DAKOTA STATE UNIVERSITY

A SELF-REGULATED LEARNING APPROACH TO EDUCATIONAL RECOMMENDER DESIGN

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DISSERTATION APPROVAL FORM

This dissertation is approved as a credible and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this dissertation does not imply that the conclusions reached by the candidate are necessarily the conclusions of the major department or university.

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ABSTRACT

Recommender systems, or recommenders, are information filtering systems prevalent today in many fields. One type of recommender found in the field of education, the educational recommender, is a key component of adaptive learning solutions as these systems avoid "one-size-fits-all" approaches by tailoring the learning process to the needs of individual learners. To function, these systems utilize learning analytics in a student-facing manner.

While existing research has shown promise and explores a variety of types of educational recommenders, there is currently a lack of research that ties educational theory to the design and implementation of these systems. The theory considered here, self-regulated learning, is underexplored in educational recommender research. Self-regulated learning advocates a cyclical feedback loop that focuses on putting students in control of their learning with consideration for activities such as goal setting, selection of learning strategies, and monitoring of one's performance.

The goal of this research is to explore how best to build a self-regulated learning guided educational recommender and discover its influence on academic success. This research applies a design science methodology in the creation of a novel educational recommender framework with a theoretical base in self-regulated learning. Guided by existing research, it advocates for a hybrid recommender approach consisting of knowledge-based and collaborative filtering, made possible by supporting ontologies that represent the learner, learning objects, and learner actions. This research also incorporates existing Information Systems (IS) theory in the evaluation, drawing further connections between these systems and the field of IS. The self-regulated learning-based recommender framework is evaluated in a higher education environment via a web-based demonstration in several case study instances using mixed-method analysis to determine this approach's fit and perceived impact on academic success. Results indicate that the self-regulated learning-based approach demonstrated a technology fit that was positively related to student academic performance while student comments illuminated many advantages to this approach, such as its ability to focus and support various studying efforts. In addition to contributing to the field of IS research by delivering an innovative framework and demonstration, this research also results in self-regulated learning-based educational recommender design principles that serve to guide both future researchers and practitioners in IS and education.

DECLARATION

I hereby certify that this dissertation constitutes my own product, that where the language of others is set forth, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions or writings of another.

I declare that the dissertation describes original work that has not previously been presented for the award of any other degree of any institution.

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CHAPTER 1

INTRODUCTION

Background of the Problem

Recommender systems, often referred to as recommenders, are information filtering systems that enable users to find useful information online quickly and easily from a wealth of information. The recommendations provided by these systems are typically personalized for individual users or groups (Ricci et al., 2015, p. 1). While achieving notoriety through applications by popular online sites and services such as Netflix and Amazon, recommenders have seen applications in a variety of domains including entertainment, health, tourism, e-commerce, education, and social media (Roy & Dutta, 2022). Recommenders vary in their design as they can use various filtering methods to provide recommendations for users. Often employed and commonly discussed methods include content-based filtering, collaborative filtering, and hybrid-based approaches. These filtering methods tend to result in recommendations based on user ratings of items or other similar user actions. Another type of recommender method, knowledge-based, makes recommendations based on knowledge often explicitly gained such as a survey that informs a user's profile (Middleton et al., 2009), permitting the user to "explicitly specify what they want" (Aggarwal, 2016, p. 16). Given the various recommender methods and designs, it is important to pair the correct approach with a given problem domain.

Educational recommender systems, often referred to as educational recommenders, are a key component of web-based adaptive learning solutions that aid students in their educational journey, making it possible to personalize their efforts to accommodate learning differences. Students have different learning needs that can be contributed to various backgrounds, learning styles, strengths, and weaknesses. Applying a "one-size-fits-all" approach to the learning process seems counterintuitive, much like a business recommending the same product or service to every consumer is not always an optimal strategy. Adaptive learning solutions serve to transform the way that students learn by dynamically adjusting learning materials based on abilities and/or skills (Pugliese, 2016). There are many benefits to employing adaptive approaches, such as increasing student success (Kakish & Pollacia, 2018) and engagement (El-Sabagh, 2021). A variety of recommenders in education have been explored including but not limited to those that recommend courses to take, discussion threads to read, learning materials to explore, and fellow students for learners to interact with (Khalid et al., 2020). Educational data associated with students such as learning analytics applied in recommender environments could be employed to better guide and improve student learning processes, leading to improved student success.

Statement of the Problem

The field of education has seen rapid growth in learning analytics. As demonstrated in the systematic literature review by Mangaroska and Giannakos (2019), analytics have found many uses by educators including but not limited to informing the design of learning activities, monitoring and evaluating student engagement, increasing awareness of one's teaching skills, and improving orchestration in order to better support learners. However, there is a lack of research as to how students can directly use educational data to improve learning. Also many learning analytic solutions are often devised around what is technically possible given data available instead of student needs (Galaige et al., 2022). As part of a student-facing solution, the analytics can serve to close the feedback loop to "increase awareness, reflection, and achievement" and ultimately improve student success (Bodily & Verbert, 2017b, p. 1). Learning analytics 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). Higher education stands to benefit from being more efficient in its use of data as it has a history of "substantial delays in analyzing readily available evident data and feedback" that then results in delayed actions and interventions (Long & Siemens, 2011). Learning analytics has the potential to empower reflective learning practices. Recommenders present the opportunity to utilize these analytics to directly engage students and to impact student learning, instead of more passive applications of learning analytics such as those that predict performance or success. However, many implementations of learning analytics are not based on theory (Banihashem et al., 2018) and/or are instead based on the educator's perspective or are teacher-centric (Banihashem et al., 2018; West et al., 2020). The design of systems that provide analytics need to be grounded in educational theory as theory is essential in guiding hypotheses tested, study design (including data traces utilized), data analysis, and interpretation of results (Gašević et al., 2017). Researchers have advocated for more integration of learning theories and learning analytics and state that connecting research to learning theories serves to better understand "how and why" certain factors influence learning (Wong et al., 2019, p. 15).

Examples of student-facing solutions that employ learning analytics include intelligent tutoring systems, learning analytic dashboards, and educational recommenders (Bodily & Verbert, 2017b). Each can play a role in adaptive learning systems. Educational recommenders may also play a role in intelligent tutoring systems, blurring the line between technologies. One of the key differences between traditional recommenders and educational recommenders is that educational recommenders are often influenced by pedagogical factors (Garcia-Martinez & Hamou-Lhadj, 2013). Some existing implementations of recommenders rely on learning style as the key theoretical educational contribution to the recommender design with the Felder-Silverman Learning Style Model (FSLSM) the most often applied (Raj & Renumol, 2021; Thongchotchat et al., 2021). Learning style refers to "the process by which the learner organizes, processes, represents, and combines this information and stores it in his cognitive source, then retrieves the information and experiences in the style that reflects his technique of communicating them" (El-Sabagh, 2021, p. 4). Their use in the design of educational systems is a point of contention when considering that learning styles have also been labeled a myth (Kirschner, 2017) . This research seeks to go beyond the concept of learning style to incorporate self-regulated learning (SRL) theory into recommender design as a way of improving student learning in the development of a recommender-based study system for students.

The use of SRL as the theoretical lens to apply the learning analytics in a recommender system design will provide the foundation needed to develop this tool with a focus on improving student learning. SRL places individuals in control of their learning by making students more aware of the link between their learning processes and learning outcomes, and the strategies they use to reach their learning goals (B. J. Zimmerman, 1990) making it an ideal theory to connect learning analytics to recommenders. Wong et al. (2019) has cited SRL as an area where learning theory and learning analytics converge, making it an ideal choice of a theoretical base. Yet many of the existing recommender and learning analytic studies do not incorporate SRL. In a 2019 systematic literature review on learning analytics, it was discovered that there was little research in this area (Mangaroska & Giannakos, 2019). In a different systematic literature review that looked at educational recommender employed in traditional classrooms in higher education environments, it was found that only one of the 53 recommender solutions investigated included a focus on SRL (McNett & Noteboom, 2022). SRL is underexplored in recommender research and, given SRL's focus on self-awareness of one's learning processes, it is ideal for situations such as studying or practicing. That is, situations where students are more in control of their learning activities, learning autonomously, seeking assistance when needed, and, at some point, reevaluating their own learning processes.

By developing an educational recommender, one can customize learning experiences with the aid of learning analytics in a student-facing manner, acknowledging and supporting the needs of individual students instead of providing a "one-size-fits-all" model. This research seeks to apply the educational theory of SRL in exploration of a recommender built on existing ontology- and knowledge-based recommender research in the fields of education and information systems (IS). The main research questions are:

RQ1: How can recommender design best be supported by self-regulated learning theory?

RQ2: What is the influence of recommender-based self-regulated learning on academic success?

The goal of this research is to better understand if this theory-based approach can improve student learning when applied to recommender system design by building on existing recommender design and IS research. RQ1 permits exploration of the design of these systems while RQ2 considers the impact that the proposed system will have on "academic success." Academic success can be defined in several ways. For some, it can mean the grade earned by the student. It has been recommended that the studies that evaluate recommenders in education look beyond grades when investigating the effects these systems have on learning (Deschênes, 2020). Similarity, research in learning analytics recommends adopting measures that focus beyond performance by looking at learning processes and environments (Knobbout & Van Der Stappen, 2020). For this research, success will be measured by considering academic achievement and student perceived success, that is, if a student feels they that have reached predefined goals with consideration for learning environment and process.

Objectives of the Dissertation

This research uses the design science research methodology to combine SRL theory with aspects of IS system design, development, and evaluation. The major deliverable, the envisioned artifact, is a framework that will consist of a reference model and methods for a study recommender system. The reference model will represent components of the recommender and their relationships while the method will focus on the algorithm(s) utilized to provide recommendations. It is intended that the artifact applies a SRL model such as the three classic phases of Zimmerman's SRL theory using the cyclical phases model (B. J. Zimmerman & Moylan, 2009) and establishes a profile based on aspects of the Motivated Strategies for Learning Questionnaire (MSLQ) (P. Pintrich et al., 1993), a self-reporting tool that permits assessment of student motivation and learning strategies. This will be followed by an instantiation of the framework to permit real-world testing and summative evaluation of the framework.

This work also seeks to incorporate elements of IS theory by using the task-technology fit (TTF) model in the proposed evaluation of the system, permitting evaluation to go beyond student grades. Existing recommender research (Jordán et al., 2021) has also noted the need to survey users for direct feedback as a way of better understanding if recommendations are perceived as being useful. TTF theory (Goodhue & Thompson, 1995) aims to quantify the effectiveness of the system given the task at hand. Provided that the goal of the proposed recommender framework is to support the task of learning, a model that aids in determining if the technology is a "good fit with the task it supports" (Goodhue & Thompson, 1995, p. 213) appears appropriate as a tool in the system's evaluation. The proposed model to use for evaluation will focus on six classic constructs of this theory including task characteristics, technology characteristics, individual characteristics, task technology fit, utilization, and performance impact. While this model will be used as part of the summative evaluation of the proposed framework, the constructs will also serve to influence the development of the artifact's requirements.

When addressing the research questions, ties will be made to existing recommender research. Evaluation of this research will inform proposed design principles to guide the creation of SRL educational recommenders for both practical applications and future research. When presented, these principles will follow the proposed schema for design principles as recommended by Gregor et al. (2020). This schema supports innovation in IS by presenting the principles in a way that is of value to both researchers and professionals, supporting the mindset of design science research.

The research contribution of this paper is two-fold: it explores the application of recommenders in a novel way and presents an applied theoretical approach to the design. In keeping with IS research, the results would be of benefit to both practitioners and researchers alike. IS researchers are uniquely situated to address many of the issues and gaps discussed previously in this research, for the problem exists in an interdisciplinary field with an emphasis on analytics. The results of this research will be shared in both a manner that adds to the existing body of knowledge in IS and education. The process for developing the framework and the artifact will be shared in detail along with the evaluation process. The findings will also be shared in a way that managers (in this case, school administrators and educators) may understand the value and impact of the approach in solving the problem, but also will provide an appreciation for the resources needed to construct and use the artifact.

Ultimately this framework intends to improve the learning process aided by educational recommenders and will be evaluated on its impact on student success and learning as advocated by existing research. IS research like this would enable higher education institutions to better adapt to individual learners with the goal of improving student success. Furthermore, the design science research methodology supports the creating and evaluating of artifacts that serve as these solutions (Hevner et al., 2004). This establishes a link between the goal of this research and IS discipline.

Structure of the Dissertation

This first chapter has provided the background of the problem, statement of the problem to be investigated by this research, and the objectives of this dissertation. The remainder of this dissertation is organized as follows:

- Chapter 2 presents a comprehensive review of the literature

- Chapter 3 discusses the implementation of the design science methodology
- Chapter 4 presents the analysis of the results and discussion
- Chapter 5 discusses future research opportunities and limitations of this research, and presents the conclusion

CHAPTER 2

LITERATURE REVIEW

Recommender Systems

Recommenders first appeared in the early 1990s as a way to address information overload by predicting which information the user would like to see (Konstan & Riedl, 2012). Since then, they've become a mainstay in e-commerce by suggesting products or services to users. They are beneficial to both parties involved. They aid the user by reducing the effort needed to find an item of interest, and they aid the provider by selling more products or services (Isinkaye et al., 2015). They can also serve to keep users satisfied and to increase user fidelity (Ricci et al., 2015, p. 5). Recommenders have applications in a variety of areas such as e-commerce, education, entertainment, books/documents, tourism/travel, health care, and social media (Xu et al., 2014).

Recommenders predict ratings or rank items to form recommendations, often with the primary goal of increasing sales in e-commerce environments (Aggarwal, 2016, p. 3). Systems may be implemented in various ways, but they all tend to follow a general process. Isinkaye et al. (2015) describes a recommender process as having three phases: an information collection phase, a learning phase, and a prediction/recommendation phase. The information collection phase involves collecting data about the user or developing a model to be used for prediction. This data can be collected explicitly by using instruments such as a questionnaire or the data can be collected implicitly by observing user behavior. In the learning phase, the data collected in the information collection phase is preprocessed if needed and then filtered through a learning algorithm. Here "learning" can be done in many ways, often involving a machine learning algorithm, and is dependent on the goals of the system and the recommendation filtering technique employed. For example, in a collaborative filtering-based approach that utilizes a memory-based technique, a cosine similarity measure may be employed. In model-based recommender implementations, the optimal parameters must be learned before determining the final model (Medel et al., 2022). The final phase, prediction/recommendation, presents the top N predicted or recommended items to the user for consideration. While the main functionality of the three phases is evident in most recommender designs, there can be many variations in the design of the phases.

When considering various recommender designs, the filtering technique is of importance and tends to distinguish different applications. The filtering techniques of recommenders commonly include content-based filtering, collaborative filtering, knowledge-based, and hybrid filtering. Recommenders are typically categorized by their filtering technique. The common filtering techniques are categorized below in Figure 1.

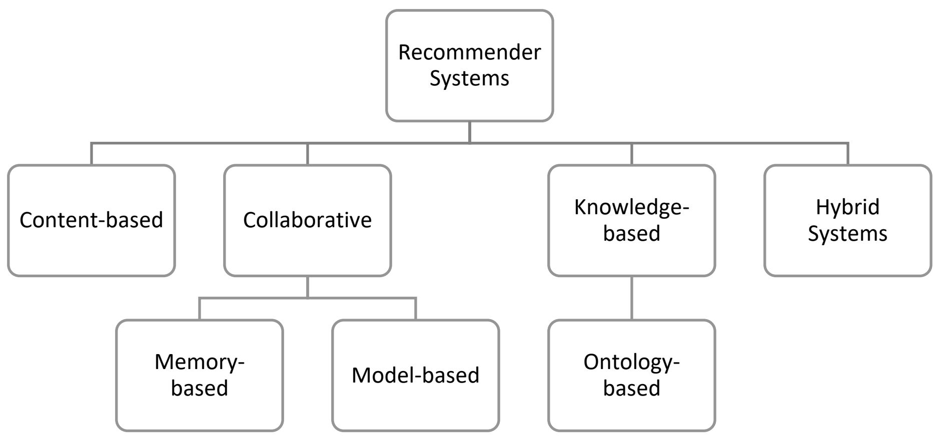

Figure 1. Types of Filtering in Recommenders

Content-based filtering determines recommendation candidates, such as items to recommend, based on similarities between candidates. It often uses attributes that describe the candidates in determining the recommendation (Aggarwal, 2016, p. 14). It can provide recommendations by understanding user behavior, such as attributes of items that the user likes, and then find and suggest similar items. It is the most basic of the models and found in many early recommenders (Ko et al., 2022). It does not consider actions of other users, such as items that other similar users like. The way data is stored for this approach varies. Often feature vectors are used for quantifiable data, where features represent attributes that describe the item. These vectors can contain both user-based information and item-based information, as demonstrated in the binary features of the matrix presented below in Figure 2.

	feature1	feature2	feature3	…	featureN
item1	1	0	1	…	1
item2	1	0	0	…	0
item3	0	1	1	…	0
…	…	…		…	…
itemN	0	0	1		1
user1	1	0	0		1

Figure 2. Matrix based on Item Features

When mostly textual data, such as the description of an item, is used to determine recommendations, a different approach is required. Here natural language processing (NLP) is used to extract keywords, and quantifiable data is then obtained using methods such as term frequency-inverse document frequency (TF-IDF). This then results in quantifiable data that contains vectors for each item. In either case, the vectors are then combined to create a matrix used to generate recommendations.

Using these vectors, items can be selected in a variety of ways to determine recommendations. Similar items may be found most simply by using similarity measures (e.g. cosine similarity, dot product), the k-nearest neighbors algorithm (KNN), or other techniques often found with other types of recommenders such as decision trees and other clustering methods (Marcuzzo et al., 2022). Here the method deployed often depends on the context and the results of prior research as some methods may have shown to outperform others. For example, the cosine similarity has been shown to outperform other methods such as the Pearson coefficient when a recommendation is based on similarities between items (item-based) (Jannach et al., 2010, p. 16).

Collaborative-filtering is based on the similarities between users and items simultaneously. This is found in more modern recommender approaches. For this approach, data is often stored as a user-item matrix. As demonstrated below in Figure 3, the matrix holds numeric ratings provided by the users for items.

	item1	item2	Item3	…	itemN
user1	3	5	1	…	2
user2	4	2	2	…	3
user3	4	1	3	…	5
…	…	…		…	…
userN	2	3	4		1

Figure 3. User-item Matrix

Recommendations are determined using a memory-based or model-based approach. Memory-based techniques tend to determine predictions by calculating the similarity between items or users by using measures such as the Pearson correlation coefficient (Isinkaye et al., 2015). Other popular memory-based approaches to calculate similarity, such as KNN, are referred to as neighborhood methods (Marcuzzo et al., 2022). Model-based techniques represent data in the form of a user-item interaction matrix (Marcuzzo et al., 2022) and use pre-computed models such as regression, clustering, or decision trees (Isinkaye et al., 2015) to recommend items by determining neighbors with similar preferences and focusing on items neighbors prefer. The use of latent factor models has also become a popular approach in many applications of collaborative filtering. For example, the use of matrix factorization to create a compact representation of the user-item matrix results in more affordable complexity than comparing all of the available user-item pairs (Marcuzzo et al., 2022).

Knowledge-based systems provide recommendations based on domain knowledge and typically require a knowledge base and a user profile (Bouraga et al., 2014). Explicit information about users (e.g. user requirements) is gathered for this approach. Recommendations in these systems can be constraint-based or case-based. The use of constraints involves user entered specific desired values or limits to use as requirements, while case-based focuses on retrieving items similar to ones specified by the user (Aggarwal, 2016, pp. 16–17). These constraints or cases are used to drive the rules that automate the generation of recommendations (Bouraga et al., 2014). The main challenge associated with building knowledge-based recommenders is construction of the knowledge base as it requires expertise of the content area and in how the knowledge may be represented (Bouraga et al., 2014).

Data can be represented in a variety of ways in knowledge-based systems. One common and popular type of knowledge-based recommender has a distinct approach. The ontology-based recommender relies on an ontology and domain knowledge such as the user's profile to make recommendations. Ontologies provide a way to classify and structure (e.g. demonstrate relationships) the knowledge-based instances (Middleton et al., 2009). Creating these ontologies is a challenging and time-consuming process (Tarus et al., 2018). In many cases, it is found that ontologies are represented with ontology-specific languages such as Web Ontology Language (OWL) or Research Description Framework (RDF) schema (Tarus et al., 2018). Approaches like these pair well with certain domain areas such as education. Other ontology storage models include object and relational database management systems. These have the advantage of providing "full-fledged database functionality" but do not directly support the hierarchical nature of ontologies (Abburu & Golla, 2016, p. 542) and therefore require more upfront consideration for schema design to support the ontology.

The last type of recommender, hybrid, combines any of the above techniques and therefore often avoids limitations of other methods, and can have improved prediction performance at the expense of increased complexity of the implementation (Alyari & Jafari Navimipour, 2018). Any or all of the techniques can be combined in order to avoid limitations or improve predications. Common limitations or issues associated with recommenders include the cold-start problem, the gray sheep problem, lack of serendipity, scalability, and lack of diversity. The cold start problem occurs when there is not enough data present in the system to determine recommendations. This is often due to a lack of user-rated items, such as a new user as they do not have previous recommendations that can be utilized for the purpose of making similar recommendations. The gray-sheep problem occurs when a user or group of users in the system is distinctively unique, preventing the ability to make similar recommendations. Lack of serendipity refers to the inability of the system to surprise the user with a relevant item that otherwise would not be discovered (Herlocker et al., 2004). Some implementations have an issue with scalability; they are unable to provide recommendations in real-time when users and/or items in the system increase. Lastly, recommendations may be lacking in diversity, which implies evidence of overfitting or too closely aligning with other items liked. Diversity can be measured in different ways, and the metrics that measure diversity vary (Kunaver & Požrl, 2017). Table 1 summarizes the advantages and disadvantages of each approach and takes into account some of the common limitations of recommenders.

Table 1. Advantages and Disadvantages of Recommender Approaches

Category of Recommender	Advantage	Disadvantage
Content-based	+ Good at recommending new items that lack user ratings (avoid item cold start)	- Requires content/features of items to be extracted/known - Lack of diversity in recommendations (overspecialization) - Inability to provide recommendations for new users (user cold start)
Collaboration	+ More diverse recommendations + Does not require feature/context to be extracted from or known of from items	- Data sparsity (gray-sheep problem) - Relies on user ratings (cold-start problem) - New items are not yet rated (cold-start problem)
Knowledge-based	+ Good at working with new items or users (no cold-start problem) + No issues with sparsity	- Requires extensive knowledge about users and items
Hybrid	+ Avoids issues associated with other recommenders	- More complex to create and maintain

Recommenders, IS, and Education

Recommenders lie at the intersection of education and IS research, and involve learning analytics. Learning analytics alone is multidisciplinary in nature with influences from several fields including “artificial intelligence (AI), statistical analysis, machine learning, and business intelligence” (Siemens, 2013, p. 1383). It is a growing field with many areas of research and application. Figure 4 below demonstrates the multidisciplinary nature of learning analytics. Historically there have been many techniques applied to obtain information and several applications of these techniques are intended to influence higher education practices.

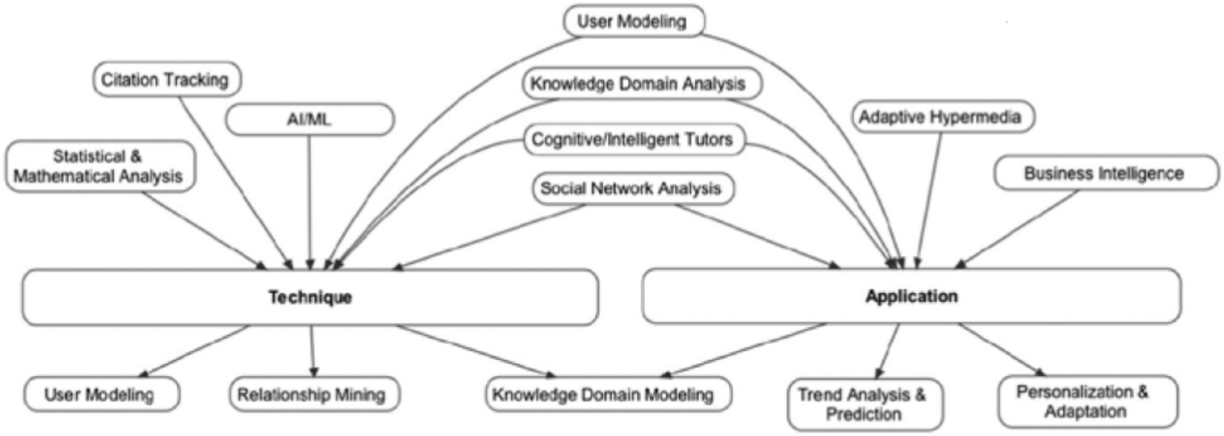

Figure 4. Learning Analytics Influences (Siemens, 2013)

The Institute for Operations Research and the Management Sciences describes three main categories of analytics: descriptive, predictive, and prescriptive. Descriptive analytics focus on historical data in order to provide insight on events that have already happened. This type of analytics tends to rely on basic statistical methods. Conversely, predictive analytics provide insight on future events. It helps with the discovery of patterns and/or trends, and often involves the use of machine learning and statistical modeling. Prescriptive analytics provide insight on the best form of action to aid in decision-making. This is another area where machine learning algorithms are utilized.

Clow (2012) describes the learning analytics cycle as a process that consists of four cyclical steps: learners, data, metrics, and interventions. This process is depicted in Figure 5. The process begins with learners. Data is then collected from learners explicitly through methods like surveys or forms, and/or implicitly through interactions with software, such as logs that contain data pertaining to logins and user clicks. This is then followed by the metrics or analytics which are often presented to the audience through the use of tools such as dashboards, modeling, and/or recommenders. To complete the cycle, interventions are needed. The type of intervention depends on the individual utilizing the metrics. If the metrics are student-facing (presented in some manner to the student), a student may use the metrics to adjust their learning activities or goals. If the metrics are educator- or administrative-facing, this may result in educator or administrator actions, such as an educator modifying their teaching or providing additional assistance to a student. Chow (2012) reports that effective use of learning analytics typically involves all four of these steps.

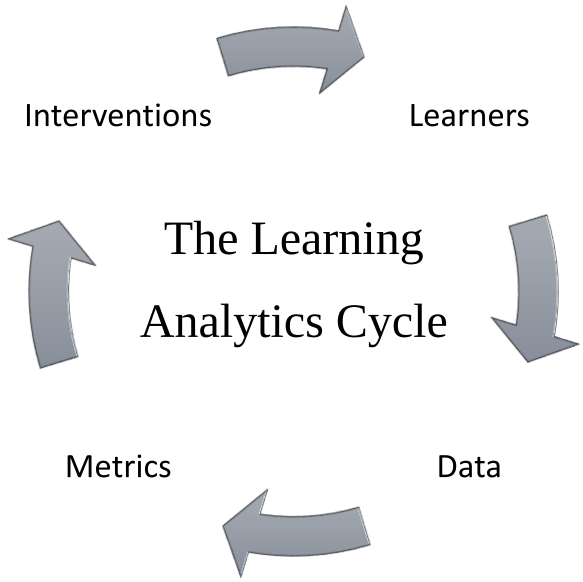

Figure 5. Learning Analytics Cycle (Clow, 2012)

Information systems have been transformative in the field of education. EDUCAUSE, a nonprofit organization that focuses on the use of information technology (IT) in higher education, dedicates a report to the use of data and analytics in education, with its 2022 report identifying several trends in higher education including social, technological, economic, environmental, and political trends (Reinitz et al., 2022). Furthermore, a similar report published in 2022 by EDUCAUSE that focuses on teaching and learning recognizes that the impact of artificial intelligence (e.g. machine learning) in higher education has the "potential for helping drive decision-making and creating adaptive and personalized education experiences" (Pelletier et al., 2022, p. 17). The field of IS lies at this intersection of information systems and analytics, and researchers in IS have the ability to help shape the future of IT in higher education. Chiang et al. (2012) advocate that the IS discipline provide leadership in education concerning business intelligence and analytics.

From an educational perspective, learning analytics brings a variety of benefits to learners including enhanced engagement, improved learning, personalization of the learning, increased adaptivity, enriched learning environments, and increased self-reflection and self-awareness (Banihashem et al., 2018). Much of the existing learning analytics research focuses on the educator's use of analytics to evaluate the effect of different teaching approaches, improve classroom orchestration, and/or predict student performance (Mangaroska & Giannakos, 2019). The application of recommenders to higher education permits the use of analytics to better design a personalized learning experience for students that is student-facing and therefore serves to improve student autonomy. It has been suggested that autonomy yields intrinsic motivation (Scharle & Szabó, 2000). Some researchers have explored the links between autonomy and motivation. When considering the impact of learning analytics, a comprehensive literature review of student-facing learning analytics dashboards and recommenders documents several studies where student use of these systems resulted in improvements in student achievement and behavior, demonstrating the various benefits of student-facing analytics (Bodily & Verbert, 2017a).

A recommender is a common element in the design of adaptive learning systems (Nurjanah, 2016). The adaptive learning system model consists of three components, a content model, learning model and an instructional design model (Gynther, 2016; Martin et al., 2020). This model in depicted below in Figure 6.

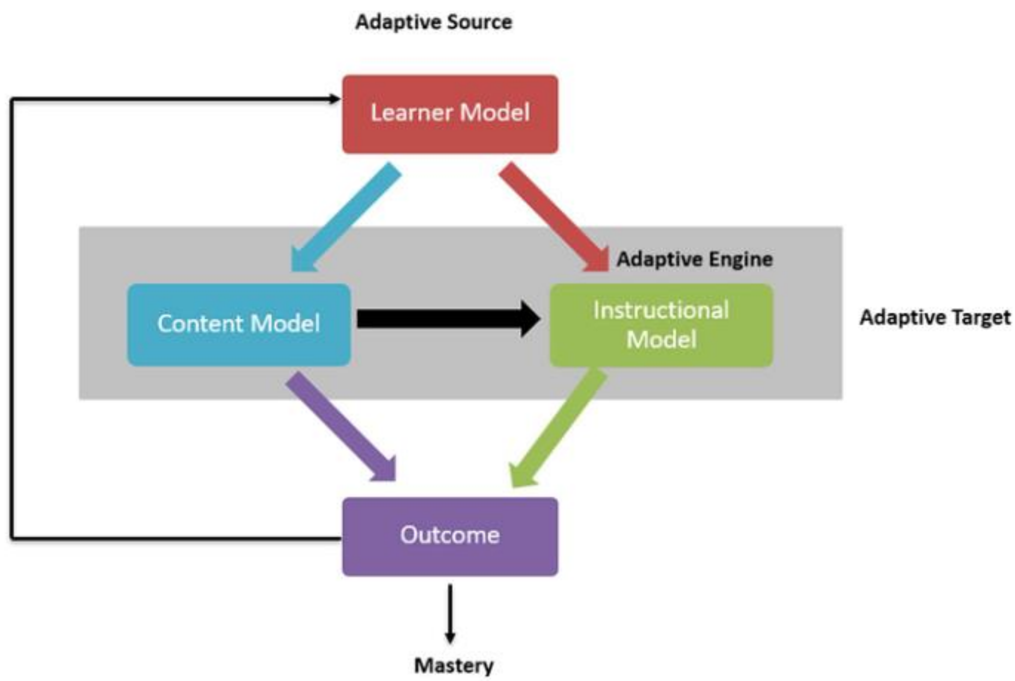

Figure 6. Framework for Adaptive Learning Model (Martin et al., 2020)

The content model is the domain model that provides details such as learning outcomes and objectives. The learning model contains characteristics of the learners. The learning model is different from a learning profile because the model is "the system's beliefs about the learner" and may contain dynamically learned data about the learner in addition to profile information (Abyaa et al., 2019, p. 1106). The instructional model, also known as the pedagogical model, adapts the learning material based on the content and learner model, and consists of the algorithm that adapts instruction. The instructional model is often where the recommender component is found.

In a systematic literature review on adaptive learning content recommenders (Raj & Renumol, 2021), a variety of recommendation filtering methods were found to be used in adaptive content recommenders including collaborative filtering, content-based, ontology-based (knowledge-based), and hybrid approaches. The machine learning algorithms applied also included a variety of algorithms with KNN and k-means being the most prevalent in the literature review. When reviewing parameters used as part of the learner model that influenced the recommender, it was found that that learning style/preference parameters are most often utilized with FSLSM being the most popular model applied. Other parameters included knowledge level, learning path/patterns, performance/score, learner ratings, portal hit similarity, social tags, social trust, learning need/goal, and cognitive/emotional state. In a different study, Apoki et al. (2022) referred to recommenders in personalized adaptive learning systems as pedagogical agents. Instead of focusing on specific techniques, this systematic review focused on the role of these pedagogical agents and their projected impact. The authors explored the responsibilities of these agents as adaptivity and intelligence, where adaptivity changes the system's behavior (i.e. presentation, navigation, and information filtering) and intelligence applies approaches from AI to assist learners (i.e. monitoring, collaborative learning, and tutoring). Their research showed that intelligence was more often explored in pedagogical agents than adaptivity, and that most of the agents explored (80%) focused on improved performance as the projected impact.

The field of education has seen a variety of uses of recommenders. One of the prevalent topics is course recommenders. These systems aid students in selecting the best course or combination of courses to take (Aher, 2012; Maphosa et al., 2020; O'Mahony & Smyth, 2007). Many studies have looked at recommenders in education outside of course recommendations and have a focus that consists of recommendation of learning objects /(Dias & Wives, 2019; Jordán et al., 2021; Joy et al., 2021; Pereira et al., 2018; Wan & Niu, 2018;

Zheng, 2021) and/or learning paths (Carbone et al., 2021; Shi et al., 2020; Vagale et al., 2020; Zhu et al., 2018). 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. Learning paths include learning objects but recommend an order in which the learning objects are consumed (Machado & Boyer, 2021). A variety of recommender filtering approaches have been applied as well. Content-based recommenders such as Albatayneh et al.'s (2018) recommendation architecture used semantic filtering of negative ratings to provide content-based recommendations to learners. The authors note how future directions in this research would be to include more contextual student information, much like that of a knowledge-based recommender to improve the recommendation process. Collaborative recommenders have also been explored. Toledo et al.'s (2018) application used fuzzy modeling with collaborative filtering in order to make appropriate programming practice problem recommendations to learners. The authors cite the need to explore additional recommendation techniques and to consider "behavior of the users across [...] time" in future research (2018, p. 15). Klašnja-Milićević et al. (2018) explored expanding available metadata of items through collaborative tagging (using collaborative filtering techniques) in their recommender approach, but do so with attention to the development of a learning profile that establishes learning style to aid in filtering of recommendations. Some researchers used a hybrid approach by combining both content-based and collaborative filtering techniques, such as Jordán et al.'s (2021) video recommender. This approach permitted accurate recommendations by avoiding shortfalls of a given technique, such as cold-start problem. Kapembe and Quenum (2019) applied a similar hybrid approach when recommending learning objects that also consider student learning style using the Visual, Auditory, Read/Write, and Kinesthetic (VARK) learning preferences questionnaire. In knowledge-based recommender research, El-Sabagh (2021) explored the impact on engagement of adaptive e-learning based on the VARK model and use of an instructional design model. Prior to accessing adaptive e-course modules, students were first asked to complete a learning styles (VARK) questionnaire. This also requires knowledge of learning objects as part of the recommendation process. Chrysafiadi et al. (2019) applied a similar approach by considering the user's knowledge level, the learning material content, and the display mode of the material when providing their recommendations. A VARK questionnaire was again used to determine the display mode most appropriate for a given learner.

Table 2. Recommender Use in Education

Recommender Use	**Articles**	**Filtering Method**
Course Recommenders	Maphosa et al., 2020 (Systematic literature review)	Various including content-based, collaborative, knowledge-based and hybrid approaches
Learning Object Recommenders	Albatayneh et al, 2018	Content-based
	Chrysafiadi et al., 2019	Knowledge-based
	Dias & Wives, 2019	Collaborative
	El-Sabagh	Knowledge-based
	Jordán et al., 2021	Hybrid
	Joy et al., 2021	Knowledge-based
	Kapembe and Quenum, 2019	Hybrid
	Klašnja-Milićević et al., 2018	Collaborative
	Pereira et al., 2018	Hybrid
	Toledo et al., 2018	Collaborative
	Wan & Niu, 2018	Hybrid
	Zheng, 2021	Collaborative
Learning Path Recommenders	Carbone et al., 2021	Hybrid
	Shi et al., 2020	NA – Knowledge graph
	Vagale et al., 2020	NA – Knowledge graph
	Zhu et al., 2018	NA – Knowledge map

Ontology-based approaches to knowledge-based recommenders are evident in a variety of existing research. These types of systems permit the collection of information that is not typically learned implicitly by the system, such as user profiles. Both Joy et al.'s (2019) ontology-based model and Aeiad & Meziane's (2019) ontology-based approach extract or organize user and domain information to be used by the system and therefore permit recommendations when historical data is initially scarce, avoiding the cold start problem. By using existing information to guide recommendations, the hope is that the use of ontologies will also produce greater accuracy and quality of recommendations.

Yet many gaps and challenges exist in the fields of learning analytics and recommenders in education. Research in learning analytics calls for more transformative approaches that go beyond predication, a typical use of analytics (Long & Siemens, 2011). A need exists to better understand features used in analysis and their impact, with a shift from prediction to explanatory analytics (Namoun & Alshanqiti, 2020). With significant factors understood, students could then better monitor their progress and evaluate and adjust learning strategies accordingly to learning outcomes (Papamitsiou & Economides, 2019). Analytics research also calls for more and improved data sources and moving beyond the learning management system as the sole provider of data (Long & Siemens, 2011; Namoun & Alshanqiti, 2020). Research has also shown that the data collected should not be general, but instead have a specific scope and focus (Banihashem et al., 2018). Often this goes back to the learning outcomes of the course and an understanding of how students learn.

One of the most reiterated problems in learning analytics research is the lack of a theoretical approach. Several recent systematic literature reviews concerning learning analytics focused on the gap between theory and practice (Banihashem et al., 2018; Mangaroska & Giannakos, 2019; Matcha et al., 2020). There has been limited research concerning a theoretical lens through which to apply learning analytics. This is where SRL theory could be applied. SRL theory provides the means by which to compensate for learning differences (B. Zimmerman, 2002). This aligns with the need to break out of the "one-size-fits-all" learning approach. Zimmerman describes it as a "self-directive process by which learners transform their mental abilities into academic skills" (2002, p. 65)

When considering recommenders, a systematic literature review of educational recommenders for non-massive open online courses in higher education environments found that only 26% of recommenders had an educational theory as a significant factor influencing design, with learning style-related theories being the most often applied theories (McNett & Noteboom, 2022). Of these, FSLSM and VARK were the most prominent as depicted in Figure 7.

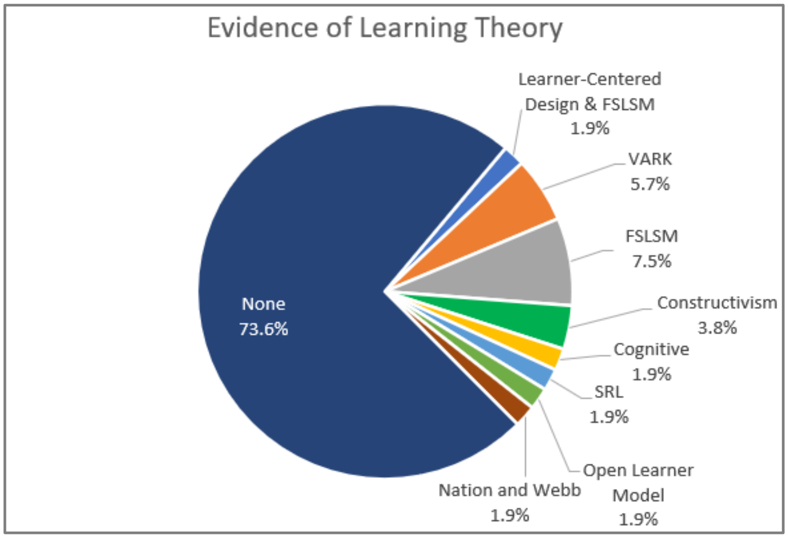

Figure 7. Learning Theory in Recommender Design (McNett & Noteboom, 2022)

A systematic literature review that explored its use in intelligent e-learning systems from 2011 - 2020 found that incorporating learning styles, specifically FSLSM, in the design may improve system quality (Supangat & Saringat, 2022). This is at a time when many researchers (Kirschner, 2017; Pashler et al., 2008) have advocated against the use of learning styles. Kirschner (2017, p. 167) states that:

> *"… there is no real scientific basis for the proposition (actually it should be relegated to the realm of beliefs) that (1) a learner actually has a certain optimal learning style, (2) (s)he is aware of what that personal learning style is and/or there is a reliable and valid way to determine this style, and (3) optimal learning and instruction entails first determining this learning style and then aligning instruction accordingly."*

They advocate that the use of a learning style by which to group learners is not effective as it lacks evidence-based research to support its claims. Therefore a different approach is needed such as those recommended by Ambrose et al. (2010) where the focus instead is on facets such as studying styles, diversity of learning instruction, and factors that influence motivation. In looking at pedagogical theory that encompasses several of these factors, we find SRL.

Self-regulated Learning

Self-regulated learning (SRL) theory was first introduced by Barry J. Zimmerman in 1985. This theory puts learners in more control of the learning environment for “learning is viewed as an activity that students do for themselves in a proactive way rather than as a covert event that happens to them in reaction to teaching” (B. Zimmerman, 2002, p. 65). This requires students to have an understanding of their strengths and weaknesses while also setting goals and strategies for learning. It includes several aspects of learning including cognitive, metacognitive, behavioral, motivational, and emotional/affective (Panadero, 2017). For example, the self-monitoring of ones’ learning advocated by SRL results in students finding weaknesses in their learning which then can prompt students to replace inadequate learning methods with more adequate ones, empowering them to learn (B. J. Zimmerman & Paulsen, 1995).

As depicted below in Figure 8, SRL consists of three phases as described by Zimmerman (2002): forethought phase, performance phase, and self-reflection phase. Each phase consists of two major classes of tasks, as depicted in Figure 8. In the forethought phase, learners set goals for themselves, develop a plan concerning how to achieve that goal, and uncover beliefs that motivate them to achieve their goals. In the performance phase, learners deploy the plan they developed in the forethought phase and keep track of their progress. In the self-reflection phase, learners evaluate their performance and seek to determine what contributed to their success or errors. One distinguishing feature of this process is that these phases are cyclical, providing a feedback loop where students monitor and react to their learning (B. J. Zimmerman, 1990).

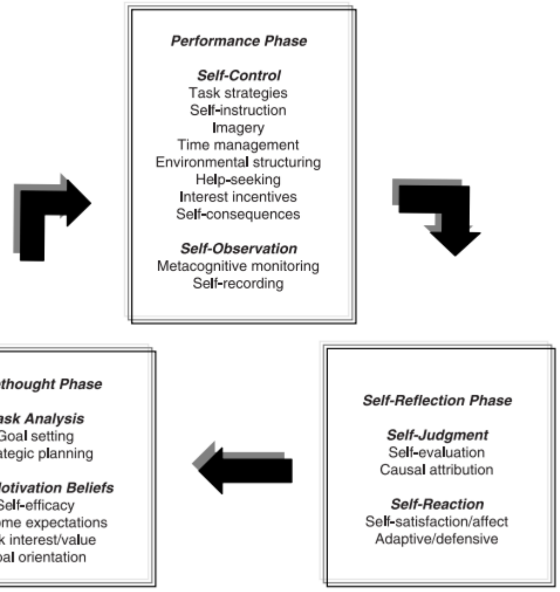

Figure 8. Cyclical Phase Model of SRL (B. J. Zimmerman & Moylan, 2009)

Since Zimmerman's original model was published, there have been several other models developed concerning SRL theory in addition to instruments that can be used for evaluation (Panadero, 2017). There are three primary models: the triadic model of SRL (B. J. Zimmerman, 1989), the cyclical phases model (1st version) (B. Zimmerman, 2002) and the current version of the cyclical phases model (B. J. Zimmerman & Moylan, 2009). Another major contribution of SRL is the conceptual framework created by Paul Pintrich (P. R. Pintrich, 2000). His work included four phases (forethought, planning, and activation; monitoring; control; and reaction and reflection), each associated with possible areas of self-regulation. Pintrich's approach was notable for its emphasis on motivational variables to SRL (Schunk, 2005). He contributed to the development of the Motivated Strategies for Learning Questionnaire (MSLQ) (P. Pintrich et al., 1993) that serves as a valid and reliable measure of self-reported learning strategies and motivation of students.

There have been studies that have explored SRL and the use of analytics. One study emphasized the ability of learning analytics to enable SRL which can result in improvements in student learning (Bos & Brand-Gruwel, 2016). In this study, university psychology students' study methods were logged in order to reveal differences in study strategies and their impact on course performance. This study focused on differences in regulation strategies and the impact of these strategies on performance. In a different approach, researchers built a study tool called nStudy designed to support evolving self-regulated learning (Winne et al., 2019). The system used artifacts, such as items the user highlights, and trace data as a source of analytics and then applied various learning theories to suggest varying study tactics to users of the system. In another study by Kizilcec et al. (2017), researchers used analytics from a Massive Open Online Course (MOOC) to better understand the SRL skills of online learners. While this was not a student-facing use of analytics, the researchers were able to determine how SRL behaviors manifest in these courses and also suggested interventions based on individual differences in SRL. Their recommendations for future research encouraged development of systems that "facilitate self-monitoring of SRL strategies" and "interventions to support SRL for a global and diverse learner population" (2017, p. 30). Viberg et al. (2020) conclude in their literature review of learning analytics research focusing on SRL in online environments that studies have a tendency to focus on the "calculation of student behaviour" instead of suggesting interventions that could improve student learning (2020, p. 8).

Research Gap

In the systematic literature review of higher education recommenders, only one of the articles (Odilinye & Popowich, 2021) included in the study connected the approach to self-regulated learning theory (McNett & Noteboom, 2022). Odilinye and Popowich (2021) developed their recommender as a plug-in for the nStudy system that provides recommendations based on items that the user highlights. This use of highlights was found to be another way to provide recommendations and to aid in metacognition activities. Metacognition, "the awareness of and knowledge about one's own thinking," is a defining aspect of self-regulated learners (B. Zimmerman, 2002, p. 65).

Existing research has demonstrated the benefits of sharing analytics with students to aid the learning process. Recommenders provide the mechanism for implementing these analytics in a meaningful way. The impact of using educational recommenders in the classroom includes increased student performance and increased motivation (Garcia-Martinez & Hamou-Lhadj, 2013). Educational theory can serve to inform system design decisions to produce a more effective system. In this research, SRL, an underexplored area in recommender research, is being proposed as the theoretical lens through which to guide the design and development of a study recommender system. As advocated in recent EDUCAUSE reports (Pelletier et al., 2022; Reinitz et al., 2022), analytics and artificial intelligence (e.g. machine learning) stand to have a substantial impact on teaching and learning. Recent research in the field of educational recommenders has also called for continued research, such as Leite da Silva et al.'s (2023) call for researchers to investigate user attributes to guide recommendations that may have been overlooked.

Chapter Summary

Recommenders have become a mainstay of the e-commerce industry. The design of recommenders consists of three basic phases, but can employ a variety of different techniques in the way the systems work with data and provide recommendations. Recommenders are often differentiated by their filtering approach. Common approaches include content-based, collaborative, knowledge-based, and hybrid filtering, each with advantages and disadvantages that need to be weighed when considering the context. In adaptive learning systems, recommenders provide a student-facing application of learning analytics. Educational recommenders stand to impact the field of education by personalizing educational experiences and can do so in a variety of ways (e.g. course recommenders, learning content recommendations). While researchers have employed a variety of designs and applications of educational recommenders, there is a lack of research showing recommender design driven by pedagogical theory. One underexplored area of research that aligns with the autonomous nature of recommenders is SRL theory. The use of learning analytics can aid the metacognition and the continuous feedback loop at the heart of SRL, making SRL theory ideal as a theoretical base for educational recommender design.

CHAPTER 3

SYSTEM DESIGN (RESEARCH METHODOLOGY)

Introduction

This research seeks to solve a real-world information systems problem through the rigorous design and evaluation of an educational recommender system. It aims to provide relevant and novel IT artifacts of value to researchers and practitioners alike as it brings together research across the domains of IS and education. The design science research methodology is used to guide and structure this research.

About Design Science

The goal of the design science paradigm is to create a novel solution to a known but unsolved problem in IS by providing researchers a way to scientifically design and evaluate a solution to an organizational problem. Design science research permits the opportunity to explore the utility of artifacts informed by behavioral science research (Hevner et al., 2004). This methodology allows a researcher to create an IT artifact that is novel, differentiating it from professional design (Hevner et al., 2010). The design science methodology includes a focus on its contribution to existing research and communication of research contributions. Researchers utilizing this methodology are expected to show rigorous research demonstrating that their work is grounded in previous research including applications of appropriate theories. It also emphasizes a cyclical design cycle, permitting researchers to obtain feedback and refine designs.

Both formative and summative evaluation are key to the design science research methodology. Formative evaluations include “empirically based interpretations” that inform the design decisions of the artifact to aid in improving the artifact’s goals while summative evaluations allow real-world evaluation of the artifact to create “shared meanings” that allow the researcher to explore if the artifact meets expectations or goals (Venable et al., 2016, p. 78). With design science focusing on the utility of the proposed artifact, the evaluation of the artifact is crucial and involves integration of the realization of the artifact within the organization (Hevner et al., 2004).

This research follows the Peffers et al. (2007) methodology for conducting design science research in IS as depicted in Figure 9. This figure depicts six steps as found commonly in previous design science research.

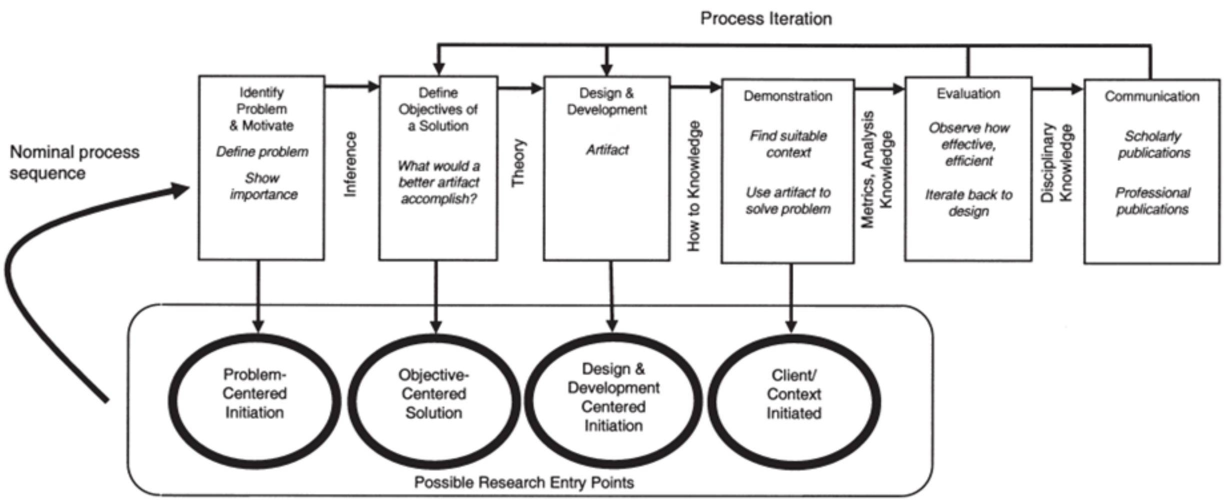

Figure 9. Design Science Research Methodology Process Model (Peffers et al., 2007)

As it pertains to this research, each process element of the six steps is discussed in further detail in this chapter. The table below provides a summary of activities included at each step of the process and references where evidence of these activities can be found.

Table 3. Activities of Design Science Process

Design Science Research Methodology Steps	**Activities**
Identify Problem & Motivate	Statement of problem/motivation discussed (see Chapter 1) Extensive literature review provided (see Chapter 2)
Define Objectives of a Solution	Established research goal (Chapter 1) Requirements stated and connected to prior research (Chapter 3)
Design & Development of IT Artifact	Design detailed as guided by existing research with consideration given for alternative method(s) discussed; justifications for techniques chosen provided (Chapter 3)
Demonstration	Instantiation of artifact within multiple case studies as described along with test environment (Chapter 3)

Evaluation	Evaluation methods of student survey using both qualitative and quantitative analysis; TTF model used in evaluation (Described in Chapter 3/Results in Chapter 4)
Communication	Publish research with IS community and beyond (plans described in Chapter 3)

Artifact

The envisioned artifact is a framework that consists of a reference model and methods for a recommender system designed to help students study. The reference model represents components of the recommender and their relationships. The methods focus on the algorithm(s) utilized to provide recommendations. This is followed by an instantiation of the framework to permit real-world testing and evaluation of the framework. Figure 10 below demonstrates the relationship between artifacts.

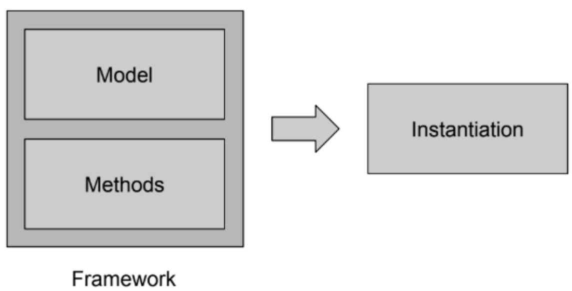

Figure 10. Artifacts

As discussed in the literature review, a basis for this work has been provided. Recommenders enable adaptive learning solutions to better fit the needs of individual learners. However, there is a lack of research that focuses on educational theory and its impact on educational recommender design. SRL theory is underexplored in this research and is an ideal theory to apply. More research is needed to explore transformative student-facing learning analytic approaches, such as recommenders, that empower reflective learning with the goal of improving student success.

Requirements

Existing research will drive the design of the IT artifact. To steer the design more clearly and comprehensively, it is advocated that requirements for design science artifacts be established (Braun et al., 2015). This research has been consulted to determine the following requirements of the proposed solution. The requirements are presented in Table 4 and discussed below.

Table 4. Artifact Requirements

Artifact Requirements
1. Consider traditional college environment (e.g. not MOOC)
2. Informed by pedagogy/learning theory
3. Use learning analytics in a student-facing manner
4. Make recommendations with consideration for course learning outcomes
5. Consider student learning style
6. Use quality learning objects as the recommender candidates
7. Consist of a simple and quick interface to promote usability (ease of use)
8. Protect privacy of students

The system is required to work in a traditional college classroom environment in that the number of students in a course will not be in the hundreds or thousands, like in MOOCs. It is clear from existing research that there is a need for the framework to be grounded in learning theory and with a understanding of pedagogical implementation (Zawacki-Richter et al., 2019). While recommenders have their origins in commercial applications, the shift to the domain of higher education requires consideration of how best to shape recommendations for learning and an understanding of how these tools can aid in the learning process. A recommender approach is chosen as the student-facing application of learning analytics as the goal is to help students learn autonomously instead of focusing on the instructor’s use of data. Data gathered about students and their behaviors is used to present information directly to students. In presenting analytics to students, the recommender will serve to aid students in reflecting on and further recognizing their own learning processes (Durall & Gros, 2014).

In aligning with the pedagogical focus of the second requirement, the recommendations presented should be derived from learning outcomes of the course or area of study. This ensures the relevance of the recommendations. A focus on student learning outcomes is suggested by Mangaroska and Giannakos (2019). As demonstrated in the literature review conducted by Raj and Renumol (2021), existing research on educational recommenders has explored how to present materials when considering student learning style as user parameters. Research has shown that it is effective at aiding learning in these environments (Alshammari et al., 2015). However, a learning style theory-based approach is not the primary driver of this recommender.

Several types of recommenders exist in education, such as course recommenders. Instead of a course recommender, the recommender being developed, referred to as the study system, will focus on delivering learning objects to students in a single course. Examples of learning objects include, but are not limited to, videos, self-assessments, articles, slides, and diagrams. In following basic pedagogical principles, learning objects must be relevant and of good quality to ensure they aid in the learning process. When of good quality, learning objects should serve to motivate and engage students (Kay & Knaack, 2008).

While the task-technology fit (TTF) model is later discussed as part of the summative evaluation of the proposed artifact, its constructs also serve to influence the development of the artifact's requirements. For example, the functionality provided by the recommender should have a positive influence on performance. To aid with this, incorporating learning style and alignment of materials to course outcomes supports the requirements which should ultimately lead to improved performance. To improve utilization of the system, consideration is given to privacy, quality of learning materials, and usability (perceived ease of use) with a focus on supporting the learning outcomes while adapting to the needs of students.

It would be remiss to not also focus on the importance of student privacy when constructing adaptive learning systems. While the use of analytics may serve to benefit students, this data does carry an inherent privacy risk and it is important that student privacy is protected. Tsai et al. 2020 provides three guiding elements to consider with respect to privacy: the purpose of the data, the access to the data, and anonymity. When considering the data's purpose, only data needed by the system and the research should be collected. Students should understand how their data is being collected and used. Students expect to be asked for their consent to use their data and expect to be the primary beneficiary of the data collected (Tsai et al., 2020). Expectations of anonymity should be met when sharing of the research results and multiple controls should be implemented for keeping data safe while the system is in use and at rest.

Design and Development of the Artifact

SRL theory is the guiding theory in this design as it is an area in educational recommender design that lacks research and for its convergence with learning analytics. It is worth noting that the recommender's goal is to assist with and promote SRL and not replace a student's ability to regulate learning, but instead support it.

The model supports SRL by facilitating the three phases as described by Zimmerman (2002): forethought phase, performance phase, and self-reflection phase. When considering the forethought phase, the recommender needs to aid the learner's goals related to the learning outcome and/or the support strategies applied to meet those goals. The performance phase involves self-control activities that allow the learner to keep track of their progress. This can come in the form of features that allow the flagging of a topic or concept that is difficult or misunderstood by the learner to enable help seeking activities. The self-reflection phase can be facilitated by reporting analytics related to the recommender. Presenting a breakdown of items viewed with respect to the learning outcomes can facilitate that reflection. While activities like these were done manually by students before, the recommendation system can better enable many SRL processes automating selection of learning objects, the tracking of data viewed, and reporting this data back to the user. Learners can then use this data to adjust goals and repeat the studying process as needed, keeping with the cyclical nature of the SRL. This differs from the Odilinye and Popowich (2021) SRL informed design that focuses on students highlighting data in order to obtain recommendations. The approach advocated for the proposed study system acts more like a search engine, centered around learning outcomes of the course and presenting data with respect to the learning outcomes, making this approach unique.

When considering the artifact, the model supports recommendations using components in an approach similar to Chrysafiadi et al.'s ICALM system (2019), other educational recommenders (Eryılmaz & Adabashi, 2020; Joy et al., 2021; Sarwar et al., 2019; Wan & Niu, 2018), and is consistent with the adaptive learning models as described in Chapter 2. Three logical levels of adaptation are envisioned: learner, content, and display mode. While the content level will provide the domain ontology and the display mode will take into consideration the learner's learning style in a fashion similar to ICALM, the learner level is based on SRL MSLQ data (P. Pintrich et al., 1993). Architectures for e-learning content recommender have been provided in recent research such as Joy et al.'s (2019) ontology-based model and Aeiad & Meziane's (2019) ontology-based approach. A general high-level model based on their existing research is shown below with MSLQ highlighted as the unique contribution.

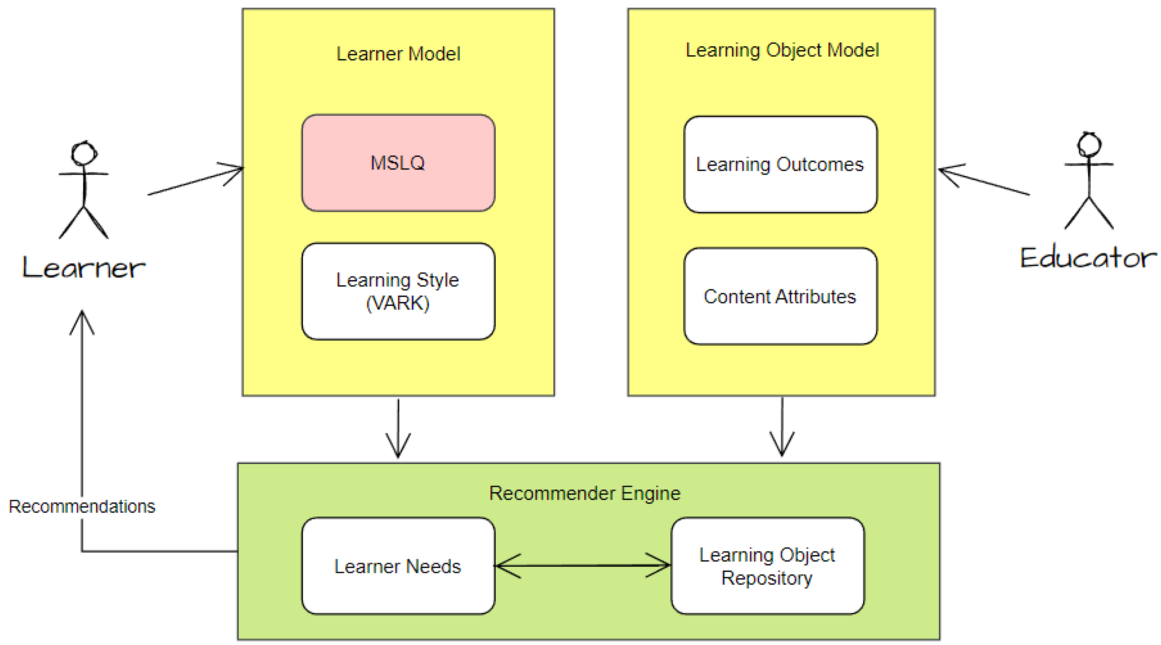

Figure 11. High-level Model of the Study System

Artifact Methods

The artifact methods consist of the recommender type/filtering technique, system inputs, and algorithms. The techniques chosen as part of the methods should align with the requirements of the artifact. In this section, the methods are discussed in detail with supporting evidence for their selection.

Recommender Type/Filtering Technique

Konstan & Riedl (2012) state that a key challenge in implementing recommenders is how to best integrate the different recommendation techniques. A hybrid approach is chosen for the study system based on the requirements for this system. The hybrid approach consists of a knowledge-based ontology approach whose results are enhanced by collaborative filtering.

This application is designed to support learners autonomously in a traditional college classroom environment, not in a MOOC where hundreds if not thousands of learners are present. A traditional college classroom presents both cold start and gray sheep recommender difficulties. The cold start problem is the inability to provide predictions due to the lack of data initially faced when recommenders rely on user ratings 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. Both content-based and collaborative filtering methods when used alone suffer from cold start and gray sheep difficulties. Since content-based filtering is often dependent on a user's rating of a given item in order to find similar items, and does not consider a user-profile, it also suffers from over-specialization of results and lacks serendipity. Collaborative filtering works by looking for similar users, and then makes predictions on items based on what similar users like. Tarus et al. (2018, p. 22) notes that making recommendations based on peers does not consider important characteristics of learners such as "learners' background knowledge, learners' history, competence level, learning style and learning activities." Systems that incorporate this information tend to include a user profile. Both content-based and collaborative approaches do not consider the user's profile as the primary mechanism for filtering recommendations.

The knowledge-based recommender approach relies on domain knowledge and often includes user profiles. The use of the knowledge-based recommendation system was commonly found in existing recommender research in higher education (Agarwal et al., 2022; Chrysafiadi et al., 2019; El-Sabagh, 2021; Joy et al., 2021) due to its ability to address the cold start and gray sheep problems associated with recommenders. A knowledge-based design enables the development of recommendations by first implementing learner profiles by which to guide the recommendations. By using a knowledge-based approach, the cold-start problem/data sparsity can be avoided. The use of a knowledge-based recommender also permits mapping of user profile characteristics to appropriate learning objects instead of relying on existing ratings and/or similar users.

One form of knowledge-based recommender, the ontology-based approach, has many benefits such as improved accuracy and quality of recommendations (Tarus et al., 2018). The ontologies can mimic relationships between learning objects and come in a form that offer reusability (Sarwar et al., 2019). The ontology-based approach is known for improving recommendation quality but development of the ontology is difficult and time consuming (Tarus et al., 2018), and requires expertise in the knowledge domain.

Single recommender approaches are becoming rare in research due to the advantages that a combined recommender approach can provide. Hybrid-based approaches, while having a more complicated design, aid in addressing the problems encountered when only using one approach. Collaborative filtering is a popular approach and often found in educational based recommenders. In a systematic literature review (Urdaneta-Ponte et al., 2021) of recommenders for education that included 98 articles in the results, the collaborative approach was found in 32% of the articles with hybrid approaches being found in 20% of the research. It was noted that the collaborative approaches were known for their ability to improve performance. Purely knowledge-based approaches only accounted for 16% of the articles. It is not uncommon for knowledge-based approaches to be used in combination with other recommendation techniques (Tarus et al., 2018). Joy et al. (2021) used a ontology-based approach combined with collaborative filtering to establish accurate learning groups and provide satisfactory recommendations. The goal of incorporating collaborative filtering would be to expand recommendations to help learners find new learning objects that users with similar profiles also liked. When considering knowledge-based recommenders, the design will follow an ontology-based approach. Ontology-based approaches provide minimal structure to the learning process with the purpose of ensuring the accuracy of recommendations.

If an approach is hybrid, consideration must be given to how results are combined. A hybrid approach can be deployed in many forms including mixed, cascade, feature combination, switching, and weighted (Burke, 2002). Given the complexity of the hybrid approach and the disadvantages to overcome, a knowledge-based approach will primarily drive recommendations for the study system, with collaborative results aiding to promote serendipity and address a possible lack of diversity in the results. A mixed approach, where recommendations from different approaches are presented together, will help further avoid additional complexity of the design while gaining advantages of a hybrid approach. In additional, some of the hybridization techniques, such as cascade where the output of one filtering technique is the input for another, are more critical in situations where a very large knowledge base exists, and further refinement of the results is ideal. It is not anticipated that the knowledge base will require this.

System Inputs

In keeping with knowledge-based system design, both knowledge about items and knowledge about users is needed. The primary inputs of the system are user profiles (information about the user) and learning objects (materials for the user to study). To permit reflective SRL activities, a user/learner log is also populated as students use the system.

The user profiles are created based on learner ontologies. To populate the learner ontologies, learners are required to complete an initial survey before receiving learning object recommendations. The survey includes selected questions from the MSLQ and VARK questionnaire. The survey administered for this research is provided in Appendix A. From this survey, a basic user profile is created. Questions 1-16 were selected as a sample from the MSLQ in order to represent each of the dimensions of the MSLQ, and questions 17 and 18 were selected as a sample from the VARK questionnaire. None of the questions on the survey are required and the survey is designed to be retaken at any time during the use of the system.

The Motivated Strategies for Learning Questionnaire (MSLQ) was published in 1991 by Pintrich et al. as a self-report survey instrument for college students to assess academic motivation orientations and learning strategies used. The survey is designed to help students reflect on their learning. It can also be used by educators to adjust teaching approaches when provided survey results and has been used by hundreds of researchers throughout the world (Duncan & Mckeachie, 2010). The survey consists of various scales with two main sections: motivations and learning strategies. The motivation scales include value components (intrinsic and extrinsic goal orientation, task value), expectancy components (control beliefs, self-efficacy for learning and performance), and test anxiety. The learning strategies scale includes cognitive and metacognitive strategies including rehearsal, elaboration, organization, critical thinking, and metacognitive self-regulation. The last four scales, also found in the learning strategies, assess resource management strategies using scales that consider time and study environment, effort regulation, peer learning, and help seeking. All questions are answered using a seven-point Likert scale. In a comprehensive view of its history and use, researchers have found the MSLQ to be “efficient, practical, and ecologically valid measure of students’ motivation and learning strategies" that can be applied to both practical and empirical research settings (Duncan & Mckeachie, 2010, p. 124). It is a well-established instrument and has been reported to be "the most verified instrument in SRL research" (Roth et al., 2016, p. 244). By employing questions adopted from the MSLQ for this research, results can be used to construct a user profile that takes into consideration student goals, learning strategies, and cognitive strategies.

The VARK questionnaire was established in 1995 to better understand a learner's preference of information presentation mode (Fleming, 1995). The modes of information included in this approach are aural, read/write, visual, and kinesthetic. Aural learners have a preference to learn things by ear. Read/write learners prefer written words. Visual learners have a preference for visually presented information such as charts and flow diagrams. Kinesthetic learners like to use all of their senses when they learn and therefore prefer to learn by doing. It is important to also recognize that learners may have a dominant mode but still prefer a variety of modes (Fleming, 1995). Not all approve of the use of the VARK questionnaire and have debated its validity (Husmann & Mussell, 2019). Yet other researchers note that perhaps "learning style […] be used as a component of, or in conjunction with, other teaching or learning theories" (Li et al., 2016, p. 92) as it may provide scaffolding and increase awareness of learner differences.

Several studies of educational recommenders in higher education have also employed the VARK questionnaire in their approach (Aeiad & Meziane, 2019; Chrysafiadi et al., 2019; El-Sabagh, 2021). It is worth noting that there are other learning style surveys, several of which have been used often in educational recommender research such as the Index of Learning Styles Questionnaire for the Feldman-Silverman Learning Style Model (FSLSM) (Soloman & Felder, 1999). Thongchotchat et al. (2021) in their systematic literature review of learning style utilization in recommenders note that the use of the FSLSM appears to be due to its popularity alone and that further studies are needed to compare the performance of the models where it has been applied. Since the focus of this research is to present material in a preferred mode, the VARK questionnaire appears to be the best fit while also offering an approach in a style different from FSLSM research. Also, by recognizing and supporting multiple modes, we can avoid placing students in a single category which is a criticism of employing learning styles. This learning style, or more accurately, "presentation mode" will be used in addition to several other SRL-based factors when determining recommendations.

The user profile is modeled using the ontology provided in Figure 12 and is described in further detail in Table 5. This ontology is unique from other research in that in addition to considering learning style or presentation mode, data is gathered related to SRL via the MSLQ for the purpose of influencing the recommendations.

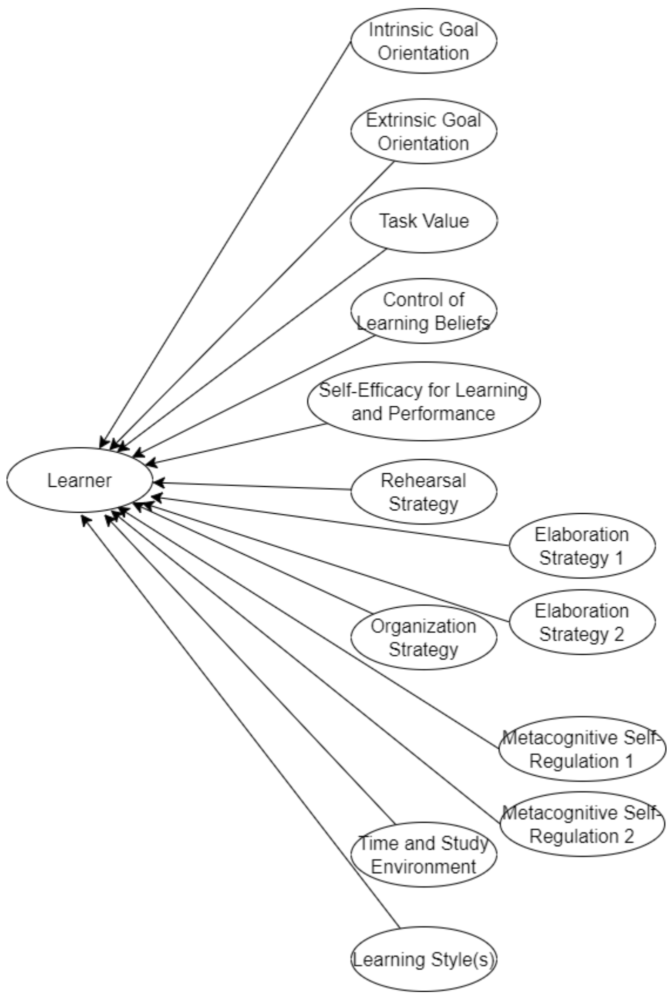

Figure 12. Learner Ontology

Table 5. User Profile Attributes

Attribute	**Description**
Intrinsic Goal Orientation	A numeric value that ranges from 0 to 1, with 1 indicating that the student has a strong desire to understand course content thoroughly.

Extrinsic Goal Orientation	A numeric value that ranges from 0 to 1, with 1 indicating that the student is very motivated to obtain a good grade in the course.
Task Value	A numeric value that ranges from 0 to 1, with 1 indicating that the student feels that it is very important to learn the course material.
Control of Learning Beliefs	A numeric value that ranges from 0 to 1, with 1 indicating that the student is very confident that they can understand the course material if they apply themselves.
Self-Efficacy for Learning and Performance	A numeric value that ranges from 0 to 1, with 1 indicating that the student can understand the most basic and complex topics in a course.
Rehearsal Strategy	A numeric value that ranges from 0 to 1, with 1 indicating that the student strongly prefers to revisit important course materials.
Elaboration Strategy (1)	A numeric value that ranges from 0 to 1, with 1 indicating that the student strongly prefers a mix of resources when studying.
Elaboration Strategy (2)	A numeric value that ranges from 0 to 1, with 1 indicating that the student strongly prefers to establish relationships between materials.
Organization Strategy	A numeric value that ranges from 0 to 1, with 1 indicating that the student strongly prefers well-organized and structured materials.
Metacognitive Self-Regulation (1)	A numeric value that ranges from 0 to 1, with 1 indicating that the student strongly prefers prompting questions to help engage and motivate them.
Metacognitive Self-Regulation (2)	A numeric value that ranges from 0 to 1, with 1 indicating that the student strongly prefers revisiting material not well understood.
Time and Study Environment	A numeric value that ranges from 0 to 1, with 1 indicating that the student dedicates significant time to studying efforts.
Learning Style(s)	A label that stores “visual,” “auditory,” “read/write,” or “kinesthetic” to depict the presentation mode. Permits selection of up to two styles given Fleming (1995) makes the argument for multimodality.

Learning objects are based on a learner ontology and represent various materials such as videos, lecture notes, diagrams, assessments, and exercises that the study system will suggest as candidates for recommendations. The learning object structure utilized here is similar to that in existing research in knowledge-based adaptive learning recommenders. When considering attributes of learning objects, Sarwar et al. (2019) also considered difficulty level, topics, and subtopics in their ontology. Joy et al. (2019) ontology also has many similarities to the ontology used for this research as their ontology also considers the type and difficulty, and also includes a learner log that keeps track of user visits to individual learning objects. This ontology builds off of the IEEE Learning Object Metadata (LOM) standard which standardizes how learning objects are represented in extensible markup language (XML) in order to support interoperability and exchange of data (IEEE Computer Society, 2020).

The learning objects are the main entities of the knowledge base. Construction of the knowledge base requires expertise in the knowledge base subject area. The learning object entries are populated by the knowledge base expert prior to system use by students. The basic ontology for the learning objects is provided below in Figure 13. Each attribute is described in more detail in Table 6. All attributes are required; they cannot be left blank or empty. The main concepts are derived from the learning outcomes of the course and are broken into subtopics. For example, when considering the learning outcome "develop and contrast simple and intermediate sorting and learning searching techniques" the main concepts of "arrays," "multidimensional arrays," and "arraylists" were already present within the ontology based on a previous outcome. The subtopic this new outcome was related to is the "processing" of those structures. To address that learning outcome, various searching and sorting method learning objects were also connected to this subtopic of "processing" and corresponding main concepts ("arrays," "multidimensional arrays," and "arraylists").

While the basic ontology below builds on existing research and the IEEE LOM standard, consideration for SRL has led to the inclusion of several attributes including *level of detail*, *importance*, *relevance*, *time commitment*, and *question*. These attributes have been selected based on dimensions of the MSLQ. *Level of detail* is concerned with the value of the task. Task value refers to the student's evaluation of the importance or usefulness of a given task; it is their perception of the topic to be learned (P. Pintrich et al., 1991). *Importance* aligns with the MSLQ dimensions of self-efficacy and the learner's control of learning beliefs. Self-efficacy is important because it reflects the student's belief as to whether they can learn the material where control of learning beliefs depicts whether they feel their efforts will make a difference in their learning (P. Pintrich et al., 1991). The attributes *level of detail* and *importance* both speak to motivational factors. *Relevance* relates to the elaboration dimension. Elaboration is a cognitive and metacognitive strategy that focuses on created connections between new and previously learned materials (P. Pintrich et al., 1991). *Time commitment* relates to metacognitive self-regulation in that it requires students to have an understanding of the time available to them for studying. *Relevance* and *time commitment* are included to help understand existing learner strategies when considering learning objects to recommend. The *question* attribute reflects a question that is in the form of a prompt to engage the learner and enable them to focus on the learning object.

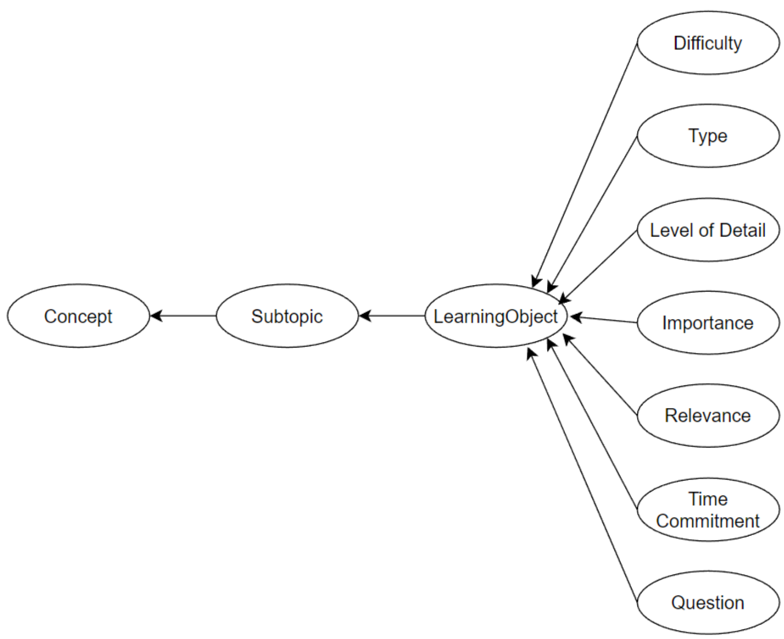

Figure 13. Ontology for Learning Objects

Table 6. Learning Object Attributes

Attribute	**Description**
Concept	A label containing the learning outcome. Each learning object must be associated with a learning outcome via a subtopic.
Subtopic	A label containing the subtopic of the learning outcome as learning outcomes can consist of many topics. Each learning object must be associated with a subtopic.
Difficulty	A numeric value that measures the degree of difficulty. It ranges from 0 to 1, with 1 being the most difficult.

Type	A label reflecting the kind of learning object. Learning objects can be one of the following: table, slide, figure, narrative, exercise, self-assessment, video, or diagram.
Level of detail	A numeric value ranging from 0 to 1, with 1 being a lot of detail provided by the learning object.
Importance	A numeric value ranging from 0 to 1, with 1 indicating a very important learning object when considering the learning outcome.
Relevance	A numeric value ranging from 0 to 1, with 1 representing high relevance to previous materials. This represents the degree to which this learning object builds on previously learned material.
Time Commitment	A numeric value representing the number of minutes estimated to consume (e.g. read, watch, complete problem, do exercise) the learning material.
Question	A prompting question that motivates the student to review the material.

This knowledge base also maintains a learner log ontology to facilitate aspects of SRL. The learner log keeps track of each learning object visited by the learner (e.g. learner actions). This aids the performance and self-reflection phases in SRL. It also indicates if the item was flagged or liked, as depicted in Figure 14. The *liked* attribute is also referenced during the collaborative filtering process. The attributes are described in Table 7.

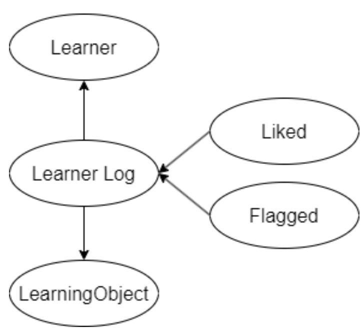

Figure 14. Learner Log Ontology

Table 7. Learner Log Attributes

Attribute	**Description**
Liked	A numeric value that holds a 1 or 0, where 1 indicates that the object was liked by the user.

Flagged	A numeric value that holds a 1 or 0, where 1 indicates that the object was flagged as “difficult to understand” by the user.

Algorithms

The selection of a method of filtering then leads to determining the algorithm that best suits the goals of the system within the filtering context. The algorithm developed incorporates a knowledge-based approach combined with collaborative filtering and utilizes ontologies previously described. Note that collaborative filtering only uses the SRL-based dimensions and ignores the VARK dimensions. The distinct steps of the algorithm are provided below. This process is also depicted in Figure 15.

Algorithm: Determine recommendations

Input:

L = learner ontology

LO = learning object ontology

T = topic selected by learner

Output:

Top N learning object recommendations

Method:

1. Filter LO by T to create object vector based on learning objects.
2. Apply scores to object vector based on VARK presentation mode.
3. Determine learner vector based on L.
   Note: Not all learner profile attributes are used in this vector. Some are instead used to apply the rules indicated in step 4.
4. Apply MSLQ dimensions as rules.
   a. If the learner values rehearsal method of reviewing course readings, learning objects associated with read/write style are included.
   b. If the learner values rehearsal method of memorization, self-assessments learning objects are included.
   c. If the leaner values organization methods that include tables, charts, and diagrams that emphasize important points, table and diagram learning objects are included.

d. If the learner values a mix of resources, the presentation mode of the learning object is ignored in the filtering.

e. If the learner identifies difficulties in finding time to study, learner objects that require greater than 5 minutes to consume are excluded.

f. If the learner likes questions that help them focus and motivate learning, the question display mode is added for the learning object.

5. Determine individual learning object scores by taking the dot product of the learner vector and each learning object in the object vector.
6. Select first N recommendations with the highest score.
7. Find recommendations liked by similar users by using k-means with the learner vector sans learning style/VARK presentation mode.
8. Add additional recommendations to the original N recommendations and remove duplicates.

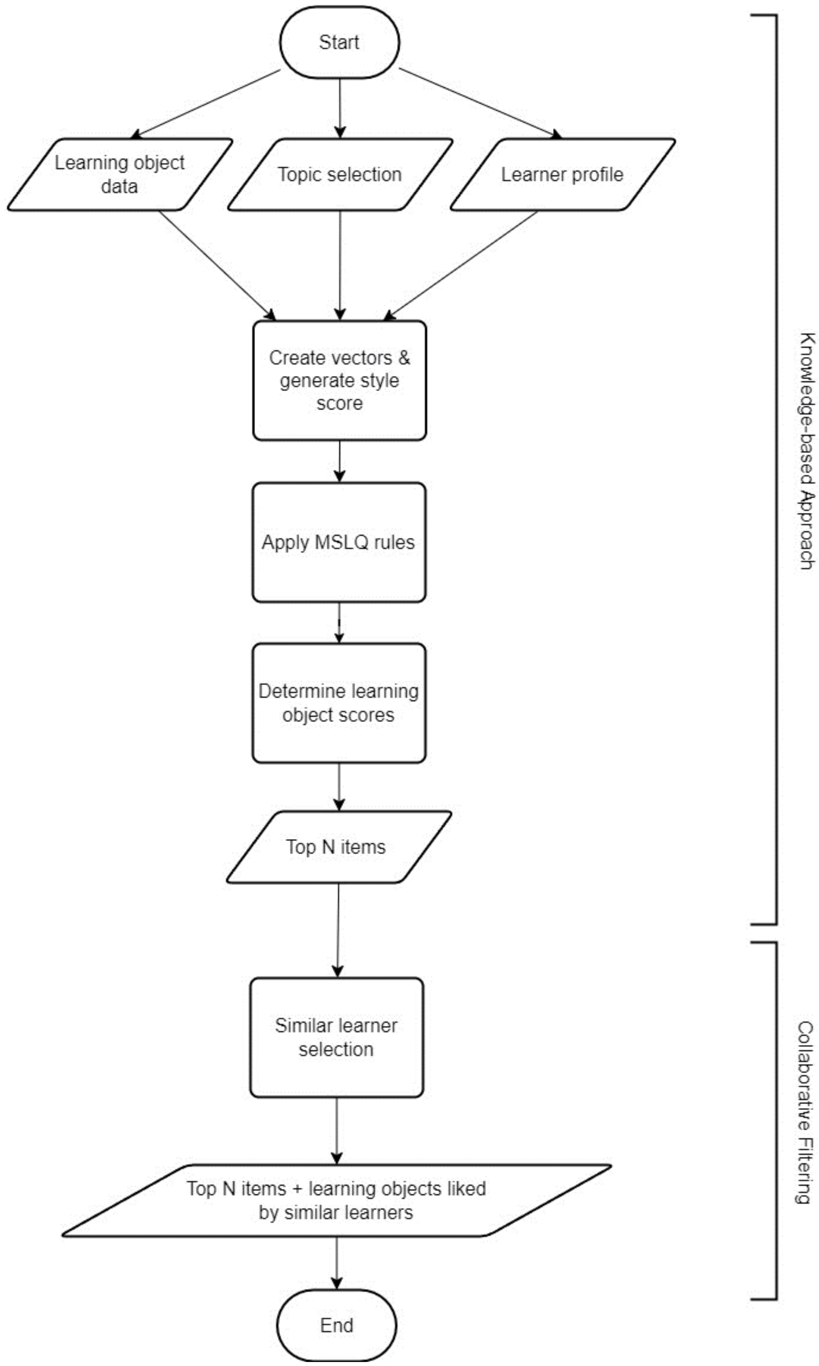

Figure 15. Process of Learning Object Selection for Study System

The first step of the algorithm involves creating the learning object vector by loading the learning object ontology. This represents all the objects in the knowledge base but is filtered by the topic and/or subtopic selected by the user. The vector-based learning object consists of eight features: *type, importance, level of detail, difficulty*, *relative* (relation to prior material*), time commitment, style, and style score*. While the first six features are populated from the learning object ontology, the *style* is populated based on the type of learning object. The type of the learning object is used to determine the presentation mode as guided by Fleming (1995) and is depicted in Table 8.

Table 8. Mapping of Learning Object to VARK Presentation Style/Mode

Learning Object Type	**VARK Presentation Style/Mode Assignment**
Table	Visual, Read/Write
Slide	Read/Write
Figure	Visual
Narrative	Read/Write
Exercise	Kinesthetic
Self-assessment	Kinesthetic
Video	Aural, Kinesthetic
Diagram	Visual

In step 2, the *style score* is generated. This is a numeric value ranging from 0 to 1, where 1 most closely matches the presentation style reflected by the learner's response to the VARK-based questions. This is followed by the creation of the learner vector which is loaded from the learner ontology. The vector-based profile consists of five features: *importance, level of detail, difficulty, relative* (relation to prior material)*, and time commitment*. In step 4, the rules for the knowledge-based recommender are applied with consideration for the MSLQ dimensions in the learner ontology. Specific rules were used to better reflect learning objects that align with the learner's cognitive and metacognitive strategies. In particular, rehearsal, organization, and elaboration methods were found to be more easily implemented as rules. Each rule is depicted in the algorithm.

In step 5, to determine which learning objects are to be recommended, the dot product is taken of the learner vector and each learning object in the object vector in order to calculate a sum that is stored in a resulting learning object vector feature called *score*. In this approach, learner vector features are used as weights against learning object vector corresponding features. A weighted approach is found in several knowledge-based recommenders. For example, Bouihi and Bahaj (2019) built an ontology-based recommender for the recommendation of learning objects. In their approach, weights of learning objects are updated based on what the system knows about the learner. Chrysafiadi et al. (2019) uses a weighted sum model in conjunction with an artificial neural network to determine rank recommendations. After the *score* is calculated, the top N recommendations with the highest score can be presented as recommendations (step 6).

Before the recommendations are presented, collaborative-based filtering must also take place. This is step 7. Several approaches to collaborative filtering can be applied in this scenario. Some of the most commonly employed computations in educational recommender research include KNN and k-means (Joy & Pillai, 2021; Raj & Renumol, 2021). A comparison of the approaches can be found in

Table 9. KNN is a supervised learning algorithm than can be used to classify a dataset using distance-based weighting to determine similarities (Ko et al., 2022). K-means is known as a simple unsupervised clustering algorithm that works by iteratively finding cluster centers by assigning a point to the closest cluster center and then determining the mean of the data points assigned to the cluster in order to determine its center (Muller & Guido, 2016). K-means is ideal for this collaborative approach as it does not rely on user ratings but instead relies on the profile available due to the initial knowledge-based approach. This alleviates any cold start issues associated with a collaborative approach based on ratings. It is anticipated that the smaller class sizes in traditional college environments may lead to sparsity of “likes” that will make it impractical to use the KNN approach. The user profile MSLQ features were used to generate the clusters. The k-means method typically relies on Euclidean distance as its similarity calculation. To speed up convergence, the k-means++ method of initialization is used. The k-means algorithm used is Lloyd’s algorithm (Lloyd, 1982), which reflects the two-step iterative procedure described earlier, due to its more efficient nature.

Table 9. Comparison of K-Means and KNN Algorithms

	K-means	**KNN**
Type	Unsupervised, partitioning cluster formation	Supervised, lazy learning algorithm
Advantages	Popular and works well with smaller data sets (Aljarah et al., 2021)	Popular and can be used for classification and regression

Disadvantages	Sensitive to outliers (Aljarah et al., 2021) Performance speeds worsens when K is small and numbers of users and items increases (Ko et al., 2022)	Performance in dependent on determining appropriate value for K and degraded by large input size (Ko et al., 2022)
Algorithms (as depicted by Joy & Pillai, 2021)	"1. Specify the number of clusters K. 2. Initialize centroids. 3. Repeat 3.1 Compute the sum of the squared distance between data points and all centroids. 3.2 Assign each data point to the closest cluster (centroid). 3.3 Compute the new centroids for the clusters by taking the average of the all data points that belong to each cluster. 4. End"	"1. Choose the value of K, i.e. the nearest data points. K can be any integer. 2. For each point in the test data do the following 2.1 Calculate the distance between test data and each row of training data with the help of a distance measure (Example: Euclidean distance). 2.2 Based on the distance value, sort them in ascending order. 2.3 Select the top K rows from the sorted array. 2.4 Now, assign a class to the test point based on most frequent class of these rows. 3. End"

One important aspect to consider when using k-means is the optimal number of clusters. Methods often employed to determine this number include the Elbow method and cross validation. However, these methods require visual inspection of a chart that compares the number of clusters to their resulting calculation (e.g. sum square error calculation for Elbow method), allowing the viewer to pinpoint the optimal cluster number (Nainggolan et al., 2019). Given that the system is live and adding new users in real-time, other methods such as the elbow method are not practical given they typically involve manual visual inspection in order to determine the optimal number and will result in significant overhead. The optimal number of clusters is determined here by using an empirical method, depicted below, where k is equivalent the square root of n (the number of data points) divided by two (Han et al., 2011). For this system, the data points are users and will allow the number of clusters to change in real-time as new users are added without adding significant overhead in determining the value of k.

$$k \approx \sqrt{n/2}$$

In the last step (8), results from the collaborative filtering (step 7) will be appended to the list of items generated from knowledge-based filtering after duplicates are removed.

Instantiation

The IT artifact demonstrated initially as a framework and later as an instantiation permits real-world summative evaluation of the system. The design was primarily constructed using a MySQL database, for the ontology data, and Flask, for the web-based application. Flask is a framework for building web applications with Python. Various Python libraries were employed to support the application (e.g. scikit-learn, NumPy, pandas, SQLAlchemy). The application was deployed on an Amazon Web Services (AWS) Elastic Compute Cloud (EC2) with the database hosted on a Relational Database Service (RDS). A relational database is considered an acceptable storage model for ontologies (Abburu & Golla, 2016). While other formats were considered for the ontology such as OWL, the ability for the MySQL database to create and depict the relationships is also present. Also, integration between the application and MySQL is easily facilitated using SQLAlchemy. SQLAlchemy has an object relational mapper to enable Python classes to be mapped to the database for decoupled querying. Also, the ontology was not extensive and therefore could be easily emulated in a relational database as the researcher has a background in database design and development. Bulma, an open-source Cascading Style Sheet (CSS) framework, was used for the front-end in order to provide a clean, professional-looking interface that is user-friendly and responsive for mobile users.

To use the system, students first create an account and then complete the profile survey. Upon completing the survey they are taken to a dashboard page as shown in Figure 16 below. This is where they can monitor their progress and choose topics to study. The dashboard and examples of learning objects recommended are provided in Figure 17. The dashboard displays the various study topics. When they click on a study topic, they are then taken to their recommended learning objects (shown in Figure 17) for the given topic.

To better promote transparency in recommender design as advocated by van Capelleveen et al. (2019), the learning presentation style/mode of the student is displayed on the dashboard. The dashboard will enable the students to see a breakdown of topics they have viewed, and the number of items viewed per topic. For each learning outcome, typically about 50 learning objects are available in the knowledge base. When viewing learning objects, students have the ability to “like” items or “flag” items as not understood. These lists are then viewable from the dashboard as well and can be revisited by the student.

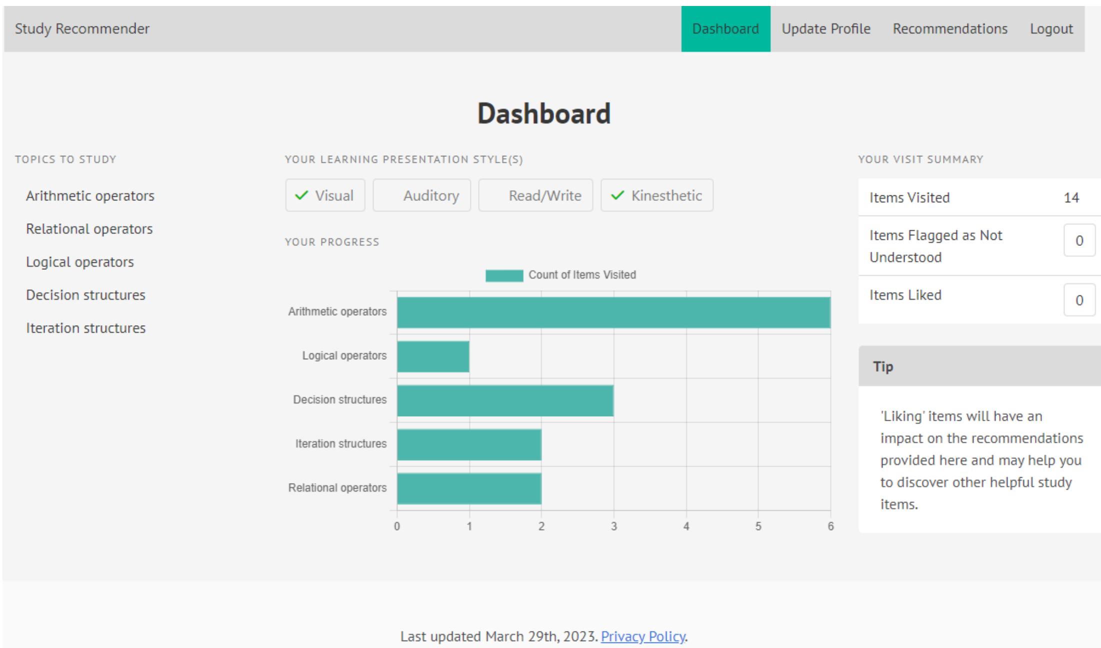

Figure 16. Instantiation of Study Recommender: Dashboard

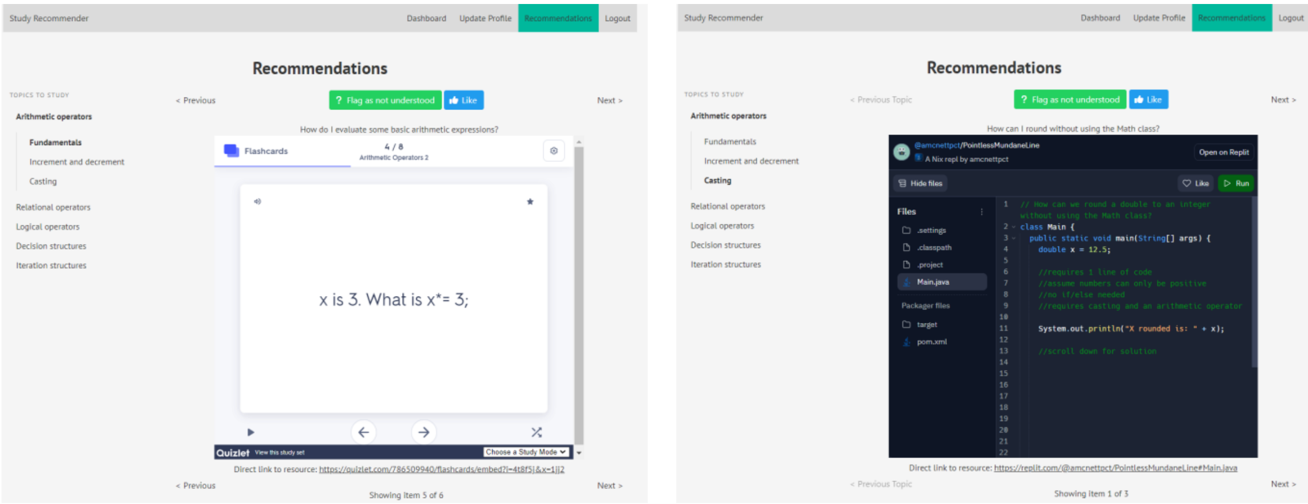

Figure 17. Instantiation of Study System Recommender: Recommendations

Evaluation

Summative validity will be explored via empirical testing of the theory in survey form, that is, artifact evaluation with consideration for the TTF model. Previous literature reviews of educational recommenders state the need to go beyond accuracy in the evaluation of prototypes and look beyond learner grades to goal achievement and engagement (Deschênes, 2020).

The evaluation of the research is to be conducted after demonstration of the instantiation. A case study-based approach has been selected for the evaluation process. This involves student participation in testing of the instantiation in a higher education classroom environment in the field of IT. A case study approach is the most practical and realistic approach due to the fact that the researcher does not have access to a larger sample and that multiple studies will permit more data to be collected. Two instances of the case study were designed to be conducted in programming courses within the Information Technology department. The case studies differ in that the recommender will be integrated at different times in the courses, each time with a focus on different learning outcomes and utilizing a different knowledge base.

Participants

The demonstration was designed to be carried out in a single college environment in higher education. The study population consisted of college-aged students most likely ranging in age from 18 to 22 years old. IRB approval was provided and all participants, students in specific programming-based IT courses, were volunteers. A maximum of 70 participants were sought.

Prior to agreeing to participate in the study, students within selected programming-based IT courses received an email explaining the study and asking for their cooperation. The email explains the purpose of the research, includes a consent document, and outlines participant commitment if the student decides to participate. All participants were informed that they would be entered into a drawing for a $100 bookstore gift card as compensation for participating. All participants were to be volunteers, so volunteer bias may be present in the results. The consent letter addressed confidentiality and all survey data was to be submitted anonymously in order to help address this possible bias. Consenting students received an email with instructions on how to start using the system. Students had access to the system for roughly a two-week period in order to use the system as they studied for an upcoming exam.

Data Collection

After their exam, students were distributed a survey electronically in order to assess the fit of the technology using the TTF model. No names or identifying information were collected on the survey. The survey administered is provided in Appendix B and is also summarized below in the

Table 10 below. The questionnaire was designed and adopted according to previous studies concerning TTF. It consists of several 7-point Likert scale questions designed to facilitate assessment via the TTF model. A few questions at the end of the survey served to provide qualitative data. The form was created using Microsoft Forms and students were contacted via email.

When considering privacy of students, the data collected to analyze for this research was only anonymous survey data. The data collected via the system is not being analyzed as part of this research. This information was shared with students in the consent statement so that they would understand how their data was to be used.

Table 10. Participant Survey Questions

Quantitative Survey Questions			
TTF Construct		**Questions**	**Adapted and Modified from**
TASK	TAS1 TAS2 TAS3	I use the study system to review class material. I use the study system to check facts. I use the system to address gaps in my knowledge.	(D'Ambra et al., 2013; Goodhue & Thompson, 1995)
TECH	TECH1 TECH2 TECH3	The system helps me set study goals. The system helps me monitor my studying. The system helps me reflect on my study process.	(Goodhue & Thompson, 1995; B. Zimmerman, 2002)
IND	IND1 IND2	I feel very confident using web-based systems for education I am comfortable learning using web-based materials.	(Goodhue & Thompson, 1995; Navarro et al., 2021)
TTF	TTF1 TTF2 TTF3	I think that using the system would be well suited for the way I like to study. A system would be a good tool to provide the way I like to study. The system fit well for the way I like to study.	(Navarro et al., 2021; Ouyang et al., 2017)
PIM	PIM1 PIM2 PIM3	The system helps me improve my studying. The system helps me learn the material. The system helps me perform better in a course.	(D'Ambra et al., 2013; Goodhue & Thompson, 1995)
UTIL	UTL1 UTL2 UTL3	I use the system to study. I use the system to review materials. I use the system to adjust my learning goals and/or strategies.	(D'Ambra et al., 2013; Goodhue & Thompson, 1995; B. Zimmerman, 2002)
Qualitative Survey Questions			
TTF	-	What aspects of the system do you feel best supported your studying?	

PIM	-	Do you feel the system helped to improve your academic performance? Why or why not do you feel the system helped to improve your academic performance?	
UTIL	-	Would you consider using a system like this in the future to study? Why or why not would you consider using a system like this in the future to study?	

Data Analysis

Design science research focuses on the utility of artifacts. In a systematic literature review of adaptive content recommenders in e-learning (Raj & Renumol, 2021), common evaluation methods include statistics (MAE, precision, recall, RMSE), learner score, learner satisfaction, use of learning objects, run time, and learn time, with statistical methods and learner scores/grades being the most often used evaluation methods. It has been recommended that studies that evaluate recommenders in education look beyond grades when investigating the effects these systems have on learning (Deschênes, 2020). As reported by Galaige et al. (2022), it is important to consider students' perspectives in the design of these systems. Satisfaction surveys are often used to demonstrate utility and efficacy in information systems. Summative evaluation of the artifact was conducted via a survey intended to collect both quantitative and qualitative data; they'll serve to provide a more wholistic assessment of this approach. This survey was administered to participants after system use. The use was designed to coincide with studying for an upcoming exam and was sent to students after completing the exam.

The TTF model, as depicted in Figure 18, provided the lens through which the system was evaluated. It focuses on six of the classic constructs of TTF including task characteristics, technology characteristics, individual characteristics, task technology fit, utilization, and (academic) performance impact. This model facilitated the assessment of the requirements of the proposed artifact to measure if it was effective in meeting the learner's goals. The following hypothesis were to be tested:

H1: Task characteristics are positively related to perceived fit.

H2: Technology characteristics are positively related to perceived fit.

H3: Individual characteristics are positively related to perceived fit.

H4: Perceived fit is positively related to the utilization.

H5: Technology fit is positively related to (academic) performance impact.

H6: Utilization is positively related to (academic) performance impact.

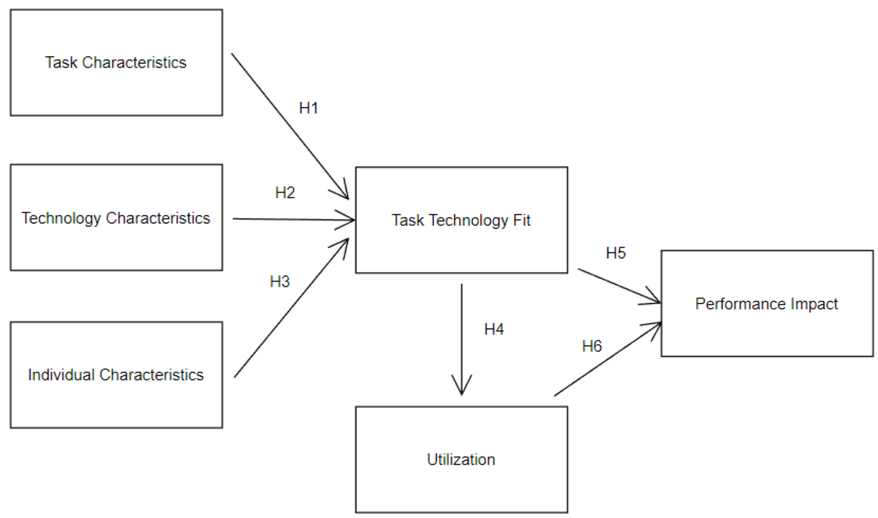

Figure 18. Model and Hypothesis

This part of the analysis required the use of structural equation modeling (SEM), a multivariate technique. Hair et al. (2022, p. 4) describes SEM as a method that enables "researchers to simultaneously model and estimate complex relationships among dependent and independent variables." One type of SEM, partial least squares structural equation modeling (PLS-SEM), is not used confirm or reject theories, but looks to allow researchers to analyze relationships between observed and latent variables. PLS-SEM is noted as a method that is increasingly gaining attention in the development of software for it enables the ability to analyze constructs contributed to human factors (Russo & Stol, 2021).

A two-step analytical procedure was planned. First, evaluation of the measurement model was to take place. This was then to be followed by assessing the structural model (Hair et al., 2019). This is important because we need to ensure we have good measures before attempting to analyze the structural model. When considering a sample size, the 10-times rule was consulted. This rule recommends that the minimum "sample size should be equal to the larger of (1) 10 times the largest number of formative indicators used to measure one construct or (2) 10 times the largest number of structural paths directed at a particular latent construct in the structural model" (J. F. Hair et al., 2016, p. 24). In following this rule, a minimum sample size of 30 participants is needed. As depicted in the diagram above, the latent construct “Task technology Fit” has three structural paths which is the largest number of structural paths. Also each construct has a max of three formative indicators (as shown in the survey design presented in

Table 10), leading to a minimum sample size of 30. Power tables have also been consulted. With at least 30 observations, it is reasonable to achieve a statistical power of 80% for detecting R^2 (coefficient of determination) values of at least 0.75 (with a 5% probability of error) (J. F. Hair et al., 2016).

While the TTF model was to be used to assess the system as described previously and relies on the quantitative data provided in survey responses, qualitative data can also provide rich insights in terms of the constructs of the TTF model. Open coding techniques were to be applied to open-ended survey questions to discover factors influencing each of the constructs and to inform the evaluation of the system. As stated by Corbin and Strauss (1990), open coding enables analytical interpretation of the data in the development of categories by which to group data. This can then be followed by axial coding in an effort to demonstrate relationships between the categories. This then is followed by selective coding in order to unify the categories around a core category. Following standard grounded theory, coding of the open-ended question responses will assist in identifying themes to address findings concerning the research questions and will be used to assess the artifact’s initial requirements and aid in the building of the design principles. This mixed method approach is chosen for the evaluation in order to “provide even deeper insights into the quality of the evaluation object” (Cleven et al., 2009, p. 3).

Communication

Several different outlets were sought for communication of this research. Initially, an emergent research forum paper (McNett & Noteboom, 2023) was submitted and accepted to the Americas Conference of Information Systems (AMCIS) 2023 conference. This research aligns well with the conference’s “IS in Education, IS Curriculum, and Teaching Cases” track as the track has a focus on innovative e-learning systems and learning analytics. When the research reached its final stages, full-paper dissemination focusing on qualitative results included a submission and acceptance to the Hawaii International Conference on System Sciences (HICSS) 2024. This paper fit well into their analytics decision analytics and service science track. This annual conference is attended by researchers worldwide and ranks highly among IS conferences.

Possible venues for dissemination in the education realm are also being considered, such as the Penn State 2024 Symposium for Teaching and Learning with Technology. This event is designed for both researchers and practitioners as it focuses on how technology can be used to enhance learning.

Chapter Summary

This research utilizes the design science research methodology to develop a novel IT artifact. This artifact is an educational recommender framework, consisting of models and methods, with a design guided by self-regulated learning theory and existing research. The general design of the recommender is presented below using Capelleveen et al.'s (2019) proposed canvas for designing and documenting recommender design. This canvas document provides a structured way of concisely communicating the design of this system.

This artifact is evaluated formatively by existing research and in a summative manner by deploying the instantiation in multiple case studies in a higher education environment. Analysis includes both quantitative and qualitative methods that infuse IS research with emphasis on the TTF model. Plans for communication of this research have also been considered within IS and beyond.

Table 11. Summary Canvas for SRL-informed Recommender

Recommender Design Areas	**Design Concepts**	**Study Recommender System**
Goals *What do we try to achieve with the recommender?*	Recommender Goals	Provide students with customized learning objects to help them reach educational goals; Adapt to unique needs of learners
	Recommender Use-Cases	Not included

Domain Characteristics *What characteristics may influence design?*	Role of System Users	Users are individual students in higher education programming course
	Type of Available Data	Explicit Data: Student SRL data and presentation mode (VARK) data Implicit Data: Student actions online (clicks, likes) Knowledge base: Programming language domain of learning objects & user profile
	Preference	Gained via explicit and implicit data
Functional Design Considerations *What functionality the user expects in the design?*	Degree of Personalization	Focus on recommendations for individuals Explicit profile helps to shape recommendations
	Degree of User Control	Ability to retake profile survey Ability to choose study area
	Interactivity	Ability to like or flag learning object recommendations Ability to select topic and subtopic
	Context-awareness	Activity-aware focus
	Restrictions	Multiple controls used to protect privacy
Technique Selection *What techniques best apply to this case?*	Filtering Algorithm	Hybrid (knowledge-based and collaborative)
	Hybrid Model	Mixed
	Dimensionality Reduction & Scalability	Dimensionality reduction not needed due to reliance on knowledge-base approach for filtering Traditional classroom size helps to reduce scalability needs
	Preference Solicitation Technique	Profile survey
Evaluation & Optimization	Evaluation	Student Feedback Survey
	Optimization	Not addressed. Topic for future research

How to test the recommendations are and remain relevant to users?	Protection	Recommendations that are the result of collaborative filtering are presented last to reduce impact of possible fictitious profiles.
Interface Design *How to present the recommendation?*	Presentation Modality	Visually via a list
	Item Organization	List organized by learning outcome and ontology
	Item Notification	Recommendations present at initial system access; after assessments
	Item Information	Topics provided; possibility of providing additional information would be good to explore in future research.
	Item Explanation	Justification for recommendation is not included beyond presentation mode. Topic for future research.

CHAPTER 4

RESULTS AND DISCUSSION

Results

Participant Information

Four instances of this case study were conducted to reach the minimal sample size of 30 participants needed for analysis. In total, 112 possible participants at one higher education institution in various IT programming courses were approached to participate in the study. To complete the study, students had to use the system to study for an upcoming exam and then complete a survey. Surveys were collected electronically using Microsoft Forms.

In total, 32 students completed the study, resulting in a 29% participation rate. Participation results are presented in Table 12 below. The initial pilot, which involved one section of an intermediate programming course in fall of 2022, only resulted in one volunteer participating in the study. This student was not asked to complete the survey since their feedback would not be anonymous. The second iteration involved three sections of the same intermediate programming course during the spring of 2023. Of this cohort, ten students fully completed the study by using the system and completing the final survey. As the minimum sample size was not yet met, this was followed by a third iteration the same semester involving one section of an introductory programming course. This yielded five students who fully completed the study. The fourth and final iteration involved two sections of an intermediate programming course. The instructor of the fourth iteration offered extra credit to students who participated in the study. An alternative extra credit exercise of equal effort and worth was also provided so as not to coerce students to participate. This yielded 17 students who completed the study.

Table 12. Participant Population

Participant Group	**Recruitment Population Student Count**	**Number of Students Completing Study**
Fall 2022 Intermediate Programming class (pilot)	16	0 (only 1 student participated and was not asked to complete survey)
Spring 2023 Intermediate Programming class	44	10
Spring 2023 Introductory Programming class	22	5
Spring 2023 Intermediate Programming class	30	17
Total	**112**	**32**

Each participant group required the creation of a new knowledge base as each iteration targeted different learning outcomes. The initial iteration for the pilot included over 50 learning objects, while later iterations included at least 80, and in one case, over 100.

Quantitative Analysis Results

The initial results of the survey are provided below (n=31). While 32 responses were obtained, one response was removed due to lack of variation in scale responses that were also not consistent with responses to open-ended question. Results of the survey Likert scale questions are depicted in Figure 19 below. Actual results are provided in Appendix C.

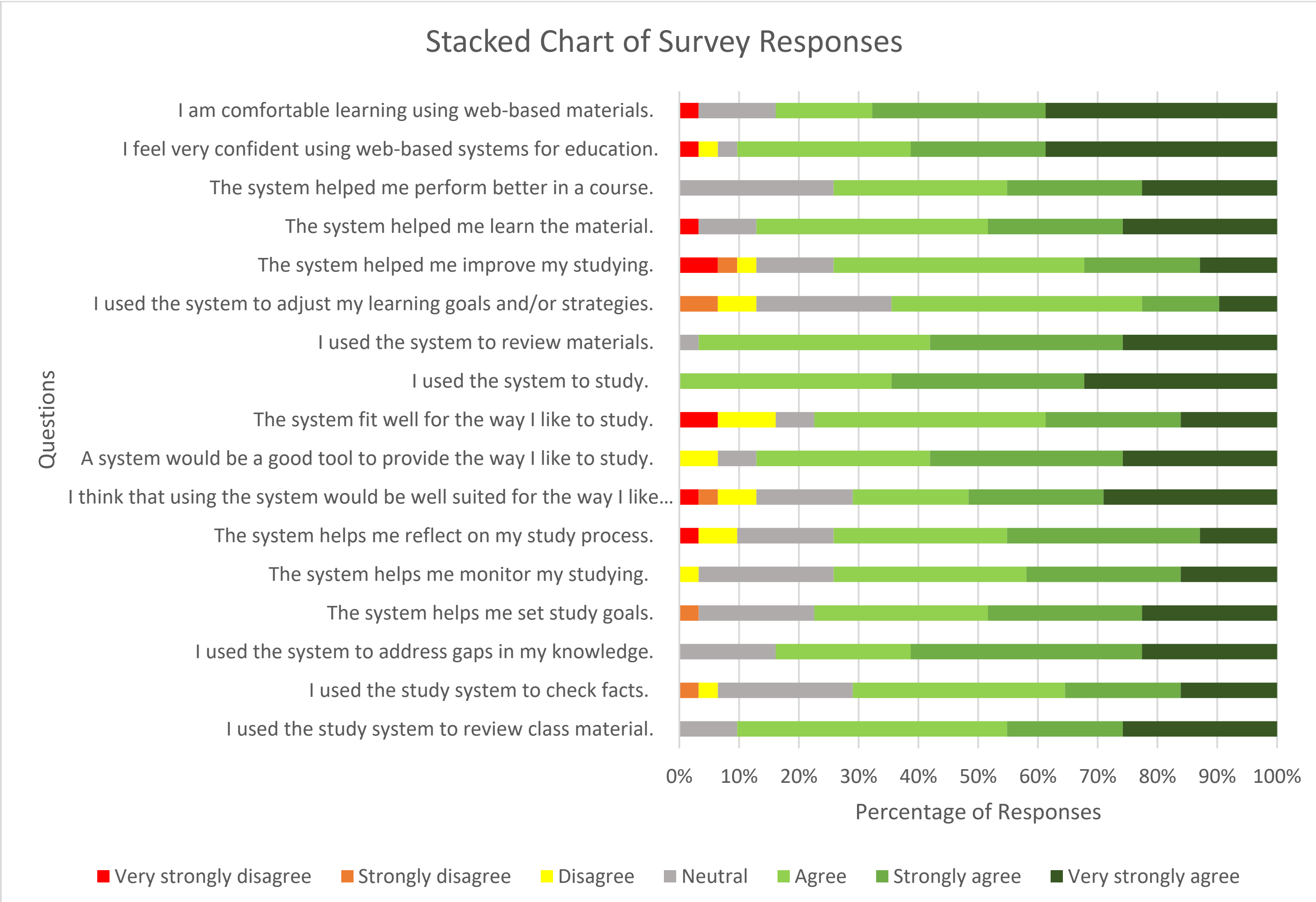

Figure 19. Chart of Survey Results

When participants were asked if they felt the system helped their academic performance, all but one (97%) student answered "yes." This was followed by a question asking if the student would use a system like this one to study in the future. All but one (97%) student answered "yes". These results are shown in Figure 20 below.

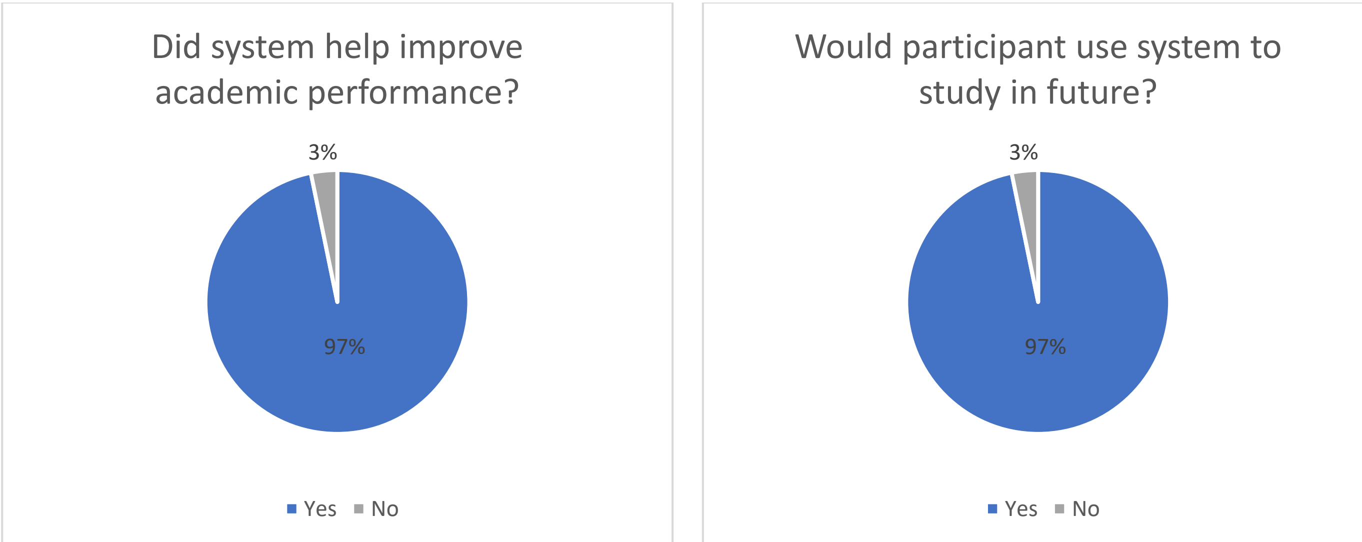

Figure 20. Additional Survey Results

SmartPLS 4 was used for the remainder of the quantitative analysis. As indicated in the previous chapter, this evaluation consisted of two steps as suggested by Hair et al. (2019). In the first step, the measurement model is assessed using various methods. This is then followed by the structure model assessment. The model evaluation does not include the concept of fit as this tends to not be applied to PLS-SEM (J. Hair et al., 2022, p. 20).

Assessment of Measurement Model

The original measurement model is shown below in Figure 21. As the constructs for this model are reflective, the model measurements are assessed for internal consistency using composite reliability using Cronboch's alpha, convergent validity using factor loadings and average variance extracted (AVE), and discriminant validity using heterotrait-monotrait (HTMT) ratio of correlations. A summary of these results can be found in Table 13.

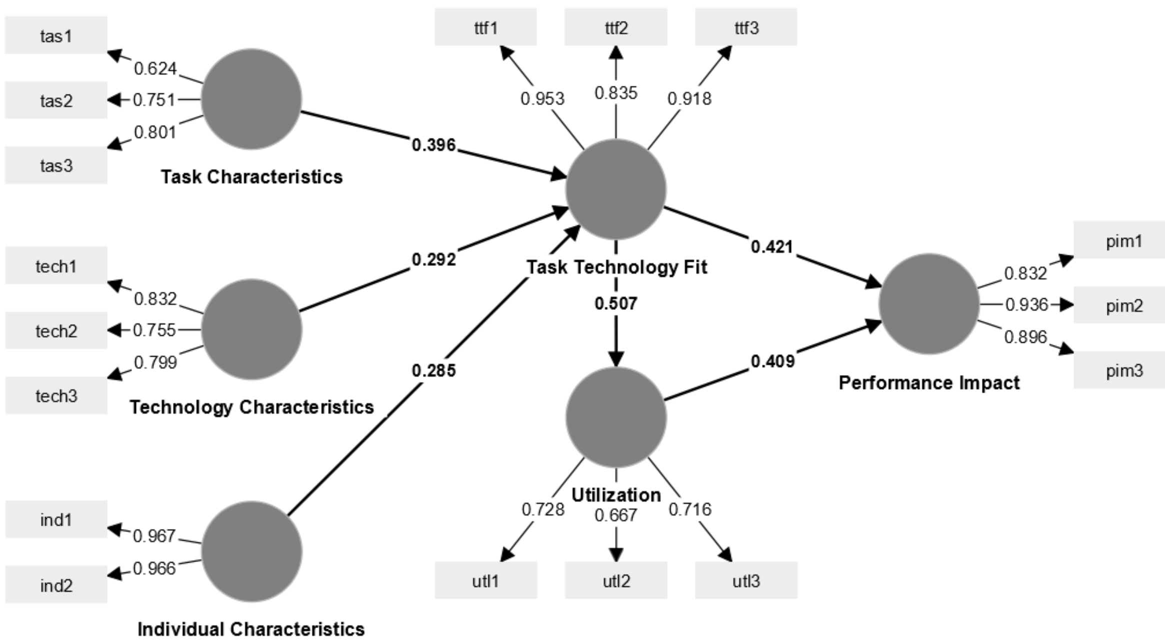

Figure 21. Initial Model Results with Loadings

The first step of assessing reflective measurement models involves examination of the item loadings as these can indicate item reliability. Loadings should be above 0.708 as this indicates "that the construct explains more than 50 per cent of the indicator's variance" (J. F. Hair et al., 2019, p. 8). Lower loadings indicate that the item is "not adequate to measure the target construct" (Russo & Stol, 2021, p. 8). As shown in Table 13 below, two items "tas1" of Task Characteristics and "utl2" have loadings slightly lower than 0.708 with the remainder of item loadings appearing to fall into the desirable range. Next, Jöreskog's composite reliability (indicated as "rho_c" in SmartPLS) is determined to assess internal consistency reliability. Internal consistent reliability looks at the consistency across items influencing a factor with the "aim to discover if the correlation between items are high enough" as this suggests similarities among these items (Russo & Stol, 2021, p. 11). Acceptable values range from 0.6 to 0.9 with values higher than 0.95 problematic as they indicate redundancy (J. F. Hair et al., 2019). As shown in the table below, one construct, Individual Characteristics, has the measure of 0.966 indicating that some redundancy is evident. The other constructs show measures that fall into the acceptable range. Chronbach's Alpha was also calculated to determine internal consistency reliability. Desired values are those above 0.70. Two constructs have lower values, Task Characteristics and Utilization. It is worth nothing that these two constructs are associated with the items that have low loadings. AVE was used to assess the convergent validity of the measure of each construct. Convergent validity indicates which items "correlate positively with different items of the same latent variable" (Russo & Stol, 2021, p. 11). Here desired values are those above 0.50 as these measures indicate "that the construct explains at least 50 per cent of the variance of its items" (J. F. Hair et al., 2019, p. 9). Here one construct measure, Utilization, AVE is slightly low at 0.495.

Table 13. Summary of Model Measurement Assessment

Latent Variables/Construct	**Reflective Items/ Indicators**	**Convergent Validity**		**Internal Consistency Reliability**	
		Loadings	**AVE**	**Cronbach's Alpha**	**Composite Reliability**
Task Characteristics	tas1	0.624*	0.531	0.568*	0.771
	tas2	0.751			
	tas3	0.801			
Technology Characteristics	tec1	0.832	0.633	0.733	0.838
	tec2	0.755			
	tec3	0.799			
Individual Characteristics	ind1	0.967	0.935	0.930	0.966*
	ind2	0.966			
Task Technology Fit	ttf1	0.953	0.816	0.886	0.930
	ttf2	0.835			
	ttf3	0.918			
Utilization	utl1	0.728	0.495*	0.541*	0.746
	utl2	0.667*			
	utl3	0.716			
Performance Impact	pim1	0.832	0.790	0.866	0.919
	pim2	0.936			
	pim3	0.896			

* indicates values that fall outside of traditionally acceptable levels

Lastly, discriminant validity is evaluated by determining the HTMT ratio of the correlations. Discriminant validity "indicates if a latent variable is measuring a distinct construct and the degree of which items exemplify the targe construct" (Russo & Stol, 2021, p. 11). These results are shown in Table 14 below. Desired results should be below 0.90 if constructs are effectively capturing different constructs as this suggests uniqueness of each construct and therefore discriminant validity (J. F. Hair et al., 2019). Two results, Performance Impact → Technology Characteristics and Task Characteristics → Utilization, are above 0.90.

Table 14. Initial Heterotrait-monotrait Ratio (HTMT) Matrix

	Individual Characteristics	**Performance Impact**	**Task Characteristics**	**Technology Characteristics**	**Task Technology Fit**	**Utilization**
Individual Characteristics						
Performance Impact	0.621					
Task Characteristics	0.542	0.667				
Technology Characteristics	0.410	0.922*	0.640			
Task Technology Fit	0.480	0.711	0.861	0.607		
Utilization	0.518	0.335	1.016*	0.335	0.465	

* indicates values that fall outside of traditionally acceptable levels

In order to address the low loadings, internal consistency reliability, convergent reliability, and discriminant reliability issues, changes were made to the model. First the tas1 item was dropped due to the low loading. Exploration of Utilization items showed that utl3 had a relatively low correlation with the other Utilization items and was therefore dropped. When considering Technology Characteristics, tch1 had consistent correlation to an opposing construct (PIM items) and was therefore dropped as proposed by Henseler et al. (2015) to address the HTMT results. The resulting measurement model assessment is provided below in Table 15 (summary assessment) and Table 16 (HTMT matrix).

Table 15. Updated Summary of Model Measure Assessment

Latent Variables	**Reflective Items /Indicators**	**Convergent Validity**		**Internal Consistency Reliability**	
		Loadings	**AVE**	**Chronbach's Alpha**	**Composite Reliability**
Task Characteristics	tas2 tas3	0.775 0.852	0.663	0.495*	0.797
Technology Characteristics	tec2 tec3	0.751 0.965	0.749	0.712	0.854
Individual Characteristics	ind1 ind2	0.967 0.966	0.935	0.930	0.966*
Task Technology Fit	ttf1 ttf2 ttf3	0.954 0.833 0.919	0.816	0.886	0.930
Utilization	utl1 utl2	0.928 0.903	0.838	0.807	0.912
Performance Impact	pim1 pim2 pim3	0.856 0.935 0.872	0.789	0.866	0.918

* indicates values that fall outside of traditionally acceptable levels

Table 16. Updated Heterotrait-monotrait Ratio (HTMT) Matrix

Latent Variables	**Individual Characteristics**	**Performance Impact**	**Task Characteristics**	**Technology Characteristics**	**Task Technology Fit**	**Utilization**
Individual Characteristics						
Performance Impact	0.621					
Task Characteristics	0.315	0.700				
Technology Characteristics	0.350	0.739	0.590			
Task Technology Fit	0.580	0.711	0.941*	0.464		
Utilization	0.518	0.335	0.627	0.325	0.465	

* indicates values that fall outside of traditionally acceptable levels

Removal of these items introduced an undesired high HTMT value considering Task Characteristics -> Task Technology Fit. As dropping an item was not supported by the data, Henseler et al. (2015) suggests that constructs may be merged into a more general construct when treating discriminant validity problems. The solution was to collapse task technology fit into one item by taking the average of ttf1, ttf2, and ttf3. This resulted in the HTMT values show in Table 17. While all resulting values are now below .9 cutoff, but it is worth nothing that Task Characteristics → Task Technology fit is still rather close to the cutoff at 0.891.

Table 17. Final Heterotrait-monotrait Ratio (HTMT) Matrix

Latent Variables	**Individual Characteristics**	**Performance Impact**	**Task Characteristics**	**Technology Characteristics**	**Task Technology Fit**	**Utilization**
Individual Characteristics						
Performance Impact	0.621					

Latent Variables	Individual Characteristics	Performance Impact	Task Characteristics	Technology Characteristics	Task Technology Fit	Utilization
Task Characteristics	0.315	0.700				
Technology Characteristics	0.350	0.739	0.590			
Task Technology Fit	0.533	0.684	0.891	0.459		
Utilization	0.518	0.335	0.627	0.325	0.410	

Assessment of Structural Model

With the assessment of the measurement model complete, assessment of the structural model can take place. This consists of tests that explore collinearity using Variance Inflation Factor (VIF), path significance using path coefficients, coefficient of determination using R^2, effect size using f^2, and predictive relevance using Q^2.

Collinearity, the degree of correlation between constructs, is measured using VIF. Too much collinearity can demonstrate that constructs represent similar concepts (Russo & Stol, 2021). Acceptable results of this test should be "close to 3 or lower" (J. F. Hair et al., 2019, p. 11). As shown in Table 18 below, all values fall into the desired range.

Table 18. Summary of VIF Results

Latent Variables	Individual Characteristics	Performance Impact	Task Characteristics	Technology Characteristics	Task Technology Fit	Utilization
Individual Characteristics					1.092	
Performance Impact						
Task Characteristics					1.181	

Latent Variables	Individual Characteristics	Performance Impact	Task Characteristics	Technology Characteristics	Task Technology Fit	Utilization
Technology Characteristics					1.191	
Task Technology Fit		1.159				1.00
Utilization		1.159				

The bootstrap procedure for path coefficients is used to determine t-values and p-values in order to determine relationship significance between the constructs. The path coefficients can be between +1 (indicating a positive relationship) and -1 (indicating a negative relationship) with relationships closer to zero considered to be weak (Russo & Stol, 2021). Bootstrapping produces the sample distribution/confidence intervals needed for a normal distribution that is used to establish both the t-values and p-values. To run this procedure in SmartPLS, 5000 samples with complete bootstrapping was selected along with bias corrected and accelerated bootstrap types. A two-tailed test type was selected and significance level of 0.05 was selected. Results are shown in Table 19 below. The chosen significance of is 0.05. Three paths have values higher than the selected significance. The low coefficient (0.030) of utl->pim and very high p value (0.911) means that it is possible that Utilization construct needs to be reconsidered for this model. The path ind->ttf has a stronger relationship (0.357) and a slightly high p value (0.065) indicating that some changes are needed to improve the Individual Characteristics construct. The tech->ttf path has a lower coefficient (0.183) with a higher p value (0.218) which indicates a similar problem with the Technical Characteristics construct.

Table 19. Summary of Path Coefficients and Significance

Path	Original sample (O)	Sample mean (M)	Bias	2.5% (Lower bound)	97.5% (Upper bound)	T Stats	p value	p < 0.05
ind -> ttf	0.357	0.313	-0.044	-0.023	0.712	1.847	0.065*	No
tas -> ttf	0.482	0.469	-0.012	0.170	0.765	3.066	0.002	Yes
tech -> ttf	0.183	0.232	0.049	-0.435	0.401	1.233	0.218*	No
ttf -> pim	0.631	0.554	-0.077	-0.023	0.865	2.625	0.009	Yes
ttf -> utl	0.370	0.374	0.004	-0.131	0.662	1.983	0.047	Yes
utl -> pim	0.030	0.108	0.078	-0.394	0.634	0.111	0.911*	No

(ind = Individual Characteristics, ttf = Task Technology Fit, tas = Task Characteristics, tech = Technology Characteristics, pim = Performance Impact, utl = Utilization) * indicates values that fall outside of traditionally acceptable levels

The model's explanatory power is shown using the coefficient of determination. The R^2 value, also known as the in-sample predictive power, indicates "the proportion of variance explained by each endogenous construct" (Russo & Stol, 2021, p. 16). The R^2 value can be between 0-1, where the higher value represents a higher percentage of variation that can be explained by the construct. Results are shown below in Table 20. Two of the values shown below, Performance Impact and Task Technology Fit, are considered to be moderate in their explanatory power as they are near 0.5, while the remaining value for Utilization is considered to be weak as it is below 0.25 (J. F. Hair et al., 2019).

Table 20. Summary R^2 values

Latent Variable	**R-square**	**R-square adjusted**
Performance Impact	0.413	0.371
Task Technology Fit	0.569	0.521
Utilization	0.137	0.107

The f^2 effect size measures weather an "exogenous latent variable has a substantial impact on the endogenous ones" (Russo & Stol, 2021, p. 16). The results are shown below in Table 21. The rankings of the values correspond to the path coefficient ranking order, so no further analysis here is required.

Table 21. Summary of F^2 Values

Latent Variables	**Individual Characteristics**	**Performance Impact**	**Task Characteristics**	**Technology Characteristics**	**Task Technology Fit**	**Utilization**
Individual Characteristics					0.272	
Performance Impact						
Task Characteristics					0.456	
Technology Characteristics					0.065	
Task Technology Fit		0.586				0.159
Utilization		0.001				

Q^2 values can also be used to assess the model's predictive accuracy. Values less than 0.25 but higher than zero are considered to be small, greater than 0.25 are considered to be medium, with values greater than 0.5 are considered to be large (J. F. Hair et al., 2019). However, SmartPLS 4 has discontinued support for the blindfolding method historically used to determine Q^2 values. The current recommendation is that PLSPredict be used instead to determine and assess out-of-sample predictive power ($Q^2_{predict}$), as the PLSPredict technique uses k-fold cross-validation of the data set to generate "holdout sample-based predications." (J. F. Hair et al., 2019, p. 12). When using this technique, it is suggested that each fold meets the minimum sample size (J. F. Hair et al., 2019). Given that the dataset just meets the minimum sample size, this technique would not be appropriate as additional data points would be needed to apply this technique in order to demonstrate predictive accuracy.

Results of Hypothesis Testing

Figure 22 below provides the results of the final adjusted model. It illustrates the path coefficients and the R^2 values.

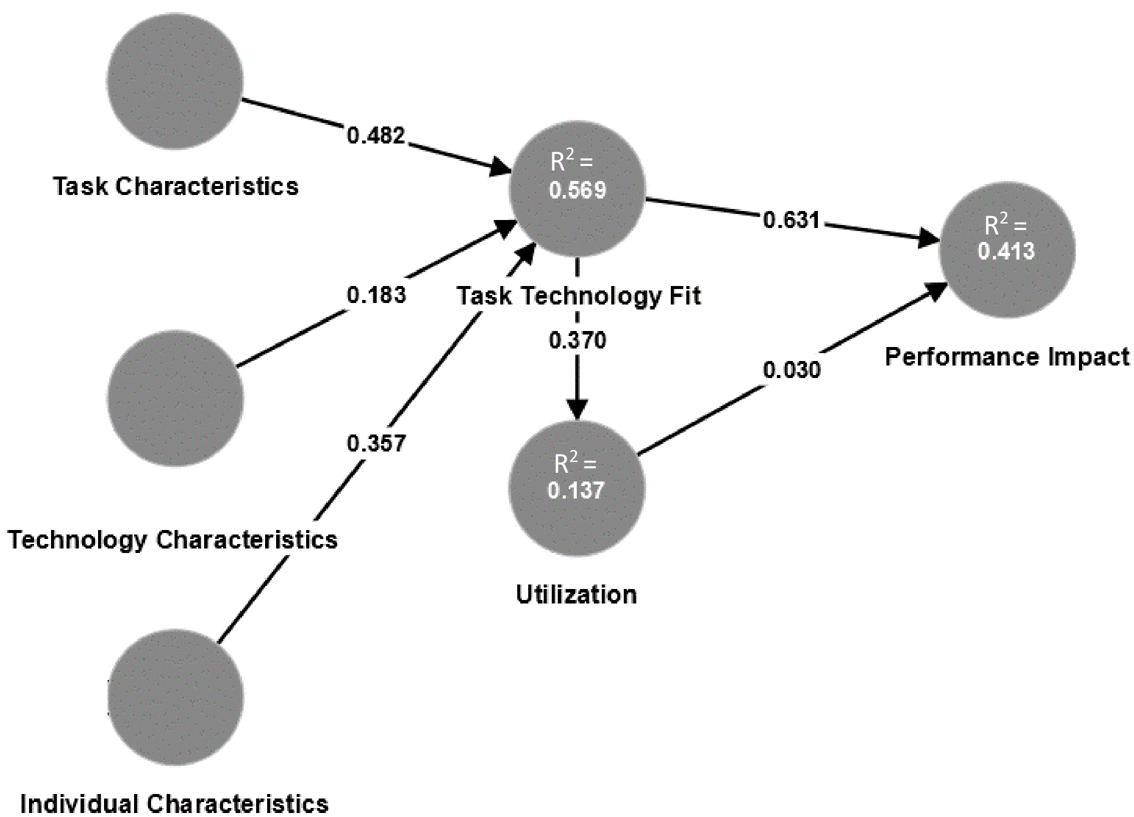

Figure 22. Final Model

The results of the hypothesis testing are provided in Table 22. Supporting H1, Task Characteristics had a significant effect on perceived Task Technology Fit ($\beta = 0.482$, $p <$

0.05). Inconsistent with H2, Technology Characteristics did not have a significant effect on Task Technology Fit ($\beta = 0.183$, *ns*). While the effect was positive, the significance was not in the acceptable range ($p < 0.05$). Inconsistent with H3, Individual Characteristics did not have a significant effect on Task Technology Fit ($\beta = 0.357$, *ns*). While the effect was positive, the significance was not in the acceptable range ($p < 0.05$). Supporting H4, perceived fit had a significant effect on Utilization ($\beta = 0.370$, $p < 0.05$). Supporting H5, perceived fit had a significant effect on (academic) Performance Impact ($\beta = 0.631$, $p < 0.05$). Inconsistent with H6, utilization did not have a significant effect on (academic) Performance Impact ($\beta = 0.030$, *ns*). While the effect was positive, the significance was not in the acceptable range ($p < 0.05$). As discussed earlier, (academic) Performance Impact ($R^2 = 0.413$) and Task Technology Fit ($R^2 = 0.569$) are moderate in their explanatory power while Utilization ($R^2 = 0.137$) is not considered to explain much variance.

Table 22. Results of Hypothesis Testing

Hypotheses	**Results**
H1: Task characteristics are positively related to perceived fit.	Supported $\beta = 0.482$, $p < 0.05$
H2: Technology characteristics are positively related to perceived fit.	Not supported $\beta = 0.183$, but lacks statistical significance
H3: Individual characteristics are positively related to perceived fit.	Not supported $\beta = 0.357$, but lacks statistical significance
H4: Perceived fit is positively related to the utilization.	Supported $\beta = 0.370$, $p < 0.05$
H5: Technology fit is positively related to (academic) performance impact.	Supported $\beta = 0.631$, $p < 0.05$
H6: Utilization is positively related to (academic) performance impact.	Not supported $\beta = 0.030$, but lacks statistical significance

Qualitative Analysis Results

Open coding techniques were applied to responses of the three open-ended survey questions on the final survey to discover factors influencing each of the constructs and to inform the evaluation of the system. QDA Miner Lite was used for coding. Each response was evaluated one line at a time, often with at least one code recorded per line. The resulting codes and corresponding categories created from the open coding are provided below. This was followed by axial coding to demonstrate relationships between the categories. This was then followed by selective coding in order to unify the categories around a core category. All codes are depicted below in in Table 23.

Table 23. Coding Results

Selective Code	**Axial Code**	**Code**	**Count of Occurrence**	**Percent of Learners Reporting**
Facilitate study efforts for improved outcomes	Individual Characteristic	Lack of motivation	4	12.9
	Benefits of System Use	Encouraged studying	3	9.7
		Increased study efforts	1	3.2
		Improved academic performance	2	6.5
		Better prepared for exam	2	6.5
		Retained knowledge	3	9.7
	Study Process Improvements	Focused studying efforts	7	16.1
		Provided study path	1	3.2
		Easier way to study	5	16.1
		Better way to study	3	9.7
		Faster way to study	4	12.9
	System/Technology Expectations	Usability/Easy to use	5	16.1
		Needs more explanation	2	6.5
		Simple tool	1	3.2
		Quick response	1	3.2
		Needs dark mode	1	3.2

Provide a variety of quality relevant study materials	Study Material Likes	Good and relevant examples	4	12.9
		Like practice problems	7	22.6
		Liked videos	7	22.6
		Liked self-assessments	7	22.6
		Liked documented practice problems	1	3.2
		Provided in-depth examples	1	3.2
		Different study material (from lectures)	5	9.7
		Multiple sources	3	6.5
	Study Material Dislikes	Needs more assessments	1	3.2
		Needs more study material	1	3.2
Customize and support several study methods for every learner	Study/Task Methods	Supported multiple study methods	5	16.1
		Combined study methods	1	3.2
		Tracked progress	1	3.2
		Helped student learn concept missed	2	6.5
		Helped learn independently	1	3.2
		Guided study process	1	3.2
		Easier access to study material	1	3.2
		Organized study materials	4	9.7
	Personalized Learning	Personalization of study methods	10	25.8
		Helped variety of learners	1	3.2

The selective codes established provided three key themes derived from participant feedback: (1) facilitate study efforts for improved outcomes, (2) provide a variety of quality relevant study materials, and (3) customize and support several study methods for every learner. Each theme is discussed below with detailed participant feedback.

Theme 1: Facilitate study efforts for improved outcomes

Self-motivation is an important quality of self-regulated learners (B. Zimmerman, 2002). Motivation was discussed as a challenge to study efforts by several participants. Some indicated a lack of motivation and/or focus required to aid the studying process.

> *"... I tend to find flashcards and short questions like the one in the system extremely helpful to use and study but often don't have the time, energy, or focus to complete them to help myself with studying."* – Participant 17

Participant 5 indicated that "finding a way to study is half of the problem for me, then I just get too tired and lazy to study." The existence of a system designed to support their study efforts resulted in motivating some of the participants to study. Several participants reported that the system helped to focus their study efforts as it helped them recognize not only the areas that they needed to study for the upcoming exam, but also helped recognize areas of deficiency. Participant 3 stated that "[the system] helped [me] focus on the areas I did not know as well as others." The mere presence of the system helped to keep students focused on their study efforts.

> *"It gave me a location that was easy to reference where I had a general idea of the material I needed to study, which allowed for me to focus more on the material I knew I currently need rather than reviewing information that is not helpful for me at the moment."* – Participant 17

Organization of the learning objects supported participant studying. Participant 24 indicated that system provided some structure to study efforts: "… there's a clear path of studying that keeps me on track of what topics I want to go for next."

System use was perceived to have several advantages over other means of studying in that it made studying easier and quicker while offering better ways to study. Participant 9 stated “I believe it helped me learn the information easier and faster.” The time savings and ease of learning were commented on by several participants. The system also provided for a better overall experience, as participant 10 noted that it offered a “better way to study other than just looking over notes.” In addition, participants reported that they felt their academic performance improved after using the system. Participant 5 indicated that they “… felt better and […] was retaining knowledge better …” as a result of using the system. It was reported that information was easier to recall due to use of the system for studying.

Participants also had expectations when interacting with the system. While several participants reported that the system had an intuitive, user-friendly design and was straightforward to use, not all were happy with the interface. One participant commented on the need for a “dark mode” to better accommodate longer study durations. Participant 16 reported that “some of the material that [the system] provided was very confusing to use and not at all intuitive furthering my frustration with the material.” Participant 21 indicated that additional instructions could be added to increase usability.

Theme 2: Provide a variety of quality relevant study materials

As students monitor their learning, progress can be hindered if learning objects are not sufficient in form and relation. Participants reported an appreciation for the different forms of study materials provided. Participant 8 stated that the system provided “… a good change of pace from the semester of slides, book, assignment[s] and exercises. It was a slight benefit because it was a different approach to what I’d known beforehand.” Participants also appreciated that the learning objects came from differing sources and viewpoints, and offered methods to learn that were outside of what was typically presented during classes. Participant 25 found enjoyment in these various methods: “I really enjoyed the encompassing methods used to learn about a topic. Visuals, reading, and broken down examples all help to learn material in different ways.”

The quality of the learning objects was also of importance to participants. Participants noted that they considered the material to be good, relative, and/or tangential to what they were learning in class, in addition to practical examples. As all courses had a focus on programming, real code examples with explanatory comments were provided as learning objects. These snippets could be modified and executed to enhance the studying process.

Participant 2 stated "I also appreciated the inclusion of an embedded IDE service that could allow me to see a program's code and running output." These code examples often served as practice problems. Participants found that these learning objects were very helpful in learning the material.

The various self-assessments that served as learning objects were also well-received by many participants. Some participants commented that they liked the ability to try multiple choice questions until they got them right and appreciated the flashcard assessments. One participant commented that the system would benefit from more of these types of learning objects.

Videos were also well-received by many participants. Participant 11 stated that "having videos helps so much because I can see the process and duplicate it on my own system." Participants noted that the step-by-step nature of how problems were solved in the videos helped with their understanding and helped them review concepts.

Students also found that access to multiple sources of information was helpful. Participant 21 noted that one benefit of having multiple sources was that "different creators can discuss topics not mentioned by others" leading to a more complete education. It was felt that the different material helped to reinforce what was taught in class. One participant advocated for adding to the repository additional materials related to course outcomes outside the scope of the study. This could serve to strengthen the quality and relevance of learning objects presented.

Theme 3: Customize and support several study methods for every learner

As part of the performance phase, SRL places emphasis on self-control strategies that support students reaching their goals (B. Zimmerman, 2002). The system aided the self-control process with the customization of task strategies presented in the form of recommendations. Personalization of the study process as it was tailored to participant needs was a widely appreciated aspect of the system as participants recognized the advantages of this approach. Participant 8 found that the system provided students with the "opportunity to learn the way they learn best." Participant 3 stated that "the different types of study tools given was nice and allowed me to find what I liked most when studying." Participant 25 found that the system provided "something for every kind of learner." It was also noted that the system permitted for the ability to combine different study processes. Several participants found the variety of study modes beneficial. Participant 2 stated that the system was “useful for providing a one-stop-shop for multiple modes of study.”

The organization and reporting provided by the system of learning concepts also supported the self-observation aspect of the SRL performance phase. Participant 1 noted that the system “helped me see my progress in real time.” Participant 22 stated “I liked that the application allowed you to like specific studying sets, so when I would go to look back on material, I could find the ones I thought to be the best.” The system was said to be well organized in its manner of presenting learning material and progress, helping students to recognize and find what they needed to know and study.

The system also helped students fill in gaps from classes by reiterating class topics. Participant 30 stated that the system “helps me understand something […] the teacher might have missed or not have to fully touched on.” Another participant indicated that the system provides a study guide for “very specific questions” pertaining to course materials. There was value found in this system as a tutor. Participant 6 stated that the system could “help students especially when there might not be a teacher around to help (after school hours)” strengthening the idea the system provides support for autonomous learning.

Discussion

Each of the original research questions are revisited below separately with their corresponding findings from this research. Included in the discussion is an introduction to SRL educational recommenders design principles informed by the results of this research.

RQ1: How can recommender design best be supported by self-regulated learning theory?

The system was designed to support student regulation of their learning; the system should not replace the process that supports metacognitive activities but sought to put in place recommender functionality to support this process. As described earlier, the process of self-regulated learning can be captured in three phases: the forethought phase, the performance phase, and self-reflection phase. When considering the forethought phase, the study system created for this research was built with a specific goal in mind. In each case, the system was built around specific learning outcomes covered on an exam for a given course. The selection of the learning object, the breadth and depths of the topics covered, were designed to support student learning as it pertained to these learning outcomes. While participants did not explicitly enter personal goals, the system provided the knowledge structure while selection of learning objects to review was driven by student choice. MSLQ questions concerning self-motivation beliefs were stored as part of the learner profile which was then utilized in the recommendation process. Selection of topics from which to obtain recommendations for studying in order to achieve personal goals was an area of self-regulation delegated to the student.

The performance phase was facilitated by the recommendations provided. The approach employed seeks to adapt for individual learning differences. As demonstrated in open-ended survey question results, personalization of study methods was well-received. The recommender type/filtering technique, system inputs, and algorithm employed by the system were selected to support SRL-based recommendations. The framework facilitating this personalization consisted of a learner model which consisted of attributes pertaining to the MSLQ and VARK questionnaire results which were then the basis for populating the learner ontology. Next the learning object model consisted of general object attributes driven by prior research with the addition of specific SRL-based attributes which served as the basis for the learning object ontology. Lastly, the recommender engine was responsible for matching the learner's needs to the learning objects based on the two ontologies, a knowledge-based filtering approach. This was then enhanced by also including in the results the recommendations of others (collaborative filtering). This was made possible by use of a learning log ontology that allowed students to "like" items and also revisit these items. This process encourages metacognition by helping students become more self-aware of the items they prefer to use when learning.

The framework used by the system allowed for reflection of learning, as in the self-reflection phase of SRL. Participants were able to easily understand where their time studying was spent and where additional time was needed. In addition, to support this reflection and encourage students to revisit topics, participants were able to "flag" items that were not well-understood. In bridging the connection between the learner ontology and learning object ontology, the learner log ontology also served as the basis of providing basic analytics about topics visited so that students would understand where their study efforts have been spent.

Also, the system supports multiple learning modes to provide opportunities for students to learn in different ways, allowing them to adapt if they find upon reflection that their learning is ineffective, supporting the cyclical nature of SRL.

In looking at the system under the microscope of TTF as a diagnostic tool, several findings were apparent. A few, but not all paths, proved to be significant. Task Characteristics had a positive impact on the Task Technology Fit, emphasizing that the system has a good fit with the tasks it was designed to support. There was also a significant relationship between Task Technology Fit and (academic) Performance Impact. This indicates that the fit was shown to have a positive impact on improving academic success. Factors that may have led to a positive impact are discussed when addressing R2 below.

Not all constructs had a significant impact. Since utilization of the system was required for participation in the study, its use as a construct may have been out of place in this study. As Goodhue and Thompson (1995, p. 230) state "TTF might be a good surrogate [construct] if utilization were assured." Technology Characteristics also proved to be insignificant. As shown in both qualitative and quantitative results, there are opportunities to improve the Technology Characteristics. As reported by participants, additional considerations are needed to better support the fit, such as providing a "dark mode" and additional instructions and/or explanations for students. The data concerning the impact on Individual Characteristics did also not appear to be significant in this case. Survey questions relevant to this construct focused on a student's perceived ability to use technology to study (e.g. technical abilities). Qualitative data does not appear to indicate why this was inconsequential. Additional data and/or research may be needed to explore this.

RQ2: What is the influence of recommender-based self-regulated learning on academic success?

Almost all (30 out of 31) participants felt that the system helped to improve their academic performance. Additionally, quantitative analysis showed that the fit of this technology for the task of studying had a moderate impact on academic success. As discussed in the qualitative results, demonstration of this framework resulted in an experience that participants reported as an easier studying experience, and better retainment and recall of knowledge learned, demonstrating the impact on academic success. Its existence also served to motivate students to study and make more efficient use of student time, all leading to improved academic performance.

When exploring the fit of the system, three themes were discovered that may have had an impact on success: facilitation of study efforts, the quality and relevant study material, and the customization and support of several student methods. These, and other lessons learned, are reflected in the proposed design principles.

Resulting Design Principles

Results of both the quantitative and qualitative methods have led to specific insights on SRL-guided educational recommender design. The three themes uncovered demonstrate factors that serve to support several facets of the SRL process. These insights are presented in the form of design principles. Gregor et al. (2020) advocate for sharing design principles in a way that is clear and supports their implementation in the real world in addition to supporting future research. This research uses their schema to present the design principles with consideration for the themes identified from participant feedback, as depicted in Figure 23.

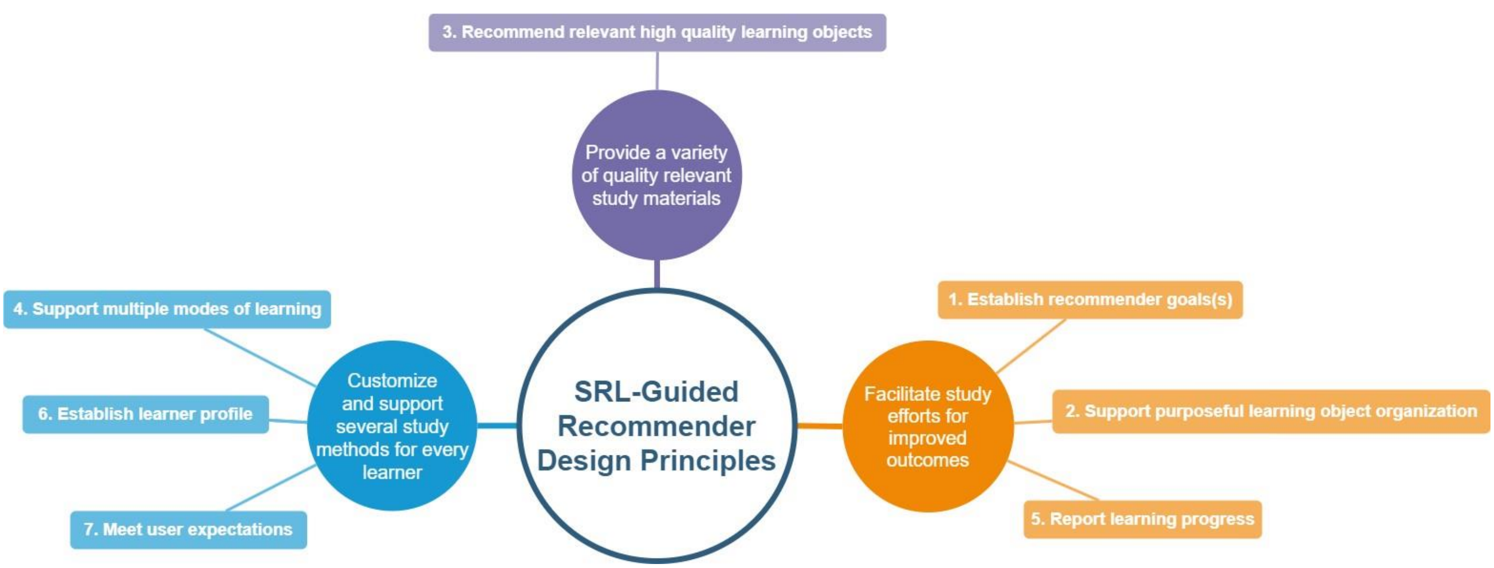

Figure 23. SRL-Guided Recommender Design Principles

Design principle title	**1. Establish recommender goal(s)**
Aim, implementer, and user	For designers and researchers (implementors) to facilitate learning (aim) for students (user)
Context	SRL-guided educational recommender system

Mechanism	The design of the recommender should be built with specific goal(s) in mind (e.g. improve student study efforts).
Rationale	The recommender goal will impact decisions made concerning recommender profile, organization of learning objects, and presentation of analytics.

Understanding task or actions of the users when using the system, as identified as Task Characteristics in TFF, is critical is supporting the fit of the technology. Analysis supported that Task Characteristics are positively related to perceived fit, which prior research has also shown (Goodhue & Thompson, 1995). Tasks should be determined by their ability to support the goal(s) of the system. The goal of the recommender in this case was to improve student learning by facilitating the study process. This drove the selection of each aspect of the recommender methods: the recommender type/filtering technique, system inputs (profile development), and algorithm employed. This then also led to a better understanding of how possible recommendation candidates should be organized (e.g. ontology structure). As research on student-facing analytics has shown, understanding the goal should also guide the development of analytics reported back to the user (Bodily & Verbert, 2017b). This importance was highlighted in the first theme discovered from student feedback given its focus on supporting the goals of students.

Design principle title	**2. Support purposeful learning object organization**
Aim, implementer, and user	For designers and researchers (implementors) to facilitate the ease of learning (aim) for students (user)
Context	SRL-guided educational recommender system
Mechanism	Learning outcomes should guide organization of digestible learning objects in a way that also guides student learning. This should assist in helping students understand what they are responsible for knowing with similar items grouped together while being born from learning outcomes.
Rationale	Organization or learning objects helps students recognize what they need to know, what they know, and what they don’t know. This organization helps to guide the study process and serves to group similar objects together.

The forethought phase of SRL sets the stage for learning, as learners consider what to learn and set learning goals. Prior research has shown that learning objects are the most popular recommendation object in e-learning recommenders (Rahayu et al., 2022).

Participants reported organization of learning objects as key to guiding their learning process. The organization also served to provide students with reflection concerning topics studied, and choices when it came to choosing a topic to study. This is comparable with the locatability factor of task-technology fit construct as defined by Goodhue and Thompson (1995). These aspects facilitated study efforts in order to help participants better identify knowledge areas where they may be weakest when studying and the organization of learning content to focus their efforts. Proper organization here is facilitated by the use of ontologies. These ontologies are not only used to match the system user to recommended learning objects, but they can also serve to organize learning objects in a way that can also facilitate their presentation to the learner. For example, learning objects that include associations to learning outcomes within their ontology can then be grouped together for learner display purposes.

Design principle title	**3. Recommend relevant high quality learning objects**
Aim, implementer, and user	For designers and researchers (implementors) to ensure learning (aim) and make best use of student time (user)
Context	SRL-guided educational recommender system
Mechanism	Learning objects should be of high quality and relevant to the learning outcomes of the course. Utilizing objects from a variety of sources is advisable.
Rationale	By providing high quality learning objects, students will be better supported in their efforts to learn. Items of poor quality will lead to frustration and wasted time, leading to a lack of faith in the recommender and inefficient studying. Utilize a variety of sources to provide different perspectives and address any knowledge gaps.

The themes uncovered are reiterated by experts and researchers when considering adaptive learning systems (Kabudi et al., 2022). There is an emphasis on supporting needs of individual learners by utilizing learner profiles and supporting skill mastery. One theme that perhaps stands out is the need to ensure that quality and relevant learning objects are delivered. Gordillo et al. (2014) have established tools, such as the Learning Object Review Instrument (LORI), that enables educators to more critically evaluate the quality of a learning object, and extend the basic understanding of quality to also consider the learning object’s alignment with the learning goal, its ability to feedback and support adaptation, its ability to motivate learners, its accessibility, and its usability in addition to a few other factors. In this research, only one educator determined the quality of the learning objects used, however this could be strengthened by a more collaborative-based approach to evaluating learning object quality assessment using a tool like LORI.

Developing a knowledge base is a time-consuming endeavor. While the design of some recommenders focuses on utilizing random learning objects (e.g. YouTube videos) from the internet, the knowledge base exists in this research with the assistance of ontologies. To best support student learning, the learning objects in this knowledge base need be relevant and of high quality. This is comparable with the qualify factor of task-technology fit construct as defined by Goodhue and Thompson (1995). They define several dimensions of quality including currency of data, supplying the right data to support the task, and the right level of detail. If students are not wasting time on ill-prepared and irrelevant learning materials, this is a better use of their time and can shorten the studying process. Furthermore, effectiveness of the system is dependent on the "completeness and accuracy of knowledge maintained in the ontology domain knowledge" that is utilized to guide recommendations (Tarus et al., 2018, p. 30). Feedback from participants also demonstrated an appreciation for learning objects from a variety of sources in that they provided different perspectives and addressed gaps that may exist when using a single source.

Design principle title	**4. Support multiple modes of learning**
Aim, implementer, and user	For designers and researchers (implementors) to facilitate the ensure learning (aim) and to engage students (user)
Context	SRL-guided educational recommender system
Mechanism	Learning objects provided should support various learning modes.
Rationale	By providing learning objects that support learning modes, not only will this help students improve engagement and encourage learning in a way they may feel they learn the best, but it can also help to reinforce their learning.

Existing research in recommenders has supported considering the mode of learning object presentation, as this can improve engagement (El-Sabagh, 2021). This will help students discover the way that they feel they learn best. Participant feedback supported multiple modes as students appreciated the variety and choice provided when multiple modes were presented. In this study, students found the multiple modes refreshing and good change of pace from how materials are normally presented during classes. Learning style or preferences are prevalent learning parameters for learner modeling (Raj & Renumol, 2021). Learning theories should be consulted here to determine the appropriate approach as several exist such as FSLSM and VARK. As stated by the designer of the of VARK questionnaire, the questionnaire focuses on modalities that learners may prefer and does not indicate the breadth of options representative of student learning when considering learning style (Fleming, 1995). By including MSLQ responses in addition to VARK questionnaire responses, a profile of the learner that is more reflective of the whole student can be created.

Design principle title	**5. Report learning progress**
Aim, implementer, and user	For designers and researchers (implementors) to reflective learning practices (aim) for students (user)
Context	SRL-guided educational recommender system
Mechanism	Basic dashboard functionality should support recommender goals using learning analytics in a way that is meaningful and student-facing.
Rationale	By reporting back basic analytics (e.g. learning objects visited by concept), students were able to easily recognize where they are successful and also where their efforts may be lacking. This feedback is needed to encourage the self-reflection phase and goal adjustment in SRL.

To support the self-reflection in SRL and its self-regulatory cycle, analytics should be reported back to the student. Metacognitive monitoring of one's progress is a key activity of SRL. As reported by Zimmerman and Moylan (2009, p. 303), self-recording of one's learning progress "increases the reliability, specificity, and time span of self-observations" in order to demonstrate one's learning. Recommenders can aid this process by tracking and automatically reporting learner actions and counteracting overload students encounter with their own recordings of learning progress.

When considering TTF theory, the reporting should be in line with the goals of the system. By providing this data in real-time, students can shorten self-regulatory cycles leading to more effective use of a student's time and lead to the ability of the student to address areas of known difficulty more promptly. This will require the creation of mechanisms that enable the reporting of this data, such as the learner log ontology that recorded objects visited, items liked, and items flagged. As suggested by Bodily and Verbert (2017b), consideration should be given for the most appropriate visualization technique and the type of data needed to support the goal and student needs.

Design principle title	**6. Establish learner profile**
Aim, implementer, and user	For designers and researchers (implementors) to better customize learning (aim) for students (user)
Context	SRL-guided educational recommender system
Mechanism	A learner profile should be established prior to system use to better guide recommendations. MSLQ provides many dimensions that should be considered.
Rationale	The profile can help steer recommendations to facilitate learning with more effective use of student time by finding more appropriate learning items faster. This results in a more efficient use of student time and encourages autonomous learning while also avoiding the cold start problem encountered by some recommender approaches.

As reported by Galaige et al. (2022), creating a profile is a critical step in supporting SRL in student-facing systems that employ analytics. For traditional size college classes, it can be difficult to rely on content-based or collaborative filtering as the only approaches due to the cold start problem. To avoid the cold start problem, a profile can help steer recommendations. Much research has been conducted to explore attributes that typically compose a learner profile. A learner ontology that takes into consideration both preferred learning mode(s) and factors that influence SRL provides a starting point. Here the use of MSLQ dimensions helped to drive the selection of the most appropriate learning objects to recommend. For example, if a student favors organization strategies when learning, learning objects that pull important concepts into table or charts may be of more value to that student.

Design principle title	**7. Meet user expectations**
Aim, implementer, and user	For designers and researchers (implementors) to keep learners (users) satisfied (aim)
Context	SRL-guided educational recommender system
Mechanism	Basic usability guidelines for recommenders should also be observed to meet user expectations and enhance system adoption.
Rationale	Users have expectations. It is important to meet those expectations. Failure to meet these expectations can distract

	from the overall intended experience and prevent the system from meeting the intended goal.

Student expectations should be acknowledged and met to encourage adoption. For example, the study system failed to implement a “dark mode”, something that would enable students to view study materials on a screen for longer periods of time, reducing eye strain. This is comparable with the “ease of use” factor of TTF as defined by Goodhue and Thompson (1995). While these factors are not the direct task the user, they are supporting features and can have a significant influence on adoption as shown in prior research (D’Ambra et al., 2013).

Chapter Summary

Four instances of a case study involving the use of the SRL-informed educational study recommender yielded a total of 32 participants. In summative evaluation of the system, initial quantitative data results reported many perceived benefits of this approach including improved learning and assistance in achievement of academic goals, and support for future use of the system by participants. After demonstrating reliability and validity of the assessment model, the structural assessment showed that both the Performance Impact and Task Technology Fit constructs were moderate in their explanatory power, while Utilization was perceived as weak. When considering proposed hypotheses, Task Characteristics was the only indicator to have a significant impact on Task Technology Fit. Perceived fit had a significant impact on Utilization and (academic) Performance Impact. Coding of qualitative results resulted in the uncovering of three themes in participant feedback pertaining to the participant studying experience when using the system: facilitate study efforts for improved outcomes, provide a variety of quality relevant study materials, and customize and support several study methods for learners. With consideration of the results, seven design principles were recommended to support future development of SRL-informed educational recommenders.

CHAPTER 5

CONCLUSION

The goal of this research was to address the gap between theory and practice in the field of educational recommender design by applying the design science research methodology to combine SRL theory, an underexplored learning theory in this context, with aspects of IS system design, development, and evaluation. In doing so, the major deliverable was realized, a novel artifact framework with a defined reference model and methods for an educational recommender that permitted exploration of a design that was informed by SRL theory. Existing research steered development of this artifact resulting in a hybrid recommender approach consisting of both knowledge-based and collaborative filtering. To depict a model supportive of SRL, ontologies were used to represent various aspects of learners, learning objects, and their use, with attributes guided by the MSLQ and VARK questionnaire. An algorithm with consideration of these aspects was then created to best reflect the needs of individual learners when providing recommendations. To permit summative evaluation of this artifact, real-world testing of the instantiation of the system, a web-based application, was conducted using several instances of a case study in order to examine the fit and impact of this approach as reported by participants with consideration for the IS TTF theory. The results recognized the advantages but also suggested areas for improvement in the design of the artifact.

Of the limited existing research in educational recommender design that considered learning theory, most tended to focus on learning styles with few studies implementing a SRL-based approach. When exploring learning analytics and self-regulated learning in online education, it was found that many studies “were conducted to only trace various parts of SRL rather than to help learners to plan, monitor and reflect on their learning activities and/or educators to assist them in providing relevant SRL support” (Viberg et al., 2020, p. 9). The recommender filtering technique chosen for this research, a hybrid approach, provided the means by which to embed much of the SRL-based theory into the recommendations provided, going beyond just tracing learner activities. The knowledge-based filtering approach was necessary to also avoid limitations of other filtering methods, such as the cold start problem, and then to enable the custom filtering algorithm to consider SRL aspects relating to the learner such as motivation. By incorporating other functionality such as learning object “likes” and “flags,” more reflective and cyclical aspects of the SRL could be embedded into the system use and therefore the studying process. As stated by Zimmerman (2002, p. 68), “self-regulation is cyclical in that self-reflections from prior efforts to learn affect subsequent forethought processes.” Combined with the presentation of these analytics, reflective practices were supported to aid in the improvement of learning. Each of the features of the recommender approach used for this research, from the ontologies created to the analytics displayed, were selected to support the SRL process.

Theoretical Implications

From a theoretical perspective, this research demonstrated how and why SRL theory can be used to guide educational recommender design. Instead of focusing on what is technically possible, infusing theory to guide the design creates connections between recommender design choices and what is pedagogically sound. While some existing research has focused on learning style (e.g. VARK and FSLSM), by going beyond this we can more accurately understand the learner. Existing recommender design research provided the foundation for the essential elements, but distinct design decisions altered the model and methods in order to support the SRL-based approach. Feedback from participants suggested that this approach is mostly accepted by students to enhance learning due to the solution’s fit (e.g. designed matched participant needs) and that system use had a positive impact on student learning. It supported the student studying process and made it easier, faster, and better. Finally, this research also serves to strengthen the link between the fields of education and IS as the TTF constructs were evident through the design and evaluation of the system.

Implications for Practitioners

From a practical perspective, the hope is that IS research like this will be used to enable higher education institutions to better adapt to individual learners with the goal of improving student success. Designs such as this one could be used to enhance how we provide electronic materials to learners in order to better meet the needs of all learners. In keeping with the goals of design science, communication of this research has existed throughout its development, from a published systematic literature review (McNett & Noteboom, 2022) to an AMCIS 2023 Top 25% emergent research forum paper (McNett & Noteboom, 2023). It is anticipated that the complete research will also yield future publications in the field of IS and beyond. This document provides the design on the artifact and summarizes what was learned in design principles using a manner that is of value to both researchers and professionals, supporting the mindset of design science research.

When considering the execution of this research, the lessons learned included the difficulties of recruiting participants and retaining participants throughout the duration of the study. While many students indicated that they wanted to participate in the study by consenting, many did not follow through by using the system and some who used the system did not complete the final survey. As indicated in the consent document, students were permitted to leave the study at any time, and it is unknown why students did not complete the study. This resulted in the need to conduct more case studies than originally planned. As each knowledge base was time consuming to create, having to execute several instances of the case study, each with a different knowledge base, extended the data collection period of this research and delayed the analysis of the results. The retention of student participants is a challenge to be considered when evaluating recommenders beyond narrow measures such as the accuracy of recommendations.

Limitations

This study sought to better understand how to effectively create an educational recommender that was guided by SRL theory and determine its impact on academic success. The results were self-reported by students and focused on perception of students when considering the perceived academic performance impact. Additional studies are needed to determine the accuracy of the recommendations and provide more concrete data concerning student academic success (e.g. grades). In developing the system, only one person established the knowledge base for each iteration of the study. Therefore, only the researcher coded each learning object based on their knowledge of the material and experience as an educator. This can have an impact on the effectiveness of recommendations and could be considered a limitation of this work. As suggested in the discussion section, a more collaborative-based approach to evaluating learning object quality may improve reliability.

This research would also benefit from a larger study consisting of a larger pool of participants to explore the validity of the results. As all participants were volunteers, volunteer bias may be present given the small number of volunteers, limiting the generalization of these results. While anonymity was assured in surveys submitted by participants, it remained difficult to recruit and retain participants.

Another limitation is the inclusion of the VARK learning style. This research attempts to include a learning theory that goes beyond a learning style approach, and in doing so embeds some elements of the existing VARK learning style. Given that learning styles are considered a myth by many, some may take issue with VARK's inclusion in this research. In this research it is used as the basis for the learning object presentation mode in a manner which supports multiple modes and can be overridden as necessary depending on SRL-based survey answers. Additional research may want to seek removal of VARK and discover its impact or lack thereof to address concerns relating to the use of a learning style.

Opportunities exist to explore use of an SRL-based recommender outside of this one institution and one department, as this study focused on applications at a single institution with a focus on several different programming-based courses within an IT department. This study also did not consider scalability factors as it focused on courses in a traditional environment. It did not focus on a larger scale (e.g. class sizes of 100+ students) and consider the impact this would have on system performance.

Future Research

There are several possibilities for future work. One of the most important directions for future works would be to include focusing on other evaluation measures (e.g. precision, recall) of the recommendations and the inclusion of academic achievement measures not directly reported by students such as grades in order to have a more complete picture of the effectiveness of this approach. This evaluation could be extended to other academic areas to support generalization of the results.

In keeping with a user-centered design approach advocated by similar research (Galaige et al., 2022) and in consideration of participant feedback, efforts could be expanded to consider enhancing the user interface to provide more transparency (e.g. item information and explanation) concerning why certain learning objects were recommended as suggested by Capelleveen et al. (2019).

When considering SRL, future work could address opportunities for functionality that were missed by this research. One example is integrating support for the explicit creation of student goals and automated tracking of activities in relation to these goals as needed to report student progress in real-time. In addition, Viberg et al. (2020) noted that SRL online environments tend to lack suggesting interventions. Including interventions based on student actions in the system (e.g. responses to assessment questions) may improve student learning. This is also an area missed by this research that would add value to an SRL-guided educational recommender approach.

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APPENDICES

APPENDIX A: USER PROFILE SURVEY

The following questions ask about your motivation for and attitudes when learning. Remember there are no right or wrong answers, just answer as accurately as possible. The responses will be utilized by the system to guide the recommendation of learning resources.

Part 1

Use the scale below to answer the questions. If you think the statement is very true of you, circle 7; if a statement is not at all true of you, circle 1. If the statement is more or less true of you, find the number between 1 and 7 that best describes you.

		Not at all true of me						Very true of me
1.	The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.	1	2	3	4	5	6	7
2.	Getting a good grade in this class is the most satisfying thing for me right now.	1	2	3	4	5	6	7
3.	It is important for me to learn the course material in this class.	1	2	3	4	5	6	7
4.	If I try hard enough, then I will understand the course material.	1	2	3	4	5	6	7
5.	I'm confident I can understand the basic concepts taught in this course.	1	2	3	4	5	6	7
6.	I'm confident I can understand the most complex material in this course.	1	2	3	4	5	6	7
7.	When studying for this class, I read my class notes and the course readings over and over again.	1	2	3	4	5	6	7
8.	I memorize key words to remind me of important concepts in this class.	1	2	3	4	5	6	7
9.	When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions.	1	2	3	4	5	6	7
10.	When reading for this class, I try to relate the material to what I already know.	1	2	3	4	5	6	7

11. When I study for this course, I go through the readings and my class notes and try to find the most important ideas.	1	2	3	4	5	6	7
12. I make simple charts, diagrams, or tables to help me organize course material.	1	2	3	4	5	6	7
13. When reading for this course, I make up questions to help focus my reading.	1	2	3	4	5	6	7
14. When I become confused about something I'm reading for this class, I go back and try to figure it out.	1	2	3	4	5	6	7
15. I rarely find time to review my notes or readings before an exam.	1	2	3	4	5	6	7
16. I make good use of my study time for this course.	1	2	3	4	5	6	7

Part 2

Select the best answer below that describes you.

17. When learning from the Internet I like:
    a. interesting written descriptions, lists and explanations.
    b. videos showing how to do or make things.
    c. interesting design and visual features.
    d. audio channels where I can listen to podcasts and interviews.

18. I want to learn how to play a new board game or card game. I would:
    a. use the diagrams that explain the various stages, moves and strategies in the game.
    b. read the instructions.
    c. listen to somebody explaining it and ask questions.
    d. watch other play the game before joining in.

End of Survey

APPENDIX B: PARICIPANT SURVEY

Study Recommender - Participant Survey

Thank you for participating in this research project concerning recommender design in higher education. In order to complete your participation, please complete the following survey. The survey should only take about 5-10 minutes to complete and your individual responses will remain anonymous. The data collected will only be used as part of this research as outlined in the consent form. No personal information or identifying information is collected as part of this form.

It is asked that you complete this survey by: Wednesday, March 15th

If you have any questions about the survey, please email: alicia.mcnett@trojans.dsu.edu

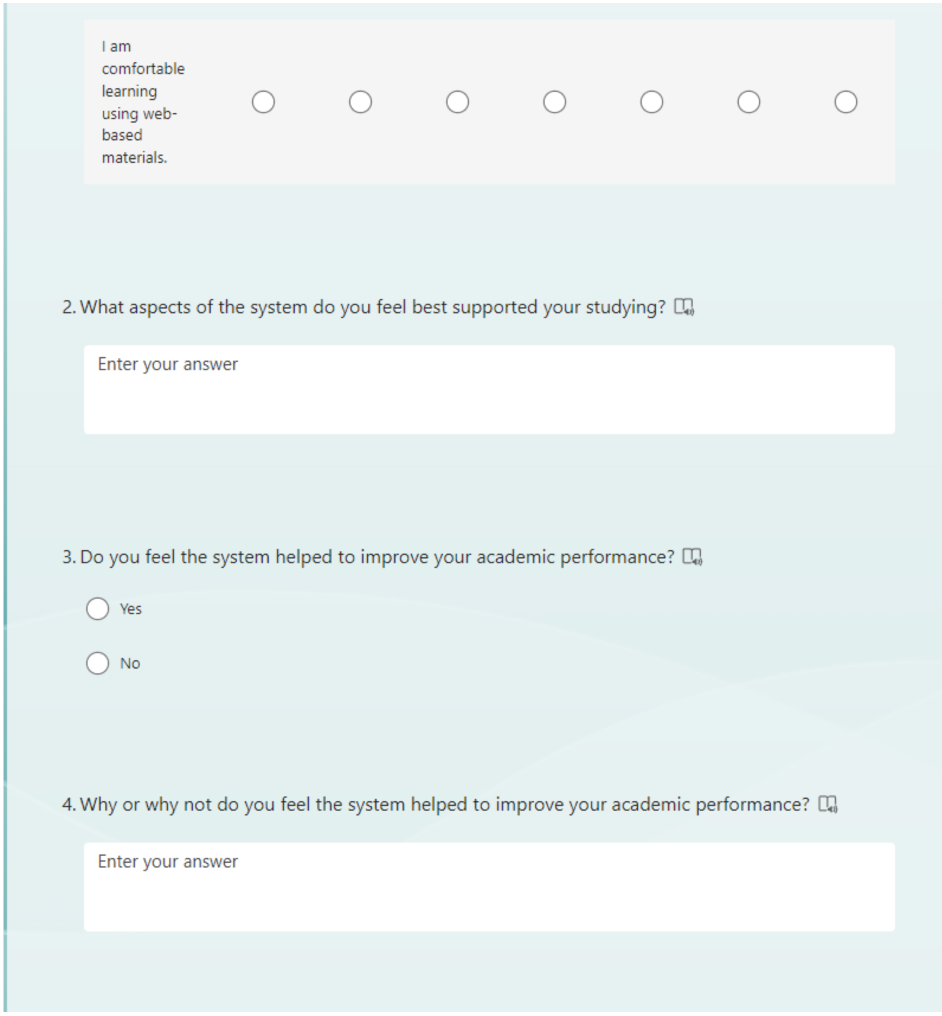
Thank you for your participation.

1. Please rate the following using the scale provided

	Very Strongly Disagree	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Very Strongly Agree
I used the study system to review class material.	○	○	○	○	○	○	○
I used the study system to check facts.	○	○	○	○	○	○	○
I used the system to address gaps in my knowledge.	○	○	○	○	○	○	○
The system helps me set study goals.	○	○	○	○	○	○	○
The system helps me monitor my studying.	○	○	○	○	○	○	○
The system helps me reflect on my study process.	○	○	○	○	○	○	○

I think that using the system would be well suited for the way I like to study.	○	○	○	○	○	○	○
A system would be a good tool to provide the way I like to study.	○	○	○	○	○	○	○
The system fit well for the way I like to study.	○	○	○	○	○	○	○

I used the system to study.	○	○	○	○	○	○	○
I used the system to review materials.	○	○	○	○	○	○	○
I used the system to adjust my learning goals and/or strategies.	○	○	○	○	○	○	○
The system helped me improve my studying.	○	○	○	○	○	○	○
The system helped me learn the material.	○	○	○	○	○	○	○
The system helped me perform better in a course.	○	○	○	○	○	○	○
I feel very confident using web-based systems for education.	○	○	○	○	○	○	○



I am comfortable learning using web-based materials. ○ ○ ○ ○ ○ ○ ○

2. What aspects of the system do you feel best supported your studying?

Enter your answer

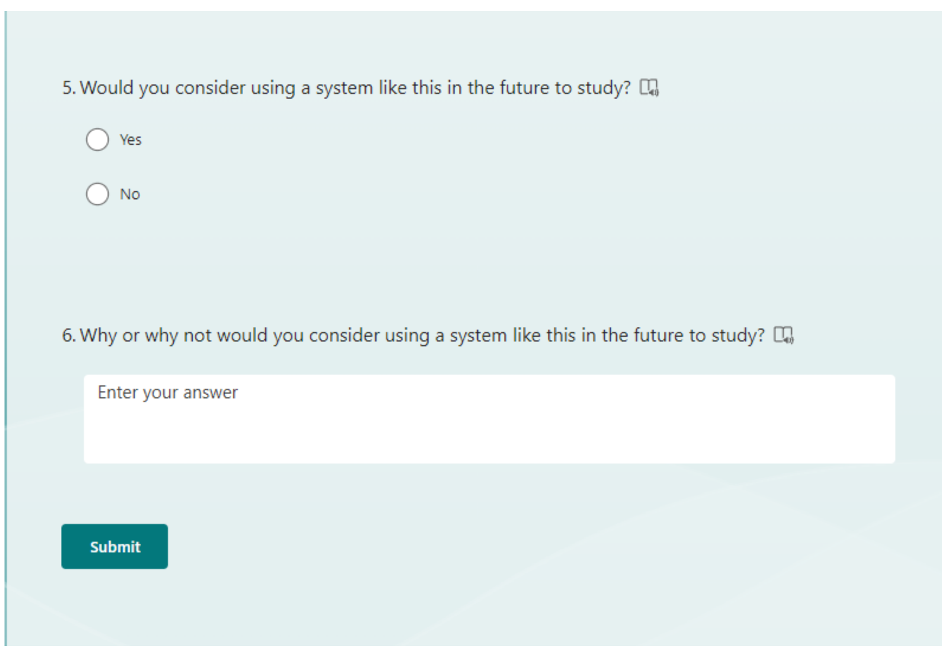
3. Do you feel the system helped to improve your academic performance?

○ Yes

○ No

4. Why or why not do you feel the system helped to improve your academic performance?

Enter your answer



5. Would you consider using a system like this in the future to study?

○ Yes

○ No

6. Why or why not would you consider using a system like this in the future to study?

Enter your answer

Submit

APPENDIX C: SURVEY RESULTS

Questions	Very strongly disagree	Strongly disagree	Disagree	Neutral	Agree	Strongly agree	Very strongly agree
I used the study system to review class material.	0%	0%	0%	10%	45%	19%	26%
I used the study system to check facts.	0%	3%	3%	23%	35%	19%	16%
I used the system to address gaps in my knowledge.	0%	0%	0%	16%	23%	39%	23%
The system helps me set study goals.	0%	3%	0%	19%	29%	26%	23%
The system helps me monitor my studying.	0%	0%	3%	23%	32%	26%	16%
The system helps me reflect on my study process.	3%	0%	6%	16%	29%	32%	13%
I think that using the system would be well suited for the way I like to study.	3%	3%	6%	16%	19%	23%	29%
A system would be a good tool to provide the way I like to study.	0%	0%	6%	6%	29%	32%	26%
The system fit well for the way I like to study.	6%	0%	10%	6%	39%	23%	16%
I used the system to study.	0%	0%	0%	0%	35%	32%	32%
I used the system to review materials.	0%	0%	0%	3%	39%	32%	26%
I used the system to adjust my learning goals and/or strategies.	0%	6%	6%	23%	42%	13%	10%
The system helped me improve my studying.	6%	3%	3%	13%	42%	19%	13%
The system helped me learn the material.	3%	0%	0%	10%	39%	23%	26%
The system helped me perform better in a course.	0%	0%	0%	26%	29%	23%	23%
I feel very confident using web-based systems for education.	3%	0%	3%	3%	29%	23%	39%
I am comfortable learning using web-based materials.	3%	0%	0%	13%	16%	29%	39%

APPENDIX D: RECOMMENDER CODE

The following contains the segments of code implemented that demonstrates the recommender's algorithm.

```
# This function performs the work to get the learning objects liked by
similar learners.
# Args: requires the current user id, concept, and subtopic
# Returns: the ids of learning objects liked by similar users
def getClusterData(userId, concept, subtopic):

    # get profile data
    query = "SELECT * FROM profile"
    profiledf = pd.read_sql_query(query, db.engine)

    # remove columns we don't need from profile before sending to KMeans -
note VARK learning style is not used for clustering
    df = profiledf.drop(columns = ['id','userId','answer17', 'answer18'])

    # use clustering to find similar users
    numUsers = User.query.count()
    k = round(math.sqrt(numUsers/2))
    kmeans = KMeans(n_clusters=k, init='k-means++', random_state=0)
    estimator = kmeans.fit(df)
    # place cluster id with original profile data
    profiledf['cluster'] = estimator.labels_

    # determine current user cluster
    userCluster = profiledf.loc[profiledf.userId==userId,
'cluster'].values[0]
    # get only user ids with same cluster number and covert this to a list
for processing
    newdf = profiledf.loc[profiledf['cluster']==userCluster]
    simIds = newdf['id'].values.tolist()
```

```
    # find object ids of items liked by these users
    query = text("SELECT materialId FROM userlog JOIN object ON
userlog.materialId = object.id where `like`= 1 AND userId in :ids AND
object.conceptId=:c AND object.subtopicId=:s")
    result = db.engine.execute(query, ids=simIds, c=concept,
s=subtopic).fetchall()

    # populate list of similar learner recommendations
    matIds = []
    for record in result:
        matIds.append(record.materialId)

    return matIds

# This function performs the work to get recommendations.
# Args: optional arguments include current page (for paging), concept, and
subtopic
# Returns: recommendation page with recommendations
ROWS_PER_PAGE = 1
@main.route('/recommendation')
@login_required
def recommendation():

    # if user is choosing a topic, get recommendation based on the topic
(and subtopic if chosen)
    page = request.args.get('page', 1, type=int)        # needed for paging
of results
    concept = request.args.get('concept', 1, type=int)  # defaults to first
topic if none selected
    subtopic = request.args.get('subtopic', 0, type=int)# defaults to first
subtopic if none selected
```

```
    ...

    # gather user information
    theUser = User.query.filter_by(email=current_user.email).first()
    theProfile = Profile.query.filter_by(userId=theUser.id).first()

    # gather concept information
    theConcept = Concept.query.filter_by(id=concept).first()

    if theProfile: # profile learner profile already exists, determine
recommendation - otherwise learner is sent to profile survey page
        # get metadata on all learning objects
        query = "SELECT * FROM object WHERE conceptId=%s and subtopicId=%s"
        df = pd.read_sql_query(query, db.engine, params=[concept,
subtopic])

        # don't show engaging questions by default in presentation of
learning object (0 == false)
        questionmode = 0

        # consider presentation mode (1 == true)
        styleScoreModifier = 1

        # first determine VARK presentation mode
        # VARK = Visual, Auditory, Read/Write, and Kinesthetic
        # if user answered questions relating to VARK, consider it
        if not theProfile.answer17 == 0 and not theProfile.answer18 == 0:
            object_vark_class = {
                "diagram": "v",
                "table": "vr",
                "slide": "r",
                "figure": "v",
                "narrative": "r",
```

```
                "exercise": "k",
                "self-assessment": "k",
                "video": "ak"
            }

            # populate style value according to VARK for each LO
            df['style'] = df.apply(lambda row: object_vark_class[row.type],
axis = 1)

            # add learning objects style score to LO based on how user
answered questions
            # encode user learning styles
            style1 = theProfile.answer17[0]
            style2 = theProfile.answer18[0]
            df['styleScore'] = np.where(df['style'].str.contains(style1) |
df['style'].str.contains(style2), 1, 0)
        else: # user did not answer survey questions relating to this so
ignore it
            df['styleScore'] = 0

        # set up SRL-based dimensions in user data frame
        userDf = pd.DataFrame(columns=['importance', 'lod', 'difficulty',
'relative', 'timeCommitment'])
        userDf.loc[0] = [1,1,1,1,1] # default values - 1 being true of
learning, 0 being not true of learner

        #1 all content levels important & most import concepts get
precedence
        #2 most important concepts should get precedence
        if not theProfile.answer1 == 0 and not theProfile.answer2 == 0: #
make sure user answered before factoring this in
            imp = (theProfile.answer2 + 1 - theProfile.answer1)/2
            userDf['importance'] = [imp]
```

```
        #3 task value
        if not theProfile.answer3 == 0: # make sure user answered before
factoring this in
            value = theProfile.answer3
            userDf['lod'] = [value]

        #4,5,6 control of learning beliefs and self-efficacy
        if not theProfile.answer4 == 0 and not theProfile.answer5 == 0 and
not theProfile.answer6 == 0: # make sure user answered before factoring
this in
            belief = (theProfile.answer4 + theProfile.answer5 +
theProfile.answer6)/3
            userDf['difficulty'] = [belief]

        #7 values repetition/rehearsal study method
        # likes to reread content/readings/course notes
        if not theProfile.answer7 == 0: # make sure user answered before
factoring this in
            df['styleScore'] = np.where(df['style'].str.contains("r"), 1,
df['styleScore'])

        #8 likes to memorize keywords/rehearsal study method
        # need to have focus on self-assessment
        if not theProfile.answer8 == 0: # make sure user answered before
factoring this in
            df['styleScore'] = np.where(df['type'] == "selfassessment", 1,
df['styleScore'])

        #9 values a mix of resources
        # types does not matter
        if not theProfile.answer9 == 0: # make sure user answered before
factoring this in
```

```
            styleScoreModifier = 1 - theProfile.answer9

        #10 make connections to prior on survey/elaboration study method
        if not theProfile.answer10 == 0: # make sure user answered before
factoring this in
            elab = theProfile.answer10
            userDf['relative'] = [elab];

        #11 & 12 prefers specific organization methods
        if not theProfile.answer11 == 0 and not theProfile.answer12 == 0: #
make sure user answered before factoring this in
            if round((theProfile.answer11 + theProfile.answer12)/2) == 1:
                # Be careful to maintain the original style score if it was
a 1
                df['styleScore'] = np.where(df['type'] == "diagram", 1,
df['styleScore'])
                df['styleScore'] = np.where(df['type'] == "table", 1,
df['styleScore'])

        #15 & 16 time and study environment factors
        if not theProfile.answer15 == 0 and not theProfile.answer16 == 0: #
make sure user answered before factoring this in
            time = (theProfile.answer15 + 1 - theProfile.answer16)/2
            userDf['timeCommitment'] = [time]

        # Metacognitive self-regulation focus
        #13 focus on making up questions to focus reading
        if not theProfile.answer13 == 0: # make sure user answered before
factoring this in
            questionmode = round(theProfile.answer13)

        #14 go back and try to figure out things they don't understand
(stress items not understood)
```

```
        # recommender should emphasize topics not understood
        if not theProfile.answer14 == 0: # make sure user answered before
factoring this in
            numOfFlagged = UserLog.query.filter_by(userId=theUser.id,
flag=1).count()
            if numOfFlagged > 0:
                flash("You may want to review items that you have
flagged.")

        # filter LOs
        # apply time commitment response when filtering LOs
        if userDf['timeCommitment'].iloc[0] > .5:
            df = df[(df['timeCommitment'] <= 5)] # only keep shorter items

        # multiply user values/preferences against each LO item
        df['importance'] = df.apply(lambda row: row.importance *
float(userDf['importance']), axis = 1)
        df['lod'] = df.apply(lambda row: row.lod * float(userDf['lod']),
axis = 1)
        df['difficulty'] = df.apply(lambda row: row.difficulty *
float(userDf['difficulty']), axis = 1)
        df['relative'] = df.apply(lambda row: row.relative *
float(userDf['relative']), axis = 1)
        df['styleScore'] = df.apply(lambda row: row.styleScore *
styleScoreModifier, axis = 1)

        # define which LO columns we want to add up to get the resulting
score
        cols = ['importance', 'lod', 'difficulty', 'relative',
'styleScore']

        # define new column that contains sum of specific columns for LO
        df['score'] = df[cols].sum(axis=1)
```

```
        # sort results
        df = df.sort_values(by=['subtopicId','score'], ascending=[True,
False])

        # get top 8 results
        toplist = df.iloc[:8]
        theids = toplist['id'].values.tolist()

        # consider peers for additional recommendations
            newIds = getClusterData(theUser.id, concept, subtopic) # calls
function below
            theids.extend(newIds) # add peer ids to end of the current list
of recommended LOs
            theids = list(dict.fromkeys(theids)) # remove duplicates from
the results

        # get the learning objects
        obj = Object.query.filter_by(id=theids[page-1]).first()

        # create variables for flag and like
        flag = 0
        like = 0

        # log item viewed
        userlog = UserLog.query.filter_by(userId=theUser.id,
materialId=obj.id).first()
        if not userlog: # not stored previously
            new_UserLog = UserLog(userId=theser.id, materialId=obj.id,
flag=0, like=0)
            db.session.add(new_UserLog)
            db.session.commit()
        else:
```

```
            flag = userlog.flag # need this for flag & like to work
properly on page and allow updating
            like = userlog.like

        # get recommendations and display page
        theSubtopic = Subtopic.query.filter_by(id=obj.subtopicId).first()
        allConcepts = Concept.query.all()
        query = text("SELECT subtopic.subtopic, subtopic.id FROM subtopic
JOIN object ON object.subtopicId=subtopic.id JOIN concept ON concept.id =
object.conceptId WHERE object.conceptId=:c group by subtopic.id ORDER BY
subtopic.id")
        allSubtopics = db.engine.execute(query, c=concept).fetchall()

        return render_template('recommendation.html', numresults =
len(theids), page=page, obj=obj, flag=flag, like=like, concept=theConcept,
subtopic=theSubtopic, questionmode=questionmode, concepts=allConcepts,
subtopics=allSubtopics)

    # no profile exists for this user
    flash("You need to complete the profile before you can review
recommendations.")
    return render_template('profile.html')
```