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# Recommender systems research and theory in higher education: A systematic literature review

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## Abstract

Recommender systems provide the ability to personalize and adapt environments for student learning. To customize learning experiences, applications of recommender systems research in education have resulted in evidence of various recommender system approaches such as content-based filtering, collaborative filtering, and knowledge-based. This research focuses on those applications in higher education when given a non-MOOC classroom setting and examines the theoretical basis for the approaches. Learning and information systems theories are considered in this systematic review of the literature published from 2017 to early 2022. Findings indicate varying adaptive learning design recommender approaches and the potential to build the theoretical base of both learning and information systems theories.

**Keywords**: recommender systems, learning theory, information systems theory, higher education

## Introduction

Recommender systems are a mainstay of many web-based services today. They influence the products consumers buy and the online media consumed daily. Their influence has spread to applications in education, shaping how education can be personalized to individual learners' needs (Khalid et al., 2020). Since students have different learning styles, strengths, and weaknesses, applying a "one-size-fits-all" approach to education seems counterintuitive, much like recommending the same product or service to every consumer is not always an optimal strategy. Recommender systems can aid students in their educational journey, making it possible to personalize their efforts to accommodate learning differences. Recommender systems lie at the intersection of education and information systems research, and involve learning analytics (LA). LA is defined as the "measurement, collection, analysis, and reporting of data about learners and their contexts, for understanding and optimizing learning and the environments in which it occurs" (LAK, 2011). A variety of uses of LA have been studied, including but not limited to learning behavior and engagement, improving teaching professional development, predicting student performance, and improving retention (Mangaroska & Giannakos, 2019). The field of education has seen rapid growth in LA, but there is a lack of student-facing solutions that make use of analytics. Higher education stands to benefit from being more efficient in its use of data (Long & Siemens, 2011). Recommendation systems present the opportunity to utilize these analytics to directly engage students and to impact student learning, instead of more passive applications of LA such as those that predict performance or success.

Massive Open Online Courses (MOOCs) have been an ideal source of LA, given that a MOOC course is taken by hundreds if not thousands of students during an offering. One the biggest MOOC platforms, Coursera, has partnered with over 175 universities and reported over 189 million enrollments in 2021 (Coursera, 2022). There have been several studies that explore recommender use in MOOC environments. However, these environments do not always parallel traditional higher education environments for various reasons, including course enrollment numbers and student motivations. For example, one study found that intrinsic motivation plays a significant factor for MOOC learners and that often these courses are taken by professionals addressing workplace learning needs (Milligan & Littlejohn, 2017). In addition, MOOCs tend to have a low completion rate, with certification rates between 2 to 10 percent of registered students (Reich, 2014). For those seeking to design and adopt recommender systems in traditional higher education settings, guidance is needed for environments that parallel their own.

Additionally, current research in LA can utilize lessons learned from business intelligence system research given its commonalities and LA's emergence from the business intelligence field. However, in applying LA to the development of recommender systems in education, "we should not strive for what is technically possible, but always ask ourselves what makes pedagogical sense" (Zawacki-Richter et al., 2019). Two key areas of theories could be infused to improve these approaches: learning theory and information systems theory. Formal learning theories are needed to develop an effective adaptive learning system, and formal information systems theories are necessary as these recommender systems are information systems.

This systematic literature review (SLR) explores how theory has guided the development of recommender systems in traditional higher education and determines what gaps exist to provide recommendations for future research. The following research questions are proposed:

> *RQ1: How have formal learning theories informed the development of recommender systems for personalized learning in higher education?*
>
> *RQ2: How have formal information systems theories informed the development of recommender systems for personalized learning in higher education?*

The remainder of this paper is structured as follows. First, the methodology for this SLR is discussed in detail. The results of the review are then provided. This is followed by a discussion of the results where implications for future research and limitations are provided.

## Methodology

This study was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) statement (Page et al., 2021). The criteria for selecting articles to include in this research follows. The search was conducted using the required combination of "recommender system" and either "personalized learning" or "adaptive learning". To recognize other ways in which recommender systems may be referred to, the terms "recommendation system" or "recommendation engine" were also searched but the inclusion of "education" was also specified in the criteria. As this field has changed rapidly over recent years, the scope of the investigation is limited to January 2017 through January of 2022, just over a 5-year period. Searches were limited to full-text works published in peer-reviewed journals or conference proceedings and works published in English. The following databases were included in this study: ACM Digital Library, IEEE/IET Electronic Library, Elsevier ScienceDirect Journals Complete, ProQuest Research Library, ProQuest Central, and EBSCOhost (Academic Search Complete).

Each article was reviewed to determine its relevance to the education domain with a specific focus on higher education. Only full-text, peer-reviewed articles with completed research that are available in English were chosen for inclusion. Articles such as books, dissertations, surveys, literature reviews, keynotes, posters, panel discussions, research-in-progress articles, extended abstracts, or tangential reviews were not included. Both journal and conference proceedings were included if they met the prior criteria. Works were excluded if they were not empirical and lacked evaluation due to being in the proposal stage of the research. Research also had to be centered on the design and development of a recommender or recommendation system to assist student learning within a course setting. To that end, works that focused on course recommendations were excluded. In addition, the research had to demonstrate a clear application to higher education by either mentioning its application to higher education or demonstrating its application through evaluation in a higher education setting. MOOC-based research was also excluded as this research aims to explore recommender systems in traditional higher education settings. All inclusion and exclusion criteria are summarized in Table 1.

**Table 1: Inclusion and Exclusion Criteria**

| Inclusion Criteria | Exclusion Criteria |
|---|---|
| • Published between 1/1/2017 and 1/31/2022<br>• Peer-reviewed<br>• Full-text available<br>• Setting is higher education<br>• Study is empirical<br>• Focus is design or development of recommender system for personalized learning in a course setting | • Work not available in English<br>• Research-in-progress or proposal<br>• Book chapter<br>• Setting not clear or focus is K-12<br>• MOOC focused or course recommender<br>• Dissertation, survey, keynote, poster, panel, discussion, abstract<br>• Literature review<br>• Tangential review |

The review process was completed in several steps as shown in the PRISMA chart provided in Figure 1. First, all full-text articles meeting basic search criteria were identified. Screening was completed in three steps. The first step reviewed all articles for duplicates and removed these duplicates. The second step involved reviewing titles and abstracts and excluding necessary articles that did not meet the inclusion criteria or demonstrated evidence of the exclusion criteria. The third step involved reviewing the full-text of the articles to remove articles that did not meet inclusion criteria or presented evidence of exclusion criteria.

Each article reference was loaded into Zotero in order to ascertain possible article duplication and to note database origin. The only automation tool utilized was Zotero's ability to generate citation data. A spreadsheet was developed to include select article data. Information that was manually extracted from articles included the author(s), year published, keywords, source of publication (journal or proceeding), objective of the research, information systems theory (if available), learning theory (if available), type of recommenders (e.g. content-based, collaborative filtering, knowledge-based, hybrid, or other), the recommender focus (e.g. learning resource recommendation, learning path recommendation), data source of analytics, machine learning algorithm applied (if applicable), methodology, conclusion, and any other notes of interest about the research. To address researcher bias, a second researcher independently reviewed 10% of the article titles and abstracts using the same inclusion and exclusion criteria and the results were then compared.

## Results

The initial search of all the previously specified databases using the established keywords yielded 596 results consisting of 131 records from the ACM Digital Library, 41 from the IEEE/IET Electronic Library, 142 from Elsevier ScienceDirect Journals Complete, 10 from the ProQuest Research Library, 252 from ProQuest Central, and 20 from EBSCOhost (Academic Search Complete). Among the records, 15 duplicates were found and removed from the results. The initial screening of the titles and abstracts according to criteria resulted in the exclusion of 440 records, leaving 141 records remaining. Each of the 141 remaining records was then subject to a second screening according to criteria that required full-text

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review. Of these, 88 were excluded. About half of the exclusions (n=43) were due to a lack of a higher education focus. This was often due to a lack of explicit mention of higher education or if it was difficult to ascertain application to higher education as evident in the evaluation environment. Several articles were not empirical in nature (n=23) and proposed an approach that had yet to be evaluated. Some of the results (n=15) did not include a focus on student learning and a few (n=4) were focused on course recommendations. One article was found to have been published earlier than citation metadata had stated and therefore was removed. The review process led to the final inclusion of 53 articles. This process is detailed in Figure 1. A second reviewer's independent review of title and abstracts demonstrated a 92% agreement when reviewing 10% (n=56) of the articles, demonstrating minimal bias in the results.

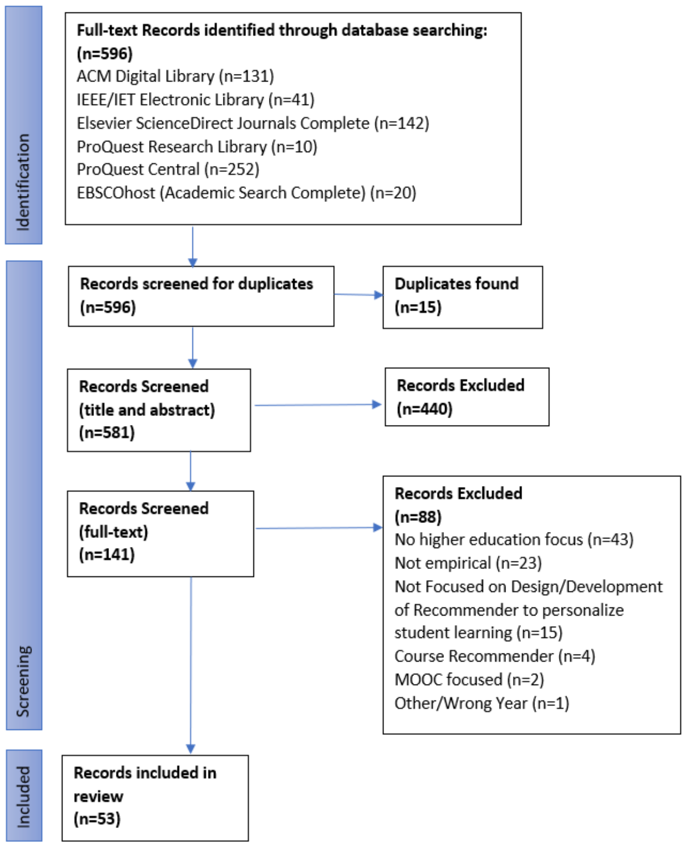


**Figure 1: PRISMA Chart**

Of the 53 articles, 16 were conference articles and 37 were journal articles. As demonstrated in Figure 2, the number of published articles was steady from the years 2017 to 2020, with an increase in works published in 2021.

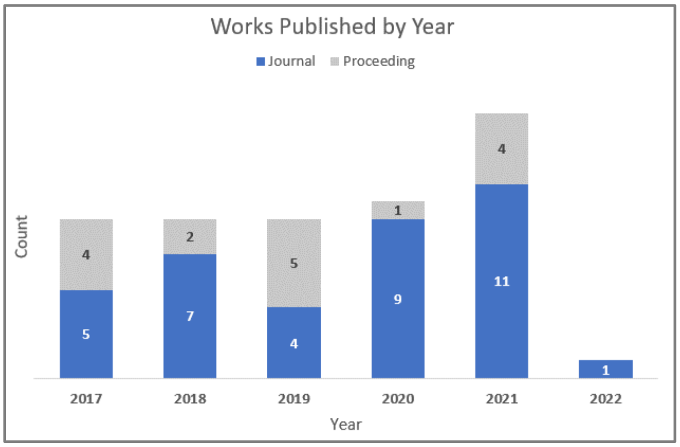


**Figure 2: Articles published from January 1, 2017 to January 31, 2022**

Over half of the included results published were located from ProQuest Central while about one-third were from the ACM Digital Library. A breakdown of results by database are presented in Table 2.

**Table 2: Filtering of Articles by Database**

| **Database** | **Initial Results** | **After Duplicates Removed** | **1st Round Filtering** | **2nd Round Filtering** |
|---|---|---|---|---|
| ACM Digital Library | 131 | 131 | 39 | 16 |
| IEEE/IET Electronic Library | 41 | 41 | 12 | 1 |
| ScienceDirect (Elsevier ScienceDirect Journals Complete) | 142 | 142 | 14 | 4 |
| ProQuest Research Library | 10 | 2 | 0 | 0 |
| ProQuest Central | 252 | 252 | 69 | 31 |
| EBSCOhost (Academic Search Complete) | 20 | 13 | 7 | 1 |
| **Total** | **596** | **581** | **141** | **53** |

Of the 53 articles, 43 articles included keywords or words to index as provided by the author(s). The keywords were evaluated using R to generate a simple frequency analysis. The top 7 keywords are provided in Figure 3 with "e-learning" being the most frequent keyword.

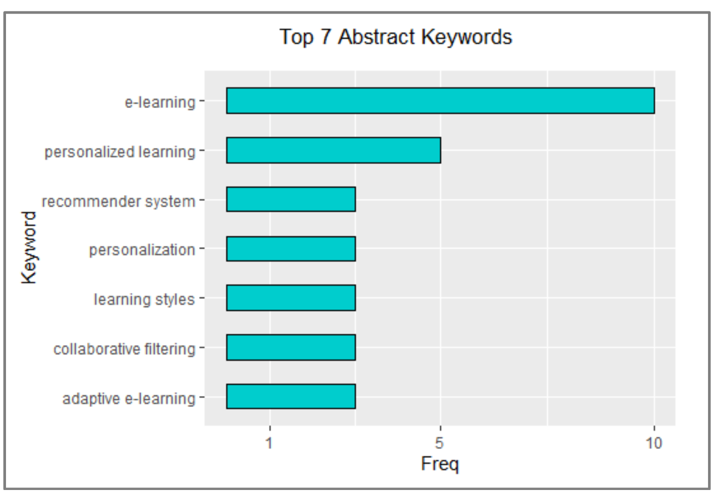


**Figure 3: Top 7 Abstract Keywords**

In addition to the keyword analysis, abstracts were analyzed. Each article's abstract was extracted to a CSV file to generate a word cloud listing the top 75 terms as shown in Figure 4. Prior to generating the image, the text was prepared by converting all characters to lowercase. Preprocessing also included the removal of standard English stop words, punctuation, and numbers. Stemming was applied to obtain the common origin of terms before generating the word cloud. The term "learn" was the top term, followed by "recommend," "system," and "learner." R was used to perform all preprocessing and to generate the word cloud.


**Figure 4: Top 75 Abstract Terms**

After this initial meta-data analysis, articles were explored with respect to each of the research questions. The results of each question are discussed below.

**Contribution of learning theories to recommender development (RQ1)**

Of the 53 articles selected, only about 26% (n=14) included a focus on educational theory as a significant contributing factor in the recommender design. This percentage is consistent with findings in other research concerning intelligent adaptive learning technologies *(*Zawacki-Richter et al., 2019*)* and is consistent with findings that have found the Felder-Silverman Learning Style Model (FSLSM) to be the most often applied learning style theory *(*Thongchotchat et al., 2021*)*. Several learning theories or models were referenced as shown in Figure 5 and their implementations are described in the proceeding section.

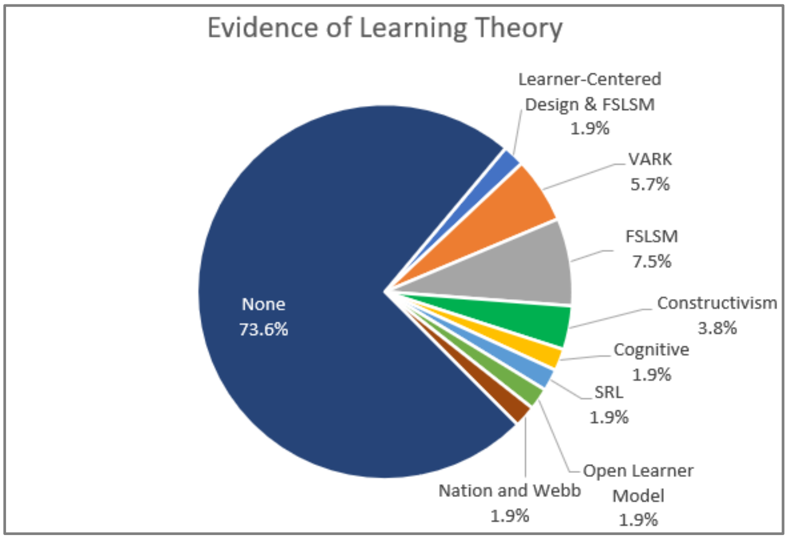


**Figure 5: Learning Theories**

The following table lists the theories found and their recommender approach.

**Table 3: Theories and Candidate Generation Technique**
**(CB = Content-based filtering, CF = Collaborative filtering, K = Knowledge-based, O = Other)**

| Theory | Approach | | | | Articles |
|---|---|---|---|---|---|
| | CB | CF | K | O | |
| Learner-Centered Design & FSLSM | | | X | | (Soukaina et al., 2020) |
| VARK | | | X<br>X<br>X | | (El-Sabagh, 2021)<br>(Aeiad & Meziane, 2019)<br>(Chrysafiadi et al., 2019) |
| FSLSM | X<br><br><br> | X<br><br>X<br>X | <br>X<br>X<br> | | (Trusthi & Nurjanah, 2017)<br>(Sarwar et al., 2019)<br>(Joy et al., 2021)<br>(Dwivedi et al., 2018) |
| Constructivism | X<br>X | | | | (Zhu et al., 2021)<br>(Albatayneh et al., 2018) |
| Cognitive | | | X | | (Chenyuan et al., 2021) |
| SRL | | | X | | (Odilinye & Popowich, 2021) |
| Open Learner Model | | X | | | (Abdi et al., 2020) |
| Nation and Webb's Checklist | | | | X | (Zou & Xie, 2018) |
| Self-Organization Theory | X | | X | | (Wan & Niu, 2018) |

When considering learning theory, several articles cited the use of specific theories. To meet diverse learning needs, Soukaina et al. (2020) developed a new model to enable tech-aided adapted learning with mobile tools and pedagogical methods. This research was guided by Learner-Centered Design (LCD) theory (Soloway et al., 1994). In doing so, the authors developed a design with consideration for the learning context, task, tools, and interface. This resulted in a system that considered the learner's characteristics and university as the context, adaptation of the learning task as the task, the mobile device as the course delivery tool, and the Android application as the learning interface. Additionally, the authors consulted FSLSM to develop learning style scores as part of the determination of learner context. Experiment results indicated that students' knowledge level improved and students were motivated to use the app.

Sarwar et al. (2019) developed a framework to enhance learning productivity through use of personalized learning with machine learning techniques. A learner attributes profiler was established before categorizing and recommending content. Learner attributes consisted of various factors, including but not limited to pre-test scores, professional experience, and learning style. Learning style was determined using a FSLSM questionnaire. Learner profiles once determined were then categorized using a hybrid approach consisting of Case based Reasoning (CBR), fuzzy logic, and an artificial neural network (ANN). These categories then served as the basis for learning recommendations. This proposed solution indicated better performance than other techniques used alone such as fuzzy logic or ANN. Joy et al. (2021) implemented an ontology-based approach to address the cold-start problem in recommender systems. Here, FSLSM was utilized to create a sub-ontology needed to match learners with learning materials. Learner similarity was determined by using K-means clustering in order to support the recommendation process. Experimentation revealed that the majority of learners were satisfied with the personalized recommendations provided by this solution. Dwivedi et al. (2018) developed a learning path recommendation system focusing on adaptive learning styles and paths that utilized FSLSM and a variable length genetic algorithm in its design. Learning styles were collected during pre-enrollment using the Index of Learning Styles questionnaire. This data was utilized along with learning ratings of resources and post-test scores to complete the learner's profile and then as part of the construction of a predefined learning path. Results from an experiment indicated that students obtained on average higher post-test scores when recommendations were based on learning styles and knowledge levels. In another application of FSLSM, Trusthi and Nurjanah (2017) employed a hybrid filtering approach that focused on recommending materials by learning style determined by FSLSM. The learning style similarity calculation was used alongside a collaborative filtering process to predict scores. However, this research found through experimentation that utilizing rating similarity calculation alone yielded the best prediction scores.

While FSLSM was referenced more often by authors, the Visual, Auditory, Reading, and Kinesthetic (VARK) learning styles model was also prominent in the included articles, serving as a different approach to determining learning styles. El-Sabagh (2021) explored the impact on engagement of adaptive e-learning based on the VARK model and use of an instructional design model. Researchers explored the impact of VARK learning style path recommendation on student engagement. Prior to accessing adaptive e-course modules, students were first asked to complete a learning styles (VARK) questionnaire. The findings of their experiment indicated that students learned more because of the adaptive learning process. VARK was used in a similar fashion by Aeiad and Meziane (2019). Their work proposed a generic architecture for e-learning that incorporated VARK. Much like the El-Sabagh (2021) system, this system used the VARK questionnaire to determine the learning style of the learner. The learning style score is incorporated with other student feedback pertaining to their learning experience in order to rank content for future users. While this research was in its early stages, the authors noted that it received positive comments concerning its ability to personalize adaptive learning material. In a slightly different approach, Chrysafiadi et al. (2019) used an artificial neural network (ANN) when given student learning styles based on VARK to determine the display mode of the learning material. Unlike some of the other solutions that only place students into one of the VARK learning modes (Visual, Auditory, Reading, or Kinesthetic), this system permitted learners to apply different weights to each of the learning modes which may result in a mix of learning modes recommended. Results from evaluation indicated that the system was successful presenting personalized and adaptive content for learners.

Constructivism-based theories were also present in the included articles. Zhu et al. (2021) developed an intelligent English teaching platform that provided personalized learning with a student centered approach based on a constructivist learning environment. This required the researchers to ensure that learners were presented with several problems relevant to their learning goal and enhanced cognitive flexibility by providing various perspectives on the problems solved. The learning model constructed by the researchers employed several means by which to explore a given topic and build a personalized learning corpus. Results indicated that students were able to solve problems after using this platform and 70% of students liked the environment this approach created. In another constructivism-based approach, Albatayneh et al. (2018) built a system that provided recommendations based on discussion items using semantic content-based filtering and negative ratings provided by learners. Authors were guided in this process through the use of constructivism learning theory and therefore the system sought to aid learners in constructing their knowledge in a progressive manner. In their approach, the recommendations align with the learner's learning context by first constructing a profile built by using Latent Semantic Analysis (LSA) and negative discussion post ratings. This unique approach has shown to outperform similar systems when considering student performance and to increase system accuracy.

In a cognitive approach, Chenyuan et al. (2021) provided students personalized learning recommendations with use of a knowledge graph. This work is based on the cognitive construction process where "the mastery degree of knowledge points" is used to better understand the depth of a learner's knowledge. This is paired with Bloom's taxonomy to construct levels of knowledge point mastery. An ontology was then created in the form of a graph using these knowledge points for relevant chapters that then connected to learning resources for a given curriculum. Personalized recommendations were then provided using a long short-term memory (LSTM) network. This technique demonstrated superiority to traditional collaborative filtering when considering recommendation accuracy.

The last few results provided unique theory applied approaches. Abdi et al. (2020) used a transparent and understandable open learner model to provide learners insight on recommendation justification with the goal of studying the impact on engagement and effectiveness. The authors provided visualizations of the learning model data alongside recommendations. By providing students insights on recommendations, the goal was to build trust in recommendations, improving system acceptance. Results indicated increases in engagement and perception of effectiveness. Odilinye and Popowich (2021) employed self-regulated learning theory (Zimmerman, 2002) while exploring the recommendation of personalized learning resources through metacognitive reading activities. A Latent Dirichlet Indexing (LDI) model was created to guide learning document recommendations. In this system, instead of predefined possible learning paths for the student, the learner's metacognitive activities served to guide recommendations.

Lastly, Zou and Xie (2018) designed a system to recommend word learning tasks for English learners guided by word learning theory. The authors stress that these systems should be designed on "comprehensive learning theories". The authors used Nation and Webb's (Nation & Webb, 2011) checklist which is a specific learning approach applicable to the domain of this system. The use of a metric called the technique feature analysis allowed a score to be assigned to a given word and can indicate various loads of learning. This system was demonstrated to be effective. The authors cite some distinct benefits for this approach, including "degradation of excessive recommendations" and "improvement of diversity."

### Contribution of information systems theories to recommender development (RQ2)

The 53 articles included in this review yielded only one article that referred to a theory considered to be tangential to information systems theories. Wan and Niu (2018) applied self-organization theory to learning objects found in a recommender system. These learning objects acted as intelligent entities that can transmit information and self-organize to reach a stable state that permits appropriate recommendations to be made. Results indicated that this approach increases adaptability and diversity of results while still providing precision. Wan and Niu (2018) used a unique solution that focuses on both content and learner profiles, and therefore appeared to be a content and knowledge-based recommendation approach. This recommendation approach considers both the similarity between learning objects using cosine similarity and Jaccard coefficient, and similarity between learning objects and the learner. The learner model is presented as the learner's goals, learning style, and learning behaviors. Learning objects are described in terms of their basic attributes (e.g. level of importance, difficulty level) and extended metadata (e.g. visited frequency, similarity ranking). This article demonstrates the diversity of recommender approaches when considering existing theories.

### Learning theories and recommender approach

The first stage of a recommender system is candidate generation (Google, Inc., 2021). This is where the initial search of relevant candidates (e.g. videos, articles) is determined. Many of the articles included in this study had a focus on learning objects in their recommender design (Dias & Wives, 2019; Jordán et al., 2021; Joy et al., 2021; Pereira et al., 2018; Wan & Niu, 2018; Zheng, 2021) as the candidates. Learning objects are reusable resources that provide the form and relation that facilitate learning (Polsani, 2003) and are found in forms including, but not limited to, videos, articles, images, and animations. These learning objects are often presented as the result of the recommender system.

Several common candidate generation approaches exist:

- Content-based filtering (CB): This filtering determines candidates based on similarities between candidates. It can provide recommendations by understanding the attributes of items that the user likes, and then find and suggest similar items. It is the most basic of the models (Ko et al., 2022).
- Collaborative filtering (CF): This filtering determines candidates based on the similarities between users and items simultaneously. This is found in more modern recommender approaches. It can use a memory-based or model-based approach.
- Knowledge-based (K): This approach provides recommendations based on domain knowledge (e.g. the user's profile with user preferences) (Bouraga et al., 2014) and knowledge about the candidates. The main challenge associated with building knowledge-based recommender systems is the construction of the knowledge base (Bouraga et al., 2014).
- Hybrid filtering (H): This filtering combines any of the above techniques, often avoids limitations of other methods, and can have improved prediction performance at the expense of increased complexity for implementation (Alyari & Jafari Navimipour, 2018).
- Other (O): These recommenders do not follow one of the standard recommender approaches, but a different approach that often includes a custom algorithm.

In exploring the articles where learning theory was evident in the recommender system design, several approaches to the candidate generation were found as documented in Table 3. As shown in the table, 8 out of the 14 articles included educational theory followed a knowledge-based approach. The single article with a more information systems-based theory base also included the knowledge-based approach. Knowledge-based recommender systems are not faced with issues that other types of knowledge-based recommender systems such as large data set requirements, new items, and gray sheep problem (Bouraga et al., 2014), and the cold start problem. One type of this recommender, the ontology-based recommender, relies on ontology knowledge to map learning objects to a learner (Tarus et al., 2018). The use of an ontology was found in several of the knowledge-based approaches (Aeiad & Meziane, 2019; Chenyuan et al., 2021; Joy et al., 2021; Sarwar et al., 2019; Wan & Niu, 2018).

## Discussion

Learning theories can describe the learning processes and help educators better understand and design learning processes. There are three prominent viewpoints of theories that explain how individuals learn.

They are behaviorism, cognitivism, and constructivism. Behaviorism focuses on the learner's environment and eliciting the desired response when presented stimulus, cognitivism stresses the learner's internal mental structuring of new knowledge with a focus on active learning, and constructivism is an active learning approach where the learner constructs knowledge by assigning meaning (Ertmer & Newby, 2013). Of these three views, cognitivism and constructivism are best represented within the results of this study. Of the articles that focused on learning theory, many of the resulting articles did not focus on one of these theories, but instead served to classify learners by learning style. These approaches tended to focus on determining learning style utilizing FSLSM or VARK. This focus on learning styles dominated the results that included a learning theory focus. Minimally presented in the resulting literature, learner-centered design, also includes a focus in understanding the learner but goes beyond this focus to include aspects of a more effective learning environment for learners. Self-regulated learning was also minimally represented in the results by using meta-cognitive activities of learners to shape the recommendations provided. Lastly, the open learner model approach involves demonstrating the learning model in an understandable format for the learner to enhance learning through self-reflection and other metacognition activities.

The adoption of LA presents a wealth of opportunities to customize learning experiences. The use of the knowledge-based recommendation system was found often due to its ability to address the cold start and gray sheep problems associated with recommender systems. The cold start problem is the inability to provide predictions due to the lack of data initially faced by recommenders that rely on user rating or recommendations of others. The gray sheep problem is found in small or medium-sized settings where the system is unable to find users with similar ratings or opinions and therefore cannot make effective demonstrated diversity in approaches. While content-based and collaboration-based filtering methods are evident in some of the articles, many of the approaches that applied a learning theory focused on knowledge-based approach recommendations. Since this research focused on traditional classroom settings where class sizes may be smaller than other environments like MOOCs, it is understandable that many of the recommenders discussed previously were knowledge-based. This enabled the development of recommendations by first implementing learner profiles by which to guide the recommendations.

More work is needed to connect theories to recommender system approaches given that many articles did not include a focus on learning or information systems theories. While 40 of the 53 articles included in this study as a result of the second round of screening lacked inclusion of either a learning or information systems theory, each tended to include a specific focus on the need for adaptive learning. One example is an innovative approach of a hybrid recommender system utilizing knowledge-based techniques that focus on semantics and dynamic user profiles built automatically and, therefore, are better suited to recommend adaptive content (Ezaldeen et al., 2022). Works like this provide the foundation for the technical implementation and evaluation of different methods in educational recommender development.

Review of the education recommender literature demonstrated that little connection has been made to the field of information systems. Addressing adoption, use, and evaluation of these learning systems needs development. Due to the technical nature of the systems, their evaluations tend to be more statistical in nature, focusing on accuracy as the metric. This lack of a wider focus on evaluation may be contributed to the fact that the application of recommenders to the field of education is still in its early stages.

**Future research directions**

There appears to be a clear need to include more of a theory-based approach in educational recommender research in traditional higher education when considering both learning and information systems theories. When considering learning theories, the use of profiles often found in knowledge-based approaches lends well to using VARK and FSLSM. Research is needed to explore other methods of developing theory-based profiles and consider how best to design and evaluate these profiles. Other learning theories also need to be explored, such as theories that consider self-awareness and self-regulation in learning. By expanding beyond profiles and providing a clear link to the personalization of learning and learning theory for the design, researchers can set the stage for a more holistic and meaningful assessment beyond a focus that looks at what is technically possible. Much of the existing research has shown the technical aspects of recommender construction and has set the stage for this next step. Researchers should utilize existing research to make ties to theoretical-based approaches and evaluate the use of these systems for learning.

The field of LA has emerged from business intelligence systems research. These systems have been in place for many decades. The lessons learned from the design, use, and evaluation of these systems, including information system theories, offer guidance and structure needed in developing, implementing, and evaluating recommender systems. Theories aid in shaping research. They can provide the foundation needed to analyze, understand, and/or explain a phenomenon. Established processes like the iterative knowledge discovery (KDD) process (Fayyad et al., 1996) demonstrate how knowledge is to be discovered in a systematic way. Actionable information gained from business intelligence systems is known to have the following characteristics: integrated, data integrity, accessible, credible, and timely (Chee et al., 2009). These characteristics can serve to guide recommender design. Adaptive structuration theory (AST) as adapted by DeSanctis and Poole (1994) can be used to better understand how these recommender systems enact change in classroom and social structures. We also have ways to evaluate these systems such as the DeLone and McLean information systems success model (2003) which has shown to be a common model through which these systems are assessed. The technology acceptance model (TAM) is also a useful information systems model and can be utilized to better understand why individuals will use the technology (Legris et al., 2003). These are just a few samples of processes and formal theories that could be adopted to recommender system creation in higher education.

### Limitations

Limitations of this research include exclusive use of only academic databases for this study and therefore the authors cannot guarantee that all relevant articles were found. A second reviewer evaluated articles in terms of inclusion and exclusion criteria to address any bias or misclassification, however, this only occurred with 10% of the initial 596 articles. In addition, this study also focused on the non-MOOC environment in higher education and articles published in English. Lastly, there may be pertinent articles missing due to a lack of environment specificity. While some of the articles clearly indicated the environment of their application, there were many articles that did not do so. Therefore, there may be other approaches relevant to higher education that were not included as part of this research.

## Conclusion

Various recommender system approaches to using LA in higher education are currently being explored. In this systematic literature review, 53 articles published between 2017 and early 2022 explored the use of recommender systems in non-MOOC classrooms in higher education. The candidate selection approaches used by these systems varied and included examples in content-filtering, collaborative-filtering, knowledge-based, and hybrid systems. The use of knowledge-based selection appears to be a popular approach in personalizing education given its ability to overcome the limitations of other techniques. Only 26% of the articles included a specific learning theory as the theoretical focus, and only one of the articles applied a theory that could be considered related to information systems theory. Future research would benefit from further exploration of these approaches with a theoretical application in these fields.

## References

Abdi, S., Khosravi, H., Sadiq, S., & Gasevic, D. (2020). Complementing educational recommender systems with open learner models. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 360–365). Association for Computing Machinery. http://doi.org/10.1145/3375462.3375520

Aeiad, E., & Meziane, F. (2019). An adaptable and personalised E-learning system applied to computer science Programmes design. *Education and Information Technologies*, *24*(2), 1485–1509. ProQuest Central. https://doi.org/10.1007/s10639-018-9836-x

Albatayneh, N. A., Ghauth, K. I., & Fang-Fang, C. (2018). Utilizing Learners' Negative Ratings in Semantic Content-based Recommender System for e-Learning Forum. *Journal of Educational Technology & Society*, *21*(1), 112–125.

Alyari, F., & Jafari Navimipour, N. (2018). Recommender systems: A systematic review of the state of the art literature and suggestions for future research. *Kybernetes*, *47*(5), 985–1017. https://doi.org/10.1108/K-06-2017-0196

Bouraga, S., Jureta, I., Faulkner, S., & Herssens, C. (2014). Knowledge-Based Recommendation Systems: A Survey. *International Journal of Intelligent Information Technologies*, *10*, 1–19. https://doi.org/10.4018/ijiit.2014040101

Chee, T., Chan, L.-K., Chuah, M.-H., Tan, C.-S., Wong, S.-F., & Yeoh, W. (2009). *Business Intelligence Systems: State-of-the-art Review and Contemporary Applications*. 7.

Chenyuan, S., Jinbao, T., Fangyao, G., & Wenwen, F. (2021). Learning Resource Recommendation Method Based on Knowledge Graph and Neural Network. *2021 4th International Conference on Artificial Intelligence and Pattern Recognition*, 599–606. https://doi.org/10.1145/3488933.3488965

Chrysafiadi, K., Troussas, C., Virvou, M., & Sakkopoulos, E. (2019). ICALM: An Intelligent Mechanism for the Creation of Dynamically Adaptive Learning Material. *Sensors & Transducers*, *234*(6), 22–29.

Coursera. (2022). *2021 Impact Report* (p. 33). https://about.coursera.org/press/wp-content/uploads/2021/11/2021-Coursera-Impact-Report.pdf

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

DeSanctis, G., & Poole, M. S. (1994). Capturing the Complexity in Advanced Technology Use: Adaptive Structuration Theory. *Organization Science*, *5*(2), 121–147. https://doi.org/10.1287/orsc.5.2.121

Dias, A., & Wives, L. K. (2019). Recommender system for learning objects based in the fusion of social signals, interests, and preferences of learner users in ubiquitous e-learning systems. *Personal and Ubiquitous Computing*, 1–20. http://dx.doi.org/10.1007/s00779-018-01197-7

Dwivedi, P., Kant, V., & Bharadwaj, K. K. (2018). Learning path recommendation based on modified variable length genetic algorithm. *Education and Information Technologies*, *23*(2), 819–836. http://dx.doi.org/10.1007/s10639-017-9637-7

El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education*, *18*(1). http://dx.doi.org/10.1186/s41239-021-00289-4

Ertmer, P. A., & Newby, T. J. (2013). Behaviorism, Cognitivism, Constructivism: Comparing Critical Features From an Instructional Design Perspective. *Performance Improvement Quarterly*, *26*(2), 43–71. https://doi.org/10.1002/piq.21143

Ezaldeen, H., Misra, R., Bisoy, S. K., Alatrash, R., & Priyadarshini, R. (2022). A hybrid E-learning recommendation integrating adaptive profiling and sentiment analysis. *Journal of Web Semantics*, *72*, 100700. https://doi.org/10.1016/j.websem.2021.100700

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). The KDD process for extracting useful knowledge from volumes of data. *Communications of the ACM*, *39*(11), 27–34. https://doi.org/10.1145/240455.240464

Google, Inc. (2021). *Candidate Generation Overview*. Recommendation System | Google Developers. https://developers.google.com/machine-learning/recommendation/overview/candidate-generation

Jordán, J., Valero, S., Turró, C., & Botti, V. (2021). Using a Hybrid Recommending System for Learning Videos in Flipped Classrooms and MOOCs. *Electronics*, *10*(11), 1226. http://dx.doi.org/10.3390/electronics10111226

Joy, J., Raj, N. S., & V. G., R. (2021). Ontology-based E-learning Content Recommender System for Addressing the Pure Cold-start Problem. *Journal of Data and Information Quality*, *13*(3), 1–27. https://doi.org/10.1145/3429251

Khalid, A., Lundqvist, K., & Yates, A. (2020). Recommender Systems for MOOCs: A Systematic Literature Survey (January 1, 2012 – July 12, 2019). *The International Review of Research in Open and Distributed Learning*, *21*(4), 255–291. https://doi.org/10.19173/irrodl.v21i4.4643

Ko, H., Lee, S., Park, Y., & Choi, A. (2022). A Survey of Recommendation Systems: Recommendation Models, Techniques, and Application Fields. *Electronics*, *11*(1), 141. http://dx.doi.org/10.3390/electronics11010141

LAK. (2011). *Lak '11: Proceedings of the 1st International Conference on Learning Analytics and Knowledge*.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management*, *40*(3), 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4

Long, P., & Siemens, G. (2011). Penetrating the Fog: Analytics in Learning and Education. *Educause Review*, 6.

Mangaroska, K., & Giannakos, M. (2019). Learning Analytics for Learning Design: A Systematic Literature Review of Analytics-Driven Design to Enhance Learning. *IEEE Transactions on Learning Technologies*, *12*(4), 516–534. https://doi.org/10.1109/TLT.2018.2868673

Milligan, C., & Littlejohn, A. (2017). Why Study on a MOOC? The Motives of Students and Professionals. *The International Review of Research in Open and Distributed Learning*, *18*(2). https://doi.org/10.19173/irrodl.v18i2.3033

Nation, I. S. P., & Webb, S. (2011). *Researching and analyzing vocabulary*. Heinle, Cengage Learning Boston, MA.

Odilinye, L., & Popowich, F. (2021). Leveraging Learners' Metacognitive Activities for Recommendation in Technology Enhanced Learning Systems. *Journal of Organizational Psychology*, *21*(2), 22–55.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, n71. https://doi.org/10.1136/bmj.n71

Pereira, C. K., Campos, F., Ströele, V., David, J. M. N., & Braga, R. (2018). BROAD-RSI – educational recommender system using social networks interactions and linked data. *Journal of Internet Services and Applications*, *9*(1), 1–28. http://dx.doi.org/10.1186/s13174-018-0076-5

Polsani, P. R. (2003). Use and Abuse of Reusable Learning Objects. *Journal of Digital Information*, *3*(4), Article 4. https://journals.tdl.org/jodi/index.php/jodi/article/view/jodi-105

Reich, J. (2014, December 8). *MOOC Completion and Retention in the Context of Student Intent*. EDUCAUSE Review. https://er.educause.edu/articles/2014/12/mooc-completion-and-retention-in-the-context-of-student-intent

Sarwar, S., Qayyum, Z. U., García-Castro, R., Safyan, M., & Munir, R. F. (2019). Ontology based E-learning framework: A personalized, adaptive and context aware model. *Multimedia Tools and Applications*, *78*(24), 34745–34771. http://dx.doi.org/10.1007/s11042-019-08125-8

Soloway, E., Guzdial, M., & Hay, K. E. (1994). Learner-centered design: The challenge for HCI in the 21st century. *Interactions*, *1*(2), 36–48. https://doi.org/10.1145/174809.174813

Soukaina, E., Zouhir, M., & Laila, A. (2020). A context-aware mobile learning system for adapting learning content and format of presentation: Design, validation and evaluation. *Education and Information Technologies*, *25*(5), 3919–3955. http://dx.doi.org/10.1007/s10639-020-10149-9

Tarus, J. K., Niu, Z., & Mustafa, G. (2018). Knowledge-based recommendation: A review of ontology-based recommender systems for e-learning. *The Artificial Intelligence Review*, *50*(1), 21–48. http://dx.doi.org/10.1007/s10462-017-9539-5

Thongchotchat, V., Sato, K., & Suto, H. (2021). Recommender System Utilizing Learning Style: Systematic Literature Review. *2021 6th International Conference on Business and Industrial Research (ICBIR)*, 184–187. https://doi.org/10.1109/ICBIR52339.2021.9465832

Trusthi, S. L., & Nurjanah, D. (2017). Combination of hybrid filtering and learning style for learning material recommendation. *2017 IEEE Conference on E-Learning, e-Management and e-Services (IC3e)*, 24–29. https://doi.org/10.1109/IC3e.2017.8409233

Wan, S., & Niu, Z. (2018). An e-learning recommendation approach based on the self-organization of learning resource. *Knowledge-Based Systems*, *160*, 71–87. https://doi.org/10.1016/j.knosys.2018.06.014

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27. http://dx.doi.org/10.1186/s41239-019-0171-0

Zheng, H. (2021). Multi level Recommendation System of College Online Learning Resources Based on Multi Intelligence Algorithm. *Journal of Physics: Conference Series*, *1873*(1). http://dx.doi.org/10.1088/1742-6596/1873/1/012078

Zhu, J., Zhu, C., & Tsai, S.-B. (2021). Construction and Analysis of Intelligent English Teaching Model Assisted by Personalized Virtual Corpus by Big Data Analysis. *Mathematical Problems in Engineering*, *2021*. http://dx.doi.org/10.1155/2021/5374832

Zimmerman, B. (2002). Becoming a Self-Regulated Learner: An Overview. *Theory Into Practice*, *41*, 64–70. https://doi.org/10.1207/s15430421tip4102_2

Zou, D., & Xie, H. (2018). Personalized Word-Learning based on Technique Feature Analysis and Learning Analytics. *Journal of Educational Technology & Society*, *21*(2), 233–244.