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Review

Learning path personalization and recommendation methods: A survey of the state-of-the-art

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ABSTRACT

A learning path is the implementation of a curriculum design. It consists of a set of learning activities that help users achieve particular learning goals. Personalizing these paths became a significant task due to differences in users' limitations, backgrounds, goals, etc. Since the last decade, researchers have proposed a variety of learning path personalization methods using different techniques and approaches. In this paper, we present an overview of the methods that are applied to personalize learning paths as well as their advantages and disadvantages. The main parameters for personalizing learning paths are also described. In addition, we present approaches that are used to evaluate path personalization methods. Finally, we highlight the most significant challenges of these methods, which need to be tackled in order to enhance the quality of the personalization.

1. Introduction

Technological and pedagogical innovations are redefining education. At the nexus of this convergence is E-learning. Nowadays using E-learning systems such as Intelligent Tutoring Systems (ITS) (Polson & Richardson, 2013) has become a routine. These systems aim to deliver educational resources to users (Nabizadeh, Mário Jorge, & Paulo Leal, 2017). They have several advantages over the traditional learning methods where a teacher was playing the main role and controlling a classroom. The main advantages are availability (Thakkar & Joshi, 2015), reduced cost (Gilbert, 2015), improved collaboration (Thakkar & Joshi, 2015), enhanced flexibility (students learn at their own convenience), etc. (Dargham, Saeed, & Mcheik, 2012).

In the traditional form of E-learning systems, these often caused learning disorientation and cognitive overload by providing users with a bag of disorganized learning materials (Basu, Bhattacharya, & Roy, 2013; Yang, Liu, & Huang, 2010). These problems could become nontrivial ones when the users had a restricted learning experience, particularly when they were not familiar with a course, or when they had limited time to learn a course (Naidoo, 2017).

Hence, during the early 1960s, E-learning systems started using a directional sequence of learning materials (Yang et al., 2010; Yang & Dong, 2016), and became relying on curriculum sequencing mechanisms. These mechanisms provided users a learning path through learning materials (Chi, 2010; Markowska-Kaczmar, Kwasnicka, & Paradowski, 2010). By generating the learning paths, the E-learning systems offered a "one size fits all" approach, since they provided the same educational resources in the same way to users with different profiles.

"One size fits all" causes several problems. One of the problems is frequent users' failure (i.e. failing a course), since by using this approach the E-learning systems simply ignore the users' knowledge background and their ability to learn. Thus, users are at risk of wasting time with the materials that they are not able to learn. Inability to persuade the users and engage them with the system is another problem, since the users' preferences (e.g. learning style) are disregarded by using the "one size fits all" (Matar, 2011). Another problem is ignoring the users' progresses and changes during the learning process, which negatively influences the efficiency of the E-learning systems (Karampiperis & Sampson, 2005). All mentioned problems cause users' abstention from using the system before completing a learning process. This incident is called dropout (Sahin, Arseven, & Kiliç, 2016), and its high rate

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indicates users' dissatisfaction or mismatch with the learning process and method (Karampiperis & Sampson, 2005).

Personalized learning is proposed as an alternative to the "one size fits all", in order to cover the mentioned problems (Bray & McClaskey, 2013). It refers to approaches that generate learning paths considering the individual differences in learning preferences, goals, abilities, knowledge background, etc (Deng, Huang, & Chung, 2017). Since the late 1960s, researchers have attempted to address the personalization, using different parameters, approaches and algorithms. In this study, a systematic and comprehensive research on learning path personalization methods is presented. This paper provides the readers a fairly broad background on the recent learning path personalization studies. In this paper, our main objectives are:

1. Presenting the main reason for emerging the learning path personalization methods.
2. Explaining the key concepts in E-learning (particularly in learning path personalization methods), such as learning object and learning path, which reduces readers confusion reading various terms and names.
3. Describing the main parameters to personalize learning paths, such as users' learning style and competency level, while presenting the most used ones and detailing the difference between the static and dynamic parameters.
4. Discussing the proposed methods and algorithms for path personalization, while explaining their types and pros and cons.
5. Illustrating the current approaches and techniques that are used to evaluate path personalization methods while explaining their types and advantages and disadvantages.
6. Presenting the most significant challenges of path personalization methods.

Therefore, the questions we intend to answer in this study are the following:

1. Why are path personalization methods proposed?
2. What are the key terms and concepts in these methods?
3. What parameters are used by these methods to personalize learning paths? Which ones are the most used?
4. What are the main methods introduced to personalize learning paths? What are their differences, advantages and disadvantages?
5. What are the main techniques and methods to evaluate the path personalization? What are their pros and cons?
6. What are the challenges in these methods that need to be addressed?

In order to conduct this review paper, we have consulted around 160 studies, which are mostly published since the beginning of 1990. These studies are in different types, such as conference papers, journal papers, PhD and Master theses. To find these publications, we have used several key terms such as, learning path recommendation/generation/personalization, course generation, course sequence, curriculum planning, curriculum sequencing, long term goal recommender in E-learning, course planning, task sequencing, adaptive navigation support. After reviewing all publications, we only included those that have focused on generating learning paths/sequences for users. We then put our main concentration on the recent publications. For that, we included the studies that are published mainly after 2010. After refining the publications, we consider 66 publications to use in this review. The map of our review is presented in Fig. 1. Our review starts by clarifying the main terms and explaining the content hierarchy in the path personalization approaches, and ends by presenting the main challenges of these methods.

The remainder of this paper is structured as follows. In section **Terminology**, we present the terminology that is commonly used in the E-learning area. Section **Personalization Parameters** highlights the parameters that are applied for personalizing the learning paths. This section is followed by section **Personalization Methods**, which covers the main methods that are proposed for path personalization (Course Generation: CG, Sequential Pattern Recognition: SPR, and Course Sequence: CS), as well as their advantages and disadvantages. Section **Evaluation Methods** describes the methods that are used to evaluate the learning path personalization methods. In section **Challenges**, we present the main challenges that the personalization methods are facing. Finally, we conclude our study in the last section.

2. Terminology

Currently, a large variety of terms is used in the literature on E-learning systems. We start by providing a set of operational definitions on some of the main terms. For this purpose, we use a modular content hierarchy, which is introduced in (Duval & Hodgins, 2003). In this hierarchy, the contents are divided into five abstraction levels, but we only describe three of them: learning object (LO), Lesson, and Course. The two other levels (Raw content, Information object) are disregarded since they have never been mentioned in any path personalization study as best of our knowledge. Furthermore, reviewing the literature enabled us to add one more level, called Topic,[1] to the modular content hierarchy (Fig. 2).

1. **Course**: In the course level, which is the topmost level, the collections are gathered from the topic level (regarding a large objective) in order to build a thematic course. A course might be mentioned as a "subject" in some studies. The courses are often represented as oriented graphs. In these graphs, vertices indicate the LO or topics (depending on the abstraction level), and directed edges represent the prerequisite relations among the vertices (Nabizadeh et al., 2017).
2. **Lesson**: Each course needs several lessons in order to be learnt, and each lesson can cover one or more sections of a course (these sections are called topics which are explained in the following.). For instance, in the *C* programming language course, the loop topic needs a lesson, while several topics, such as data types and arrays, require one lesson.
3. **Topic**: A course is composed of a few learning units called topics. Each topic covers a unique concept. For example, in the *C* programming language course the topics are arrays, data types, pointers, functions, loops, etc. The topics might be referred as "chapters" or "learning units".
4. **Learning object**: LO are the small units of learning content that are reusable and constructed regarding a certain learning objective (Belacel, Durand, & Laplante, 2014; Dharani & Geetha, 2013). A LO might appear in different form, such as a text file, a power point, an audio, a video, etc. In some studies, LO are referred as "learning materials" or "knowledge units".

Any sequence of the mentioned contents (LO, topics, etc.) that satisfies their prerequisites, while guiding the users in order to accomplish the learning goals, is called a **learning path** (Muhammad, Zhou, Beydoun, Xu, & Shen, 2016; Adorni & Koceva, 2016). Generating a path that satisfies the preferences and requirements of a user is the main goal of path personalization methods. For this purpose, the **personalization parameters** are applied to determine the users' characteristics and needs. These parameters explain the users' requirements and their divergent features, such

[1] Word topic is introduced in (De & Ellis, 2006; Cornford, 1997).

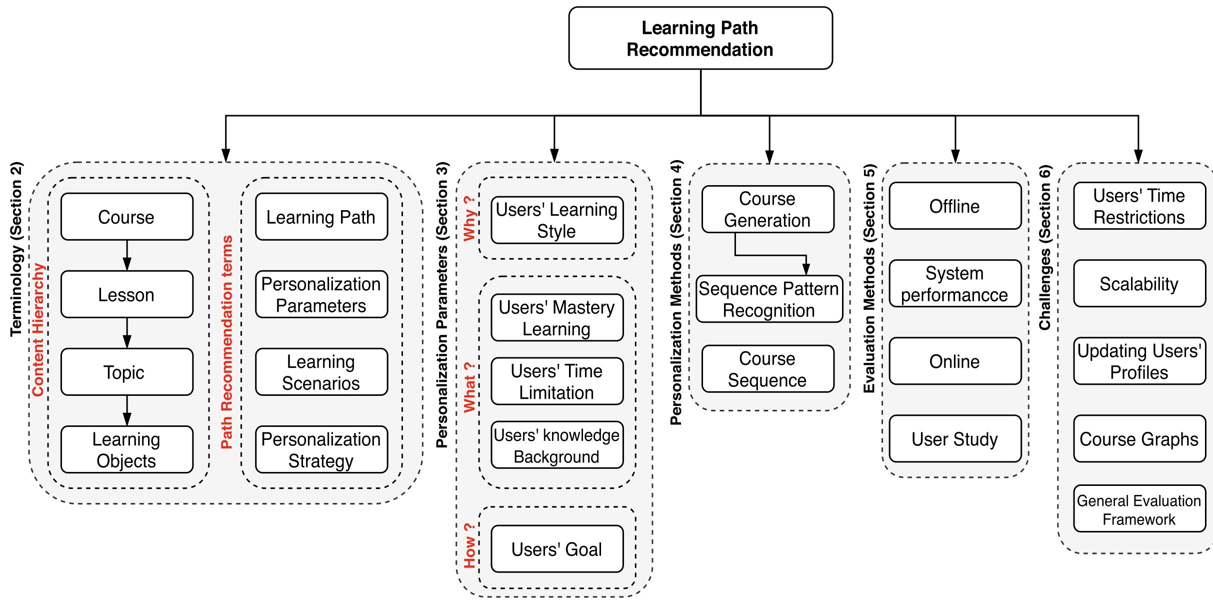

Fig. 1. Literature map.

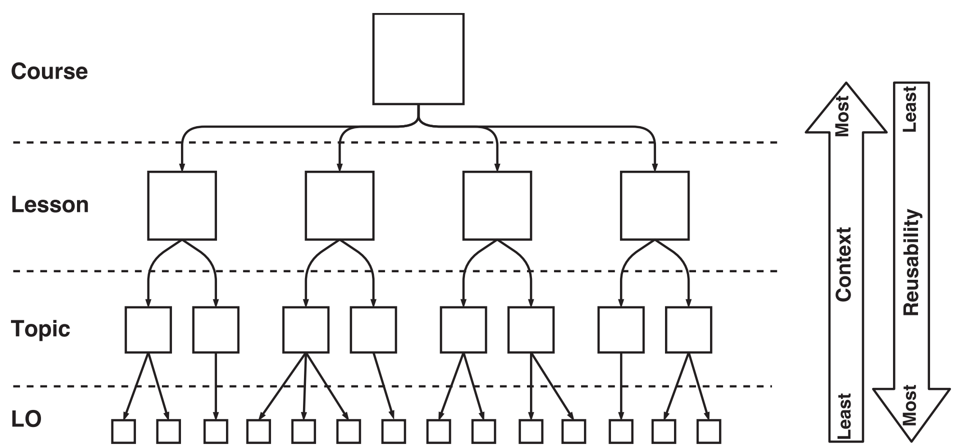

Fig. 2. Content hierarchy.

as learning styles, knowledge background, etc., and are applied to deliver personalized learning scenarios (Essalmi, Ayed, Jemni, & Graf, 2010). **Learning scenarios** help not only focus on generating a path to keep the users motivated and engaged with the learning process, but also providing them with the best possible educational materials that effectively improve their knowledge. The combination of the personalization parameters to personalize the learning scenarios is called **personalization strategy** (Essalmi et al., 2010).

3. Personalization parameters

As mentioned before, personalization parameters are critical for providing essential information to personalize the learning paths. These parameters describe various characteristics and requirements of the users, such as users' knowledge background, their goals and learning styles, etc. (Essalmi et al., 2010; Zoakou, Tzanavari, Papadopoulos, & Sotiriou, 2007). In this section, we detail the personalization parameters that are mainly used in path personalization methods.

Several researchers have considered different personalization parameters to personalize the learning paths, such as (Dharani & Geetha, 2013; Garrido, Morales, & Serina, 2012; Jin, 2011; McGaghie, Issenberg, Barsuk, & Wayne, 2014; Nabizadeh et al., 2017), but all can be classified as parameters about why, what and how to learn? (Fig. 3). The parameters about "why to learn?" consider the learning goal and the motivation as users individual differences. The parameters about "what to learn?" allow learning path personalization with respect to the users knowledge background, competency level, limitations, and the requested information. The parameters about "how to learn?" regard individual differences of users as manner that they deal with learning scenarios (Essalmi, Ayed, Jemni, & Graf, 2015; Jin, 2011). Hence, parameters about "why to learn?" include the learning goal, and the motivation level of a user. Parameters about "what to learn?" include the information seeking task, the users level of knowledge, competency level and limitations. Parameters about "how to learn?" include the users media and navigation preferences, learning styles model, and cognitive traits and language. For example, a learning goal of a user is to maximize his/her grade on a course

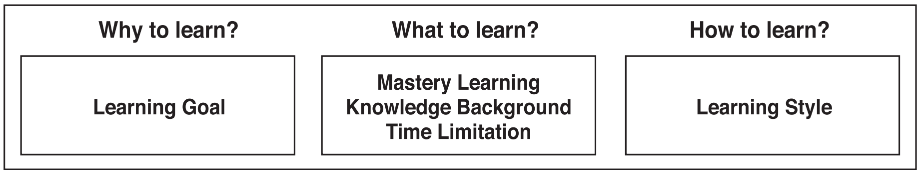

Fig. 3. Personalization parameters classification.

within three months (why to learn?). For that, the user needs to focus only on those learning materials (i.e. a path) that match his/her knowledge background and competency level, while can be completed within three months (what to learn?). Finally, the way that he/she prefers to learn the course or learning materials (e.g. language and appearance of a course, learning style) are the parameters about "how to learn?".

This classification simplifies the parameter identification. In addition, classifying all parameters within a few categories, enables us to compare them easier and more accurate.

Although researchers, such as Essalmi et al. (2010) and Alian and Jabri (2009), have considered different personalization parameters (navigation preferences, language preferences, and participation balance used by Essalmi et al. (2010), or financial situation used by Alian & Jabri (2009)), according to our survey the most used ones are as follows:

1. **Users' time limitations**: This refers to a user's available time (Li, Papaemmanouil, & Koutrika, 2016; Nabizadeh et al., 2017). In existing path personalization methods, if users intend to learn a path, they are required to spend a specified amount of time, which is often fixed and given by the method. Due to various reasons, a user might not be able to allocate enough time to follow an entire path. Some of the main reasons are: user's lack of time because of multitasking, mismanaging time, etc. Hence, the information that this parameter provides is used to generate a path that a user is able to learn properly in his/her available time.
2. **Users' mastery learning**: Mastery learning, which is a stringent form of competency-based education, indicates how much the users have mastered the knowledge and skills (competencies) required for a particular course or task (McGaghie et al., 2014). This is a dynamic parameter that might change during the learning process.
3. **Users' learning style**: This is an important parameter that indicates how a user learns and likes to learn (Dharani & Geetha, 2013). There are several well-known learning style theories and indexes that are used by researchers, such as La Garanderie, Honey-Mumford, Kolb, and Felder and Silverman, which are described in Essalmi et al. (2010) and Klašnja-Milićević, Vesin, Ivanović, and Budimac (2011). According to our survey, the Felder and Silverman is the most frequent used index in the path personalization area. This index assesses variations in individual learning style preferences across four dimensions: Active/Reflective users, Sensing/Intuitive users, Visual/Verbal users, and Sequential/Global users.
4. **Users' knowledge background**: It considers the knowledge that the users obtained before receiving the recommendations. This knowledge has several benefits such as easing the learning

Table 1
Personalization parameters that are used in the studies. In this table, column "Type" indicates the type of personalization methods that are used in the studies. "CG" indicates the Course Generation, "SPR" addresses the Sequential Pattern Recognition, and "CS" stands for Course Sequence methods, which are detailed in Section 4.

Ref.	Type	Time	Mastery	Style	Know. Back	Ref.	Type	Time	Mastery	Style	Know. Back
(Belacel et al., 2014)	CG		✓			(Feng et al., 2010)	CG	✓		✓	✓
(Shi et al., 2020)	CG	–	–	–	–	(Cun-Ling et al., 2019)	CG			✓	✓
(Li et al., 2016)	CG	✓				(Yang et al., 2010)	CG			✓	
(Adorni & Koceva, 2016)	CG		✓	✓	✓	(Carchiolo et al., 2010)	CG	✓	✓		
(Dwivedi et al., 2018)	CG		✓	✓		(Zhu et al., 2018)	CG	✓			✓
(Zhou et al., 2018)	CG			✓	✓	(Krauß, 2018; Krauß et al., 2018)	CG	–	–	-	-
(Ye et al., 2018)	CG		✓	✓	✓	(Nabizadeh et al., 2018)	CG	✓	✓		✓
(Durand et al., 2013)	CG		✓			(Garrido et al., 2012)	CG			✓	✓
(Garrido et al., 2013)	CG	✓		✓		(Suazo et al., 2012)	CG		✓		
(Yang et al., 2014)	CG		✓			(Essalmi et al., 2010)	CG		✓	✓	✓
(Dharani & Geetha, 2013)	CG		✓	✓		(Durand et al., 2011)	CG		✓	✓	
(Yang et al., 2010)	CG		✓			(Klašnja-Milićević et al., 2011)	SPR		✓	✓	
(Wilkowski et al., 2014)	CG				✓	(Wang & Zaïane, 2018)	SPR		✓		
(Xu et al., 2016)	CG	✓	✓		✓	(Vesin et al., 2013)	SPR		✓	✓	✓
(Xie et al., 2017)	CG	✓			✓	(Fournier-Viger et al., 2010)	SPR		✓		
(Janssen et al., 2010)	CG		✓			(Yarandi et al., 2013)	CS		✓	✓	
(Sivakumar & Praveena, 2015)	CG		✓			(Li et al., 2012)	CS	✓	✓		
(Yang et al., 2013)	CG			✓		(Garrido & Onaindia, 2013)	CS				✓
(Chi, 2010)	CG		✓			(Ullrich & Melis, 2010)	CS		✓		
(Bhaskar et al., 2010)	CG			✓		(Govindarajan et al., 2016)	CS		✓		
(Basu et al., 2013)	CG	✓				(Colace et al., 2014)	CS	✓	✓	✓	
(Nabizadeh et al., 2017)	CG	✓			✓	(Salahli et al., 2013)	CS		✓		
(Alian & Jabri, 2009)	CG	✓	✓	✓	✓	(Yang et al., 2012)	CS		✓		
(Gordón et al., 2015)	CG			✓		(Rafsanjani, 2018)	CS	✓	✓		✓
(Zaporozhko et al., 2018)	CG			✓		(Xi et al., 2018)	CS		✓		✓
(Segal et al., 2019)	CG		✓			(Vanitha et al., 2019)	CS		✓		
(Christudas et al., 2018)	CG		✓	✓		(Nabizadeh et al., 2020)	CS	✓	✓		✓
(Xia et al., 2019)	CG		✓			(Li & Zhang, 2019)	CS			✓	
(Liu & Li, 2020)	CG	–	–	–	–	(Cai et al., 2019)	CS		✓		
(Niknam & Thulasiraman, 2020)	CG		✓		✓	–	–	–	–	–	–

process, improving reading comprehension, etc. (Adorni & Koceva, 2016; Garrido et al., 2012). It can be divided in two different types:

(a) Objective pre-knowledge level : Objective data such as user's grades on a past course, or pre-test scores on a course.
(b) Subjective pre-knowledge level : Users specify their pre-knowledge levels explicitly with respect to their own understanding (Xie et al., 2017; Feng, Xie, Peng, Chen, & Sun, 2010).

5. **Users' goal**: Learning goals are applied to design and plan the learning process, and to arrange the LO in the form of paths that satisfy the users' goals. Depending on the users, the learning goals might be different. Goals can be deadline-driven, when a user intends to complete a learning process by a given time (Li et al., 2016). They can be score-driven, when a user aims to maximize his score (Nabizadeh et al., 2017). Learning rewards (Durand, Laplante, & Kop, 2011), users' competency (Belacel et al., 2014; Chi, 2010), and length of the paths (i.e. shortest path) (Belacel et al., 2014) are other types of goals that have already been considered by the researchers.

It should be clear that some of the personalization parameters are dynamic (e.g. learning style, mastery learning) and their values might change during the learning process. Furthermore, some of the parameters (e.g. knowledge level) might not be identified accurately in advance, but only during the users' interactions with the system. Therefore, a user profile,[2] which is modeled based on the personalization parameters, needs to be contemplated and updated regularly (Dharani & Geetha, 2013; Iglesias, Angelov, Ledezma, & Sanchis, 2012).

Finally, the personalization parameters that are used by the researchers (main focus is on the studies after 2010) are summarized in Table 1. As it is shown in this table, Mastery level is the most frequently used parameter, while learning time is the one that is used the least (around 22% of the studies used this parameter). In this table, the learning goal was omitted since each paper has its own learning goals, and only the type of goal is different. In complement to Table 1, Fig. 4 presents the proportion of personalization parameters that are used by researchers per year.

4. Personalization methods

Automatic generation and personalization of a learning path, based on a user's learning goals and preferences, is the main task of path personalization methods. Given a set of LO (lessons or courses) and personalization parameters, researchers have proposed various approaches that automatically generate a personalized learning path for a user. The quality of these methods' outcomes depends highly on the quality of the path personalizer method per se, on the LO, and on the parameters that are used for personalization. These personalization methods automatically retrieve the LO (lessons or courses) from a repository and assemble them in the form of learning paths. Selecting and assembling LO needs to support the users' goals. Such goals require a concise and clear definition and representation.

Since the late 1960s and early 1970s, various learning path personalization methods have been proposed, using different sets of goals, parameters, techniques, and algorithms. According to Nabizadeh, Jorge, and Leal (2015) and Nabizadeh et al. (2017), path personalization methods can be categorized into two main classes:

[2] This profile includes information about a users skills, strengths, interests, background, goals, etc.

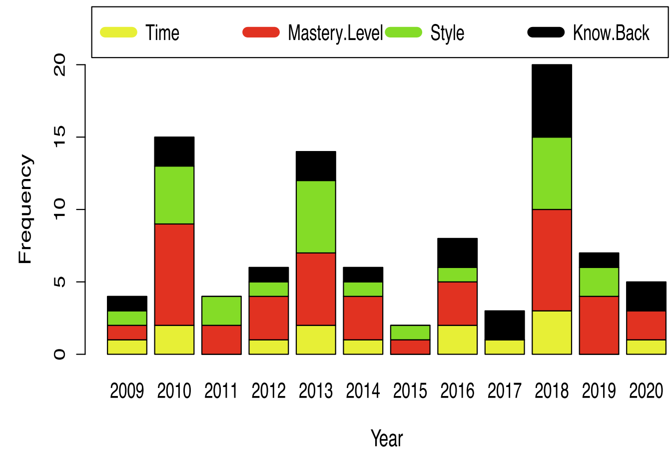

Fig. 4. Proportion of personalization parameters that are used per year. For instance, among the studies of 2010, mastery level is used in six different studies, while the time limitation parameter is only used in two studies. In this figure, the learning goal was omitted since each paper has its own learning goals, and only the type of goal is different.

1. Course Generation (CG): These methods generate and recommend the entire path to a user in a single recommendation, and the learning assessment occurs only after completing the path. Some studies, such as (Nabizadeh et al., 2017; Cun-Ling, De-Liang, Shi-Yu, Wei-Gang, & Jun-Yu, 2019; Xia et al., 2019), used these approaches. A conceptual view of CG approaches is presented in Fig. 5.
2. Course Sequence (CS): These methods generate and recommend a path to a user step by step considering the user's progress, and the learning assessment occurs as the user proceeds on the path. Some studies, such as Nabizadeh, Gonçalves, Gama, Jorge, and Rafsanjani (2020), Govindarajan et al. (2016) and Cai, Zhang, and Dai (2019), used these methods. Fig. 6 shows a conceptual view of CS approaches.

In this section, we describe recent learning path personalization methods in detail, as well as their advantages and disadvantages.

4.1. Course Generation (CG)

In the Course Generation methods (CG), after determining a user's characteristics and requirements, the entire learning path is generated and recommended to him/her in a single recommendation (Belacel et al., 2014; Bhaskar, Das, Chithralekha, & Sivasatya, 2010; Carchiolo, Longheu, & Malgeri, 2010). Some researchers focused on the course generation to facilitate a group of users rather than a single user (Kardan, Ebrahim, & Imani, 2014; Xie et al., 2017; Feng et al., 2010). To this end, Kardan et al. presented a method called ACO-Map, which generates paths in two stages (Kardan et al., 2014). In the first stage, K-means algorithm (Jain, 2010) is applied to divide users into groups based on the results of a pre-test. In the second stage, the ant colony optimization method (Dorigo & Stützle, 2010) is used to generate a path for each group. Groupized learning path discovering (GLPD), which was introduced by Feng et al. in 2010, is another CG group recommender method. In this method, a topic graph is initially generated, and pre-knowledge and preferences of the users are collected. The GLDP then estimates the temporal boundaries for a group of users (max and min time to learn a path). Finally, regarding the estimated temporal boundaries for a group and the required time to learn a path, a corresponding strategy is selected to discover a path (Feng et al., 2010).

Other methods, instead of generating a path for a group of users, concentrate on personalizing a path for a single user. For instance, Belacel et al. proposed a CG method based on graph theory. In their graph, the LO are vertices and the edges present the dependency relations among vertices (prerequisite). Their method starts with reducing the solution space by obtaining an induced sub-graph of the learning graph (eliminating LO that are irrelevant to obtain the goal). It then utilizes the branch-and-bound algorithm in the sub-graph to find the shortest path by minimizing the number of required competencies (Belacel et al., 2014).

Another CG method that is based on graph theory is called CourseNavigator (Li et al., 2016). This method is based on a graph search algorithm. It generates all paths given a set of users' inputs. The users' inputs are constraints (e.g., maximum number of courses to take per semester, courses to avoid), learning goals (e.g., graduation semester, a set of desired courses), users' enrollment status (e.g. starting point), and their preferred ranking for the output paths (e.g., shortest, most reliable, etc.). Given the set of inputs, this method is able to generate three types of learning paths: (a) deadline-driven paths, (b) goal-driven paths and (c) ranked paths (regarding the user's ordering preferences). In the CourseNavigator, a recommended path is a sequence of semesters. In each semester a user needs to take a number of courses. In this method, the researchers do not estimate how much time a single course might take for a user, and therefore, the learning time of a course is the same for all users. Similar to the CourseNavigator method, Xu et al. developed an automated method to generate a sequence of courses for a user (Xu, Xing, & Van Der Schaar, 2016). The main goal of this method is to minimize the graduation time of the users while maximizing their overall GPA. In this method, a forward-search is first executed, from quarter 1 (each academic year consists of four quarters) to quarter *T*, to identify all possible course states that can be in a path. Then, a backward-induction is performed, from quarter *T* to 1, to compute the optimal set of courses that should be considered in each possible course state. Finally, an algorithm, which was developed using multi-armed bandits (Gittins, Glazebrook, & Weber, 2011), recommends a course sequence that reduces the graduation time while increasing the overall GPA of a target user. However, in both CourseNavigator and the method that is proposed by Xu et al., the researchers do not take into account how much time a single course takes for a user in a semester (i.e. learning time of a course is a fixed value for all users).

Educational Concept Map (ECM) (Adorni & Koceva, 2015) is also employed successfully in CG methods. As an example of an ECM based method, we can refer to Adorni and Koceva's, which is presented in Adorni and Koceva (2016). In their method, a user initially determines his/her knowledge background by selecting a set of topics from ECM, which trims the known topics from the map. The trimming output is checked by an expert, and finally, after the user chooses the initial and target topics, the paths are generated using ENCODE (Koceva, 2016), which executes an algorithm to linearize the map.

The methods that we have detailed so far, are mainly focused on generating learning paths, regardless of the user's time restriction to learn them. There are some methods that take into account this limitation, such as (Garrido et al., 2013; Basu et al., 2013; Nabizadeh et al., 2017). For example, Nabizadeh et al. introduced a method called RUTICO, which is an example of Long Term goal Recommender Systems (LTRS) (Nabizadeh et al., 2015). The main goal of RUTICO is to generate a path that maximizes a user's score under a time restriction. In this method, after locating a user in the course graph, a Depth First Search (DFS) algorithm is applied to find all possible paths for a user, given a time restriction. RUTICO also estimates learning time and score for the generated paths, and finally, recommends the path with the maximum score that satisfies the user's time restriction. Basu et al. also developed a CG system to recommend a path to a user that satisfies his/her time restriction (Basu et al., 2013). Their system consists of two major components: Learning Path Indicator (LPI) generating component and Learning Path Generating (LPG) component. In this system, a function is initially defined based on three system parameters: (1) number of post-requisite of a subject (course), (2) learning time of a subject, and (3) number of credit for a subject. Then, a fitness function is defined regarding personal restrictions and preferences of a user, such as affordable time. Ultimately, an LPI is generated using the estimated values from the fitness function and the system parameters' function. The gen-

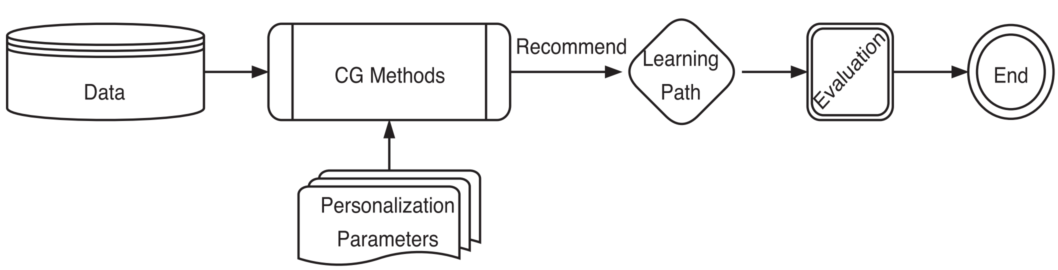

Fig. 5. Conceptual view of CG methods.

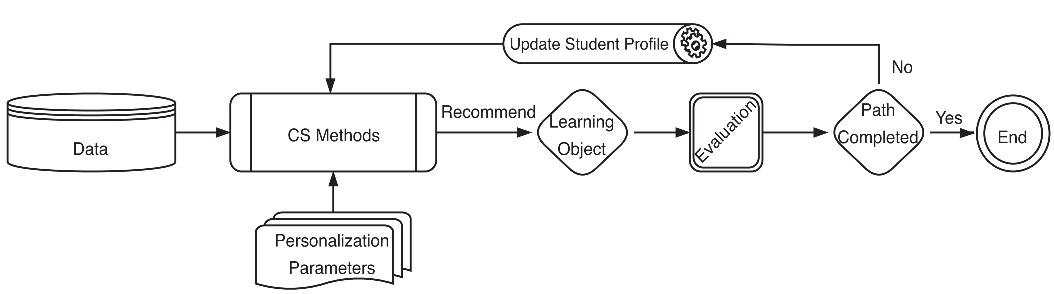

Fig. 6. Conceptual view of CS methods.

Table 2
Summarizing the algorithms/methods/techniques in the literature, as well as their types and recommendation strategies.

Reference	Type	Main techniques/algorithms/methods	Recommendation strategy
(Shi et al., 2020)	CG	Graph traversal algorithm, Knowledge graph, Cohen kappa coefficient	Generating all paths considering the students' learning objective and learning need, and recommending the one with the highest score.
(Cun-Ling et al., 2019)	CG	Graph Theory, Improved Immune Algorithm (IIA), Felder-Silverman	Recommending a path that improves the students learning outcomes considering their learning style, goal, and knowledge background.
(Xia et al., 2019)	CG	Markov chain, Learning scenarios	Recommending a customized sequence of questions to individual learners, based on the exercise history of other users in a similar learning scenario.
(Liu & Li, 2020)	CG	Complex network theory, MOOC	Paths are made in 3 different scenarios based on learning history (records) and learners' similarity.
(Niknam & Thulasiraman, 2020)	CG	Fuzzy C-Mean (FCM) Clustering algorithm, Ausubels learning theory, Ant colony optimization algorithm (ACO).	Clustering the learners into groups and selects a path for learners based on their prior knowledge.
(Dwivedi et al., 2018)	CG	Evolutionary algorithm (variable length genetic algorithm), Felder&Silverman index	A path with the highest fitness function value having the correct topological order
(Zhu et al., 2018)	CG	Depth First Traversal Algorithm, Edit distance algorithm	Recommending a user's required path (7 different types) for a learning scenario (4 scenarios)
(Zhou et al., 2018)	CG	Clustering method, LSTM (Long short-term memory) neural network	Recommending a path the matched a user's features
(Krauß, 2018; Krauß et al., 2018)	CG	Course graph, Zografos and Androutsopoulos algorithm (Zografos & Androutsopoulos, 2008)	Recommending top-N paths between starting and target points with different branches
(Ye et al., 2018)	CG	Ant colony, Analytic Hierarchy Process (AHP), K-means algorithm	Recommending a path using act colony algorithm
(Nabizadeh et al., 2018)	CG	Item Response Theory, Depth First Search algorithm, Probability of Error for learning time and score	A path that maximizes a user's score under a limited time
(Belacel et al., 2014)	CG	Branch and bound algorithm	Shortest path (number of competency)
(Li et al., 2016)	CG	Graph search algorithm	Deadline driven, Goal driven, Ranked driven
(Adorni & Koceva, 2016)	CG	Educational Concept Map (ECM), ENCODE (linearize the map)	Minimizing the number of LO
(Durand et al., 2013)	CG	Greedy algorithm	Shortest path (number of competency)
(Garrido et al., 2013)	CG	PDDL, HTN, Non–HTN	Maximizes the total reward without exceeding a user's time
(Yang et al., 2014)	CG	Bloom's taxonomy	A path generation method that formulates learning activities and their assessment criteria using the Bloom's taxonomy.
(Hwang et al., 2010)	CG	RFID,repertory grid-oriented technique, Heuristic Algorithm	Minimizing the relevance loss between consecutive LO along a path
(Tam et al., 2014)	CG	Explicit Semantic Analysis, Evolutionary algorithm + hill climbing, Clustering	Minimizing the sum of the violated distances regarding the reference paths
(Kardan et al., 2014)	CG	Ant-colony (ACO-Map), Ausubel Meaningful Learning Theory, Clustering	Shortest path
(Dharani & Geetha, 2013)	CG	Case Based Reasoning (CBR), Colored Petri Nets, Classification	Finding similar solution regarding learning style, goal and performance
(Yang et al., 2010)	CG	Bloom's taxonomy	It is a path generation method that formulates learning activities and their assessment criteria using the Bloom's taxonomy.
(Xu et al., 2016)	CG	Clustering, Multi-armed bandits	Minimizing the graduation time while maximizing the overall GPA
(Lin et al., 2013)	CG	Decision tree classifier, feature weighting, feature selection	Maximizing users' creativity
(Xie et al., 2017)	CG	Topic graph extraction, group profiling, estimating time boundaries	Minimizing learning time and Maximizing the learning enjoyment
(Janssen et al., 2010)	CG	Search engine	Finding a path that meets a user criteria (e.g. start point)
(Sivakumar & Praveena, 2015)	CG	Ant Colony Optimization algorithm (ACO)	Optimizing path regarding users' ability, goals and behavior
(Yang et al., 2013)	CG	Learning and Cognitive styles	Paths that match the cognitive and learning styles of users
(Chi, 2010)	CG	Domain ontology, Problem-solving ontology, Semantic rules	Generating path regarding a given criteria (competencies)
(Bhaskar et al., 2010)	CG	Genetic algorithm	Maximizing fitness value (consists of 3 fitness values)

(*continued on next page*)

Table 2 (*continued*)

Reference	Type	Main techniques/algorithms/methods	Recommendation strategy
(Basu et al., 2013)	CG	Greedy algorithm	Path satisfies users limitation (time) and preferences.
(Feng et al., 2010)	CG	Topic graph extraction, group profiling, estimating time boundaries	Minimizing learning time while considering users preferences
(Yang et al., 2010)	CG	Felder learning style, Broad first searching (BFS), 3-dimension semantic map	Path satisfies users learning style.
(Carchiolo et al., 2010)	CG	Peer-to-peer (P2P) networks	Generating paths that satisfy a user's time and difficulty level
(Garrido et al., 2012)	CG	PDDL, Case-Based Planning (CBP)	Minimizing the number of changes regarding a referenced path while maximizing the total reward
(Nabizadeh et al., 2017)	CG	Depth first search (DFS)	Maximizing users score under his/her time restriction
(Alian & Jabri, 2009)	CG	Weighted Graph, Eliminating and Optimized Selection (EOS)	Shortest path on a weighted graph
(Tam et al., 2012)	CG	Explicit semantic analysis, Genetic algorithm, Clustering(K-means)	Minimizing the number of precedence rules violated by the path
(Durand et al., 2011)	CG	Markov Decision Process	Maximizing reward while minimizing the number of LO
(Suazo et al., 2012)	CG	Bayesian network, Clustering	Recommending activity with the highest probability
(Essalmi et al., 2010)	CG	Personalization strategy	Matching user' characteristics with the LO features
(Zaporozhko et al., 2018)	CG	Genetic algorithm, MOOC, Vark Methodology	Building an optimal path considering a user's possibilities and features
(Gordón et al., 2015)	CG	User disability, MOOC	Adapting course content to students' needs, preferences, skills and situations
(Wilkowski et al., 2014)	CG	Google Map, Google Earth, MOOC	Providing instant feedbacks to users according to their mastery level and desired goal
(Christudas et al., 2018)	CG	Compatible Genetic algorithm (CGA), Maximum Likelihood Estimation (MLE), Particle Swarm Optimization Algorithm and Genetic algorithm (are used for comparison)	Recommending a path considering the learning style, knowledge level and interactivity level of a user
(Segal et al., 2019)	CG	EduRank, Voting method, Collaborative filtering system	Recommending a sequence of questions by increasing order of difficulty to users considering their performances
(Wang & Zaïane, 2018)	SPR	Process mining, Dependency graph (association rule mining), Sequential pattern mining (PrefixSpan), Casual footprint approach for conformance checking	Recommending a sequence of courses that positively influence GPA (increasing) and graduation time (decreasing)
(Fournier-Viger et al., 2010)	SPR	Sequential pattern mining (invented algorithm)	Successful paths that satisafy the initial and end point of a user
(Klašnja-Milićević et al., 2011)	SPR	Clustering, AprioriAll	Maximizing the sequences' rate while reducing the info redundancy
(Vesin et al., 2013)	SPR	Clustering, Collaborative filtering, Association rule mining	Maximizing success rate of sequences while reducing the info redundancy
(Rafsanjani, 2018)	CS	Item Response Theory (IRT),Matrix Factorization, Two-Layer course graph, Probability of error for learning time and score, Depth first search	A path that maximizes a user's score under a given time
(Yarandi et al., 2013)	CS	Item Response Theory (IRT)	Recommending LO that fits the user's ability
(Li et al., 2012)	CS	Collaborative Voting, Maximum Likelihood Estimation, Evolutionary algorithms (GA,PSO)	Matching a user's ability while considering his/her time limitation
(Garrido & Onaindia, 2013)	CS	PDDL, Constraint Satisfaction Problem (CSP)-based scheduling	Minimizing the length of a path while maximizing the learning reward
(Ullrich & Melis, 2010)	CS	Learning scenario selection, HTN	Matching preferred learning scenario of a user and his/her goal
(Govindarajan et al., 2016)	CS	Evolutionary algorithm (PPSO), Clustering, Bloom's taxonomy	Fitting user's need and proficiency level.
(Xu et al., 2012)	CS	Bayes formula, Pearson Correlation Coefficient (KNN), feature weighting	Recommending a LO with the highest probability
(Colace et al., 2014)	CS	Functions to estimate the closeness of each LO to a user's profile, Ontology	Matching users' characteristics with the relative parameters of LO
(Salahli et al., 2013)	CS	Item Response Theory (IRT), Law of Total Probability (LPT)	Matching the understanding degree of users with the difficulty level of LO
(Yang et al., 2012)	CS	Association Link Network (ALN), TFIDF Direct Document Frequency of Domain (TDDF)	Matching the users knowledge level with the complexity of LO
(Xi et al., 2018)	CS	Linear Regression Algorithm, Matrix Factorization, MOOC	Provide adjustable path to learners considering their behaviors and needs

Table 2 (*continued*)

Reference	Type	Main techniques/algorithms/methods	Recommendation strategy
(Vanitha et al., 2019)	CS	Ant Colony Optimization (ACO), Genetic Algorithm	Recommending a path considering the emotion and cognitive ability of a user
(Li & Zhang, 2019)	CS	Network embedding, Learning effects, Width first search, Depth first search, Random walk	Using the similarity of users and the learning effect of historical users to continuously recommend the unselected courses with the highest score to a user.
(Cai et al., 2019)	CS	Knowledge tracing model, Reinforcement learning, neural network, Markov Decision Process	Recommending the optimal path considering the requirements of each knowledge point during the learning process.
(Nabizadeh et al., 2020)	CS	Item Response Theory (IRT), Matrix Factorization, Two-Layer course graph, Probability of error for learning time and score, Depth first search	A path that maximizes a user's score under a given time.

erated LPI is passed to the LPG component to formulate a path for a user. In the LPG, to generate a path, each subject (course) is chosen by applying a forward greedy algorithm on the LPI values.

In addition to the mentioned studies, there are other CG methods that have been proposed using different algorithms and techniques: a decision tree classifier (Lin, Yeh, Hung, & Chang, 2013), a markov decision process (Durand et al., 2011), greedy algorithms (Durand, Belacel, & LaPlante, 2013; Basu et al., 2013), a Hierarchical Task Network (HTN) (Garrido et al., 2013), a Case-Based Reasoning/Planning (Dharani & Geetha, 2013; Garrido et al., 2012), genetic algorithms (Bhaskar et al., 2010; Tam, Lam, & Fung, 2012), a Planning Domain Definition Language (PDDL) (Garrido et al., 2012; Garrido et al., 2013), a Bayesian network (Suazo, Rodriguez, & Rivas, 2012), etc. In Table 2, we have summarized the techniques and algorithms that have been used by researchers.

Although CG methods are widely used by researchers to generate learning paths, they have several drawbacks. One of the main disadvantages is ignoring a user performance and the changes that occur during the learning process. Thus, users are at risk of wasting time, by receiving a wrong path or a path that they are not able to follow. Also, these methods often become slow when they receive a large amount of data (e.g. large number of LO and users). Therefore, they might not be able to respond quickly enough to keep the users engaged.

4.1.1. Sequential Pattern Recognition (SPR)

Sequential Pattern Recognition methods (SPR), which are a subset of CG methods, are less used than the other learning path personalization methods. In these methods, sequential pattern mining approaches (Agrawal & Srikant, 1995) are mainly applied to discover a learning path for a user from the transactions of similar users (which sequence of LO are selected by users and how the users interacted with them). Users are similar if they have similar initial states, preferences, goals, etc. In comparison with the CG methods that are able to generate paths even without users' transactions data, SPR methods require transactions data for the path generation. A conceptual view of SPR methods is presented in Fig. 7.

There are a few studies that used SPR methods, such as Klašnja-Milićević et al. (2011), Vesin, Milicevic, Ivanovic, and Budimac (2013) and Fournier-Viger, Faghihi, Nkambou, and Nguifo (2010). As an example, we refer to the Protus method that was introduced by Vesin et al. in 2013 (Vesin et al., 2013). In Protus, users are clustered regarding their common attributes (e.g. age, class, etc.) and preferences. Then, the method finds a cluster for a target user and considers the sequence of lessons that each member in that cluster selected (lessons are rated by users and based on sequences which successfully guided the users). Finally, Protus uses association rule mining to find all successful sequences of the target cluster, and recommends a sequence based on users' ratings. As another example, we explain the Fournier-Viger et al. proposal (Fournier-Viger et al., 2010) that is illustrated in the context of CanadarmTutor (Kabanza, Nkambou, & Belghith, 2005). CanadarmTutor is an Intelligent Tutoring Systems (ITS) (Polson & Richardson, 2013) to learn how to control a robotic arm. This system initially (in the observing phase) records the solutions of the users to move the arm from an initial configuration to a goal configuration. In the next phase (learning phase), an algorithm (Fournier-Viger, Nkambou, & Nguifo, 2008) is applied to find all sequences with a support higher or equal to a minimal support (support is the proportion of transaction in the data in which a sequence X appears). In the final phase (application phase), the system provides assistance to a target user by using the knowledge that was gained in the second phase. The assistance is provided by recognizing a user's plan.

In SPR methods, researchers apply sequential pattern mining methods and algorithms, such as *Apriori* (Agrawal & Srikant, 1995), to mine patterns from transactions data, but they often face two main problems. First, current pattern recognition methods such as *Apriori* might require a lot of memory, and second, they find frequent patterns and rare cases are ignored.

4.2. Course Sequence (CS)

Unlike CG methods, Course Sequence approaches (CS) recommend a path LO by LO, as a user progresses in the learning path

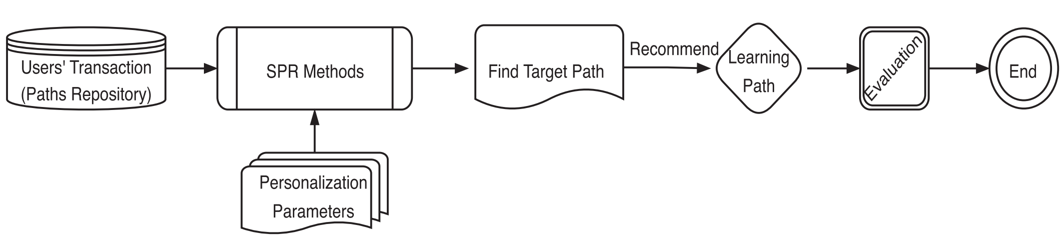

Fig. 7. Conceptual view of SPR methods.

(Karampiperis & Sampson, 2005; Nabizadeh et al., 2017; Nabizadeh et al., 2015). Different CS approaches have been proposed: using an Association Link Network (ALN) (Yang, Li, & Lau, 2012), Evolutionary Algorithms (EAs) (Li, Chang, Chu, & Tsai, 2012; Govindarajan et al., 2016), Item Response Theory (IRT) (Yarandi, Jahankhani, & Tawil, 2013; Salahli, Özdemir, & Yasar, 2013), Bayes theorem (Xu, Wang, Chen, & Huang, 2012), etc. In 2016, Govindarajan et al. applied an evolutionary algorithm (Parallel Particle Swarm Optimization) to predict a dynamic path for users (Govindarajan et al., 2016). Their method clusters users into four groups according to their proficiency level. The proficiency comprises both measuring a target outcome achievement, and the competence and meta-competence changes during the learning process for each defined learning outcome. Then, the method predicts a dynamic path based on the clustered information.

Similarly, two evolutionary algorithms were used by Li et al. to develop a CS method. In their method, learning concepts are composed in the form of a sequence, which is the base for presenting a sequence of LO. Next, the collaborative voting method is applied to automatically adjust the difficulty level of LO according to the users' feedback (step 2). In step 3, Maximum Likelihood Estimation (MLE) is used to analyze the users' ability and goals. Finally, a Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are applied to generate a path using the results obtained in step 3. Once a user completes a LO, the feedback information will be used to adjust the difficulty level of LO in step 2, and update the user's ability and goals in step 3 (Li et al., 2012). The users' ability is also noted by (Yarandi et al., 2013) to personalize learning paths. In this study, an adaptive e-learning system is proposed using an ontology-based knowledge modeling. This system receives the user's ability, knowledge background, learning style and preferences as inputs and recommends a path. It then analysis the user's responses using the Item Response Theory (IRT) (An & Yung, 2014) and updates the user's ability. The updated data is used to modify the path by recommending the LO that matches the user's ability.

Another system that uses the Item Response Theory was proposed by Salahli et al. (2013). Their system takes a few steps for path personalization. Initially, the topics are identified, their relations and difficulties are determined, and the users' profiles are also generated. Item Response Theory (IRT) (An & Yung, 2014) is then applied to estimate the understanding degrees of the topics for each knowledge level. In the next step, when a target user starts using the system, his/her knowledge level and the difficulty of a selected topic are retrieved to estimate his/her understanding degree. Then, the LO are recommended to the user according to his/her understanding degree. After completing a LO, the system checks if the user understood the LO. If the user was able to understand the LO, the user's knowledge on the topic is tested, and his/her knowledge level is re-estimated. Accordingly, the understanding level of the user is re-estimated with the Law of Total Probability (LTP) (Khrennikov, 2010). If the understanding degree is low, the system recommends the LO to improve the user's knowledge on the prior topics.

Although CS methods take into account the users' progresses and changes during the learning process, which is one of the main problems with CG methods, they still have several problems that need to be considered. The first one is estimating a personalized time period to evaluate the user's knowledge and updating his/her profile. The current studies consider a fixed amount of time for all users to evaluate and update their profiles. Evaluating a user and updating his/her profile is time consuming and might be unnecessary, while postponing the tasks might result in recommending improper LO (mismatching the user's ability), which causes misleading the user and wasting his/her time. In addition, identifying the critical information that needs to be updated is important because the personalization parameters may have different weights for different users.

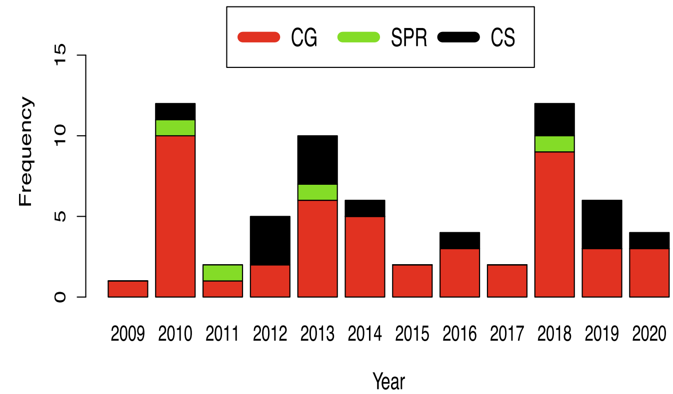

Fig. 8. Proportion of personalization methods per year.

After describing different types of learning path personalization methods (CG, SPR and CS), we present in Table 2 the main algorithms/methods/techniques that were used by researchers mainly after 2010. In the same table, we describe the recommendation strategies that were used in these studies, as well as their types. In addition, Fig. 8 presents the proportion of personalization methods used by researchers per year.

5. Evaluation methods

Evaluation is always one of the main challenging phases in the learning path personalization methods. Besides offline evaluation, these methods must be evaluated with real users in a live environment. Researchers evaluated these methods with Information Retrieval (IR) measures (*Precision*, *Recall*, etc.) (Govindarajan et al., 2016), Machine Learning (ML) measures (*RMSE*, *MAE*, etc.) (Nabizadeh et al., 2017; Klašnja-Milićević et al., 2011) and Decision Support System (DSS) approaches (e.g. measuring user satisfaction, user loyalty, etc.) (Essalmi et al., 2010). Although path personalization methods are often evaluated by IR and ML measures, it is important to monitor the users' transactions and measure their satisfaction. This is important because if users are unsatisfied with the recommendations, they might drop out (Monteiro et al., 2016; Lee & Choi, 2011; Tekin, Braun, & van der Schaar, 2015), and subsequently the learning goal might not be accomplished.

In this section, we describe the experiments that are applied to evaluate learning path personalization methods and categorize them into four main classes: offline, system performance, online and user study experiments. We start with offline experiments, which do not require live users interactions and are easier to perform. We then describe the system performance experiments, which aim at attaining the highest performance for the method. System performance experiments are followed by online evaluation, which are the most reliable experiments when the users of the path personalization method are not informed about the evaluation. Finally, we describe the user study evaluation, where a path personalization method is tested by users in a controlled environment. The users then report according to their experience.

5.1. Offline evaluation

Offline experiments simulate the users' behavior with the path personalization method. The main assumption of these experiments is that the users have similar behavior during the data collection phase and when they are using the method. Being standalone is one of the main advantages of these experiments, which do not require live users' interactions. In addition, this advantage allows us to compare the performance of various algorithms and methods with a small cost (Shani & Gunawardana, 2011).

Although measures such as *Precision*, *Recall*, *MeanAbsoluteError* (MAE) are required to assess the path personalization methods, they are only used by a few studies. For example, Klašnja-Milićević et al. (2011) applied the Mean Absolute Error (MAE) (Willmott & Matsuura, 2005) to measure the deviation of recommendations from their true user-specified values. Similarly, the MAE is used by Nabizadeh et al. (2017) and Nabizadeh et al. (2020) to evaluate the quality of methods that are proposed to estimate the learning time and score for generated paths.

Despite being easy to use and having a low implementation cost, this type of experiments present some reliability risks, since the users' behaviors might change during the learning process and these experiments do not take these changes into account.

5.2. System performance

The main goal of the system performance experiments is to measure the performance of the system. These experiments are used in response to questions such as "How fast is the system?" (response time), "Does the system work with large datasets?" (scalability), or some other questions that address the performance quality of the system. They are often performed after offline experiments, since we initially need to be sure that the system generates acceptable results, and then we attempt to evaluate and improve the performance of the system.

In the learning path personalization methods, some studies such as Li et al. (2016), Carchiolo et al. (2010); Li et al. (2012) and Janssen et al. (2010) employed system performance evaluations. For instance, in Durand et al. (2013), the authors measured the average calculation time for learning paths. Similarly, Li et al. assessed their method by analyzing the execution time (Li et al., 2012). In this study, the execution time of two evolutionary algorithms (GA (Kumar, Husian, Upreti, & Gupta, 2010) and PSO (Kennedy, 2011)) were compared regarding different numbers of LO. Another example is measuring the stability, which was performed by Garrido et al. (2012). In their study, the path stability was evaluated regarding the number of changes (expressed in terms of number of LO) between the generated path and the referenced one. They also evaluated the system scalability by considering the time that a CPU takes to generate a path.

In this section, we attempted to mention various experiments that were performed on the system performance. A glance at the literature indicates that researchers often used these experiments to analyze the required time for generating paths. Despite having a low evaluation cost when compared with the online evaluation, system performance experiments present some difficulties. First, it is not an easy task to determine the critical parts of the method that need to be improved, and second, evaluating the detected parts to achieve optimum performance is time consuming and not a trivial task.

5.3. Online evaluation

The main objective of learning path personalization methods is to enhance the users' knowledge and skills. In order to evaluate how much a method was successful in accomplishing this goal, it is necessary to measure the users' improvement when they are using the method. For this purpose, online experiments can be used. These experiments provide more reliable results than offline experiments since, in these experiments, the method is used by real users performing real tasks.

Online experiments were used in several studies, such as Vesin et al. (2013), Yang, Hwang, and Yang (2013). In Klašnja-Milićević et al. (2011), the successful completion of a course was used to assess the method. In this study, users were divided into two groups when using the method (control and experimental groups). The results of the experiment show that the users in the experimental group were able to complete a course in less time than the users in the control group. Xu et al. compared the performance of the *C* programs that were written by the users in two different groups (control and experimental groups) (Xu et al., 2012). In the same study, the researchers also compared the grades' differences in two groups. Similarly, Colace, De Santo, and Greco (2014) and Feng et al. (2010) compared the grades of the users in two groups to evaluate their methods.

Although online experiments provide the most reliable results about the method and assisting to prevent users' dissatisfaction, these evaluations are time consuming and have a high performance cost.

5.4. User study

Another type of evaluation is the user study, which can be used as a complement to online evaluation. In this type of evaluation, a controlled experiment is performed by asking a group of users to perform a set of predefined tasks. This evaluation enables us to analyze the users' interactions with a method. It also allows us to collect both quantitative and qualitative information about the method. In order to collect the qualitative information, we might use the questionnaires and ask the users to answer some questions like "Did you have enough time to follow the path?" or "Do you think the presented task was easy to complete?", etc. These questions can be asked before, during and after completing a task. The quantitative information, such as time to perform a task, can be collected based on the quantities achieved for a task (Ricci, Rokach, & Shapira, 2011; Shani & Gunawardana, 2011).

As mentioned above, distributing questionnaires among the users in order to report on their experiences, is one of the main methods to conduct the user study. It facilitates collecting information about the users' experiences with the method. For example, in Li et al. (2012), the researchers designed a questionnaire that is composed of five questions (questions are in a five-point scale) to evaluate the users' satisfaction. Their evaluation was conducted in two stages. In the first stage, the feedback information from 41 users was collected to adjust the difficulty level of LO. In the second stage, after adjusting the difficulty level of LO, the feedback from 62 users, who did not participate in the first stage, was collected. In 2011, Klašnja-Milićević et al. evaluated the users' satisfaction regarding four main features of their system (speed, accuracy, adaptive, convenience) by means of a non-mandatory questionnaire (Klašnja-Milićević et al., 2011).

Although user studies might provide information about aspects that are hard to evaluate, such as users' satisfaction, these experiments have several drawbacks. First, user studies are costly to conduct both in terms of time and money. Second, due to the difficulty and high cost, normally user studies are conducted on a small portion of the users and tasks. Therefore, the results of user studies cannot be trustable and generalized for all the users. To overcome this problem, the population size of the experiment should be large enough to represent the users of the method in a real environment (i.e. represent a real situation). Selecting such a population to perform the experiments is not a trivial task.

5.5. Summary of evaluation methods

This section details techniques and methods that are applied to evaluate the learning path personalization methods. They can be

Table 3
The evaluation methods used in studies (mainly since 2010). Column "Type" shows the personalization methods (CG, SPR, CS) used in the studies.

Ref.	Type	Offline	Performance	Online	User study	Ref.	Type	Offline	Performance	Online	User study
(Dwivedi et al., 2018)	CG			✓		(Zhu et al., 2018)	CG		✓		
(Shi et al., 2020)	CG			✓	✓	(Cun-Ling et al., 2019)	CG		✓	✓	✓
(Zhou et al., 2018)	CG	✓	✓			(Krauß et al., 2018)	CG	✓			
(Ye et al., 2018)	CG			✓		(Nabizadeh et al., 2018)	CG	✓	✓		
(Belacel et al., 2014)	CG					(Yang et al., 2010)	CG				
(Li et al., 2016)	CG		✓			(Carchiolo et al., 2010)	CG		✓		
(Adorni & Koceva, 2016)	CG					(Garrido et al., 2012)	CG		✓		✓
(Durand et al., 2013)	CG		✓			(Nabizadeh et al., 2017)	CG	✓	✓		
(Garrido et al., 2013)	CG		✓		✓	(Alian & Jabri, 2009)	CG		✓		
(Yang et al., 2014)	CG		✓		✓	(Tam et al., 2012)	CG		✓		
(Hwang et al., 2010)	CG		✓	✓	✓	(Durand et al., 2011)	CG				
(Tam et al., 2014)	CG		✓			(Suazo et al., 2012)	CG				✓
(Kardan et al., 2014)	CG					(Essalmi et al., 2010)	CG				✓
(Dharani & Geetha, 2013)	CG		✓	✓		(Fournier-Viger et al., 2010)*	SPR				✓
(Wilkowski et al., 2014)	CG			✓	✓	(Wang & Zaïane, 2018)	SPR		✓	✓	
(Yang et al., 2010)	CG				✓	(Klašnja-Milićević et al., 2011)	SPR	✓	✓	✓	
(Xu et al., 2016)	CG		✓	✓		(Vesin et al., 2013)	SPR			✓	✓
(Lin et al., 2013)	CG			✓		(Yarandi et al., 2013)	CS				
(Xie et al., 2017)	CG			✓	✓	(Li et al., 2012)	CS		✓		✓
(Janssen et al., 2010)	CG		✓		✓	(Garrido & Onaindia, 2013)	CS		✓		✓
(Sivakumar & Praveena, 2015)	CG			✓		(Ullrich & Melis, 2010)	CS				✓
(Yang et al., 2013)	CG			✓	✓	(Govindarajan et al., 2016)	CS		✓	✓	
(Chi, 2010)	CG					(Xu et al., 2012)	CS			✓	
(Bhaskar et al., 2010)	CG					(Colace et al., 2014)	CS			✓	
(Basu et al., 2013)	CG					(Salahli et al., 2013)	CS		✓		
(Feng et al., 2010)	CG			✓		(Yang et al., 2012)	CS		✓	✓	
(Gordón et al., 2015)	CG					(Rafsanjani, 2018)	CS	✓	✓	✓	✓
(Zaporozhko et al., 2018)	CG		✓			(Xi et al., 2018)	CS	✓	✓		
(Segal et al., 2019)	CG		✓	✓		(Vanitha et al., 2019)	CS		✓	✓	✓
(Christudas et al., 2018)	CG		✓	✓	✓	(Nabizadeh et al., 2020)	CS	✓	✓	✓	✓
(Xia et al., 2019)	CG				✓	(Li & Zhang, 2019)	CS	✓			
(Liu & Li, 2020)	CG	✓				(Cai et al., 2019)	CS	✓	✓		
(Niknam & Thulasiraman, 2020)	CG			✓		–	–	–	–	-	–

* We consider the proposal that is illustrated in the context of CanadarmTutor.

categorized in four different groups, which are offline, system performance, online and user study. Table 3 shows which evaluation methods are used for different types of learning path personalization methods (CG,SPR,CS). This table summarizes the evaluation methods of 58 different studies with respect to their path personalization methods and shows that the system performance evaluations were applied frequently, while offline experiments were applied less than all the other evaluation types. In fact, offline methods do not provide reliable results since they assume students' behavior does not change with time, which in reality it is not the case. In addition, this table shows that 17 % of the studies (10 papers) did not apply any types of evaluation. It may be the case that authors of these studies had no access to a public source of data, which could be fitted to their experiments (E-learning datasets are often private).

Finally, as shown in Table 3, most studies used different combinations of the evaluation methods to assess the quality of their path personalization approaches. This suggests that none of the evaluation methods is guaranteed to provide trustable results. Fig. 9 presents the proportion of evaluation methods used by researchers per year.

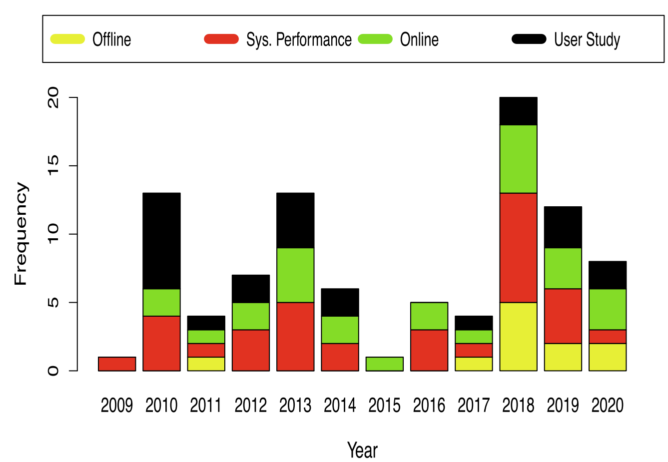

Fig. 9. Proportion of evaluation methods per year.

6. Challenges

Although there are several studies that were conducted on learning path personalization methods, such as Adorni and Koceva (2016), Nabizadeh et al. (2015), Vesin et al. (2013), Fournier-Viger et al. (2010), Li et al. (2012) and Yarandi et al. (2013), there are still a set of limitations and challenges with regard to these methods. Introducing these challenges can help researchers addressing current drawbacks and give rise to significant results. We previously mentioned several challenges and difficulties regarding path personalization methods, but in this section we present additional challenges, which we consider important for the development of the research on these methods.

6.1. Users' time restrictions

One of the main users' requirements is to learn a path that they are able to timely complete. Fulfilling this requirement and recommending such paths becomes more challenging when a user is not able to devote enough time to learn a path. Due to various reasons, a user might not be able to allocate enough time to follow an entire path. Some of the main reasons are: multitasking, being lazy, mismanaging time, etc. Therefore, in a situation where a user does not have enough time to learn the entire path, he/she faces two main questions:

1. What am I able to learn from a path in my limited time?
2. Do the learning outcomes (e.g. score) justify the time that I spend?

Hence, we require a path personalization method that takes into account the users' time constraints. There are a few studies that consider this limitation, such as Garrido et al. (2013), Li et al. (2016) and Xu et al. (2016). CourseNavigator (Li et al., 2016), which was proposed in 2016, is able to generate deadline driven paths. In this method, given a deadline by a user, the method generates a path that consists of a sequence of semesters, each semester presenting a number of courses that the user needs to take regardless of the time that each course might take in that semester. Similarly, Xu et al. proposed a method to generate a sequence of courses for a user given a time-to-completion (Xu et al., 2016). In Durand et al. (2011), the researchers introduced a system that recommends a path taking into account the time constraint of a user. In this study, the available time of a user is represented in minutes.

Despite addressing the users' time restrictions, in the aforementioned studies the learning time of a LO or a course is often assigned by an expert and is fixed for all users. Hence, estimating a learning time for a LO or a course taking into account the users' responses and abilities can help generate more efficient paths for the limited time of the users.

6.2. Scalability

The amount of data used as input to the learning path personalization methods is growing, as more users and LO are added. Subsequently, the size of stored users' interactions data can be large. This is particularly the case with Massive Open Online Course (MOOC) (Hoy, 2014), which aims at increasing the participation in open web courses. Despite the large amount of data, the path personalization methods aim to respond quickly in order to keep users engaged. Therefore, a key challenge is designing scalable methods that can cope with the large scale datasets. Although scalability is one of the main problems in learning path personalization methods, it is addressed only by a few studies, such as Durand et al. (2013), Garrido et al. (2012) and Garrido et al. (2013).

In path personalization methods, scalability is often measured by checking a method's responses and resources consumption during the scaling up task (i.e. increasing the number of LO and users) (Garrido & Onaindia, 2013; Durand et al., 2013). For example, Garrido et al. evaluated the scalability of their method by generating paths with 1, 2, 4, 8, 16, 32 and 64 users while measuring the running time (Garrido et al., 2013). In Garrido et al. (2012), the researchers assessed the scalability by estimating the time that a CPU required to obtain the paths. As another example, we can refer to Durand et al. (2013), where the researchers measured the average calculation time for learning paths given a set of LO.

Although researchers often measure the technical effects of the scalability on the methods, such as running time of the methods, it is significant to measure the side effects that the scalability imposes on the methods, such as its influence on the accuracy of the recommendations. Such analysis provides valuable information for future research direction.

6.3. Updating users' profiles

The users' progresses, abilities and preferences might change during the learning process. In addition, some of the users' characteristics, such as their knowledge level, cannot always be identified precisely in advance, and their actual values can be exposed during the learning process. Therefore, the users' profiles should be updatable, taking into account the users' responses and changes during the learning process. This would enable us to generate paths that fit the users' requirements.

There are methods, such as the CS methods, that update the users' profiles during the learning process (CS methods are explained in Section 4.2). These methods apply explicit or implicit feedback to update the users' profiles. Implicit feedback is derived from the users' interactions with the path personalizer, such as the time that a user spends on a LO, or which LO are not selected by the user. Although the information that the implicit feedback provides cannot be obtained explicitly, the implicit feedback is more difficult to collect than the explicit one. Explicit feedback is obtained through the users' rates and comments. In spite of being easy to collect, it does not always represent the actual information about a user. Therefore, it is a nontrivial task to determine which type of feedback can be more useful to update the users' profiles.

Besides the ones mentioned, there are other challenges when updating the profiles of the users. Some of these challenges are represented in the questions that are listed below:

1. When does a user profile need to be updated? Should it happen after the same amount of time for all users or does it depend on the user? Determining the updating time is a challenging task since evaluating a user and updating his/her profile frequently is time consuming and might not be necessary, while delaying it might result in recommending improper LO (not fit to that user), which causes misleading the user and wasting his/her time.
2. Which information in a user's profile needs to be updated?
3. Do the updated users' characteristics have the same importance when generating recommendations? Is there a ranking (weight) among them?
4. How can we check the validity of the updated information?

6.4. Course graph

In current studies, a course is often designed manually, in a difficult and time consuming task. A course, which is designed by a teacher, is a static graph, not changeable, and it will be the same (regarding graph topology, weights for edges and nodes, etc.) for all users. This means we have a graph that is **teacher – centered** rather than **user – centered** (Ahmed, 2013). The **teacher – centered** design can be problematic, since the way that the users follow the LO/lessons/courses might be different from the paths that the teacher designed. Therefore, it is of interest to design a course taking into account the collected information from the users, including the one collected from the users' interactions with the path personalizer (i.e. similar to the SPR methods where a path is generated considering the users' transactions).

6.5. General evaluation framework

Due to various reasons, the evaluation is always a challenging task in learning path personalization methods. One reason is the lack of a general evaluation framework that would allow us to compare different learning path personalization methods. Such evaluation framework should include an overall guidance on data sources and principles to conduct a reliable evaluation. In particular, it should include information about:

1. Evaluation objectives and questions:
   - What is the main purpose of the evaluation?
   - What questions it needs to address?
2. Evaluation measures:
   - What metrics should be used?
3. Data sources:
   - Which kind of datasets should be used for a certain evaluation?
   - What are the features of a reliable source of data (i.e. having a certain number of students, LO, transactions, etc.)?
   - What are the available datasets?
4. Online experiment requirements:
   - How should an online experiment be conducted (e.g. number of students, what items need to be considered during the experiment)?
5. Data analysis strategy:
   - How should the results be analyzed, discussed and elaborated?
   - How should the results of different studies be compared?
6. Presenting results methodology:
   - How the results need to be presented?

As mentioned above, an evaluation framework should include information about reliable public datasets that can be used for evaluating the learning path personalization methods. The current datasets are often proprietary and cannot be released due to privacy concerns. Therefore, they cannot be used as benchmark. The availability of such datasets can facilitate having a general evaluation framework and would allow researchers to compare their methods accurately.

Although a general evaluation framework would assist researchers in having trustable and reliable evaluation results, evaluating would still be a time consuming task with a high cost since personalization needs to be evaluated with real users in a live environment.

7. Conclusion

In this paper, we have described learning path personalization methods along with their advantages, disadvantages, evaluation techniques, and the terminology used in these methods. In addition, we pointed out the most significant challenges of these methods, which must be addressed to enhance the quality of path personalization methods. This review paper enables the promotion of the discussion of these topics and to serve as a resource for researchers working in this area.

Although we have not focused specifically in MOOC based e-learning platforms, we understand that this is a fast growing trend that may justify a future extension of this work. We also have not considered work dimensions such as the incremental versus batch nature of the update of models and taking into account the dynamics of user profiles.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Summarized studies

In this section, we have summarized the papers that we used in this study (Table A.4). Take into consideration that this information was collected until the beginning of May 2020. In Table A.4, column "Country" refers to the country of the first author. Furthermore, in this table, the learning goal (one of the personalization parameters) is ignored since all papers have learning goals, and only the type of goal might be different. Our goal by presenting this table is to provide a brief summary and a clear view of all summarized studies (all information in a single table), which leads to have a better and quicker comparison among studies. Also, by looking at

Table A.4
Summarized papers.

No.	Ref.	Type	Main techniques/algorithms/tools	Evaluation methods			
				Offline	Performance	Online	User study
1	(Dwivedi et al., 2018)	CG	Evolutionary algorithm (variable length genetic algorithm), Felder & Silverman index	–	–	✓	–
2	(Zhu et al., 2018)	CG	Depth First Traversal Algorithm, Edit distance algorithm	–	✓	–	–
3	(Zhou et al., 2018)	CG	Clustering method (Rafsanjani, 2013; Rafsanjani et al., 2013), LSTM (Long short-term memory) neural network	✓	✓	–	–
4–5	(Krauß, 2018; Krauß et al., 2018)	CG	Course graph, Zografos and Androutsopoulos algorithm (Zografos & Androutsopoulos, 2008)	✓	–	–	–
6	(Ye et al., 2018)	CG	Ant colony, Analytic Hierarchy Process (AHP), K-means algorithm	–	–	✓	–
7	(Nabizadeh et al., 2018)	CG	Item Response Theory, Depth First Search algorithm, Probability of Error for learning time and score	✓	✓	–	–
8	(Belacel et al., 2014)	CG	Branch and bound algorithm	–	–	–	–
9	(Li et al., 2016)	CG	Graph search algorithm	–	✓	–	–
10	(Adorni & Koceva, 2016)	CG	Educational Concept Map (ECM), ENCODE (linearize the map)	–	–	–	–

Table A.4 (*continued*)

No.	Ref.	Type	Main techniques/algorithms/tools	Evaluation methods			
				Offline	Performance	Online	User study
11	(Durand et al., 2013)	CG	Greedy algorithm	–	✓	–	–
12	(Garrido et al., 2013)	CG	PDDL, HTN, Non–HTN	–	✓	–	✓
13	(Yang et al., 2014)	CG	Bloom's taxonomy	–	✓	–	✓
14	(Hwang et al., 2010)	CG	RFID,repertory grid-oriented technique, Heuristic Algorithm	–	✓	✓	✓
15	(Tam et al., 2014)	CG	Explicit Semantic Analysis, Evolutionary algorithm + hill climbing, Clustering	–	✓	–	–
16	(Kardan et al., 2014)	CG	ant-colony (ACO-Map), Ausubel Meaningful Learning Theory, Clustering	–	–	–	–
17	(Dharani & Geetha, 2013)	CG	Case Based Reasoning (CBR), Colored Petri Nets, Classification	–	✓	✓	–
18	(Yang et al., 2010)	CG	Bloom's taxonomy	–	–	–	✓
19	(Xu et al., 2016)	CG	Clustering, Multi-armed bandits	–	✓	✓	–
20	(Lin et al., 2013)	CG	Decision tree classifier, feature weighting, feature selection	–	–	✓	–
21	(Xie et al., 2017)	CG	Topic graph extraction, group profiling, estimating time boundaries	–	–	✓	✓
22	(Janssen et al., 2010)	CG	Search engine	–	✓	–	✓
23	(Sivakumar & Praveena, 2015)	CG	Ant Colony Optimization algorithm (ACO)	–	–	✓	–
24	(Yang et al., 2013)	CG	Learning and Cognitive styles	–	–	✓	✓
25	(Chi, 2010)	CG	Domain ontology, Problem-solving ontology, Semantic rules	–	–	–	–
26	(Bhaskar et al., 2010)	CG	Genetic algorithm	–	–	–	–
27	(Basu et al., 2013)	CG	Greedy algorithm	–	–	–	–
28	(Feng et al., 2010)	CG	Topic graph extraction, group profiling, estimating time boundaries	–	–	✓	–
29	(Yang et al., 2010)	CG	Felder learning style, Broad first searching (BFS), 3-dimension semantic map	–	–	–	–
30	(Carchiolo et al., 2010)	CG	Peer-to-peer (P2P) networks	–	✓	–	–
31	(Garrido et al., 2012)	CG	PDDL, Case-Based Planning (CBP)	–	✓	–	✓
32	(Nabizadeh et al., 2017)	CG	Depth first search (DFS)	✓	✓	–	–
33	(Alian & Jabri, 2009)	CG	Weighted Graph, Eliminating and Optimized Selection (EOS)	–	✓	–	–
34	(Tam et al., 2012)	CG	Explicit semantic analysis, Genetic algorithm, Clustering(K-means)	–	✓	–	–
35	(Durand et al., 2011)	CG	Markov Decision Process	–	–	–	–
36	(Suazo et al., 2012)	CG	Bayesian network, Clustering	–	–	–	✓
37	(Essalmi et al., 2010)	CG	Personalization strategy	–	–	–	✓
38	(Zaporozhko et al., 2018)	CG	Genetic algorithm, MOOC, Vark Methodology	–	✓	–	–
39	(Gordón et al., 2015)	CG	User disability, MOOC	–	–	–	–
40	(Wilkowski et al., 2014)	CG	Google Map, Google Earth, MOOC	–	–	✓	✓
41	(Christudas et al., 2018)	CG	Compatible Genetic algorithm (CGA), Maximum Likelihood Estimation (MLE), Particle Swarm Optimization Algorithm and Genetic algorithm (are used for comparison)	–	✓	✓	✓
42	(Segal et al., 2019)	CG	EduRank, Voting method, Collaborative filtering system	–	✓	✓	–
43	(Shi et al., 2020)	CG	Graph traversal algorithm, Knowledge graph, Cohen kappa coefficient	–	–	✓	✓
44	(Cun-Ling et al., 2019)	CG	Graph Theory, Improved Immune Algorithm (IIA), Felder-Silverman	–	✓	✓	✓
45	(Xia et al., 2019)	CG	Markov chain, Learning scenarios	–	–	–	✓
46	(Liu & Li, 2020)	CG	Complex network theory, MOOC	✓	–	–	–
47	(Niknam & Thulasiraman, 2020)	CG	Fuzzy C-Mean (FCM) Clustering algorithm, Ausubels learning theory, Ant colony optimization algorithm (ACO)	–	–	✓	–
48	(Wang & Zaïane, 2018)	SPR	Process mining, Dependency graph (association rule mining), Sequential pattern mining (PrefixSpan), Casual footprint approach for conformance checking	–	✓	✓	–
49	(Fournier-Viger et al., 2010)	SPR	Sequential pattern mining (invented algorithm)	–	–	–	✓
50	(Klašnja-Milićević et al., 2011)	SPR	Clustering, AprioriAll	✓	✓	✓	–
51	(Vesin et al., 2013)	SPR	Clustering, Collaborative filtering (Rafsanjani et al., 2013), Association rule mining	–	–	✓	✓
52	(Rafsanjani, 2018)	CS	Item Response Theory (IRT),Matrix Factorization (Nabizadeh et al., 2016), Two-Layer course graph, Probability of error for learning time and score, Depth First Search	✓	✓	✓	✓

(*continued on next page*)

Table A.4 (*continued*)

No.	Ref.	Type	Main techniques/algorithms/tools	Evaluation methods			
				Offline	Performance	Online	User study
53	(Yarandi et al., 2013)	CS	Item Response Theory (IRT)	–	–	–	–
54	(Li et al., 2012)	CS	Collaborative Voting, Maximum Likelihood Estimation, Evolutionary algorithms (GA,PSO)	–	✓	–	✓
55	(Garrido & Onaindia, 2013)	CS	PDDL, Constraint Satisfaction Problem (CSP)-based scheduling	–	✓	–	✓
56	(Ullrich & Melis, 2010)	CS	Learning scenario selection, HTN	–	–	–	✓
57	(Govindarajan et al., 2016)	CS	Evolutionary algorithm (PPSO), Clustering, Bloom's taxonomy	–	✓	✓	–
58	(Xu et al., 2012)	CS	Bayes formula, Pearson Correlation Coefficient (KNN), feature weighting	–	–	✓	–
59	(Colace et al., 2014)	CS	Functions to estimate the closeness of each LO to a user's profile, Ontology	–	–	✓	–
60	(Salahli et al., 2013)	CS	Item Response Theory (IRT), Law of Total Probability (LPT)	–	✓	–	–
61	(Yang et al., 2012)	CS	Association Link Network (ALN), TFIDF Direct Document Frequency of Domain (TDDF)	–	✓	✓	–
62	(Xi et al., 2018)	CS	Linear Regression Algorithm, Matrix Factorization, MOOC	✓	✓	–	–
63	(Vanitha et al., 2019)	CS	Ant Colony Optimization (ACO), Genetic Algorithm	–	✓	✓	✓
64	(Nabizadeh et al., 2020)	CS	Item Response Theory (IRT),Matrix Factorization, Two-Layer course graph, Probability of error for learning time and score, Depth First Search	✓	✓	✓	✓
65	(Li & Zhang, 2019)	CS	Network embedding, Learning effects, Width first search, Depth first search, Random walk	✓	–	–	–
66	(Cai et al., 2019)	CS	Knowledge tracing model, Reinforcement learning, neural network, Markov Decision Process	✓	✓	–	–

No.	Ref.	Recommendation strategy	Personalization parameters				Year	Citation	Country
			Time	Mastery level	Style	Know. Background			
1	(Dwivedi, Kant, and Bharadwaj, 2018)	A path with the highest fitness function value having the correct topological order	–	✓	✓	–	2018	2	India
2	(Zhu et al., 2018)	Recommending a user's required path (7 different types) for a learning scenario (4 scenarios)	✓	–	–	✓	2018	4	China
3	(Zhou, Huang, Hu, Zhu, and Tang, 2018)	Recommending a path the matched a user's features	–	–	✓	✓	2018	15	China
4–5	(Krauß, 2018; Krauß, Salzmann, and Agathe, 2018)	Recommending top-N paths between starting and target points with different branches	–	–	–	–	2018	2	Germany
6	(Ye et al., 2018)	Recommending a path using act colony algorithm	–	✓	✓	✓	2018	0	China
7	(Nabizadeh, Jorge, and Leal, 2018)	A path that maximizes a user's score under a limited time	✓	✓	–	✓	2018	1	Portugal
8	(Belacel et al., 2014)	Shortest path (number of competency)	–	✓	–	–	2014	10	Canada
9	(Li et al., 2016)	Deadline driven, Goal driven, Ranked driven	✓	–	–	–	2016	4	USA
10	(Adorni and Koceva, 2016)	Minimizing the number of LO	–	✓	✓	✓	2016	4	Italy
11	(Durand et al., 2013)	Shortest path (number of competency)	–	✓	–	–	2013	39	Canada
12	(Garrido et al., 2013)	Maximizes the total reward without exceeding a user's time	✓	–	✓	–	2013	15	Spain
13	(Yang, Li, and Lau, 2014)	It is a path generation method that formulates learning activities and their assessment criteria using the Bloom's taxonomy.	–	✓	–	–	2014	24	HongKong
14	(Hwang, Kuo, Yin, and Chuang, 2010)	Minimizing the relevance loss between consecutive LO along a path	–	–	–	–	2010	187	Taiwan
15	(Tam, Lam, and Fung, 2014)	Minimizing the sum of the violated distances regarding the reference paths	–	–	–	–	2014	11	HongKong
16	(Kardan et al., 2014)	Shortest path	–	–	–	–	2014	14	Iran
17	(Dharani and Geetha, 2013)	Finding similar solution regarding learning style, goal and performance	–	✓	✓	–	2013	8	India
18	(Yang, Li, and Lau, 2010)	It is a path generation method that formulates learning activities and their assessment criteria using the Bloom's taxonomy.	–	✓	–	–	2010	20	UK

Table A.4 (*continued*)

No.	Ref.	Recommendation strategy	Personalization parameters				Year	Citation	Country
			Time	Mastery level	Style	Know. Background			
19	(Xu et al., 2016)	Minimizing the graduation time while maximizing the overall GPA	✓	✓	–	✓	2016	19	USA
20	(Lin et al., 2013)	Maximizing users' creativity	–	–	–	–	2013	108	Taiwan
21	(Xie et al., 2017)	Minimizing learning time and Maximizing the learning enjoyment	✓	–	–	✓	2017	9	HongKong
22	(Janssen et al., 2010)	Finding a path that meets a user criteria (e.g. start point)	–	✓	–	–	2010	7	Netherlands
23	(Sivakumar and Praveena, 2015)	Optimizing path regarding users' ability, goals and behavior	–	✓	–	–	2015	1	India
24	(Yang et al., 2013)	Paths that match the cognitive and learning styles of users	–	–	✓	–	2013	147	Taiwan
25	(Chi, 2010)	Generating path regarding a given criteria (competencies)	–	✓	–	–	2010	25	Taiwan
26	(Bhaskar et al., 2010)	Maximizing fitness value (consists of 3 fitness values)	–	–	✓	–	2010	27	India
27	(Basu et al., 2013)	Path satisfies users limitation (time) and preferences.	✓	–	–	–	2013	5	India
28	(Feng et al., 2010)	Minimizing learning time while considering users preferences	✓	–	✓	✓	2010	7	China
29	(Yang et al., 2010)	Path satisfies users learning style.	–	–	✓	–	2010	8	China
30	(Carchiolo et al., 2010)	Generating paths that satisfy a user's time and difficulty level	✓	✓	–	–	2010	45	Italy
31	(Garrido et al., 2012)	Minimizing the number of changes w.r.t. to a similar path in library	–	–	✓	✓	2012	29	Spain
32	(Nabizadeh et al., 2017)	Maximizing users score under his/her time restriction	✓	–	–	✓	2017	5	Portugal
33	(Alian and Jabri, 2009)	Shortest path on a weighted graph	✓	✓	✓	✓	2009	24	Jordan
34	(Tam et al., 2012)	Minimizing the number of precedence rules violated by the path	–	–	–	–	2012	17	HongKong
35	(Durand et al., 2011)	Maximizing reward while minimizing the number of LO	–	✓	✓	–	2011	20	Canada
36	(Suazo et al., 2012)	Recommending activity with the highest probability	–	✓	–	–	2012	3	Costa Rica
37	(Essalmi et al., 2010)	Matching user' characteristics with the LO features	–	✓	✓	✓	2010	146	Tunisia
38	(Zaporozhko, Bolodurina, and Parfenov, 2018)	Building an optimal path considering a user's possibilities and features	–	–	✓	–	2018	1	Russia
39	(Gordón et al., 2015)	Adapting course content to students' needs, preferences, skills and situations	–	–	✓	–	2015	25	Spain
40	(Wilkowski, Deutsch, and Russell, 2014)	Providing instant feedbacks to users according to their mastery level and desired goal	–	–	–	✓	2014	90	USA
41	(Christudas, Kirubakaran, and Thangaiah, 2018)	Recommending a path considering the learning style, knowledge level and interactivity level of a user	–	✓	✓	–	2018	23	India
42	(Segal, Gal, Shani, and Shapira, 2019)	Recommending a sequence of questions by increasing order of difficulty to users considering their performances	–	✓	–	–	2019	15	China
43	(Shi, Wang, Xing, and Xu, 2020)	Generating all paths considering the students' learning objective and learning need, and recommending the one with the highest score.	–	–	–	–	2020	0	China
44	(Cun-Ling et al., 2019)	Recommending a path that improves the students learning outcomes considering their learning style, goal, and knowledge background.	–	–	✓	✓	2019	0	China
45	(Xia et al., 2019)	Recommending a customized sequence of questions to individual learners, based on the exercise history of other users in a similar learning scenario.	–	✓	–	–	2019	1	China
46	(Liu and Li, 2020)	Paths are made in 3 different scenarios based on learning history (records) and learners' similarity.	–	–	–	–	2020	0	China
47	(Niknam and Thulasiraman, 2020)	Clustering the learners into groups and selects a path for learners based on their prior knowledge.	–	✓	–	✓	2020	0	Canada
48	(Wang and Zaïane, 2018)	Recommending a sequence of courses that positively influence GPA (increasing) and graduation time (decreasing)	–	✓	–	–	2018	2	China
49	(Fournier-Viger et al., 2010)	Successful paths that satisafy the initial and end point of a user	–	✓	–	–	2010	16	Canada
50	(Klašnja-Milićević et al., 2011)	Maximizing the sequences' rate while reducing the info redundancy	–	✓	✓	–	2011	393	Serbia
51	(Vesin et al., 2013)	Maximizing success rate of sequences while reducing the info redundancy	–	✓	✓	✓	2013	38	Serbia
52	(Rafsanjani, 2018)	Recommending a path that maximizes a user's score under a given time	✓	✓	-	✓	2018	1	Portugal
53	(Yarandi et al., 2013)	Recommending LO that fits the user's ability	–	✓	✓	–	2013	43	UK

(*continued on next page*)

Table A.4 (*continued*)

No.	Ref.	Recommendation strategy	Personalization parameters				Year	Citation	Country
			Time	Mastery level	Style	Know. Background			
54	(Li et al., 2012)	Matching a user's ability while considering his/her time limitation	✓	✓	–	–	2012	32	Taiwan
55	(Garrido and Onaindia, 2013)	Minimizing the length of a path while maximizing the learning reward	–	–	–	✓	2013	34	Spain
56	(Ullrich and Melis, 2010)	Matching preferred learning scenario of a user and his/her goal	–	✓	–	–	2010	21	China
57	(Govindarajan et al., 2016)	Fitting user's need and proficiency level.	–	✓	–	–	2016	6	Canada
58	(Xu et al., 2012)	Recommending a LO with the highest probability	–	–	–	–	2012	5	China
59	(Colace et al., 2014)	Matching users' characteristics with the relative parameters of LO	✓	✓	✓	–	2014	55	Italy
60	(Salahli et al., 2013)	Matching the understanding degree of users with the difficulty level of LO	–	✓	–	–	2013	7	Turkey
61	(Yang et al., 2012)	Matching the users knowledge level with the complexity of LO	–	✓	–	–	2012	2	UK
62	(Xi, Chen, and Wang, 2018)	Provide adjustable path to learners considering their behaviors and needs	–	✓	–	✓	2018	3	China
63	(Vanitha, Krishnan, and Elakkiya, 2019)	Recommending a path considering the emotion and cognitive ability of a user	–	✓	–	–	2019	0	India
64	(Nabizadeh et al., 2020)	Recommending a path that maximizes a user's score under a given time	✓	✓	-	✓	2020	1	Portugal
65	(Li and Zhang, 2019)	Using the similarity of users and the learning effect of historical users to continuously recommend the unselected courses with the highest score to a user.	–	–	✓	–	2019	0	China
66	(Cai et al., 2019)	Recommending the optimal path considering the requirements of each knowledge point during the learning process.	–	✓	–	–	2019	0	China

this table readers can check, which countries are investing more on learning path personalization methods while monitoring the impact of each study using its citations.

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