient repeatability. If another set of people analyzes the same group of publications using our set of features, we have confidence that our definitions would help them to make choices that are fairly consistent with our results. Although another set of people could go through a different process of extracting information, we believe that our results provide an useful contribution to the adaptive curriculum sequencing community. Finally, we make all of our survey data available and welcome further analysis.

7 Concluding remarks

In this paper, we presented a systematic literature review to identify and understand the elements related to the Adaptive Curriculum Sequencing problem addressed by metaheuristics. Furthermore, the systematic mapping of the literature was also accomplished to present a whole picture of this research field. We have followed a well-known protocol to conduct this kind of study to reduce biases and offer a reproducible study. During the review and mapping, we started with 1748 papers identified from the selected electronic sources. After the filtering process, 58 papers were completely analyzed.

We pointed out that a variety of students' parameters were explored; however, few represent intrinsic characteristics and none of the selected studies have mentioned emotional, cultural, behavioral, and socioeconomic aspects, revealing research opportunities. We support studies that aim to explore different parameters as long as they aid the learning process and are based on consistent learning theories. Also, it is worthwhile to create evidence on the use of those parameters in specific adaptive learning scenarios; there is a need to certify how the student's knowledge structure is affected by the use of a parameter according to a learning strategy. Moreover, the student's knowledge structure changes during learning, therefore, in addition to being adaptive, these solutions need to be agnostic to such a change and sequences need to be reactive during a course (and the assessment process must be equivalent to that context). We also discussed aspects of the semantic gap related to the knowledge domain; there are consistent evidences about the effects of using multimedia resources on the learning process. However, these artifacts are devalued when reduced to metadata or low-level representations. The ACS literature should target richer representations to consider multi-modal fragments of multimedia resources in the personalization process.

The adaptation process depends on the student model and the representation of the knowledge domain. However, the construction of such models are heavily dependent on manual data input. On the one hand, students tend to give vague answers when long questionnaires are presented to them. On the other hand, domain experts can be biased according to their interpretations, beliefs and background. These research topics are of great interest to researchers from several areas, such as educational data mining, learning analytics, machine learning, soft computing and knowledge representation and reasoning, which work with analysis of heterogeneous data sources, automatic classification, and approximate models to represent the student and knowledge domain. As the amount of data increases and techniques evolve, opportunities arise to develop this research scenario.

Metaheuristic is one of the first options that comes to mind when dealing with optimization problems for which an efficient algorithm is not known. It has long been proven as flexible and robust techniques with satisfactory performance. It is not surprising that this is one of the main approaches to the ACS problem. However, in accordance with the *no-free-lunch theorem of optimization*, it is still worthwhile to evaluate different techniques for the problem at hand. Recently, several metaheuristics have been presented with promising results (Dokeroglu et al. 2019). Moreover, hybrid metaheuristics can be considered an emerging technology, and most of the reported hybrid metaheuristic algorithms has obtained better solutions when compared to classical metaheuristics. The combination of diverse metaheuristics can lead to new exciting approaches since the hybridization can be used to get the advantage of different metaheuristics (Dokeroglu et al. 2019).

Despite advances and consistent evidence of ACS solutions effectiveness in improving learning, their actual impact and adoption in education remain restricted to research projects. However, we pointed out some issues that, in our view, still need to be treated, so solutions can become more popular and effectively applied in real-world scenarios. Several works do not compare their solution with existing ones and many of them lack in statistical analysis or present experiments using an insufficient number of tests or participants. Therefore, benchmarking is still an open issue in this area, and datasets must be structured to cover different student modeling, knowledge domain representation and problem formulations. The lack of a benchmark can lead to wrong choices as ACS literature presents contradictory results. Besides, the intrinsic evaluations must consider a more in-depth statistical analyzes (e.g., hypothesis testing) to attest the efficiency of the proposed solution and to better understand the relevant features in varied teaching-learning scenarios.

Finally, we did not find papers that mention ethical issues related to the automatic process of adaptation or experiments. We argue that this is an important factor to be taken into consideration, especially when it comes to a subject related to artificial intelligence, which is a topic that concerns many people.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

See Table 12.

Table 12 Paper identification used in Fig. 4

ID	Citation	ID	Citation
1	Han (2014)	24	Sharma et al. (2012)
2	Dwivedi et al. (2018)	25	Li et al. (2012)
3	Menai et al. (2018)	26	Wong and Looi (2009)
4	Shmelev et al. (2015)	27	Birjali et al. (2018)
5	Chu et al. (2011)	28	Kamsa et al. (2018)
6	Lugo et al. (2016)	29	Ballera et al. (2014)
7	Wan and Niu (2016)	30	Chang and Ke (2013)
8	Wang and Tsai (2009)	31	Huang et al. (2007)
9	Jebari et al. (2011)	32	Seki et al. (2005)
10	Gomez-Gonzalez and Jurado (2012)	33	De Marcos et al. (2009)
11	Hnida et al. (2016)	34	Wang et al. (2008)
12	Debbah and Ali (2014)	35	da Silva Lopes and Fernandes (2009)
13	Kurilovas et al. (2014)	36	Chandar et al. (2010)
14	Dharshini et al. (2015)	37	Gutiérrez et al. (2007)
15	Ahmad et al. (2013)	38	Gutiérrez et al. (2006)
16	Lin et al. (2016)	39	Wang (2012)
17	De Marcos et al. (2015)	40	Kardan et al. (2014)
18	Gao et al. (2015)	41	Zilinskiene et al. (2012)
19	Christudas et al. (2018)	42	Pushpa (2012)
20	Hsu and Ho (2012)	43	Chakraverty et al. (2012)
21	De Marcos et al. (2011)	44	Bhaskar et al. (2010)
22	Rastegarmoghadam and Ziarati (2017)	45	Dheeban et al. (2010)
23	Govindarajan et al. (2016)	46	Riad et al. (2012)

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