ATHABASCA UNIVERSITY

MOBILE EDUCATIONAL ENVIRONMENTS USING RECOMMENDER SYSTEMS: A SYSTEMATIC REVIEW

BY

MONA ABOU TAKA

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DEDICATION

To my sister Maria, who is a bright star full of hope and happiness and believes that I can always do my best.

ABSTRACT

This paper aims to identify and evaluate the findings of articles from Google Scholar's Top 20 Educational Technology publications addressing research questions about using recommender systems in mobile educational environments. Recommender systems usage in mobile educational environments is an emerging topic needing further testing and evaluation using a diverse group of learners. Therefore, a systematic review is used to identify relevant studies using recommender systems in mobile educational environments and categorizing them into four filtering techniques: collaborative-based, content-based, knowledge-based and hybrid-based. The authors discuss general recommender systems filtering mechanisms in mobile education and detail the four filtering techniques by providing a comprehensive analysis, algorithms to implement, and improvements of each technique to accommodate learners' needs and want of recommender educational content. Moreover, the systematic review produced a detailed analysis of 50 studies published within the past 15 years (i.e. 2004 – 2019). The design and development of each category in recommender systems are reviewed, while the challenges, which are outlined with methods to mitigate them, are suggested as an improvement on the methods each recommender system filtering technique provides. The review highlighted open issues and gaps in existing research on the topic with insights into future research. Finally, this review will support educators' and learning designers' understanding of the overall design and algorithms required to use a recommender system in mobile education and to provide accurate recommendations for the learner anywhere and anytime.

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It was an incredible journey in online education where I learned insightful information from each course in the program. Since I enjoyed being an online learner where I accessed the information I needed anywhere and anytime, it was beneficial to understand and discuss the aspect of online learning using mobility.

Finally, I want to thank my sister Maria who supported my endeavour.

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CHAPTER I

INTRODUCTION

Statement of Purpose

Mobile technology explores a novel learning technique that provides accessible information, resources, and communications at any time and place. Furthermore, it offers educational and informative context outside and inside the classroom (Martin & Ertzberger, 2013).

The Internet-based context uses data categorized in various subjects and interests for the learner to benefit from. However, the increasing amount of data and subsequent information overload makes it a challenge for the learner to choose useful and relevant learning material. One way to solve this issue is to design mobile educational applications using any of the four recommender systems filtering techniques: collaborative-based, content-based, knowledge-based, and hybrid-based through a systematic review.

Recommender systems filter the data that are received from the Internet and automatically provide the most suitable learning objects based on the learner's personalized preferences. Personalized preferences are composed of relevant learning resources that meet the learner's needs and interests (Tarus, Niu, & Yousif, 2017).

Research Problem

In this Master's Essay, a systematic review of the four recommender systems techniques in mobile educational environments is researched to provide a comprehensive meta-analysis of the methodologies and algorithms used to develop mobile software applications in educational environments.

To make the reader's educational mobile software application development successful, the four filtering techniques (i.e. collaborative-based, content-based, knowledge-based, and hybrid-based) are analyzed in detail. The reader will construe a mechanism in managing and filtering the overloaded information based on their needs and be able to develop a successful educational mobile application.

Definition of the Terms

Recommender systems are software applications that provide personalized recommendations of the most suitable relevant information by predicting the user's interests in the information overload. In addition, recommender systems often use three types of data: the data regarding the user, the item (e.g. services or information), and the relevant relationship between the user and the item (Park, 2018; Lu, Wu, Mao, Wang, & Zhang, 2015).

Mobile devices in education are related to the concept of mobile learning (m-learning), which was described in the 'DynaBook' as early as 1972 to enable portable computer-based learning (McKnight, 2014). By 2011, handheld mobile devices out-numbered client personal computers, which provided educators with the opportunity to deliver astute learning modules using such devices. The mobile devices used are iPads, Tablets, iPod touches and other smartphones that enabled the concept of 'here and now' learning with the steady involvement with other professionals, regardless of their geographical location (Martin & Ertzberger, 2013).

Collaborative-based recommender system uses a filtering technique that relies on the item ratings from each user. It is assumed that the users that rated the same items with similar ratings have similar preferences (Yang, Quadir, Chen, & Miao, 2016).

Content-based recommender system uses a filtering technique that matches content resources to user characteristics or information they provided (Isinkaye, Folajimi & Ojokoh, 2015).

Knowledge-based recommender system uses a filtering technique that offers item information to the user based on knowledge of the user, items and the relationship between the two. That recommender item meets the specific user's need and it often uses case-based reasoning to generate the item by retrieving the most similar cases to the user's query and profile (Lu et al., 2015).

Hybrid-based recommender system uses a filtering technique that combines the best features of the two or more recommender filtering techniques previously described into one hybrid technique (Lu et al., 2015).

Organization of the remaining chapters

The paper's remaining chapters are organized as follows: Chapter II provides an in-depth background of the recommender systems filtering techniques in mobile educational environments. Chapter III provides a systematic review of recommender systems in mobile educational environments with a summary of the review's results. Chapter IV delivers a meta-analysis of the filtering techniques of recommender systems with a comparison of the results. Chapter V details the challenges, recommendations to researchers, gaps in research, findings and results. Finally, chapter VI concludes this paper, while suggesting future research that can be done in this topic area.

CHAPTER II

RECOMMENDER SYSTEMS

Recommender systems technology usage is not a new concept in mobile education. In application development in educational environments, mobile devices are more frequently used than personal desktops. As such, the plethora of information used for suggestions must be filtered without overwhelming the learner.

Systematic Review

A systematic review is conducted in this paper to analyze each filtering technique of recommender systems, their current applications, and algorithms used in mobile educational environments. The definition of a systematic review is a type of review that identifies a clearly formulated question. It uses systematic and explicit methods to identify, select, and appraise relevant research. Additionally, it functions to collect and analyze data from the studies included in the review. The aim of the systematic methodology is to minimize subjectivity and bias and to use the literature reviewed in this paper to evaluate existing theories and have a strong implication for policy or practice (Siddaway, Wood, & Hedges, 2018).

Regarding recommender systems, there are several potential outcomes of a systematic review. First, broad conclusions must be drawn with unbiased summaries of the type of filtering techniques used in recommender systems, while designing mobile educational applications. Second, relations, contradictions, gaps and inconsistencies must be identified while exploring for those reasons. Third, existing theories must be explored and related to explain the ways in which the individual studies fit together. Finally, inference for practice and policy must be inferred, while highlighting important directions for future studies (Siddaway et al., 2018).

Recommender Systems

The Internet's information is not structured or well-organized, and its expansion has made suggestions for relevant data more complex. This complexity is due to more variables, such as those related to social, psychological, and behaviour factors, being introduced and related to the learners who create or receive the information. Chang et al. (2015) have pointed out that incorporating technology in an educational environment has the possibility to facilitate new knowledge, skills and attitudes that may not be as advanced in traditional learning environments. Therefore, the recommender systems technology is a solution to manage the complexity of data, and according to Sielis, Tzanavari, & Papadopoulos (2014), they are defined as adaptive intelligent software tools in applications that suggest information pertaining to the end user's interests, preferences, actions, tasks, or contextual information, and are used to filter and remove irrelevant information.

In this paper, the discussion of the specific usage of educational recommender systems in mobile applications must be appealing and increase the learners' interests to help them engage with the learning software. Additionally, their engagement must involve interaction and discussion with one another to exchange information and find out answers to questions through an investigation of the acquired data (Chang et al., 2015).

The filtering technique of a recommender system provides suggestions and advice, which helps in decision-making processes to further explore the type of learning objects to absorb (Klašnja-Milićević, Ivanović, & Nanopoulos, 2015). Recommender systems must be efficient and useful and provide the best option from the available filtered ones (Navlani & Dadhich, 2017). Additionally, recommender systems are primarily directed towards individuals that lack personal experience or capability to evaluate the overloaded information of alternative suggestions (Klašnja-Milićević et al., 2015).

Furthermore, Klašnja-Milićević et al. (2015) have indicated that the ideal recommender system for educational environments should assist the learner in discovering relevant learning objects that match their profile, at the right time, context, and way to keep the learner motivated to complete their learning activities. In addition, the recommender system should utilize information about the learner to recommend specific learning items such as papers, web sites, courses, lessons and other resources to meet the characteristics and interests of the learner. To design an efficient recommender system, it is important to understand the learner's goals, characteristics, prior knowledge, groupings, paths, strategies, and rated activities. A good recommender system should be highly personalized by exploiting the learner's characteristics to serve as a guideline for framework design and platform implementation. Further, it has to enable access to relevant learning resources based on their interests, knowledge, and activity level (Chen, Wang, Kirschner, & Tsai, 2018). Also, it must recommend material at an appropriate time and location to support the continuous learning process by providing an exceptional level of interactivity.

Mobile Learning

Mobile devices have increased in usage incrementally over the past few years, and it gave the opportunity for educators to make use of the devices in the design of learning environments. According to Fu & Hwang (2018), mobile learning provides a much wider educational application because of its convenience, personalization and collaborative environments with other learners. Mobile collaborative learning is the new approach to encourage and facilitate learning with the instructors and other classmates in and outside the classroom. Furthermore, Chou, Wu, & Tsai (2019) have found that mobile learning cultivates learner's critical thinking (CT) skills not only by peer interaction but through the internal decision-making processes where the learner is required to be active.

Moreover, the technology provides educators with a way to rethink and reimagine education. It provides structure-based learning where the learner accesses multiple sources that can conveniently take place at any time and anywhere (Heflin, Shewmaker, & Nguyen, 2017). Additionally, the concept of 'here and now' is used to describe mobile learning and has existed for approximately a decade when the authors Martin & Ertzberger (2013) have published their paper, and it has been widely researched as situated learning.

Mobile devices have added new dimensions to situated learning where its functionalities included the following: geospatial technologies (GIS data, GPS chips, RFID chips, Bluetooth, bar codes, sensors, and NFC), mobile visual search, use of a camera for image capturing, and social networking. Situated learning, in the context of mobility, gives the learner the opportunity to be in the environment of their learning and to access information related to what they are seeing and experiencing at any moment, regardless of geographical location.

Additionally, the learning design in mobility considers the learner's characteristics of engagement, collaboration, authentic activities, and informal learning as illustrated in Figure 1 (Heflin et al., 2017; Martin & Ertzberger., 2013).

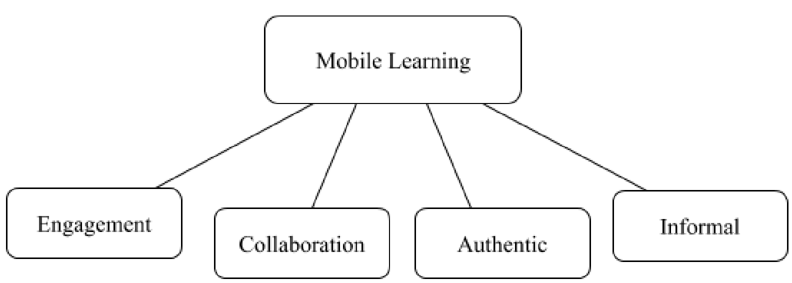

Figure 1. Learning Characteristics

The learner’s engagement is their involvement in learning activities by actively participating in the educational environment. Collaboration in learning, while being in small groups, stimulates interest in learning, helping the learners engage in the material. In the design, authentic activities allow for the learner to gain access to the type of environment that enables educators to integrate content and processes together in the design of learning activities. This increases the learner’s experience of authentic activities to achieve a deeper understanding of the subject matter. Finally, informal learning occurs without directed effort. More specifically, it is a method of learning from individuals around us that involves participating and learning from others, not just replicate learning. Therefore, mobile technology has within a specific context and learning environment can increase the effortlessness of informal learning (Heflin et al., 2017; Martin & Ertzberger, 2013).

Recommender Systems Filtering Techniques

Understanding the ways in which mobile devices and learning drastically enhanced education have in its ‘here and now’ methodology is aiming to help educators design mobile learning environments in a more inviting and personalized manner. Moreover, recommender systems implementations in these mobile learning environments suggest learning objects relevant to their path of learning. As was defined in chapter I and illustrated in Figure 2, the recommender systems ‘filtering techniques’ presented are collaborative-based, content-based, knowledge-based, and hybrid-based, while focusing on personalization of learner’s data.

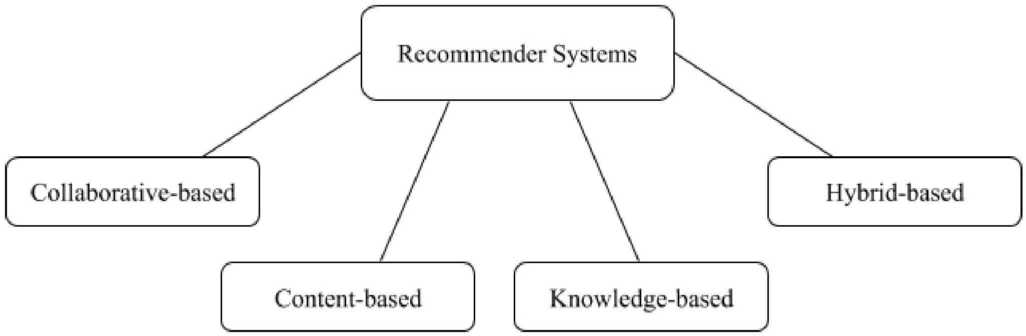

Figure 2. Recommender Systems Filtering Techniques

Meanwhile, data collection is an important part of a recommender system that is used by the learner to properly filter through the desired items. The data collected fall in four categories: demographic data, production data, user behaviour and user rating (Yang et al., 2016). The demographic data are the personal data collected from the learner, such as address and phone number, that are placed on a server. Moreover, production data are tags added to help the learner find the appropriate item. User behaviour involves ways that a learner interacts with the environment, which include the number of clicks, length of time on a certain page, and pages visited. As such, the data are stored on the server to be analyzed by appropriate data mining methods. Finally, user rating is the method where the learner rates an item that reflects their preferences, hence increasing the attention of educators to enhance the learning environment in the future.

Collaborative-based recommender systems use collaborative filtering to predict the interests of mobile learners to make proper recommendations. It relies on rating systems of each learner while noting that those who rated the same item are more likely to have the same preferences. Further, the group of users that have similar preferences are like those in a neighbourhood, and when an added item is rated by one of the users, the other neighbours become aware of it too. Additionally, it is designed to provide recommendations when detailed information about the learner is inaccessible (Yang et al., 2016).

Moreover, suggesting items using collaborative filtering is based on the way the learner interacts with the item. Subsequently, it is used to recommend an item of interest to the learner. The educators, while designing a learning environment, use this filtering technique to suggest items that similar learners have used and rated, or they find items, like one of interest, to the learner based on their preferences or activity (Chatti, Dakova, Thus, & Schroeder, 2013).

Content-based recommender systems are content filtering that use features of items to infer recommendations. For instance, a similar item's content to the currently viewed items by the learner are recommended (Oduwobi & Ojokoh, 2015). Moreover, this filtering generates recommendations using the content as objects, so certain content, such as text, images and sound, can be analyzed. With this analysis, the similarity is established between objects that are related items to the ones the learner has viewed, visited, or ranked positively (Bobadilla, Ortega, Hernando, & Gutiérrez, 2013). Also, the filtering suggested items that are similar to those preferred in the past if learners profiles are created and the techniques match content to learners' characteristics. However, content-based filtering ignores contributions from other learners, therefore limiting content analysis and inducing sparsity of data (Benhamdi, Babouri, & Chiky, 2017; Isinkaye et al., 2015).

Knowledge-based recommender systems are a detailed level of the overall recommender systems ontology, recommending an action to pursue or a decision to make for the user. It differs from other levels of a recommender system because it generates recommendations based on the domain of knowledge related to item assortments, criteria used for suggestion and learner requirements (Chopra, Moun, & Kapil, 2018). Moreover, it is observed that, over the years, the knowledge-base that takes form in a database has evolved into a collection of organized data items, thus increasing its complexity. With that complexity, components are identified of this recommender system, which includes the knowledge base, as its main one, and user profile alongside preferences (Bouraga, Jureta, Faulkner, & Herssens, 2014). Therefore, these components must work together for the recommender system to function properly.

For a knowledge-based recommender system, the activities of the system are the knowledge of the way objects preferred, chosen, and seen solely by the user are related to each other, which infers recommendations of catalogued, functional, or user-based knowledge (Cheng, Chou, & Horng, 2013). However, knowledge about an individual's preferences is difficult to obtain in mobile environments since one tends to use apps that are non-cookie based, making it difficult to obtain personal data. Though, if the user explicitly clicks buttons to transfer their personal information to be further analyzed, this can provide accurate knowledge-based recommendations. However, if such data is not provided by the learner, then, according to Frey et al. (2017), personal profiles in mobile devices can be constructed by applying machine-learning to leverage new data sets to predict interests for use in recommendations.

Hybrid-based recommender systems hybridize the features of two or more recommendation filtering techniques. This approach combines content with demographic, collaborative and content, or collaborative with content-based filtering (Noor & Khan, 2017). It is useful in overcoming the limitations by individual recommendation approaches. Also, according to Tarus, Niu, & Kalui (2018), combining different recommendation techniques leads to performance improvement. More specifically, performance is improved by reducing search space, overspecialization problem and new learners added to the educational environment.

Likewise, the inclusion of the learner context in the recommendation approach helps improve recommendation personalization. The contextual data can be derived explicitly, implicitly or deduced from the content, and can also be inferred through data mining or statistical methods. In the hybrid recommendation approach, the learner's contextual data is used to personalize their profile and preferences, and the learning object stores information about the learning resources. The learning resources are therefore recommended to the target learner based on their ratings on learning resources and contextual information (Tarus et al., 2018).

CHAPTER III

SYSTEMATIC REVIEW

The systematic review and meta-analysis in Chapters III and IV use an explicit, comprehensive and retrievable technique to identify and synthesize an existing body of completed and published work produced by researchers and scholars. The research papers utilize well-organized methods of assembling and evaluating the body of research. Therefore, the systematic review in this paper will describe the findings of the collection of research studies pertaining to using recommender systems in mobile educational environments and each of its filtering techniques to design such systems (Alyari & Jafari, 2018; Sa'don & Iahad, 2016).

Search and Selection Process

The search and selection process used the following three steps:

Step 1: researching articles

The Educational Technology Top 20 publications from Google Scholar were used to collect the articles from each journal. The initial search was conducted using each publication's web site that can be found in Appendix A. Since the subject matter is specified to mobile educational environments using recommender systems, the primary searched keywords were as follow: 'recommender systems mobile education', 'collaborative based recommender system', 'content based recommender system', 'knowledge based recommender system', 'hybrid based recommender system'. Table 1 shows the total number of papers per keyword phrase used filtered by the Top 20 Educational Technology publications.

Table 1. Paper Selection by Keyword Results in the Top 20 Educational Technology Publications.

Keywords	*Number of Papers*
recommender systems mobile education	97
collaborative based recommender system	91
content based recommender system	132
knowledge based recommender system	132
hybrid based recommender system	49
Total	501

The numbers were a collection of all keyword search results in each publication's web site, and the detailed data collected is outlined using a Microsoft Excel sheet at Appendix A.

Furthermore, the systematic review of recommender systems in mobile educational environments where the articles used from those were identified based on these criteria: a) must be available as a PDF to download through Athabasca Library's resources, b) date range was limited to 2001 - 2019, c) quality of publications and number of references used, d) duplicate studies were removed, e) articles with the majority focus on recommender systems, four filtering techniques, education, and/or mobile, and f) only English language.

Step 2: selections based on titles and abstract

Using the aforementioned keywords to extract relevant scholarly articles and conference proceedings, the titles and abstracts of the published articles deemed relevant to this paper were chosen and 129 articles were added to Mendeley Reference Management Software. The abstracts must have one or more of the primary keywords ('recommender systems', 'mobile', 'education', or ‘e-learning’). In addition, the filtering technique searched, alongside the primary keywords to be included in the review, must be mentioned in the title or abstract. In Athabasca University Library’s search of the Top 20 Educational Technology publications, only those articles limited to ‘Scholarly (Peer Reviewed) Journals’ or ‘Conference’ proceedings were selected. The papers selected were from the year 2001 onward because of their novelty toward prior years. Also, only English language studies or those translated to English were included.

Step 3: selection based on references

Firstly, in Google Scholar’s search engine, the number of cited articles is below each search item, which initially helped determine which papers have more relevant information frequently cited by other authors. Secondly, after identifying the articles, determining further eligible studies by backward citations and a forward citation was conducted as necessary (Alyari & Jafari, 2018). There were 50 papers chosen for this systematic review.

<u>*Systematic Literature Review Results*</u>

This section presents the results of the systematic review using the research papers previously mentioned after screening the titles and abstracts. The 50 papers obtained to use the specified journals from Google Scholar’s Top 20 Educational Technology publication list. Unfortunately, some of the publications did not provide any results regarding recommender systems filtering techniques in education as indicated in Appendix A. The evaluation is sectioned in five parts based on the keywords searched and Tables 2, 3, 4, 5, 6 provide contextual information of the primary studies used.

Table 2. Overview of the Primary Studies About Recommender Systems Mobile Education.

Year	Author	Journal / conference
2009	[S1] Martín et al.	IEEE Transactions on Learning Technologies
2009	[S2] Romero et al.	Computers and Education
2010	[S3] Ruchter et al.	Computers and Education
2012	[S4] Cheon et al.	Computers and Education
2013	[S5] Martin et al.	Computers and Education
2013	[S6] Eynon	Learning, Media and Technology
2013	[S7] Boticki et al.	IEEE Transactions on Learning Technologies
2014	[S8] Lazarinis	Education and Information Technologies
2014	[S9] Chao et al.	IEEE Transactions on Learning Technologies
2015	[S10] Erdt et al.	IEEE Transactions on Learning Technologies
2016	[S11] Yang et al	Internet and Higher Education
2017	[S12] Heflin et al.	Computers and Education
2017	[S13] Benhamdi et al.	Education and Information Technologies
2017	[S14] Mora et al.	International Review of Research in Open and Distributed Learning
2018	[S15] Fazeli et al.	IEEE Transactions on Learning Technologies
2018	[S16] Suárez et al.	Computers and Education
2018	[S17] Dwivedi et al.	Education and Information Technologies
2018	[S18] Bakhshinategh et al.	Education and Information Technologies
2018	[S19] Bano et al.	Computers and Education
2018	[S20] Castro	Education and Information Technologies
2019	[S21] Aeiad et al.	Education and Information Technologies

Table 3. Overview of the Primary Studies About Collaborative-based Recommender Systems.

Year	Author	Journal / conference
2011	[S22] García et al.	Internet and Higher Education
2011	[S23] Rodríguez et al.	Interactive Learning Environments
2012	[S24] Wang et al.	Computers and Education
2013	[S25] Chatti et al.	IEEE Transactions on Learning Technologies
2014	[S26] Salehi et al.	Education and Information Technologies
2016	[S27] Sergis et al.	IEEE Transactions on Learning Technologies
2017	[S28] Bodily et al.	IEEE Transactions on Learning Technologies

Table 4. Overview of the Primary Studies About Content-based Recommender Systems.

Year	Author	Journal / Conference
2007	[S29] Ochoa et al.	IEEE Transactions on Learning Technologies
2008	[S30] Vassileva	IEEE Transactions on Learning Technologies
2013	[S31] Liu et al.	British Journal of Educational Technology
2014	[S32] Colomo-Palacios et al.	Interactive Learning Environments
2015	[S33] Niemann et al.	IEEE Transactions on Learning Technologies
2019	[S34] Money et al.	Education and Information Technologies

Table 5. Overview of the Primary Studies About Knowledge-based Recommender Systems.

Year	Author	Journal / Conference
2009	[S35] Melia et al.	IEEE Transactions on Learning Technologies
2009	[S36] Zeng et al.	Computers and Education

2011	[S37] Klašnja-Milićević et al.	Computers and Education
2014	[S38] Chen et al.	Computers and Education
2014	[S39] Halimi et al.	Interactive Learning Environments
2015	[S40] Hung et al.	British Journal of Educational Technology
2015	[S41] Santos et al.	Computers and Education
2015	[S42] Sathick et al.	International Review of Research in Open and Distributed Learning
2017	[S43] Cocea et al.	IEEE Transactions on Learning Technologies
2017	[S44] Lavbič et al.	Interactive Learning Environments

Table 6. Overview of the Primary Studies About Hybrid-based Recommender Systems.

Year	Author	Journal / Conference
2010	[S45] Ghauth et al.	Australasian Journal of Educational Technology
2010	[S46] Abel et al.	IEEE Transactions on Learning Technologies
2015	[S47] Zheng et al.	IEEE Transactions on Learning Technologies
2017	[S48] Rajagopal et al.	British Journal of Educational Technology
2018	[S49] Peralta et al.	IEEE Transactions on Learning Technologies
2018	[S50] Karga et al.	Education and Information Technologies

3.1 Recommender systems in mobile educational environments

This section has three parts. The first part includes an overview that describes recommender systems in mobile educational environments. In addition, the users of recommender systems in mobile educational environments is presented. Finally, a summary of the learner's methods in using recommender systems in mobile education is discussed.

Overview. Mobile devices offer a new point of advancement that unifies digital technologies in hardware and software. The author [S20] explains that mobile devices have a reliable operating system that facilitates access to existing systems or platforms such as Learning Management Systems and Massive Open Online Courses. Further, the mobile system provides physical spaces with learning environment capabilities.

Educators have been considering mobile learning outside the traditional educational setting. There are two learning environments, the formal or traditional classroom setting, and informal where the learner can learn at their desired location and time. Informal learning using mobile devices, as stated by [S16] help the learner develop their work regimen in an unpredictable environment such as the current one where it has the ever-changing technology-driven society. There was a concern that desktop computers and online learning were not enough to allow the learner to experience on-site learning. However, mobile devices with the benefit of computer-mediated technology help to learn with direct on-hand experience transforming physical spaces, such as museums, into interactive learning spaces [S20].

Moreover, mobility promotes learning while allowing flexible and instant access to rich digital resources constituting information in text, picture and video formats. Educators use mobile technology to guide the learner and monitor their progress [S4], [S12], [S3]. The authors [S16] stated in their study that some type of guidance improved learning outcomes. Unfortunately, less support and too much freedom can be undesirable to the learner where they may struggle to select, organize and integrate relevant information to achieve the proper learning outcome.

The application fields and usage of recommender systems in mobile education should not complicate the learning process but facilitate it for mobile learners. According to [S21], the architecture of a recommender system can be implemented for various disciplines with minor changes of a few components. The standard curriculum is used to organize the learning units as required by the discipline and it allows consistency and quality of learning resources.

With minimal changes to the curriculum in online environments, strategies for instructional design and organization must involve teaching presence in online learning forums to manage discourse and provide direct instructions. The design indicates formatting consistent course content and discussions that are important to achieve learning outcomes. Further, [S11] explains that specified forms of teaching presence provide instructional leadership facilitating appropriate course structure and having a positive effect on learning establishing a high level of cognitive presence.

With the emergence of personalization tools—specifically, recommender systems—the learning platforms have become more flexible for the learner, and the system must, therefore, find the best learning resource to fit the learner’s needs in an online mobile environment [S13]. The adoption of mobile technology is complex, and it is important to evaluate the effectiveness of mobile technology use in education, especially for learners who may have difficulties in group communications, coordination and interaction with other team members [S19], [S7]. Mobile devices using a recommender system for education increases the learner’s motivation and promotes interactive learning [S1]. The technological advances may provide tools to facilitate educational processes, while sharing content and communication may increase the effectiveness of a learning system [S14].

The information in mobile educational environments must be efficient and cost-effective to improve education ‘delivery’ [S6]. Delivery can be improved by personalizing the filtered data by data mining techniques to deduce appropriate knowledge learnt from the learner to make recommendations of useful material [S2]. This enhances learning quality and intensifies the learning process [S18]. Also, the authors of the paper in [S17] found that a more effective personalized recommender system has an ordered learning path from a starting to the ending point, rather than a sequence of unordered material. Likewise, the content of the personalized data represents learner's characteristics and consist of attributes representing personal learner's data, their gender, age, formal education, knowledge level, goals, computer usage experience, Internet usage experience, blog usage experience, and preferences [S8], [S11].

Moreover, the system consists of a recommendation engine that creates a list of items sorted by relevance. To further illustrate, it is tailored to the learner based on their profile containing user preferences or demographics [S10] and combines innovative teaching approaches that are student-centered, personalized, and collaborative [S20]. The user-centric approach of personalizing recommendations is not enough to be helpful, but it should be a pleasure to use while having quality and diverse metrics [S15].

Learner, recommender systems and mobile devices. The methods that a learner uses to interact with recommender systems in mobile education must keep them interested in the feature to receive appropriate recommendations. In order for a learner to be ready for mobile learning, their perception of the usefulness of the technology must be considered in designing a recommender system. Understanding the learner's perception of the technology and usage is discussed by evaluating certain studies focusing on learning object's usage, analysis, and presentation of the desired information in educational environments.

- Planned behaviour.

  According to research done by [S4] regarding the theory of planned behaviour, it is important to consider the ways in which learners are adopting mobile learning. More specifically, there are four types of learning approaches: individualized, situated, collaborative and informal learning. Individualized learning allows the learner to learn at their own pace. On the other hand, situated learning involves the learner using a mobile device to access the learning context. Moreover, collaborative learning involves interacting with and learning from other learners by using an easily accessible mobile device. Finally, informal learning is when the learner, at their convenience, learn out of the classroom. These types of learning approaches, in theory, explain the behaviour of an individual learner. The author's methodology to determine the learner's behaviour using mobile learning was based on the learner's attitude, subjective norm and behavioural control. They studied 189 undergraduate participants from a research-intensive university in the Southwest of the United States where 86% of the students had mobile devices. As such, their findings indicated that educators and learning designers should build mobile application implementation plans that consider design guidelines, development phases and the learner's readiness. To increase the learner's positive attitude, meaningful information should be easily accessed by mobile devices.

- Social interactions.

  Studies by [S14], [S9], [S11] discuss the methods to process large information retrieved from forms in educationally-based communities and blogs where learners interact socially and may share information publicly with other learners or educators regarding a particular subject and build social relationships. Learners interests could be analyzed to understand learners' characteristics of shared content in the community. One of the methods discussed involves using data mining to analyze posts from the community to discover structures and understand the social community. It is a means to provide automatic indexing, search, and cluster within the forum's community. In addition, the social analysis of the communities is a method of mapping group interactions, communications and dynamics. In this case, recommender systems will automatically analyze the text within the forum and provide the learner recommendations based on the forum's context and previous interactions.

- Engagement and attitude.

  A study by [S5] investigated the ways in which mobile devices with the 'here and now' learning affected the attitude of the learner and its impact on increasing their engagement with the application at hand. They stated that many educators believe that mobile technology provides a way to engage students. They conducted the study with 109 participants ranging from ages 18-22 where 87% were females and 13% male, and they found by a questionnaire how they used the device that 83% of the participants used their mobile devices for school and 75% used it as a learning tool. Therefore, they performed a closed group experiment for learners to use iPad and iPod technologies to access learning material and observe their attitude using such tools. Overall, these learners enjoyed the applications and were able to easily access the required information.

- Learner satisfaction.

  A paper by [S15] focuses on the user-centric and data-centric evaluation of recommender systems in social learning platforms, and the ways in which learner satisfaction is related to its performance in terms of metrics accuracy. The author's study aimed at measuring learner satisfaction on the recommendation they provided by using data that comes from the Open Discovery Space (ODS) platform. The data-centric evaluation assesses the performance of the recommender algorithm used in terms of the accuracy of the recommendations and provides analysis to the designer. As for the user-centric evaluation, they explicitly asked learners whether they are satisfied with the recommendations by its usefulness, accuracy, novelty, diversity and serendipity. The results showed that recommender systems that used data-centric algorithms might guide learning educators and learning designers to an unsuitable path in terms of learner satisfaction.

- Personalized e-learning.

  Research by [S21] discussed personalization of data presented to the learner in educational systems using the development of an architecture for A Personalised and Adaptable E-Learning System (APELS). Personalized systems are designed for the learner to take control of their learning process and experience while offering content that is most suited for their learning style, background, and needs. The personalization model must contain three components: personal information, such as name, contact and address, prior knowledge, where the learner selects the specific domain and chooses a level of knowledge, and learning style, where a questionnaire is used to analyze and inform the learner of the initial learning style. Moreover, the APELS systems provide personalized learning material in a time-efficient way, saving time searching for the right learning materials from the vast amount of online resources.

Summary of learner's methods using recommender systems in mobile education. Recommender systems are used to filter the information overload from online resources, but the learner feels uncertain with using advanced mobile technological tools, especially mobile devices to access their learning platforms, especially in informal learning environments. As such, the application must produce highly accurate data, a personalized recommendation for the learner, and be fast and reliable. To design a recommender system in an educational setting, the learner's interaction with the system must be first analyzed, where it can provide useful results and gain their interests. The studies chosen discuss learner's interaction with the online mobile educational environment and will help learning designers and educators plan the design of a recommender system. The design must understand learner's behaviour in terms of their interaction with the system, be it individualized, situated, collaborative or informal learning. In addition, it must understand the ways in which it can filter relevant educational information in communities where social interactions occur and present it to the learner automatically. Although the mobile device allows 'here and now' learning, the effect of the learner's attitude and the way they engage with the application is critical in improving learning outcomes. The type of data, whether it is user-centric or data-centric, must be analyzed and filtered with accuracy to enhance user satisfaction. Finally, personalizing e-learning in a time-efficient way saves time in the filtering process, allowing the learner to have access to learning information tailored to their needs.

3.2 Collaborative-based recommender systems

This section first describes an overview of collaborative-based recommender systems (CBRS) in educational environments. Secondly, the frequently used collaborative-based recommender systems algorithms will be discussed. Lastly, the collaborative-based recommender systems techniques will be summarized.

Overview. CBRS in education involves grouping like-minded learners by utilizing their ratings of each item. It is predicted that those learners with similar choices will make the same selection in the future [S26], [S27]. Then, the filtering system automatically makes predictions based on user preferences using a collection of their online reactions to provide recommendations. The collaborative filtering system filters by estimating the desirability of the items and its rankings by soliciting data from learners or leveraging data from them [S24], [S28]. Figure 3 shows the ways in which learners interact based on ratings in the CBRS environment. Moreover, preferences are user-based characteristics, but there are also tagged-based items that are filtered and used to predict equivalent items that may be of interest to the learner [S26]. The amount of data that is collected attributes to a highly positive correlation with collaborative recommender system's performance [S27].

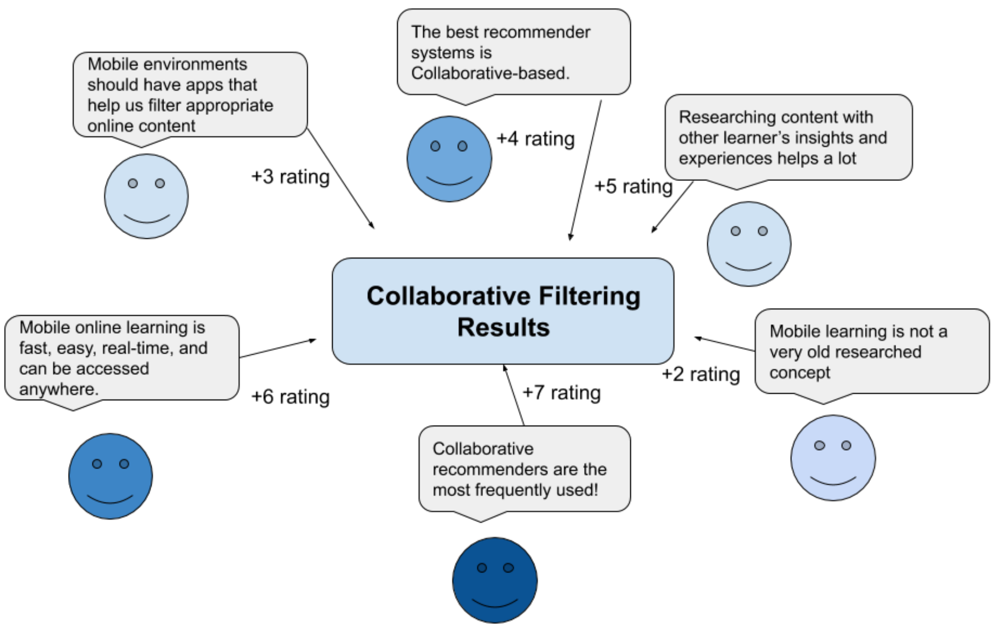

Figure 3. Collaborative-based recommender system based on learner ratings

Algorithms. The collaborative recommender techniques are traditionally classified into two categories: memory-based and model-based. Memory-based algorithms make recommendations based on the learner's past rating and user-item database, alongside tagged items, to make the prediction. The user-item database uses an item-based approach that has better precision than user-based because items are tagged. On the other hand, model-based algorithms use the collection of ratings to make rating predictions. The first approach to data modeling is a data mining method that considers two-dimensional matrices consisting of a user-tag, user-item, and a tag-item matrix.

The second approach applies topic clustering of items (i.e. two different tags with similar meaning) that assumes that co-occurring tags belong to the same topic [S25]. Moreover, [S23] found that filtering learning objects and learning activities using the collaborative technique requires a different algorithm, called blockmodeling, that helps with automation. Blockmodeling detects meaningful patterns in a network, thus transforming the non-coherent networks into comprehensible ones. It is done by identifying clusters that share similar characteristics to detect different structures of an item retrieved.

However, there are limitations of using the collaborative recommender system: it involves cold-start, sparsity, and scalability problems where available data is insufficient for identifying similar learners, which results in reduced flexibility [S25]. One method to alleviate these issues is by using data mining techniques to discover suitable rules within the recommender engine. Yet, this system requires knowing many learner profiles to make accurate recommendations. If the environment has a low learner count, then the recommender results are not accurate [S22], [S26]. The second method considers the contextual information of a learner and attributes of an item. This method considers the information rated by the learner and multidimensional attributes of the accessed material [S26]. Another method involves generating recommendations by collecting social media interactions to reveal further user preferences [S25].

Summary. CBRS in educational environments has been successfully used according to the aforementioned studies. However, the increased use of this system exposed limitations, thus preventing the system from producing accurate data. The inaccuracy causes learning frustrations and low use of the application, which prevents the learner from continuing their online learning. The most frequently cited problems with CBRS are the sparsity of data to be filtered and low prediction accuracy under cold-start conditions. In order to mitigate these issues, methods of data mining within this filtering recommender system and including contextual information about the item and its attributes should be used. Traditional collaborative memory-based and data-based algorithms include user and item-based data as an attempt to increase the accuracy of the recommendation. Also, the specified e-learning algorithm blockmodeling searches patterns in a network and identifies clusters used in a filtering technique to produce a more accurate educational recommendation.

The CBRS and its properties:

1. What is needed?
    - Learner profile
    - Learner preferences
    - Learner opinions
    - Collaborative opinion
    - Item/material ranking
    - Item attributes
2. Data inputted
    - Previous data of the access/usage of item/material by the learner
    - Tagged items/material (if any)
3. Data outputted
    - User-based and item-based data

4. Limitations
   - Scalability
   - Cold-start
   - Sparsity of data
   - No rating of an item
   - New learner and/or new item/material
5. Advantages
   - Real-time usage
   - Recommend items based on another learner's opinion

3.3 Content-based recommender systems

This section begins with an overview of content-based recommender systems in educational environments. Secondly, a discussion of the frequently used content-based recommender systems algorithms will be presented. Lastly, a summary of the content-based recommender systems techniques will be provided.

Overview. Content-based recommender systems (CRS) are based on the learner's profile that is interactively acquired by asking them about their interests or acquiring their demographic data alongside the items' attributes to produce recommendations [S30]. The filtering system only exploits the learner's profile and compares it to the item's profile to calculate recommendations. When an item is added to the database, the contents are analyzed and recommended to the user without it being rated [S33]. Moreover, the recommendation produced by content-based filtering (CF) technique suggests items that may be similar to those the learner previously preferred [S13]. The CF should be used to adapt to the needs of learners especially in the design of adaptive learning systems [S32], [S34]. Moreover, the filtering approach extracts semantics from the content, such as keywords and keyword frequencies of the learning objects and those a learner has accessed already. The system then recommends learning objects with a semantic profile similar to previous learning objects retrieved by the learner [S31].

Unfortunately, there are disadvantages of the approach of CF because it is not scalable, and it lacks sufficient insight from the learner's profile to produce quality recommendations [S29]. Further, recommender systems are known to experience cold-start problems: therefore, when it relies on CF, inevitable issues with new learner additions and overspecialization may occur. In addition, it can be a time-consuming filtering approach and expensive to maintain [S33].

Algorithms. CF algorithms find content similar to those already accessed by the learner. One type of algorithm to determine the current status of learning object ranking is described by [S29] that relies on CF calculations to assign relevance to the objects returned while the learner is searching for appropriate data. They used a tool named SMETE that acquires some variations of the vector-space algorithm to calculate similarities between the queried terms and the text contained in the learning object's data. The algorithm creates a vector for the documents and query where each dimension is a word where its frequency in the query is divided by the frequency of the entire database. Another algorithm approach is adapting full-text search approaches to rank learning objects based on the similarity between queried terms and the textual data in the object's attributes. However, there are disadvantages to this approach. More specifically, the amount of text in the learning objects data could be low, and the order of the final list reflects on the number of times the queried terms appear, but the quality of the search is not relevant to the object itself.

Another algorithm uses a keyword recommendation to explore information object where CF and data mining analysis generates concept associations from a plethora of documents. According to [S31], the concept guides learners to navigate from a limited concept to broadly-ranged concepts leading to a learner-centred approach. However, there are limitations with the learner-centred approach because it is still not clear if it influences information searching since the learner's domain knowledge is quite different than other domains. Moreover, the approach of extracting keywords has its limitations in terms of guiding the learner toward the concept-based objects.

Summary. The CRS relies on learner's profile and item's attributes. The newly-added items to the database are used to filter the information through the semantics of the keywords in the queries and their frequency and produce recommendations to the learner. The algorithms discussed are ones used in educational settings where learning object's attributes are thoroughly searched. Unfortunately, the aforementioned algorithms have their limitations since extracting keywords from the query and using a larger-scaled concept may not produce accurate recommendations in the learning domain.

The CRS and its properties:

1. What is needed?
    - Learner profile
    - Item attributes
2. Data inputted
    - Keywords to query
3. Data outputted
    - Learner-centred data

4. Limitations
    - Scalability
    - Cold-start
    - New learner
    - Learner profile insights
    - None or low item/material count
5. Advantages
    - Real-time usage
    - Using simple text-based metrics, then it is easily computed per object

3.4 Knowledge-based recommender systems

This section first describes an overview of knowledge-based recommender systems in educational environments. Secondly, there will be a discussion of the frequently used knowledge-based recommender systems algorithms. Lastly, a summary of the knowledge-based recommender systems techniques will be described.

Overview. Knowledge-based recommender systems (KBRS) are used to extract knowledge from a learner and the item's attributes for learning designers and educators to provide more accurate recommendations to them based on prior knowledge. Educators must lead the elicitation process because they have broader experience and understanding of the learner's needs. They also encode the knowledge manually by defining rules and constraints on the learning object [S44]. Furthermore, the more data that are collected, the better-outputted recommendations.

The learner's traits and level of knowledge acquired can promote personalized learning performance in the recommendation process [S41], [S36]. Additionally, prior and shareable representation of knowledge in semantic online data guarantees high-level expressiveness, flexibility and extensibility representation. There are different parameters of knowledge and other preferences for the learner that represents their own learning style where, as a result, the personalized learning style has emerged [S39]. According to [S36], the design of personalized learning requires proper data to capture knowledge within an educational environment. The design needs a predefined course ontology that represents the course's content. It also includes a user-interactive Q/A process where learners can post their questions corresponding to topics, browse answers, and select other questions to answer. Additionally, there has to be a self-reading process involving logs that track this behaviour to assess learner's knowledge. Finally, user modeling where derived Q/A logs are used associates between questions and answers of the course ontology and reading behaviour to construct a behaviour matrix and weight matrix to compute the knowledge requirements of each learner to be extracted.

However, prior knowledge recommendation is difficult to acquire and according to [S38], their experiment to deviate this difficulty involves incorporating social tagging methods to identify suitable supplementary material. Likewise, the authors [S40] stated that a well-designed educational environment enhances the learner's performance in learning if the knowledge data retrieved is well-organized. The data retrieved are in different formats and contain structures that must also be available and accessible at multiple online sources [S42]. Also, recommendations cannot be made for all learners, as even learners with similar learning interests have different knowledge levels to solve a task [S37].

Algorithms. To accurately extract and acquire knowledge, a tagged-based algorithm is introduced to extract such data and Figure 4 shows the way in which a learner interacts in such an environment. According to [S38], this tagging is socially-based and introduced as a technique to allow the learners to annotate various learning resources. Also, these tags are designed to enhance critical thinking skills by directing the learner to similar or opposing viewpoints. It allows the learner to identify the latest information from articles and help find clues within the context. As a basis of their design, TAK (tag-based prior knowledge recommendation) system was developed to include tagged items and prior knowledge to compose a tool to extract more accurate knowledgeable data to filter.

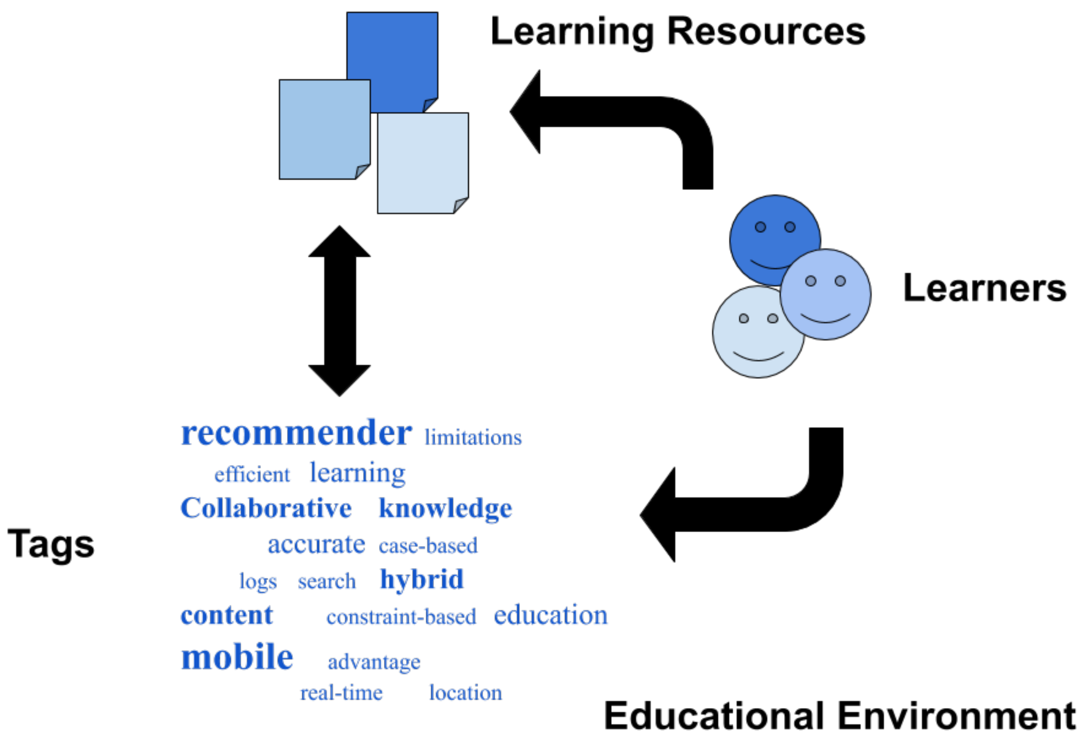

Figure 4. Learner interaction with tagged items and learning resources in an educational environment

The second algorithm involves a case-based reasoning learning technique where knowledge domains, which are complex, unpredictable, and continually changing, are developed on a certain design specification or single model. According to [S43], the case-based reasoning system stores relevant information by utilizing the knowledge of past-problem cases and providing an implicit solution in cases, adapting the cases to new experiences or adding new cases to existing or recent problems. The advantage of using a case-based approach is to provide better solutions where a knowledge domain cannot be modeled. However, the limitation of case-based reasoning is its dependency on the activity of the learner.

Lastly, the third algorithm is constraint-based reasoning where explicitly-defined constraints are presented in the knowledge domain. The study in the paper [S35] described the constraints of a courseware web tool on a learning model's context as conceptual prerequisite constraints where there is one common constraint for all models with a learner stereotype constraint to ensure the needs of stereotype groupings are covered in the learning system.

Summary. Knowledge-based filtering (KBF) in educational environment considers the learner's prior knowledge and items' attributes to produce useful learning data. However, educators add expert knowledge to the system to enhance the filtration process and provide more accurate results. Although the knowledge provided seems sufficient, the accuracy of the results is still lacking, and a social tagging algorithm is introduced to alleviate this issue. Moreover, two more common KBF techniques, constraint-based and case-based, are discussed to manage each case within the knowledge system and add constraints where needed.

The KBRS and its properties:

1. What is needed?
    - Learner's prior knowledge

- Item attributes
- Professional's domain knowledge

2. Data inputted
    - Terms to search

3. Data outputted
    - Knowledge-based results

4. Limitations
    - Learner activity
    - Not enough topics covered
    - Lack of diversity in results

5. Advantages
    - Real-time usage
    - More precise solutions
    - Interactive

3.5 Hybrid-based recommender systems

This section will begin with an overview of hybrid-based recommender systems in educational environments. Secondly, the frequently used hybrid-based recommender systems algorithms will be detailed. Lastly, the hybrid-based recommender systems techniques will be summarized.

Overview. Hybrid-based recommender systems (HBRS) combine different matching strategies or algorithms to achieve the most relevant results for the learner, such as the combination of content-based, collaborative-based or knowledge-based filtering systems [S48]. In addition, it overcomes the disadvantages that each one has separately [S49]. In terms of e-learning, the content that is recommended depends on the type of objects used, such as suggestions for courses to enrol or learning material that is deemed important [S45]. Moreover, e-learning using a recommender system should produce individualized recommendations and guide the learner in a personalized way to useful objects, while identifying suitable resources [S47]. Different personalization techniques overcome the disadvantage of a single personalization of latest items or new learner problems [S46].

Moreover, the use of hybrid filtering is suggested to overcome the cold-start problem or over-specialization problem [S50], and, if it uses topic models as a component, it presents the best performance regarding precise terms compared to individual recommender systems filtering techniques [S49]. Additionally, hybrid filtering eliminates the issue of data sparsity. More accurate recommendations are developed based on learners' professional networks and experts in the same field, and the recommender technique considers learner's attributes and preferences, and the targeted learners should be professionals in informal learning environments [S47]. Precise recommendations that favour ontologies, instead of ratings and user-defined tags, are a better result of learning resources [S49].

Algorithms. The HBRS in educational environments uses a combination of filtering techniques based on the type of learning resource. According to [S49], there are seven HBRS technique types to use:

1. The *weighted* system, where empirical methods are used to determine the best weights for each technique.

2. The *switching,* where the system chooses and applies a technique based on learner's profile.
3. The *mixed* system, where recommendations from different systems are presented next to each other.
4. The *feature combination*, where the various recommendation techniques of the system are combined to form one recommendation result.
5. The *feature augmentation*, where the system uses a recommendation technique to compute features to formulate an input for a technique and add source knowledge to an already-strong technique.
6. The *cascade* system, where recommender techniques are prioritized, and weakest refines the strongest result and not change it.
7. Finally, the *meta-level* system is applied, which produces a model that is used as input for the next technique.

Furthermore, a matching algorithm in hybrid-based systems is introduced to find a new learning contact, based on similar learners or resources that have related traits to the learner, and combines different matching strategies to achieve results relevant to the user [S48]. Another algorithm is the hybrid probabilistic matrix factorization, which linearly scales learner visits and their interactions while having a reliable performance on large and sparse data from content and collaborative data [S49].

Summary. HBRS provide precise results from various learning material using a combination of well-known filtering techniques, such as collaborative, content and knowledge-based filtering. All recommendation methods have disadvantages and limitations, but researchers have chosen to combine techniques to create a hybridized method by avoiding major disadvantages of each method, which provides the learner with a more accurate recommendation. The techniques used to produce a hybrid-based filtering (HBF) system, such as weighted, switching, mixed, feature combination, augmentation, cascade, meta-level, matching, and probabilistic matrix factorization, are alternative combinations.

The HBRS and its properties:

1. What is needed?
   - Learner’s profile
   - Item attributes
   - Professional’s data
2. Data inputted
   - Key terms to search from combined approaches
3. Data outputted
   - Precise results
4. Limitations
   - Increased complexity
   - Expensive to maintain
   - Need external information usually by professionals if available
5. Advantages
   - Real-time usage
   - Improve the accuracy of recommendations
   - Overcome drawbacks of other recommender systems

Online Recommender Systems Applications

Each filtering technique presents its usefulness using online recommender systems, and some authors in this systematic review have presented their own tools that they developed and tested using a group of learners. The tools that are researched and developed may be beneficial for educators and learning designers to use or translate to mobile application development if possible. Appendix B lists all the tools as recommender systems in online education by some of the authors papers listed in Tables 3, 4, 5, and 6.

CHAPTER IV

META-ANALYSIS

In this chapter, the results of the systematic review and comparison of the four recommender filtering techniques, collaborative-based, content-based, knowledge-based, and hybrid-based as mechanisms to filter appropriate context for the learner, is presented. Researching papers in Google Scholar's Top 20 Educational Technology publications using the five main keywords discussed in the previous chapter resulted in a broad range of results that was reduced to specified articles describing mobile education and each filtering technique in educational environments. The specified filtering techniques of a recommender system in the articles used for the systematic review did not explicitly analyze each technique's usage in 'mobile' educational environments; however, the articles discussed each technique's usage in Internet-based educational websites and online tools for learning. The minimal mention of each filtering technique and mobile devices in education together in the articles used for the systematic review is further discussed in the next chapter of this paper as a gap in research presenting a challenge to educators and designers. However, one-third of the articles collected mentioned the concept of recommender systems, education and mobility, which will help establish the grounds of understanding the ways in which designers and educators must evaluate the effectiveness of mobile device technology and plan to design recommender system tools in that environment to help the learners.

The initial research papers resulted in many duplicates and irrelevant content to what was planned, but the number was quickly reduced to specifically discuss the results of two major areas: recommender systems in a mobile educational environment and filtering techniques of recommender systems in education.

Mobile devices are a new and evolving technology and research is focusing on the effectiveness of implementing the devices while using surveys to depict learners' intentions (Gikas et al., 2013). Also, learners have different learning styles, and those that may have difficulties in group settings and communications may benefit from mobile devices, especially those that use recommender systems in educational online applications, which produce more precise learning resources, as needed [S19], [S7], [S1]. Accessing that information, anywhere and anytime, using mobile devices is an increasingly desirable feature for the learner, and there are benefits of accessing rich digital resources in their desired location [S16]. The delivery of results to the learner must be efficient and cost-effective in order for the learner to increase its usage, and personalizing the result is an effective mechanism. This mechanism is achieved by using data mining techniques to filter the content and provide proper recommendations [S2].

Furthermore, to design proper recommender systems in mobile educational environments, a thorough understanding of the learner's usage of the technology must be required. The way in which the learner perceives the technology to learn and stay engaged is crucial to the design and subsequent development of the mobile application. The learners should be satisfied with the results produced by the recommender system in the mobile application and must be personalized based on their needs, characteristics and knowledge [S18], [S17].

Table 7 shows what a learner needs and wants from recommender systems and mobile education, and what mobile educational environments using recommender systems can currently provide.

Table 7. Learners Wants and Needs of Mobile Education

Learner's wants and needs	• Personalized data • Meaningful data • Guide them by providing learning strategies • Adapt to their learning style and interfaces • Track their needs or suggest new learning material of their interest • Accurate results • Interactive results based on learning behaviour type • Easy to use • The social collaboration that provides other learner opinion results • Remain engaged with the application • Have a positive enjoyable experience • To be satisfied with the results • Time-saving results • Understand their current knowledge (if any is provided) and receive recommendations based on that

Recommender systems in mobile educational environments can provide	• Real-time access to recommendations • Location-based information • Anywhere and anytime access to results • Accurate recommender results from relevant learning resources • Adapt to learner's style by capturing personal data • Filter data based on the type of information to be analyzed • Fast filtering of results • Easy to access results • Personalized recommendations

The research articles describing mobile and education discuss the ways in which recommender systems can be used in the environment considering the learner's needs. The recommender systems have become a popular technology involving an enhanced learning domain that is used to identify learning objects [S33]. The systematic review research conducted identifies the most commonly used filtering techniques and the ways in which they help the learner find the most suitable learning objects in educational environments.

CBRS is a grouping of like-minded learners based on their ratings of an item while predicting similar choices that they may make in the future [S26], [S27]. The research articles describing how collaborative-based filtering (CBF) in education mention three algorithms. The first two algorithms, memory-based and model-based, are the traditional filtering approaches, and a blockmodeling is the third.

Memory-based filtering considers the learner's past ratings and item tags to make recommendations. Data-modeling filtering approach uses machine learning mechanisms, such as data mining, to make a prediction based on a collection of ratings [S25]. Lastly, blockmodeling detects meaningful patterns in a network and identifies clusters with similar characteristics to detect different structures [S23].

Although CBF is frequently discussed in the research papers, it consists of several drawbacks and limitations. Cold-start, sparsity, and scalability with limited or unavailable data, such as no item ratings and new learners or new materials, results in loss of flexibility [S25]. The limitations seem drastic, but there are advantages to CBF and that it is real-time data availability and recommendations of items based on other learner's opinions.

CRS relies on acquiring certain information from the learner using interactive visual forms to capture their data. That information gained is stored in a database and compared with current tagged item's data to calculate rich content and provide recommendations [S30]. There are a few suggested algorithms for CF that rely on calculations of the relevance of the item based on learner's search query. This involves adapting full-text search approaches to rank learning objects based on its attributes and similarities of the text search and using keyword recommendations to explore information from objects and filter data using data mining to generate concept associations [S31]. However, the quality of the recommendations is based on the data provided by the learner, which is disadvantageous and, therefore, jeopardizes scalability if the learner did not provide any data in their profile, to begin with [S29]. Another limitation of cold-start problems is that new learner additions make it expensive to maintain.

Before KBRS are mentioned, comparing collaborative-based and CRS shows that CBF does not require prior knowledge of the learner's profile information or item attributes. As long as their activity is monitored and recorded to use, then CBF techniques are advantageous. Moreover, the collaborative techniques differ from content-based algorithms, where collected content provided by the learner's profile is required, and item attributes are essential in finding similarities amongst the learner, the item and their search query. The limitation of these two recommender system techniques is the cold-start problem, which researchers suggest that a combination of the two recommender algorithms is essential in overcoming this shortcoming [S34].

KBRS considers prior learner's knowledge of the domain to extract the data and collect expert knowledge from learning designers and educators to provide accurate items for storing in the database [S44]. The algorithms used to acquire knowledge uses tagging of items, case-based reasoning, where cases are formulated based on past problems and new ones to provide solutions, and constraint-based reasoning, where constraints are presented in the domain of knowledge [S43]. Although the advantage of KBF produces more accurate results, there are limitations of acquiring knowledge in the domain. More specifically, there is not enough learner activity or topics covered, or there may not be diverse results.

The last recommender system, called hybrid-based, suggests more accurate results by combining the previously discussed recommender systems filtering techniques and overcoming each limitation separately [S49]. In education, accuracy for the learner is crucial to their success in gaining knowledge about the subject matter. In addition, combining filtering techniques, based on the learning resources, is essential in improving the accuracy of the results. However, HBF has disadvantages, which makes the technique overly complex, expensive, while also requiring data from external professional information.

Table 8 provides an overview of the advantages and disadvantages of each recommender system filtering technique used in educational environments, which will help the reader compare similarities and differences that each technique offers in educational environments.

Table 8. Recommender Systems Advantages and Disadvantages

Filtering Technique	Advantage	Disadvantage
Collaborative-based recommender systems	• Get recommendations for comparable items that were searched by the learner before. • Get recommendations for comparable items that other learners have tagged / shared opinion on. • Get recommendations based on ratings of items.	• Item may not have any ratings or ever searched before. • Learners are always changing or there are new learners that do not have activities yet. • Items are newly added and not yet rated.
Content-based recommender systems	• Learner can get recommendations without other learner's input or opinions.	• Item searched for may not be easily analyzed. • Not enough items or extremely low count to use for recommendations. • Recommendations to the learner can be based on their profile information.

Knowledge-based recommender systems	• Using more sophisticated models to produce more accurate results based on prior knowledge of the learner, interactivity of available course material and experts input. • Rules and constraints are added to produce better recommendations.	• More complex to develop. • Material availability may be limited or not always updated to produce better recommendations. • Topics may not be covered which produces limited results.
Hybrid-based recommender systems	• Overcomes limitations that other recommender system techniques face by combining two or more systems. • Recommendations are more accurate and diverse.	• Complex and expensive to produce. • Requires external professional input if available.

CHAPTER V

ISSUES, CHALLENGES, AND TRENDS

This section discusses the issues from gaps of research that the collected studies have not discussed regarding recommender systems in mobile educational environments. It will also discuss the challenges in recommender systems and mobile education, as well as current trends, findings, and results.

Gaps in Research

Recommender systems in education are limited by learning resources and proposes a challenge when analyzing accurate data for a learner. The research articles collected and discussed in the systematic review described the general applications and results of recommender systems in mobile education used as filtering techniques. However, the articles did not discuss the specific filtering techniques used, what situations they are used for, algorithms to use, and the ways in which mobility helps using a specific recommender system in certain learning situations to recommend the most useful learning object. As such, it was difficult specifying the search using the Top 20 Google Scholar's Educational Technology publication to a recommender system filtering technique in mobile educational environments from the four discussed in this essay and, therefore, demonstrated that it was a major gap in research that has not been thoroughly analyzed.

Fortunately, a way to alleviate the lack of specified research is having two fundamental areas to discuss, such as recommender systems in mobile education and the four filtering techniques in detail. In turn, this will help the reader understand the concepts this paper was aiming to analyze and to present the proper filtering techniques to use in certain learning situations based on the learner's needs. Moreover, the frequent term 'collaboration' was discussed in recommender systems in mobile environments. Due to the fact that mobile devices enhance collaboration and social engagement, a frequent focus by the authors on the term and usage with recommender systems is evident in their papers.

Each filtering techniques' algorithms were not specifically discussed to demonstrate its usage in mobile educational environments. In addition, there was not an extremely detailed discussion on the ways in which each filtering technique can be easily translated from personal computer online usage to mobile device-specific applications in the education journal publications. This was puzzling since there was a lack of reason regarding why each filtering technique was not fully analyzed in mobile environments, other than the fact that mobile devices in education are currently a new concept that is not well-researched with recommender systems. Yet, the research articles recognize the powerful features that a recommender system has and can help the learner receive more accurate recommendations based on their knowledge and to remain interested in the subject matter. However, each learner has different learning styles, prior knowledge, and needs. Moreover, recommender systems using mobile devices in education to help each one access recommendations from the available learning resources and in specific situations was not thoroughly discussed.

Recommender systems, be it collaborative-based, content-based, or knowledge-based, has its shortcomings with cold-start, sparsity and scalability, and the research papers discuss the reasoning behind this. In fact, some papers point out that a solution to overcome such a problem involves combining the filtering techniques into a hybrid-based recommender system. The hybrid-based techniques are more useful and popular, and a well-studied method to avoid the drawbacks from the other techniques to provide more precise results to the learner.

Although the number of articles collected for each technique is sufficient, Google Scholar's Top 20 Education Technology publications did not have professionally researched articles specifically discussing each of the four techniques in mobile environments but only focused on online education. Moreover, the authors believe that the powerful features each filtering technique possesses can help the learner in online educational environments, which was the focus of discussion regarding each of the four recommender systems techniques. Also, all the collected research papers used for the systematic review were published within the past fifteen years and focus on either the specific education domain of a recommender system development or the recommendation techniques and approaches in online education. There was not a comprehensive analysis of each of the filtering techniques of recommender system applications in the educational domain using mobile devices.

Findings and Results

Mobile devices are the most current trend in application development, and the research articles surveyed discussed that mobile devices are more frequently used than personal desktops. As such, mobile devices are an easy tool to access information anywhere or anytime in the palm of one's hand. However, the plethora of information is daunting to the learner to filter through, and applications that analyze and provide recommendations are gaining popularity since they help direct the learner to their use to personalize their learning and retrieve accurate recommendations. Although the research papers did not specify each filtering technique in mobile educational environments, the reason explaining why a recommender system should be used as a filtering mechanism is discussed thoroughly. As a result, experiments and real-learner test subjects were studied to find the correlation between recommender systems and usage of more accurate learning resources to produce proper learning objects that the learner can benefit from.

While researching the topic of recommender systems in mobile educational environments, interesting findings of many of the surveyed research papers were observed. For instance, many authors categorize the ways in which recommender systems should be designed in mobile environments, as either one where data collected from collaborative environments, such as online communities where forums or blogs are found or using a data mining mechanism to make the application an intelligent system. However, they did not always go into detail of introducing a data mining mechanism to be used in certain situations: instead, they only discussed a few that worked in their experimental designs or design theories of creating an efficient recommender system. Many authors introduced their own enhanced filtering techniques by studying a specific group of learners to use their algorithm or developed online applications and presented the results. They also suggested enhancements or additions to the discussed four filtering techniques to provide better recommendations for the learner in educational environments. Therefore, many authors observed and surveyed learners on the ways in which they interacted with a recommender system and if it provided them with the desired results.

Trends

The review has provided a discussion of specific trends in design theory, especially in collaborative-based and CRS where both filtering techniques are more frequently researched and discussed. The systematic review identified these trends and capabilities of recommender systems, especially using collaborative and content-based techniques. Also, it was suggested by some authors to combine both techniques to provide a more accurate recommendation to the learner. Further, the trend in the usage of collaborative-based and/or content-based in domains other than education has provided researchers with a base to evaluate potential filtering algorithms in educational environments that could be item tags, usage of personalized data, and querying item attributes.

Furthermore, the systematic research conducted to investigate recommender systems in education has shown remarkable progress in the domain over the years. Each recommender system filtering technique has its merits, and the journal publications have presented the techniques in detail where newer articles have evaluated the more popular trends in recommender systems and deduced advanced design theories in educational environments. Certain journals publish articles regarding recommender systems more than others, especially the journal IEEE Transactions on Learning Technologies (IEEE) where 32% of the systematic review articles were found. Further analysis of the results has shown that IEEE provided an above-average distribution of articles in collaborative-based, content-based, and hybrid-based ranging from 42% - 50% of the articles referenced. However, the KBF technique had a more diverse distribution of journals and IEEE constituted only 20% of the articles investigated on the topic. IEEE journal publication provided not only the most articles for the systematic review but the most detailed articles discussing three out of the four filtering techniques.

CHAPTER IV

SUMMARY AND CONTRIBUTIONS

Conclusion

In this paper, a systematic review and meta-analysis were performed to survey research articles in Google Scholar's Top 20 Educational Technology publications regarding recommender systems in mobile educational environments. There were 50 articles collected that were published within the past 15 years and focused on investigating recommender systems in mobile education. In addition, the following filtering techniques of recommender systems were discussed: the collaborative-based, content-based, knowledge-based and hybrid-based. Mobile devices are complex; as such, an evaluation of their effectiveness in education is required to enhance learner's motivation, coordination and interaction with others. Further, the device's advanced technology and the usage of recommender systems in the environment help facilitate educational processes, communication, and sharing content to recommend learning objects produced from appropriate learning resources. Mobility promotes learning and allows for flexible and instant access to rich digital resources, anytime and anywhere. In addition, it helps educators provide learning material and guide the learner to use appropriate learning resources.

Also, the review classified four filtering techniques that were discussed and compared, in detail, in educational environments to help learning designers and educators design and develop a recommender system in the educational domain. To further illustrate, the collaborative-based approach uses item tags from other learners alongside learner's profile information for results. The content-based approach uses learner's profile information and item attributes to provide recommendations. The knowledge-based approach uses learner's prior knowledge alongside item attributes and professional opinion for recommendation results. Moreover, the recommendation data from the previous filtering techniques have their limitations and drawbacks of cold-start, sparsity, and scalability. However, combining these techniques into an HBF mechanism is not only gaining more popularity, but it also eliminates the problems regarding filtering with data recommendation. Yet, it is more complex and expensive to develop and maintain.

Since the articles collected for the systematic review were limited to Google Scholar's Top 20 Educational Technology publications, the specific four filtering techniques usage were not specifically mentioned in mobile educational environments, but only in online educational web applications. It was difficult to research articles specifically mentioning each of the four recommender techniques usages in mobility, but the general usage of recommender systems in mobile education was thoroughly discussed in the researched paper to help the reader understand the effectiveness of a recommender system in educational environments.

Suggestions for Future Research

Future research must include longer-term studies with more diverse methods to involve differing learning styles, situations, and learner engagements using mobile devices to obtain more accurate learning objects. These insights into mobile learning using recommender systems will help suggest new directions for research studies, as well as an up-to-date understanding of research trends. Further, researchers must assess the data produced by each filtering technique in mobile environments and propose enhanced design mechanisms of each approach to produce more accurate recommendations in informal and formal mobile learning environments. In addition, researchers should suggest standardized approaches to differing mobile learning environments using recommender systems. These approaches must include efficient data mining techniques, specifically providing accurate educational data. The data mining techniques should be standardized using algorithms operational in mobile educational environments for each of the four recommender systems. Therefore, each filtering technique must be efficient, fast, cost-effective and maintainable in these educational environments.

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APPENDIX A

1		recommender systems mobile education	collaborative-based recommender systems	content-based recommender system	knowledge-based recommender systems	hybrid-based recommender systems
2	Computers & Education	16	53	61	65	21
3	British Journal of Educational Technology	5	8	10	11	3
4	The International Review of Research in Open and Distributed Learning	1	8	8	10	3
5	The Internet and Higher Education	19	3	3	4	0
6	Journal of Educational Technology & Society	0	0	0	0	0
7	Journal of Computer Assisted Learning	1	3	7	7	1
8	International Conference on Learning Analytics And Knowledge	5	0	0	0	0
9	Educational Technology Research and Development	3	0	4	1	0
10	TechTrends	3	0	0	1	0
11	Language Learning & Technology	0	0	0	0	0
12	Journal of Online Learning & Teaching	0	0	0	0	0
13	Distance Education	0	0	0	0	0
14	Learning, Media and Technology	3	1	1	2	1
15	TOJET: The Turkish Online Journal of Educational Technology	0	0	0	0	0
16	Education and Information Technologies	10	1	7	3	1
17	Interactive Learning Environments	6	13	17	16	4
18	International Conference on Technological Ecosystems for Enhancing Multiculturality	0	0	0	0	0
19	Computer Assisted Language Learning	0	0	0	0	0
20	Australasian Journal of Educational Technology	6	1	4	4	2
21	IEEE Transactions on Learning Technologies	19	0	10	8	13
22		97	91	132	132	49

Figure 6. Google Scholar's Top 20 Educational Publications and Keywords Results

Each publication was searched by the five keywords 'recommender systems mobile education', 'collaborative based recommender system', 'content based recommender system', 'knowledge based recommender system', 'hybrid based recommender system'. The resulting number of papers was used in the totals. The advanced filter in each journal's web site was used to choose the papers that ranged by date 2001 – 2019, scholarly papers and/or conference proceedings. Majority of the publications were located in the research databases: Springer, ACM, IEEE, Taylor & Francis and Elsevier.

Publication Web Site Links

1. Computers & Education - https://www.sciencedirect.com/journal/computers-and-education
2. British Journal of Educational Technology - https://onlinelibrary.wiley.com/journal/14678535
3. The International Review of Research in Open and Distributed Learning - http://www.irrodl.org/index.php/irrodl

4. The Internet and Higher Education - https://www.sciencedirect.com/journal/the-internet-and-higher-education
5. Journal of Educational Technology & Society - https://www.j-ets.net/ETS/index.html
6. Journal of Computer Assisted Learning - https://onlinelibrary.wiley.com/journal/13652729
7. International Conference on Learning Analytics And Knowledge - https://solaresearch.org/events/lak/
8. Educational Technology Research and Development - https://www.aect.org/educational_technology_researc.php
9. TechTrends - https://link.springer.com/journal/11528
10. Language Learning & Technology - https://www.lltjournal.org/
11. Journal of Online Learning & Teaching - http://jolt.merlot.org/pastissues.html
12. Distance Education - https://www.tandfonline.com/loi/cdie20
13. Learning, Media and Technology - https://www.tandfonline.com/loi/cjem20
14. TOJET: The Turkish Online Journal of Educational Technology - http://www.tojet.net/
15. Education and Information Technologies - https://link.springer.com/journal/volumesAndIssues/10639
16. Interactive Learning Environments - https://www.tandfonline.com/loi/nile20
17. International Conference on Technological Ecosystems for Enhancing Multiculturality - https://2016.teemconference.eu/
18. Computer Assisted Language Learning - https://www.tandfonline.com/loi/ncal20
19. Australasian Journal of Educational Technology - https://ajet.org.au/index.php/AJET
20. IEEE Transactions on Learning Technologies - http://ieee-edusociety.org/about/ieee-transactions-learning-technologies

APPENDIX B

Table 9. List of recommender systems online applications in education

Recommender System	Learning Tool	Objective	Authors
Collaborative-based	*Data mining tool	An association rule mining and collaborative filtering is used in order to make recommendations to instructors about how to improve e-learning courses.	García et al. (2011)
Collaborative-based	PLEM system	A personal learning environment supporting learners in creating a personalized space, where they can easily aggregate, manage, tag, and share learning items.	Chatti et al. (2013)
Collaborative-based	Learner Preference Tree (LPT)	Reflect learner's interests by considering multidimensional-attributes of materials, learner's rating simultaneously.	Salehi et al. (2014)

Content-based	IM-TAG	Provides content recommendations using semantic annotations of social web contents to users based on their profiles and tags thus supporting informal mentoring and informal learning.	Colomo-Palacios et al. (2014)
Content-based	SMETE	Acquires some variations of the vector-space algorithm to calculate similarities between the queried terms and the text contained in the learning object's data.	Ochoa et al. (2007)
Knowledge-based	Courseware Authoring Validation Information Architecture (CAVIAr)	Captures adaptive courseware authoring concerns and validates courseware using a constraint-based approach.	Melia et al. (2009)
Knowledge-based	TAK (tag-based prior knowledge recommendation)	Provides opportunities for students to interpret article contents and find knowledge connections.	Chen et al. (2014)

Tools that have * in front of it does not have a specific name: it is only a technique researched and discussed that used a small group of participants.