**Edlir SPAHO**[1]

# PERSONALIZED E-LEARNING MODELS: A SYSTEMATIC MAPPING STUDY

## Abstract

Online learning is a tangible reality today and has a growing trend due to the rapid development of information and communication technologies in education. Personalized online learning systems are designed to tailor the learning experience to individual students' needs, preferences, and learning styles. These systems leverage a combination of advanced technologies, pedagogical strategies, and data analytics to provide customized learning paths, resources, and feedback. Personalized e-learning systems have demonstrated substantial benefits in enhancing the effectiveness, performance, and motivation of learners by tailoring educational experiences to individual needs and preferences without limiting it in space and time. This systematic mapping study aims to provide a summary of the models used to enable personalization for each e-learner including personalization components, data mining models and techniques, and interaction tools between the learner and the content of personalized e-learning. Most commonly used personalization component of personalized online learning system are learner's profile and learning style, prior knowledge, behavior and preferences, meanwhile classification and clustering algorithms are mostly used to process these components. Through a detailed review of the literature, this study provides a structured overview of the landscape of personalized online learning, offering valuable insights into the evolution of this dynamic field and identifies key trends and patterns in the development and implementation of personalized online learning. The study also proposes directions for future research, emphasizing the importance of interdisciplinary collaboration and the continuous advancement of technology to meet the evolving needs of learners.

In conclusion, personalized online learning represents a significant shift towards more individualized and effective education. This study contributes to a deeper understanding of its current state, challenges, and potential, guiding future efforts to enhance and expand personalized learning experiences for all learners.

**Keywords:** *learner model, personalized e-learning system, personalization components, data mining models, data mining techniques*

[1] MSc. Edlir SPAHO Computer Science Department, University College "Bedër", Tirana, Albania.
Email: espaho@beder.edu.al

## 1. Introduction

Nowadays the trend of learning using electronic devices is on a continuous growth, due to ease of access to information, diversity of information, low-cost, etc. This has led to the traditional classroom teaching being shifted to a virtual environment, without having the limitation of time and place, so to access the necessary information without being in a certain place and time.

One of the biggest gaps in the explanation of a content in the classroom as well as in traditional online courses is the explanation in a particular form or pattern considering that all understand in the same way and with the same effectiveness.

The huge amount of information generated by online courses and the need for an explanation of the content according to the level, knowledge and skills of the learner has brought the need for the creation of different models and methods to convey the information in different ways to each learner (Jando, Hidayanto, & Harjanto, 2017).

## 2. Related Work

Rapidly increased data generated from online courses has led to new methods and techniques for creating customized e-learning systems. Some Systematic Mapping Studies (SMS) are conducted in this field, where the main ones to be mentioned are the study realized by (Romeo & Ventura, 2007), which has the main objective of Educational Data Mining, also an Learning Models-focused SMS has been conducted by (Hlioui, Alioui, & Gargouri, 2016). Analysis of data mining techniques applied to Learning Management Systems (LMS) for personalized education has been prepared by (Villegas-Ch & Luján-Mora, 2017), Integration of Knowledge Management and E-Learning Models has been prepared by (Judrups, 2015), a SMS of data mining of web-based learning systems has been prepared by (Villegas-Ch W. , Luján-Mora, Buenaño-Fernandez, & Román-Cañizares, 2017), comparison of LMS and Adaptive Educational Hypermedia Systems (AEHS) to analyze improvement with the use of Data Mining has been prepared by (Karagiannis & Satratzemi, 2014) and a comprehensive classification of collaboration approaches in E-learning has been prepared by (Al-Abri, Jamoussi, Kraiem, & Al-Khanjari, 2017, pp. 878-893). Most of the SMSs take into consideration one or another aspect of Personalization of e-Learning Environment. Our SMS contribution deals with generalizing and analyzing different aspects of Personalization of e-Learning Environment.

## 3. Research Methodology

This Systematic Mapping Study (SMS) has been conducted based on guidelines provided by (Kitchenham, Budgen, & Brereton, 2016, pp. 40 - 54), with the main stages shown in Figure 1. This part summaries the protocol of our SMS, including the research questions used to structure the study; the search strategy, inclusion and exclusion criteria were used; and the rules for extracting data and classifying primary studies.

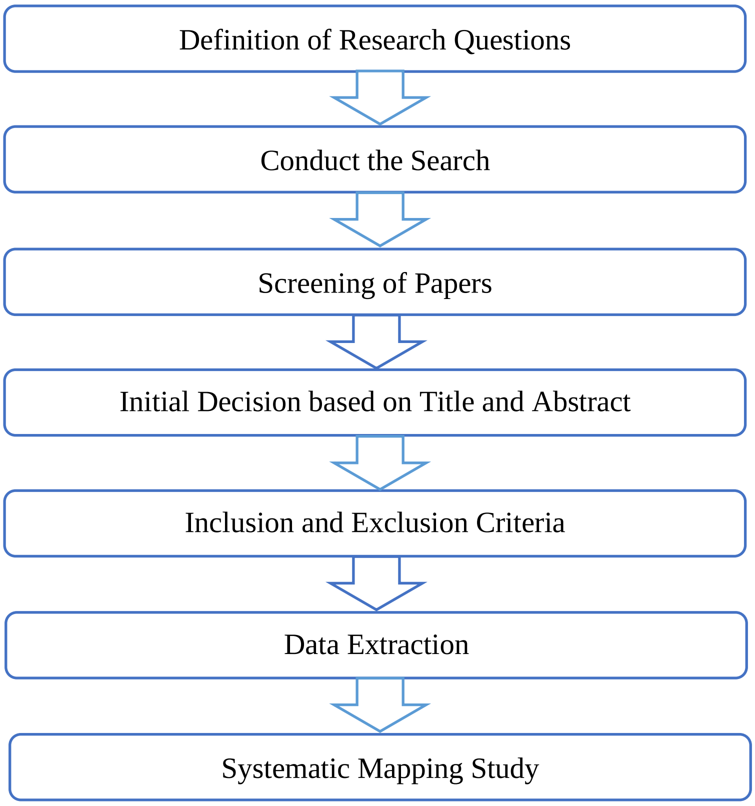


*Figure 1: The Mapping Study Process*

### 3.1. Research Questions

The following research questions and motivations (Table 1) are given to explore the components of personalized e-learning model, tools of interaction between and the content of personalized e-learning, data mining models and techniques used in personalized e-learning, theories behind used to build a personalized learning model, to the effectiveness and success of personalized e-learning learner:

| No. | Research Question | Motivation |
|---|---|---|
| RQ1 | What are main Learning Styles and their components? | To identify most used Learning Styles in e-learning, their main components, advantages and drawbacks of each of them. |
| RQ2 | What are main personalization components to build a personalized e-learning model? | To identify most commonly used personalization components in order to build adaptive e-learning model and weight of each personalization parameter. |

| | | |
|---|---|---|
| RQ3 | What are main data mining models and techniques used in the e-learning domain to make it personalized? | To identify and analyze most commonly used data mining models used in the e-learning domain to make it personalized advantages and drawbacks of each of them in order to increase learner personalization and performance. |
| RQ4 | What tools are generally used to process the interaction between the learner and the content of personalized e-learning? | To identify and analyze most commonly used interaction tools between the learner and the content of personalized e-learning. |

*Table 1 Research Questions and Motivation*

### 3.2. Research Process

The search process should ensure that keyword usage can be relevant to the research question. To conduct this research, we followed the steps described by (Kitchenham, Budgen, & Brereton, 2016, pp. 40-54) and (Brereton, Kitchenham, Budgen, Turner, & Khalil, 2007, pp. 571-583) for construction of search strings for all the articles, papers and journals we have retrieved as follow:

1. Identify major terms and synonyms by terms that are used in the research questions.
2. Identify different spellings and synonyms for major terms.
3. Use the Boolean operator "OR" to link alternative spellings and synonyms.
4. Use the Boolean operator "AND" to link major terms.

This resulted in the following keywords used in this search: E-learning OR Distance Learning OR Electronic Learning OR Online Learning AND Component OR Parameter AND Personalized OR Adapted AND Model OR Architecture AND Data Mining OR Knowledge Discovery in Databases OR KDD OR Data Pattern Analysis.

The digital libraries used to conduct this research were the Institute of Electrical and Electronics Engineers (IEEE) Xplore Digital Library, Association for Computing Machinery (ACM) Digital Library, and Elsevier ScienceDirect.

### 3.3. Inclusion and exclusion Criteria

Originally papers are evaluated based on their title if they are to be considered or not. If analyzing the title could not bring to a decision was studied the abstract, even if after studying the abstract we couldn’t be able to make a decision then read and conclusions.

For the inclusion or exclusion of a particular study we have implemented the inclusion and exclusion criteria based on (Abuhlfaia & Quincey, 2018) as in the Table 2 and Table 3 below:

| No | Inclusion Criteria |
| --- | --- |
| 1 | Papers published between January 2014 and February 2019. |
| 2 | Written in the English language. |
| 3 | Peer-reviewed literatures |
| 4 | Paper which includes a description of evaluation about the usability of e-learning and has a clear method. |
| 5 | Papers which contains and describes data mining method and tools |

*Table 2 Inclusion Criteria*

| No | Exclusion Criteria |
| --- | --- |
| 1 | Duplicate papers from the same study in different databases. |
| 2 | Publications not written in English. |
| 3 | Publications not directly related to our topic. |

*Table 3 Exclusion Criteria*

### 3.4. Data Extraction

The number of papers analyzed at the first stage was 50 papers. Subsequently, based on paper's abstract, conclusions and exclusion and exclusion criteria, 34 papers were selected for analysis where 20 of them are published in different conferences while 14 of them are published in different journals. The results of the selected papers are given in the Table 4 below.

| Source Database | Studies Found | Candidate Studies | Selected Studies | References |
| --- | --- | --- | --- | --- |
| ACM | 22 | 15 | 11 | (Teimzit, Mahnane, & Hafidi, 2018), (Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018), (Chow, Yacef, Koprinska, & Curran, 2017), (Shivanagowda, Goudar, & Kulkarni, 2017), (Wang, Sy, Liu, & Piech, 2017), (Chanaa & El Faddouli, 2018), (Liu, Du, Sun, & Zhai, 2017), (El Fouki, Aknin, & El. Kadiri, 2017), (Shi, Peng, & Wang, 2017), (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web |

| | | | | |
|---|---|---|---|---|
| | | | | Companion), (Hu, Zhang, Chu, & Ke, 2016) |
| Elsevier Science Direct | 29 | 21 | 10 | (Tarus, Niua, & Yousif, 2017), (Birjali, Beni-Hssane, & Erritali, 2018), (Kolekar, Pai, & Pai M.M, 2018), (Xie, et al., 2017), (Yi, Zhao-xia, Xiao-huan, Ming-ming, & Wen-tian, 2017), (Sergio, et al., 2017), (Garrido, Morales, & Serina, 2016), (Gulzara, Leema, & Deepak, 2018), (Zhou, Huang, Hu, Zhu, & Tang, 2018), (B.Saleenaa & S.K.Srivatsa, 2015) |
| IEEE | 25 | 17 | 9 | (Herath & Jayaratne, 2017), (Al-Abri, Al-Khanjari, Kraiem, & Jamoussi, 2017), (Karataev & Zadorozhny, 2017), (Karagiannis & Satratzemi, 2014), (Bhatia & Prasad, 2015), (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018), (Samina, Xu, Iftikhar, Zhu, & Misha, 2018), (Halawa, Shehab, & Hamed, 2015), (FeiZhou, QingPan, & Huang, 2017), (Lepouras, Katifori, Vassilakis, Antoniou, & Platis, 2014) |
| **Total** | **76** | **53** | **30** | |

*Table 4 Summary of Selected Papers*

### 3.5. Classification Scheme

The classification scheme (Figure 2) is done in accordance with the research questions and results of the research questions. Firstly, we reviewed all papers' abstracts and conclusions, and if it wasn't possible to properly classify the paper, we read the introduction part. In a lot of cases, we had to analyze the papers in detail.

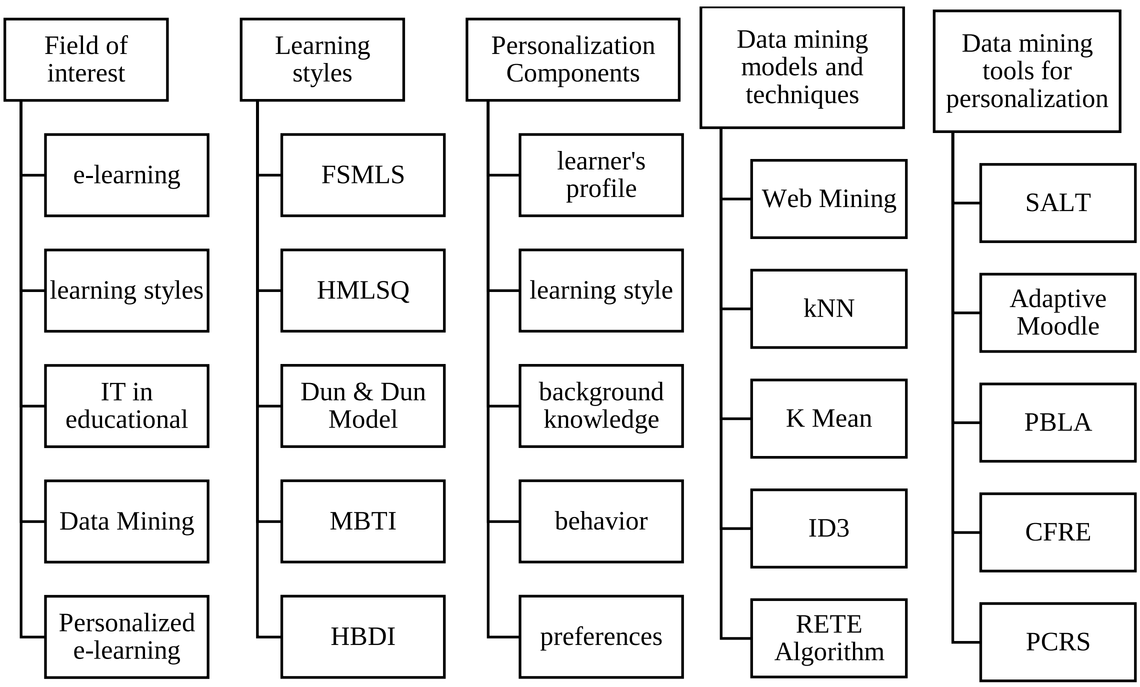


*Figure 2 Classification Scheme*

## 4. Results and Discussions

To answer all research questions, we extracted most relevant information from all papers in accordance with research questions then we analyzed by summarizing, and correlating it to answer research questions. The results are as follow:

### 4.1. What are main Learning Styles and their components?

As it is shown on Table 5, main learning styles extracted from reviewed papers are:

| Theory | Description | No of Papers | References | Percentage |
|---|---|---|---|---|
| FSLM | Felder-Silverman Learning Style Model | 7 | (Teimzit, Mahnane, & Hafidi, 2018), (Chanaa & El Faddouli, 2018), (Kolekar, Pai, & Pai M.M, 2018), (Xie, et al., 2017), (Yi, Zhao-xia, Xiao-huan, Ming-ming, & Wen-tian, 2017), (Al-Abri, Al-Khanjari, Kraiem, & Jamoussi, 2017), (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018), | 23.3% |
| Hybrid | Combination of different components | 4 | (Shivanagowda, Goudar, & Kulkarni, 2017), (Tarus, Niua, & Yousif, 2017), (Gulzara, Leema, | 13.3% |

| | | | | |
|---|---|---|---|---|
| | | | & Deepak, 2018), (Karataev & Zadorozhny, 2017), | |
| KLSI | Kolb Learning Style Inventory | 1 | (Shi, Peng, & Wang, 2017) | 3.3% |
| MBTI | Myers-Briggs Type Indicator theory | 1 | (Halawa, Shehab, & Hamed, 2015) | 3.3% |
| Unspecified | There is no clear explanation of theory used | 7 | (Chow, Yacef, Koprinska, & Curran, 2017), (Liu, Du, Sun, & Zhai, 2017), (El Fouki, Aknin, & El. Kadiri, 2017), (Hu, Zhang, Chu, & Ke, 2016) (Sergio, et al., 2017), (Herath & Jayaratne, 2017), (Samina, Xu, Iftikhar, Zhu, & Misha, 2018) | 23.3% |
| LA | Learning Analytics | 3 | (Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018), (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web Companion), (Lepouras, Katifori, Vassilakis, Antoniou, & Platis, 2014) | 10% |
| Other | Different approaches | 7 | (Wang, Sy, Liu, & Piech, 2017), (Birjali, Beni-Hssane, & Erritali, 2018), (Garrido, Morales, & Serina, 2016), (Zhou, Huang, Hu, Zhu, & Tang, 2018), (B.Saleenaa & S.K.Srivatsa, 2015), (Bhatia & Prasad, 2015), (FeiZhou, QingPan, & Huang, 2017) | 23% |
| **Total** | | **30** | | **100%** |

*Table 5 Used Learning Styles*

- **Felder-Silverman Learning Style Model (FSLM)** with main components of reflection (active, reflected), reasoning (inductive, deductive), Sensory (verbal, visual) and progression (sequential, global).
- **Myers-Briggs Type Indicator (MBTI)** with the main components of thinking/feeling, judgment/perception, introvert/extravert and sensing/intuitive.
- **Kolb Learning Style** with main components of concrete experience (doing, having an experience), reflective observation (reviewing, reflecting on experience), abstract

conceptualization (concluding, learning from experience) and active experimentation (planning, trying out what we have learned).

- **Hybrid Models.** Some of hybrid models we have retrieved from our SMS are combination of E-Learning Ontology, Learning Resource Ontology, Learner Model Ontology (Felder-Silverman Model of Learning Style) as described in (Tarus, Niua, & Yousif, 2017), or Domain Model and Question Model, Video Learning Resources, Readable Learning Resources as described in (Shivanagowda, Goudar, & Kulkarni, 2017), or social learning framework, crowdsourcing, online social networks, and complex adaptive systems as described in (Karataev & Zadorozhny, 2017) or a combination of N-Grams and Domain Ontologies as described in (Gulzara, Leema, & Deepak, 2018, pp. 518-524).

### 4.2. What are main parameters to build a personalized e-learning model?

Finding the most influential parameters for personalization of e-learning is one of the most difficult processes in building a personalized e-learning model, because human nature itself is very complex. After screening the analyzed research papers some of the personalization components that we can mention are learner personality, learner prior knowledge, learner behavior, learner interests and preferences.

| Component | Description | References | Percentage |
|---|---|---|---|
| Personality | Learner's Profile | (Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018), (Liu, Du, Sun, & Zhai, 2017), (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web Companion), (Hu, Zhang, Chu, & Ke, 2016), (Gulzara, Leema, & Deepak, 2018), (B.Saleenaa & S.K.Srivatsa, 2015), (Herath & Jayaratne, 2017), (Samina, Xu, Iftikhar, Zhu, & Misha, 2018), (FeiZhou, QingPan, & Huang, 2017), | 30% |
| | Learning Style | (Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018), (Chanaa & El Faddouli, 2018), (Kolekar, Pai, & Pai M.M, 2018), (Xie, et al., 2017), (Yi, Zhao-xia, Xiao-huan, Ming-ming, & Wen-tian, 2017), (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018), (Samina, Xu, Iftikhar, Zhu, & Misha, 2018) | 23% |
| Knowledge | Background Knowledge | (Shivanagowda, Goudar, & Kulkarni, 2017), (Wang, Sy, Liu, & Piech, 2017), (Liu, Du, Sun, & Zhai, 2017), (Tarus, Niua, & Yousif, 2017), (Birjali, Beni-Hssane, & Erritali, 2018), (Xie, et al., 2017), (Yi, Zhao-xia, Xiao-huan, Ming-ming, & Wen- | 43% |

| | | | |
|---|---|---|---|
| | | tian, 2017), (Garrido, Morales, & Serina, 2016), (Gulzara, Leema, & Deepak, 2018), (Zhou, Huang, Hu, Zhu, & Tang, 2018), (Al-Abri, Al-Khanjari, Kraiem, & Jamoussi, 2017), (Bhatia & Prasad, 2015), (Samina, Xu, Iftikhar, Zhu, & Misha, 2018) | |
| Behavioral | Performance | (Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018), (Yi, Zhao-xia, Xiao-huan, Ming-ming, & Wen-tian, 2017), (Gulzara, Leema, & Deepak, 2018), (Herath & Jayaratne, 2017) | 13% |
| Interests | Attention, Usage | (Liu, Du, Sun, & Zhai, 2017), (Tarus, Niua, & Yousif, 2017), (Xie, et al., 2017), (Zhou, Huang, Hu, Zhu, & Tang, 2018), (Halawa, Shehab, & Hamed, 2015), (Kolekar, Pai, & Pai M.M, 2018) | 20% |
| Preferences | Like and Dislike | (Xie, et al., 2017), (B.Saleenaa & S.K.Srivatsa, 2015), (Al-Abri, Al-Khanjari, Kraiem, & Jamoussi, 2017), (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018), (Samina, Xu, Iftikhar, Zhu, & Misha, 2018), (FeiZhou, QingPan, & Huang, 2017) | 20% |

*Table 6 General Personalization Components*

Table 6 contains summarization of personalization parameters most commonly used to build a personalized e-learning model. Based on retrieved results we can conclude that most influential personalization parameter is learner's background or prior knowledge then learner's profile with components like personal information (name, gender, date of birth), academic information (major, grade, GPA, learning plan). Another component of personalization is learner's learning style and some other metrics used to determine the learners learning style are the time spent on videos and other files, the number of times the learner accesses a particular file etc. (Kolekar, Pai, & Pai M.M, 2018, pp. 606-615) Interests like collaboration, learning time, and preferences like opinion and interactivity level, of e-learner takes an important role in personalization e-learning environment (Xie, et al., 2017, pp. 59-70), (Al-Abri, Al-Khanjari, Kraiem, & Jamoussi, 2017), (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018). Some other personalization components retrieved from reviewed papers are E-Learning Ontology, Learning Resource Ontology as described in (Tarus, Niua, & Yousif, 2017, pp. 37-48), number of submissions to success as described in (Chow, Yacef, Koprinska, & Curran, 2017), Map Reduce-based GA, e-assessment as described in (Birjali, Beni-Hssane, & Erritali, 2018, pp. 14-32), etc.

**4.3. What are main data mining models and techniques used in the e-learning domain to make it personalized?**

| Data Mining Techniques | Data Mining Models and Algorithms | References | Percentage |
|---|---|---|---|
| Classification | K Nearest Neighbor | (Chow, Yacef, Koprinska, & Curran, 2017), (Shivanagowda, Goudar, & Kulkarni, 2017), (Tarus, Niua, & Yousif, 2017) | 27% |
| | ID3 decision tree | (Herath & Jayaratne, 2017), (FeiZhou, QingPan, & Huang, 2017) | |
| | C4.5 | (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web Companion) | |
| | Classification and Regression Tree (CART) | (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web Companion) | |
| | Bayesian | (Shi, Peng, & Wang, 2017), (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018) | |
| | Naive Bayesian | (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web Companion) | |
| | Support Vector Machines | (Daud, et al., Companion Proceedings of the 26th International Conference on World Wide Web Companion) | |
| Clustering | Fuzzy C Means | (Kolekar, Pai, & Pai M.M, 2018) | 17% |
| | Fast Search and Finding of Density Peaks via Heat Diffusion | (Zhou, Huang, Hu, Zhu, & Tang, 2018) | |
| | k-Means | (Teimzit, Mahnane, & Hafidi, 2018), (Chow, Yacef, Koprinska, & Curran, 2017), (Shi, Peng, & Wang, 2017) | |
| Pattern Mining | Frequent Pattern Growth (FP-Growth) | (Hu, Zhang, Chu, & Ke, 2016) | 7% |
| | Sequential Pattern Mining | (Shivanagowda, Goudar, & Kulkarni, 2017) | |
| Web mining | Web content mining | (Shivanagowda, Goudar, & Kulkarni, 2017), (Wang, Sy, Liu, & Piech, 2017), (Herath & Jayaratne, 2017) | 13% |
| | Web structure mining | (Sergio, et al., 2017) | |
| | Web usage mining | (Herath & Jayaratne, 2017) | |

| | | | |
|---|---|---|---|
| Recurrent Neural Network | Long Short Term Memory (LSTM) | (Liu, Du, Sun, & Zhai, 2017), (Al-Abri, Al-Khanjari, Kraiem, & Jamoussi, 2017) | 13% |
| | Deep Neural Network | (Chanaa & El Faddouli, 2018), (El Fouki, Aknin, & El. Kadiri, 2017) | |

*Table 7 Main data mining models and techniques*

Main data mining techniques used in the e-learning domain to personalize it are Classification Techniques with percentage of 27% from reviewed papers and main data mining algorithms for classification are K Nearest Neighbor, ID3 decision tree, Bayesian and Naive Bayesian. Second most commonly used technique for personalization is Clustering Technique with k-Means algorithm used most. Web Mining with its components of web content mining, web structure mining and web usage mining is also very used. Machine Learning Recurrent Neural Network technique with its main algorithms of Long Short Term Memory (LSTM) Deep Neural Network is the new trend used in personalizing e-learning environment, as shown in Table 7.

### 4.4. What tools are generally used to process the interaction between the learner and the content of personalized e-learning?

Some of the tools that are generally used to process the interaction between the learner and the content of personalized e-learning are Collaborative Filtering Recommendation Engine (Shivanagowda, Goudar, & Kulkarni, 2017), (Herath & Jayaratne, 2017), Orange Software, a Python datamining library (Gkontzis, Kotsiantis, Tsoni, & Verykios, 2018), GATE text mining tool (Wang, Sy, Liu, & Piech, 2017), and GATE (TwitIE) adapted for Twitter (Al-Abri, AlKhanjari, Jamoussi, & Kraiem, 2018), adaptive User Interface for Moodle (Kolekar, Pai, & Pai M.M, 2018), CRETAL (Compiler of Resources in Engineering & Technology to Aid Learning) (Birjali, Beni-Hssane, & Erritali, 2018, pp. 14-32), myPTutor implemented in Moodle, provides a mixed-initiative architecture that allows teachers and students to work together during the learning cycle (Xie, et al., 2017, pp. 59-70), on-line course applicability assessment (OCAA) (Gulzara, Leema, & Deepak, 2018, pp. 518-524), WordNet (Bhatia & Prasad, 2015), and WordNet or MeSH (B.Saleenaa & S.K.Srivatsa, 2015, pp. 1-12) Ontology Dictionaries, SALT (Self-Adaptive Learning through Teaching) (Karataev & Zadorozhny, 2017), Reading Battle and Rapid Miner toolkit (Hu, Zhang, Chu, & Ke, 2016), etc.

## 5. Conclusions

As mentioned above, one of the most difficult challenges that encounter personalized e-learning models is the unique and, at the same time, extremely complex human nature. Another problem that arises in personalized e-learning models is the highly variable nature of the learner, so a pattern of e-learning that may be suitable for one learner at a time or for a particular content may not be any more suitable to the same learner at a different time or content.

## 6. Limitation and Future Research

Among the main limitations of this systematic mapping study are the number of digital libraries in which the search is done, the number of selected papers and our subjectivism in the way we understand and select a particular paper.

As future research we think that finding most important personalization components in Personalized e-learning Model based on experimental studies with broad learner diversity and contents would meet one of the current gaps of Personalized e-learning Model. Also it will be interesting in analyzing the ways and techniques how to integrate personalized e-learning model into the emerging global communication architecture of Internet of Everything.

## REFERENCES

Abuhlfaia, K., & Quincey, E. d. (2018). The Usability of E-learning Platforms in Higher Education: A Systematic Mapping Study. *Proceedings of British HCI* (pp. 1-13). Belfast, UK: BCS Learning and Development Ltd.

Al-Abri, A., AlKhanjari, Z., Jamoussi, Y., & Kraiem, N. (2018). Identifying Learning Styles from Chat Conversation using Ontology-Based Dynamic Bayesian Network Model. *2018 8th International Conference on Computer Science and Information Technology (CSIT)* (pp. 77-84). Amman, Jordan: IEEE.

Al-Abri, A., Al-Khanjari, Z., Kraiem, N., & Jamoussi, Y. (2017). A scheme for extracting information from collaborative social interaction tools for personalized educational environments. *2017 International Conference on Computing Networking and Informatics (ICCNI)* (pp. 1-6). Lagos, Nigeria: IEEE.

Al-Abri, A., Jamoussi, Y., Kraiem, N., & Al-Khanjari, Z. (2017). Comprehensive classification of collaboration approaches in E-learning. *Telematics and Informatics*, 878-893.

B.Saleenaa, & S.K.Srivatsa. (2015). Using concept similarity in cross ontology for adaptive e-Learning systems. *Journal of King Saud University - Computer and Information Sciences, 27*(1), 1-12.

Bhatia, L., & Prasad, S. S. (2015). COPAL — Cognitive personalized aid for learning. *2015 International Conference on Cognitive Computing and Information Processing(CCIP* (pp. 1-6). Noida, India: IEEE.

Birjali, M., Beni-Hssane, A., & Erritali, M. (2018). A novel adaptive e-learning model based on Big Data by using competence-based knowledge and social learner activities. *Applied Soft Computing, 68*, 14-32.

Brereton, P., Kitchenham, B. A., Budgen, D., Turner, M., & Khalil, M. (2007). Lessons from applying the systematic literature review process within the software engineering domain. *Journal of Systems and Software, 80*(4), 571-583.

Chanaa, A., & El Faddouli, N.-e. (2018). Deep learning for a smart e-learning system. *Proceedings of the 2nd International Conference on Smart Digital Environment* (pp. 197 - 202). Rabat, Morocco: Association for Computing Machinery.

Chow, S., Yacef, K., Koprinska, I., & Curran, J. (2017). Automated Data-Driven Hints for Computer Programming Students. *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization* (pp. 5-10). Bratislava, Slovakia: Association for Computing Machinery.

Daud, A., Aljohani, N. R., Abbasi, R. A., Lytras, M. D., Abbas, F., & Alowibdi, J. S. (Companion Proceedings of the 26th International Conference on World Wide Web Companion). Predicting Student Performance using Advanced Learning Analytics. *2017* (pp. 415-421). Perth, Australia: ACM.

El Fouki, M., Aknin, N., & El. Kadiri, K. E. (2017). Intelligent Adapted e-Learning System based on Deep Reinforcement Learning. *Proceedings of the 2nd International Conference on Computing and Wireless Communication Systems* (pp. 1-6). Larache, Morocco: Association for Computing Machinery.

FeiZhou, T., QingPan, Y., & Huang, L. (2017). Research on Personalized E-Learning Based on Decision Tree and RETE Algorithm. *2017 International Conference on Computer Systems, Electronics and Control (ICCSEC* (pp. 1392-1396). Dalian, China: IEEE.

Garrido, A., Morales, L., & Serina, I. (2016). On the use of case-based planning for e-learning personalization . *Expert Systems with Applications, 60*, 1-15.

Gkontzis, A. F., Kotsiantis, S., Tsoni, R., & Verykios, V. S. (2018). An effective LA approach to predict student achievement. *Proceedings of the 22nd Pan-Hellenic Conference on Informatics* (pp. 76-81). Athens, Greece: Association for Computing Machinery.

Gulzara, Z., Leema, A., & Deepak, G. (2018). PCRS Personalized Course Recommender System Based on Hybrid Approach . *Procedia Computer Science, 125*, 518-524.

Halawa, M. S., Shehab, M. E., & Hamed, E. M. (2015). Predicting student personality based on a data-driven model from student behavior on LMS and social networks. *015 Fifth International Conference on Digital Information Processing and Communications (ICDIPC)* (pp. 294-299). Sierre, Switzerland: IEEE.

Herath, D., & Jayaratne, L. (2017). A personalized web content recommendation system for E-learners in E-learning environment. *2017 National Information Technology Conference (NITC)* (pp. 89-95). Colombo, Sri Lanka: IEEE.

Hlioui, F., Alioui, N., & Gargouri, F. (2016). A survey on learner models in adaptive E-learning systems. *13th International Conference of Computer Systems and Applications (AICCSA).* Agadir, Morocco.

Hu, X., Zhang, Y., Chu, S. K., & Ke, X. (2016). Towards personalizing an e-quiz bank for primary school students: an exploration with association rule mining and clustering. *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 25-29). Edinburgh, United Kingdom: ACM.

Jando, E., Hidayanto, A. N., & Harjanto, P. (2017). Personalized E-learning Model: A Systematic Literature Review. *International Conference on Information Management and Technology (ICIMTech)*, (pp. 238 - 243). Yogyakarta.

Judrups, J. (2015). Analysis of Knowledge Management and E-Learning Integration Models. *Procedia Computer Science*, 154-162.

Karagiannis, I., & Satratzemi, M. (2014). Comparing LMS and AEHS: Challenges for Improvement with Exploitation of Data Mining. *IEEE 14th International Conference on Advanced Learning Technologies* (pp. 65-66). Athens, Greece: IEEE Computer Society.

Karataev, E., & Zadorozhny, V. (2017). Adaptive Social Learning Based on Crowdsourcing. *IEEE Transactions on Learning Technologies, 10*(2), 128 - 139.

Kitchenham, B. A., Budgen, D., & Brereton, P. (2016). *Evidence-based software engineering and systematic reviews.* 40 - 54: CRC Press.

Kolekar, S. V., Pai, R. M., & Pai M.M, M. (2018). Adaptive User Interface for Moodle based E-learning System using Learning Styles. *Procedia Computer Science, 135*, 606-615.

Lepouras, G., Katifori, A., Vassilakis, C., Antoniou, A., & Platis, N. (2014). Towards a learning analytics platform for supporting the educational process. *IISA 2014, The 5th International Conference on Information, Intelligence, Systems and Applications* (pp. 246-251). Chania, Greece: IEEE.

Liu, X., Du, Y., Sun, F., & Zhai, L. (2017). Design of adaptive learning system based on big data. *Proceedings of the 6th International Conference on Information Engineering* (pp. 1-5). Dalian Liaoning, China: Association for Computing Machinery.

Romeo, C., & Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications, 33*(1), 135-146.

Samina, K., Xu, H., Iftikhar, H., Zhu, W., & Misha, Z. (2018). Integration of Data Mining Clustering Approach in the Personalized E-Learning System. *IEEE Access, Vol. 6, 6*, 72724-72734.

Samson, P. J. (2015). Analyzing student notes and questions to create personalized study guides. *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge.* Indianapolis.

Sergio, C.-F., Itzamá, L.-Y., Wadee, A., Oscar, C.-N., Villuendas-Rey, Y., Aldape-Pérez, M., & Yáñez-Márquez, C. (2017). Instance-based ontology matching for e-learning material using an associative pattern classifier. *Computers in Human Behavior, 69*, 218-225.

Shi, Y., Peng, Z., & Wang, H. (2017). Modeling Student Learning Styles in MOOCs. *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (pp. 979-988). Singapore: ACM.

Shivanagowda, G. M., Goudar, R. H., & Kulkarni, U. P. (2017). CRETAL: A Personalized Learning Environment in Conventional Setup. *Proceedings of the 10th Annual ACM India Compute Conference* (pp. 143-148). Bhopal, India: ACM Compute.

Tarus, J. K., Niua, Z., & Yousif, A. (2017). A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining. *Future Generation Computer Systems, 72*, 37-48.

Teimzit, A., Mahnane, L., & Hafidi, M. (2018). A collaborative algorithmic problem-based learning environment using learners' learning styles. *5th Multidisciplinary International Social Networks Conference* (pp. 1-6). Saint-Etienne, Taiwan: Association for Computing Machinery.

Villegas-Ch, W., & Luján-Mora, S. (2017). Analysis of data mining techniques applied to LMS for personalized education. *IEEE World Engineering Education Conference (EDUNINE)* (pp. 85-89). Santos, São Paulo: IEEE.

Villegas-Ch, W., Luján-Mora, S., Buenaño-Fernandez, D., & Román-Cañizares, M. (2017). Analysis of web-based learning systems by data mining. *IEEE Second Ecuador Technical Chapters Meeting (ETCM).*

Wang, L., Sy, A., Liu, L., & Piech, C. (2017). Deep Knowledge Tracing On Programming Exercises. *Proceedings of the Fourth (2017) ACM Conference on Learning @ Scale* (pp. 201-204). Cambridge, MA, USA: ACM.

Xie, H., Zou, D., Wang, F. L., Wong, T.-L., Rao, Y., & Wang, S. H. (2017). Discover learning path for group users - A profile-based approach . *Neurocomputing, 254*, 59-70.

Yi, R., Zhao-xia, D., Xiao-huan, Z., Ming-ming, F., & Wen-tian, G. (2017). Exploring an on-line course applicability assessment to assist learners in course selection and learning effectiveness improving in e-learning. *Learning and Individual Differences, 60*, 56-62.

Zhou, Y., Huang, C., Hu, Q., Zhu, J., & Tang, Y. (2018, May). Personalized learning full-path recommendation model based on LSTM neural networks. *Information Sciences, 444*, 135-152.