eISSN 2783-6851

VILNIUS TECH
Vilnius Gediminas Technical University

NEW TRENDS in COMPUTER SCIENCES

2023
Volume 1
Issue 1
Pages 32–50
https://doi.org/10.3846/ntcs.2023.18278

GENERATION OF A LEARNING PATH IN E-LEARNING ENVIRONMENTS: LITERATURE REVIEW

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Article History:
- received 12 December 2022
- accepted 14 March 2023

Abstract. Education is moving into an e-learning environment, displacing contact and face-to-face learning. However, current e-learning environments cannot still personalise when creating e-learning paths. Identifying existing solutions' problems and limitations is critical to generate new, more advanced ideas for creating personalised e-learning paths. The literature analysis, for which 28 articles for 2018–2022 were used, describes the existing solutions used to adapt and optimise e-learning. The article provides an overview of existing research in the field of personalisation of e-learning systems and the creation of e-learning trajectories, proposes the development of a taxonomy of studied methods for recommending and forming individual learning trajectories, analysis of the practices described in the articles to identify the most commonly used of them. Limitations, problems and unresolved issues in previous studies are summarised and provide information for further work on improving the results obtained and for choosing the direction of future research, which is given in the final part of the article.

Keywords: adaptive e-learning, personalisation, e-learning path generation, optimisation, literature review.

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Introduction

Individual tutoring is usually better than teaching many students at once. Traditional e-learning systems are an analogue of teaching a massive group of students simultaneously. However, to achieve more effective e-learning, the students' experience and content must be adapted and personalised to achieve better learning results (Ramanauskaitė & Slotkienė, 2019).

According to Ramos et al. (2021), the current trend in adaptive e-learning is to make e-learning an analogue of individual learning rather than simultaneously teaching to a vast group. This can be achieved by generating individual learning paths for each student individually.

The information generated from Learning Management System (LMS) data can facilitate the teaching and learning process. LMS collects data about users that can help define the learner's profile and learner behaviour and identify their difficulties and needs. One way of accompanying learners is to observe the actions they perform on the system, and these actions can result in paths known as Learning Paths (LP) (Ramos et al., 2021). Possibilities for using learning path generation:

- drawing up a sequence of access to educational resources and classes, determined by teachers when planning a course;
- generation of a sequence considering the material covered by the students presented in the LMS.

The Learning Paths Generation (LPG) algorithm aims at the above limitations. It is based on the level of mastery of students in the concepts of computer science. It uses different methods to generate concept maps with different students' learning features and automatically generates learning paths. This is in accord with the characteristics of adaptive learning systems (Li et al., 2018).

An adaptive e-learning system is a system that takes into account students' learning performance and emphasises personalised learning. A vital component of an adaptive learning system is a recommendation system, which recommends the learner's following material (video lectures, practices, and so on, on different skills) (Chen et al., 2018). Adaptive learning allows each student to learn at his or her own pace. This is so that fast learners can skip the entire class, and slower learners have more time to digest the materials.

The engine of an adaptive e-learning system is a recommendation strategy that sequentially decides what to learn in the next step based on currently available information. Mastering one skill does not affect learning others. In any case, it can be assumed that educational materials can teach several skills or that mastering one skill may increase the likelihood of acquiring others. In such a system, the learner can only move on to a skill once all prerequisite skills are mastered (Li et al., 2018).

With the growth of learning resources, the workload of manually planning learning paths is increasing accordingly, which becomes a burden for experts and teachers. Therefore the generation of individual learning paths has to be automated. An individual learning path is understood as a personal strategy for the student's professional growth, the improvement of his/her personal qualities, and the formation of professional competencies, which are based on the recognition and subjectification of professional goals, values, norms, and recognition of the uniqueness of the individual as well as the creation of conditions for the realisation of its potential (Levanova et al., 2019).

Reasonably arranging the order of the learning objects to generate a well-defined learning path can help the e-learner complete the learning target efficiently and systematically. Learners may need more ability to integrate unstructured information meaningfully. With sufficient prior knowledge, learners may comprehend the concepts they need to learn. They could spend much browsing and sort through the information they find, leading to disorientation and anxiety.

Creating learning pathways automatically requires annotating the learning resources with semantically rich, standard, and recognised meta-data. This is usually seen in MOOCs (Massive Open Online Courses) or ITS/AEHS (Intelligent Tutoring System and Adaptive Educational Hypermedia Systems), where the learning resources are in closed settings and are most likely created and curated by a single source. Education stakeholders have no consensus on the standardisation and development of meta-data since it requires significant time and effort and is expensive (Diwan et al., 2019).

A clear understanding of and a vision for more advanced solutions is required for the wide variety of possible solutions and existing issues. Thus, this paper aims to structure the e-learning path generation research area so that existing solutions and unresolved issues can be better understood.

The structure of this paper appears as follows. Section 1 presents the methodology of the literature review, and Section 2 reviews related works and the development of taxonomies associated with Research Questions. Section 3 summarises the literature review results and discusses the remaining challenges. The conclusion is drawn at the end of the paper.

1. Methodology of the systematic literature review in the field of e-learning path generation

A literature review is very effective for considering the current topic. It is also helpful in searching for scientific publications on a selected topic and serves as a basis for further research. In the Systematic Review Standards (Cochrane, 2022), a systematic review is defined as "a review of the evidence on a formulated question that uses structured and explicit methods to identify, select and critically appraise relevant primary research, and to extract and analyse data from the studies that are included in the review". This literature review paper will use the systematic review approach, including the main steps for a systematic literature review.

1.1. Methodology for data source selection

To keep up with the latest research, publications were limited to 2018 to 2022. Earlier studies are reviewed and analysed in the articles of the selected period; the recent research period is also of more significant interest, given the rapid technology development and their wide use in education.

The initial phase of this study was planned as a live systematic review (Roth & Tagge, 2022). The data search was planned to be iterative and repetitive to update the archive of analysed research works. Based on the general data source search schema (see Figure 1), all data sources found by a defined search path are analysed and stored in an archive, indicating both relevant (active) and not relevant (passive) records.

The results of this paper are prepared based on the review, where data sources were gathered from February 2022 to December 2022. Multiple databases were used to select data sources: Web of Science, Scopus, ResearchGate, IEEE, IGI Global, Google Scholar, and conference pages with collections of articles with related content.

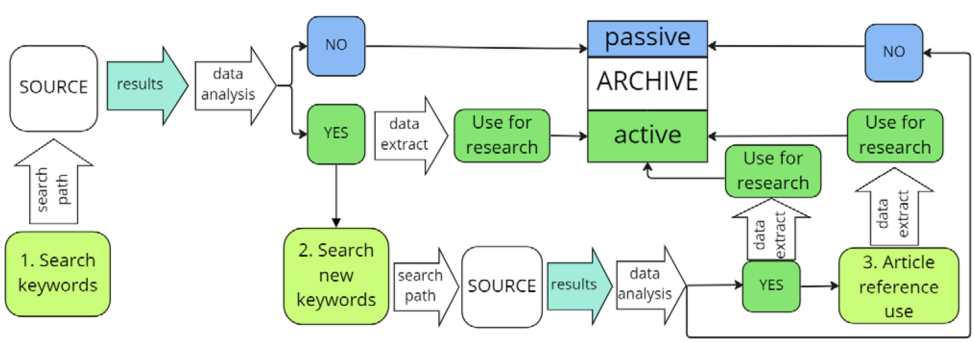

Figure 1. General scheme of systematic literature review data source searching and logging (source: article author)

In this review, the author applied the reverse snowball technique to search for keywords in titles, abstracts, and extended keyword sets (Kalibatienė & Miliauskaitė, 2021). The backward snowball technique makes it possible to find appropriate information until relevant papers are found.

The first set of keywords includes "e-learning" / "learning style" / "learning path" / "adaptive e-learning" / "knowledge graph" / "learning path optimisation" / "artificial intelligence".

The second keyword set was expanded and included "learning trajectories" / "Learning Management Systems" / "Student Behavior" / "learning-style recognition" / "artificial intelligence planning" / "clustering" / "automatic generation" / "machine learning". Various combinations of keywords and processed article references were also used in this study.

The author used all articles found to extract the data needed to organise the information following the topics of this study. After the article is found, the abstract is read first, and then the rest is reviewed to decide whether the article is included in the active or passive archive (Figure 1).

Articles found on the list of keywords used in the search engine were reviewed, and from all the articles selected for use in the study, articles that met the following criteria were chosen:

- articles published between 2018 and 2022;
- articles in English;
- articles on adaptive e-learning, automatic generation of learning paths, and individual learning paths;
- articles published in conference proceedings and scientific journals.

Exclusion criteria:

- books;
- PowerPoint presentations or publications;
- essays;
- posters;
- articles with inaccessible text;
- articles with no information about the authors, without specifying the resource of the publication.

In total, active articles were selected from the found resources (about 60 articles) for a detailed analysis of the requested topic, analysing their titles and abstracts and filtering them for the presence of complete text. The full text of 40 articles has been extracted for a comprehensive study and review. Finally, 28 articles met the eligibility criteria described in this paper and were included in this systematic review.

1.2. Methodology for data source analysis

The review of selected relevant topic papers began by identifying the main research questions (RQ):

- RQ1. What research has been carried out in the optimisation and adaptation of e-education?
- RQ2. What methods are used to make recommendations and generate an individual student learning path?
- RQ3. What are the limitations, challenges and unresolved issues in the conducted research for future work to improve the results obtained?

All active records meeting the filters were analysed and summarised to answer this study's research questions. The initial summarisation properties included basic metadata (Authors, publication year, used keywords, main idea, used technologies/solutions, achieved results, discussion summary). Analysing all the papers indicated additional properties by synthesising the paper ideas or results into more discrete categories and classes. The relations between those classes were also described. Therefore a taxonomy of research content for each research question was generated. All research papers were revised based on the taxonomies to map them to the taxonomy classes.

Using generated taxonomies allows a more aggregated presentation of the existing research papers in the context of the three research questions. So the final version of the literature review can be summarised and visualised in table format.

2. Review of related works and building of research question associated taxonomies

Even though the research questions in the paper are related, they are analysed from different perspectives. Therefore each of them was analysed separately and is presented as subsections of the section.

2.1. RQ1 – research in the field of optimisation and adaptation of e-education

Solutions for optimising e-education are applied and presented more widely in the research literature. Sanchez Nigenda et al. (2018) use the search for scalable systems that embrace more flexible standards for modelling learning and calculating more informed learning paths for students. According to Levanova et al. (2019), educational resources are complemented by the most potent information and telecommunication systems, as well as the media.

Authors Diwan et al. (2019) proposed a model for automatically creating consistent and pedagogically progressive learning paths for open educational resources. In the context of e-learning, Vanitha et al. (2019) offered personalised systems support for two types of adaptation: adaptive presentation with different content presented to the different learners and adaptive navigation support.

Wei et al. (2021) tested students' ability to learn and their learning behaviours according to educational psychology. Then characteristics of learning resources, such as degree of difficulty, were extracted, and a learning resource recommendation algorithm based on LinUCB was proposed.

Vagale et al. (2020) used their study of a personalised adaptive e-learning system based on a learner model. A student-centred approach to learning can be successfully implemented in a personalised educational system. Using this approach to learning raises the question of managing the student's learning process and following the recommended learning path within a customisable adaptive e-learning system.

It is necessary to consider learners' changing state to construct a personalised learning path (Jiang et al., 2022; Rasheed & Wahid, 2019). Navarro and Moreno-Ger (2018) propose using Learning Analytics (LA) educational datasets in open education. Zaoudi and Belhadaoui

(2020), Tavakoli et al. (2021) proposed personalised or adaptive e-learning by combining UBA (User Behaviour Analytics) and AI (Artificial Intelligence) to create an LBA model (Learning Behavior Analytics) based on a system called SBAN (Student Behavior Assessment and Analysis), and SBA (Student Behavior Analysis).

According to authors Shi et al. (2020), to accomplish the stated learning goal and create a well-defined learning path that helps learners complete the tasks, the goal of learning effectively and systematically requires that a large amount of fragmented learning content in e-learning is extracted and organised to meet the stated goals.

Ramos et al. (2021) propose a novel approach to learning trajectory models in e-learning systems using data from database records from the e-learning system and graphs to visualise learning trajectories, analyse behaviour, and help form groups for collaborative activities and, thus, help the teacher solve.

Knowledge graphs describe the characteristics of knowledge and learning resources, inspiring the development of learning paths (Gao et al., 2021). Moreover, authors Nabizadeh et al. (2020) describe two approaches to maximise users' scores maximise course while satisfying their time constraints. These approaches recommend successful paths based on users' available time and knowledge background.

Developing a multiobjective optimisation model as a knowledge-based recommender for a MOOC learning path that is common to all learning paths and can be applied to any online learning environment (Son et al., 2021).

The need to adapt training materials is becoming increasingly evident. Including professional teaching/education principles and an appropriate curriculum, such an e-learning environment can support extremely high-quality, student-centred educational programs for remote learners using the synchronous and asynchronous tools available to Internet technologies communications (Tseng et al., 2022). A fruitful e-learning infrastructure should be equipped with the ability to absorb the learning experience of users (Safitri et al., 2022) and use this information to recommend random users based on their experience and requirements and use AI to assess knowledge for educational researchers and practitioners and develop student models on various types of data with their challenges and potential solutions for a future ecosystem of adaptive e-learning environments (Minn, 2022).

For e-learning adaptation, Li et al. (2019) propose an algorithm for the automatic generation of e-learning paths LPG-algorithm based on concept maps for adaptive learning systems, on queries (Kausar et al., 2018), and on EEG signals (with Emotiv Systems) for effective learning style recognition (Zhang et al., 2021). A study by El-Sabagh (2021) showed that adaptive e-learning based on learning styles could help students stay engaged.

Ramanauskaitė and Slotkienė (2019) proposed a hierarchical structure of competencies in which a competency tree was developed to standardise and adapt the database of e-learning systems.

Using pedagogical agents to compensate for the lack of physical connection in the online environment of personalised adaptive e-learning systems (Apoki et al., 2022).

Ontology in adaptive e-learning technology (Rahayu et al., 2022), with developing a recommender system based on ontologies and recommender methods for such systems, qualitatively adapts e-learning.

E-learning systems (Xiao et al., 2022) provide a unique learning experience for each learner, with the proposal of a multiple attribute matching model (MAM) to describe the similarities between learner attributes and learning path attributes.

The landscape of the analysed papers for e-learning adaptation and optimisation research question answering can be summarised in a taxonomy presented in Figure 2. It can be divided into two prominent cases – adaptation (A) and optimisation (O). The principles of adaptation can be divided into three main classes:

- A1. Skills/knowledge. This class defines the e-learning environment according to the student's skills or knowledge. Mostly, it analyses/logs the student's skill/knowledge portfolio, and based on that, it adjusts the student's access to different material/sequences.
- A2. Learning style. Students' preferences for learning types were taken into account for this class. Styles are defined by Felder and Silverman (1988) and are identified by using the Soloman–Felder questionnaire (Felder & Soloman, 2022).
- A3. Personal properties. This class is mostly used in rule-based systems with limited learning material and student metadata. To adapt the content in such a case, it might be possible to adapt it based on factors such as students' age, education level, gender, or other characteristics.

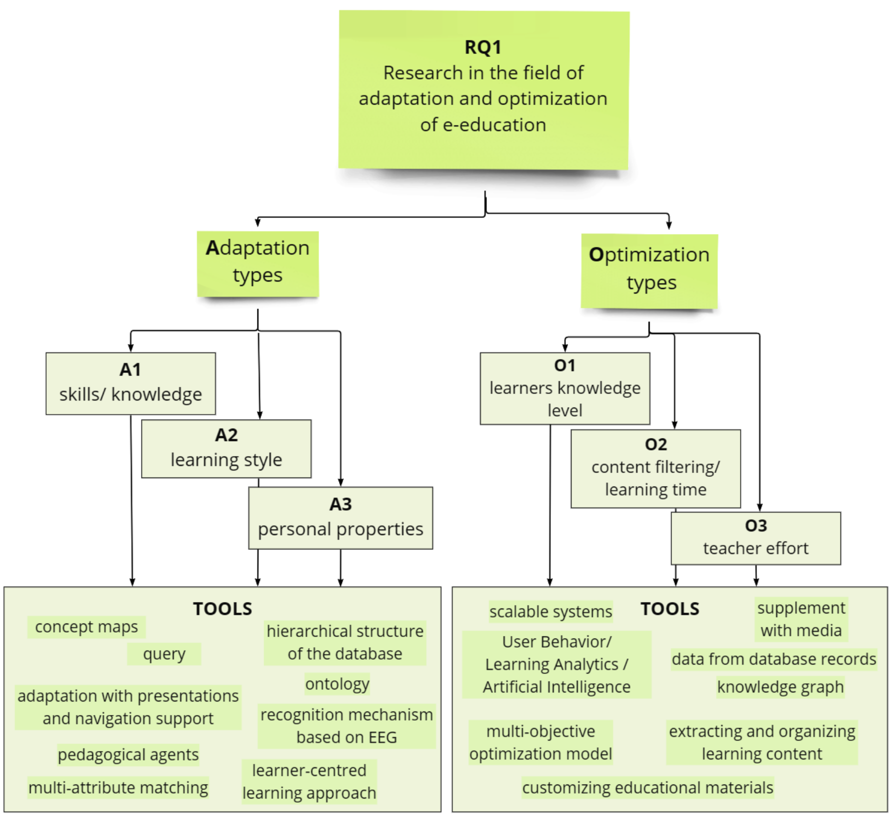

Figure 2. Taxonomy of RQ1-related classes (source: article author)

Meanwhile, the optimisation type may be divided into three classes, indicating what the aim of adaptive e-learning is:

- O1. Learner's knowledge level. This class is mostly oriented to accurate achievement/evaluation of students' knowledge. It is the main criterion when e-evaluation systems are analysed.
- O2. Content filtering/learning time. This class is mostly oriented on students learning time reduction. It solves the problem of reducing the redundancy of students' workload, closely related to students' experience.
- O3. Teacher effort. The class focuses on reducing teachers, learning materials, and knowledge evaluation resource authors or content developers.

The overall tree of classes is presented in Figure 2. The bottom level is composed of tools, solutions, and classes associated with them. The tools are not specified into discrete classes as most cases cover multiple cases simultaneously.

2.2. RQ 2: Methods for recommendations and generating of individual student learning path

Creating a learning path provides personalised learning that measures students' needs and improves learning (Rasheed & Wahid, 2019). Their study reviews learning path generation methods and evaluates the effectiveness of different methods when using e-learning materials. Learning path generation systems can analyse a learner and generate optimal learning paths. It is also an area where skill generation systems play a significant role. This is because they determine the difference between the current skill set of a learner and the required skill set. They bridge the gap between what the learner already knows and needs to know.

Ly et al. (2019) proposed an automatic learning paths generation (LPG) algorithm based on concept maps for adaptive learning systems with clustering technology used to automatically divide the students into several groups according to the mastery of concepts, combining the association rules mining method to generate several concept maps, and using the topology sorting algorithm to generate learning paths.

Kausar et al. (2018) have presented an adapted data mining clustering approach, integrated with the conceptual personalised e-learning system architecture.

Data mining and clustering effectively analyse big data and make education systems more robust. It also has the potential to solve the challenges of interdisciplinary research, emotional learning, and e-learning.

Authors Sanchez Nigenda et al. (2018) aimed to facilitate the generation of e-learning paths by developing two models, one based on AI planning and a second based on mathematical programming for generating learning paths with domain-independent algorithms. Proposed models consider a rich set of properties from the education domain, like secular activities, task hierarchies, enabling conditions, mandatory activities, quality accumulation functions, and preferred passing grades. This is done to compute learning paths.

According to the authors Tseng et al. (2022), with proper storage of learning objects, users can directly track topics based on some criteria in the time dimension, which supports a flexible, personalised e-learning environment.

A learning path recommendation algorithm for scoring learning paths based on the knowledge graph (KG) is described in the research of Shi et al. (2020), Nabizadeh et al. (2020), and Gao et al. (2021), and Son et al. (2021) in which variables and their weighted coefficients consider the different learning path preferences of the e-learner. A collaborative optimisation algorithm combining ant colony optimisation and a genetic algorithm to provide learners with a personalised learning path.

In the study by Vagale et al. (2020), the use of the topic sequences offered by the personalised adaptive e-learning system influenced the learning outcomes of the course, and an algorithm for the development of a recommended learning path was developed that considers the characteristics of the topic, with an arbitrary number of these parameters.

The paper by Jiang et al. (2022) presents a dynamic, personalised e-learning path generation algorithm that can provide suitable knowledge sequences to students based on their learning states and the prerequisite relationships for specific knowledge.

Learner Behavior Analytics is a system for analysing the level and behaviour of learners and collaboration between LMS platforms and artificial intelligence (Zaoudi & Belhadaoui, 2020). This will detect unusual actions and responses to events or questions asked instead of behaviour based on pre-established paths and profiles. A module for analysing learners' results and behaviour will be responsible for continuously monitoring and evaluating the learner's actual level throughout his training.

Shi et al. (2020) proposed a learning path recommendation model based on a multidimensional knowledge graph framework.

In Wei et al. (2021) study, AI technology and educational psychology theory are applied to design a personalised learning resource recommendation scheme to improve learning outcomes.

Ramos et al. (2021) created a novel representation model of LP and its application in group formation and behaviour analysis. This LPGtaph tool identifies and represents the LP of students who use Moodle. Another developed tool from the model was the M-Cluster, which makes grouping suggestions by applying the K-Means algorithm with attributes generated from the proposed model.

Zhang et al. (2021) developed an experimental method that can effectively stimulate differences in learning styles in terms of information processing, including labelling the basic learning styles of students, to effectively stimulate internal differences in the state of different students about learning styles, a data collection method, and to build a recognition model.

According to Rahayu et al. (2022), the recommendation process is mutual and can be initiated by either the system or the student. A multidisciplinary approach has become a new trend in developing ontology-based recommender systems.

Apoki et al. (2022) investigated the effects of including pedagogical agents in the Personalised Adaptive Learning System, particularly on predicted outcomes such as improved performance, task completion, increased motivation, and engagement.

Xiao et al. (2022) proposed an advanced differential evolution algorithm to optimise the degree of matching between the learning path and the learner.

Selection of the most well-known algorithms described in the article by authors Navarro and Moreno-Ger (2018) and Minn (2022) and analysed using a set of assessment tools and educational datasets from a higher education institution.

Under the second research question, the abovementioned research can be summarised by estimating which methods are used to generate the individual e-learning path. The structure of the methods overview for generating recommendations and an individual student learning path is presented in Figure 3.

In the one shown in Figure 3 structure, it is proposed to divide known research methods (M) into three main classes:

- M1. Artificial intelligence-based methods. It includes classification and clustering methods, while programming was identified as a separate subclass. This indicates that some methods do not directly lead to clustering or classification results but use AI solutions for gathering intermediate data for further modelling or solution implementation.
- M2. Rule-based methods include non-AI generated rules, which are used to generate or personalise the learning path.
- M3. Statistic-based methods focus not on one indivision but based on multiple situations and students.

In Figure 3, each class has its internal structure, indicating the specific method used in at least one of the analysed papers. The compiled taxonomy demonstrates the use by researchers of different methods of data analysis to generate trajectories from which it is challenging to single out the most frequently used and with clearly successful results.

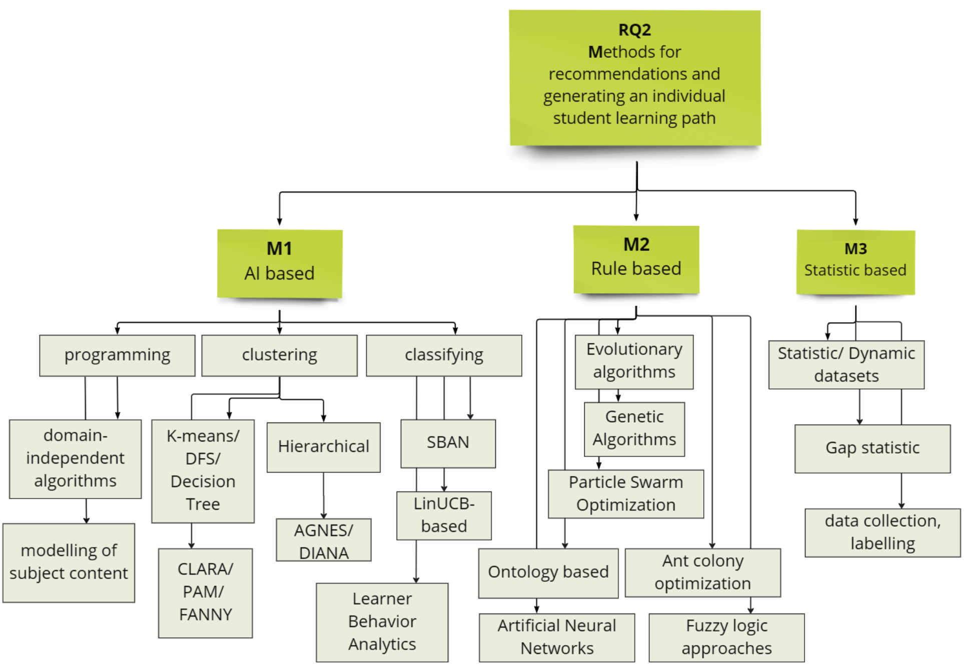

Figure 3. Taxonomy of RQ2-related classes (source: article author)

2.3. RQ3: limitations, challenges and unresolved issues in the conducted research for future work to improve the results obtained

Authors Li et al. (2019) in their article confirm that the LPG algorithm can distinguish between students, and tracking long-term student performance would improve the LPG algorithm and helps improve student grades.

In the paper by Kausar et al. (2018), adding intelligent games to the recommended approach could improve the learning capabilities of students. Different student groups can be introduced to intelligent techniques for tackling problems.

Authors Sanchez Nigenda et al. (2018) propose an integration of a hybrid method that interleaves mathematical programming with AI planning to generate efficient and effective learning paths, the integration of preferences and learning styles, the student's emotional status, and the inclusion of learning resources in the models of the mechanism of encapsulation of information about reward-objective functions. Authors Zaoudi and Belhadaoui (2020) offer a similar approach and elaborate on these models to model future LBA systems, which, with artificial intelligence, can adapt content more appropriately to the evolving learner's profiles and develop existing systems further and, thereby, promote their integration.

Authors Navarro and Moreno-Ger (2018) offer a potential expansion of the experiment by including new dimensions or by testing alternative educational datasets, using comparison methods of cluster analysis of educational datasets in higher education to select the best algorithm.

Ramanauskaitė and Slotkienė (2019) discuss the integration of the competency tree into current educational systems – introducing competency tree design tools and visualising student achievements.

Diwan et al. (2019) plan to personalise the learning pathways by creating a neural network of generic or reference learning pathways, generating learning pathways between different starting points and learning goals in an embedded learning space.

Rasheed and Wahid (2019) propose using a machine learning algorithm to extract student characteristics and analyse similar groups of students, using more training attributes to create training sequences.

Vagale et al. (2019) noticed the need to test the developed recommended learning path algorithm for a larger sample group.

According to Shi et al. (2020), a learning path recommendation model is designed to satisfy different learning needs based on the multidimensional knowledge graph framework, which can generate and recommend customised learning paths according to the e-learner's target learning object.

Ramos et al. (2021) recommend the formation of both homogeneous and heterogeneous groups, giving the teacher the option to group individuals with complementary LP, integrating with the techniques of collaborative learning, checking which types of paths are most likely to improve student performance; contribution to the creation of adaptive LMS. Teachers will be able to automate the analysis of LPS to better understand the behaviour of their students by using diagnostics and proposals for decision-making.

Tavakoli et al. (2021) offer that the approach can be used on various OER (Open Educational Recourse) repositories by collecting more data from other knowledge areas and repositories and adding more metadata capabilities, such as text parsing titles, descriptions, and keywords.

Zhang et al. (2021) discussed the optimisation of recognition accuracy in terms of four aspects: the quality and quantity of data sources, the EEG data preprocessing method and the structure of the recognition model, and the study of the use of EEG features for recognition of other aspects of learning style.

Son et al. (2021) plan to create a model for personalised learning paths based on student requirements, similarities, and user feedback.

El-Sabagh (2021) emphasises the need to investigate an efficient student model that can provide reasoning about misconceptions at a high degree of granularity for diagnostic purposes, the need for more quasi-experimental and descriptive research to better understand the benefits and challenges of incorporating adaptive e-learning in higher education institutions.

Apoki et al. (2022) offer further research, including pedagogical agents, particularly on predicted outcomes such as improved performance, task completion, increased motivation, and engagement.

Rahayu et al. (2022) noted that elements of the recommendations could be expanded according to the needs of students and applied in an open learning environment. Ontology-based recommender models and prototypes are evaluated in experiments with a specific population using non-real students, algorithmic performance tests, descriptive statistics, inferential statistics, questionnaires, and qualitative observations. Therefore, future research must evaluate such systems in a broader context or with more participants, applying appropriate testing methods.

According to the researchers (Xiao et al., 2022), the number of materials has a limited impact on the quality of learning paths produced by VLCR (Variable Length Continuous Representation) algorithms. The high scalability of VLCR when it is combined with continuous evolutionary algorithms and the constant computation time of VLCR shows the potential for dealing with large-scale learning path planning problems, which might be essential for a real-world learning management system that contains thousands of learning materials to generate a valid learning path before the learner loses patience. Future work may include a dynamic learning path update using the interaction information of a learner or a collaborative filtering mechanism. This will improve the quality of the initial learning path.

To Safitri et al. (2022) opinions, Data Mining (DM) can be used to explore information about the unique patterns of several big data. The implementation of cluster analysis using the K-means clustering algorithm can show the learning patterns of student groups formed based on access.

Tseng et al. (2022) propose integrating computerised learning objects and creating specifications that allow multiple instructors to collaborate to develop valuable and reconfigurable learning content. The importance of indexing learning objects into document warehouses to support text-centric business intelligence and propose the architecture for the next-generation e-learning environment. Document warehousing cannot only provide the ability to access learning objects quickly, even as the cube size increases, but it can also provide a wide variety of applications for content management of e-learning and enterprise business intelligence. Users can directly trace the topics based on some criteria along the time dimension.

The structure of the limitations, challenges and unresolved issues in the conducted research is presented in Figure 4. Usually, each paper falls under this taxonomy because it is oriented towards solving a specific problem.

Taxonomy in Figure 4 shows the comprehensive limitations, problems and unresolved issues grouped by the studied areas, and the largest of these is the group by the learning style used. The gaps in research and the formulated questions of their results require attention and represent options for future research directions. According to the author, when choosing the direction of future research directions, it is necessary to consider the overlap in research problems from different groups and use the results of preliminary research for further searches for solutions on the formation of learning trajectories.

- The studies carried out can be summarised for future work to improve the results as follows:
- static learning paths,
- problems of "cold start" when creating a learning path,
- individual characteristics of students,
- too much reliance on user input,
- student behaviour in the system is not used,
- testing systems with a limited number of learning objects,
- did not take into account the cognitive characteristics and the emotional side of the student,
- lack of comparisons with reference systems.

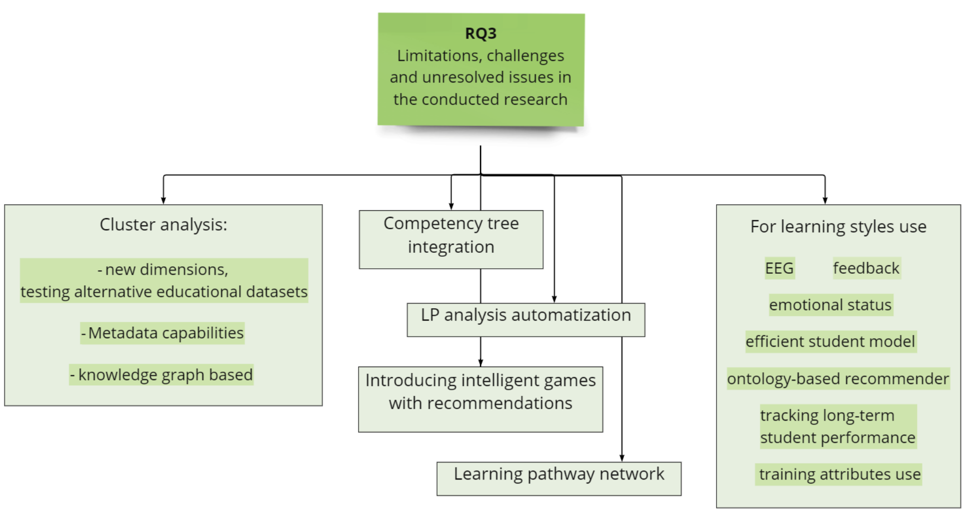

Figure 4. Taxonomy of RQ3-related classes (source: article author)

3. Results and discussion of the systematic literature review

The diagram below (Figure 5) shows the dynamics of the growth of interest in e-learning and its individualisation and adaptability. These dynamics demonstrate a trend that is explained by the growing popularity of online learning. This trend is explained by the increase in online materials resources and the need to automate the search for suitable thematic training materials to improve the learning process.

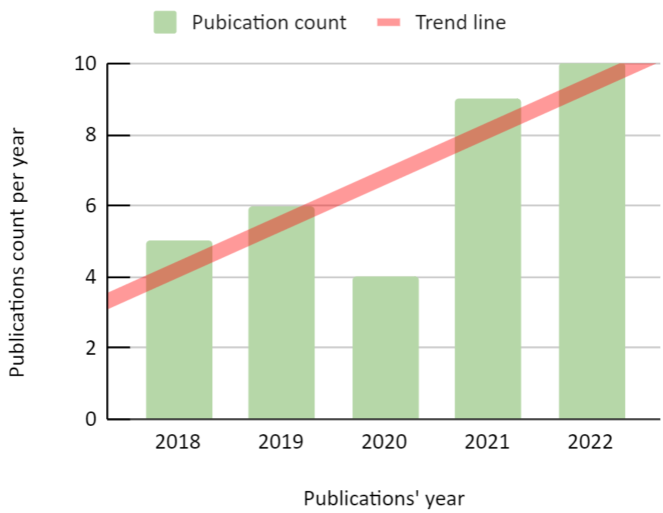

Figure 5. The number of articles by year of publication (source: article author)

The author cannot claim they could identify all publications on the desired topic for 2018–2022. Still, the trend of growing interest in adaptive e-learning and using a learning path for students is evident.

The number of publications in the e-learning and individual learning path areas has increased annually for the last five years by approximately 60%. This indicates the possibilities of more advanced solutions compared to existing solutions on the market.

The generalised result of the analysis of selected articles is presented in Table 1. It summarises all analysed topics in adaptive e-learning path generation, mapping them to the main classes of RQ1 and RQ2 taxonomies.

The summary table shows that less than 10% of papers adopt more than one data group. Considering that none of the proposed models can optimise students' knowledge level, learning time and teachers' workload, it shows there is room for multi-criteria decision-making solutions to improve the adaptability and e-learning individualisation experience.

Table 1. Articles analysis for RQ1 (Adaptation A1, A2, A3/ Optimization O1, O2, O3) and RQ2 (Methods M1, M2, M3) data (source: article author)

Author, year	RQ1						RQ2			Methods/tools/description
	Adaptation			Optimisation						
	A1	A2	A3	O1	O2	O3	M1	M2	M3	
Chen et al. (2018)	+		+		+	+		+	+	Markov chains, recommendation strategy by Gittins index
Kausar et al. (2018)		+					+			adapted data mining clustering approach “CFSFDP-HD”
Li et al. (2018)	+				+	+	+	+		an algorithm based on concept maps with clustering technology
Navarro and Moreno-Ger (2018)					+		+			different clustering algorithms: Clara, Pam
Safitri et al. (2018)					+		+			AI planning and mathematical programming, domain-independent algorithms
Diwan et al. (2019)						+	+			learning pathway network of generic/reference learning pathways
Levanova et al. (2019)			+							the personality of the student, psychological characteristics, motives, needs and interests
Ramanauskaitė and Slotkienė (2019)	+		+	+	+			+		Competency tree for standard and adaptation of the database of e-learning systems
Rasheed and Wahid (2019)			+					+		Evolutionary/Genetic/PSO/ant colony optimisation algorithms/ Fuzzy logic
Shi et al., (2020)			+					+		Evolutionary/Genetic/ PSO/ant colony optimisation algorithms/ Fuzzy logic
Vanitha et al. (2019)			+		+			+		Style-based Ant Colony System (SACS)
Nabizadeh et al. (2020)	+				+		+			K-Means/DFS algorithm
Vagale et al. (2020)			+						+	learner-centred learning approach, analysis of the influence of the topic sequences (teacher, learner, optimal)
Zaoudi and Belhadaoui (2020)				+			+			Learner Behavior Analytics
El-Sabagh (2021)		+							+	students’ learning styles (VARK) (visual, auditory, kinesthetic, reading/writing)

End of Table 1

Author, year	RQ1						RQ2			Methods/tools/description
	Adaptation			Optimisation			M1	M2	M3	
	A1	A2	A3	O1	O2	O3				
Gao et al. (2021)					+			+		knowledge graph by the topological ranking algorithm for serialising the learning objects by using ant colony optimisation
Ramos et al. (2021)			+			+	+		+	behaviour analysis with LPG and the M-Cluster by applying the K-Means algorithm with attributes
Son et al. (2021)					+			+		multiobjective ant colony optimisation
Tavakoli et al. (2021)				+			+			SBAN- combining UBA (user behaviour analytics) and AI (artificial intelligence)
Wei et al. (2021)			+		+		+			AI technology and educational psychology theory
Zhang (2021)		+							+	recognition mechanism based on EEG
Jiang et al. (2022)				+			+			knowledge mastery model-based
Apoki et al. (2022)			+				+			pedagogical agents in the Personalised Adaptive Learning System
Minn (2022)	+								+	use AI for developing student models
Rahayu et al. (2022)		+						+		multidisciplinary approach in ontology-based recommender systems
Safitri et al. (2022)			+				+			k-means/Decision Tree
Tseng et al. (2022)						+	+			Analytical Hierarchical Processing for versatile course scheme
Xiao et al. (2022)			+					+		differential evolution algorithm

Conclusions

The analysis of the studies demonstrated that adaptive e-learning solutions are mainly based on one set of data: student skills, student learning styles, and student personalities. Considering that only some of the proposed models can optimise the level of knowledge of students, teaching time and workload of teachers, this shows that using multi-criteria solutions is required to increase the adaptability and individualisation of e-learning.

Analysing the methods used to build the e-learning trajectory shows that AI-based solutions have become the most popular. However, rule-based and statistical methods can achieve similar results and outperform AI-based methods for specific tasks.

Clustering some eLearning data is also a popular topic for analysing groups of students rather than individual students.

The necessary skills and knowledge to achieve learning outcomes and the learner's existing skills/knowledge are taken as input to determine the learning path. Therefore, before deciding on the learning path, students need to have their current level of knowledge assessed by experts. Once the starting point (current level) and goal (expected level) is defined, the system can create a learning path that matches the student's expectations by presenting a set of courses and their order.

Acknowledgements

The author is very grateful to Simona Ramanauskaitė, Professor at Vilnius Gediminas Technical University, Lithuania, for her professional guidance and for providing her with a great deal about scientific research in the field of her research.

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APPENDIX

Abbreviations	Explanation
LMS	Learning Management System
LA	Learning Analytics
LP	Learning Path
RQ	Research Question
LinUCB	Linear Upper Confidence Bound
UBA	User Behaviour Analysis
LPG	Learning Path Generation
EEG	ElectroEncephaloGram
MAM	Multiple Attribute Matching
LBA	Learning Behavior Analytics
KG	Knowledge Graph
VLCR	Variable Length Continuous Representation
DM	Data Mining
SBAN	Student Behavior Assessment and Analysis
DFS	Depth First Search
PSO	Particle Swarm Optimisation
CFSFDP-HD	Clustering by Fast Search and Find of Density Peaks via HD