Something for Every Kind of Learner: Students' Perceptions of an Educational Recommender Study Tool

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Abstract

The field of education has the potential to better facilitate student learning by employing educational recommender systems that adapt the learning process to the needs of individual learners. There is a lack of research that ties educational theory to the design and implementation of these systems. In this research, the design science methodology is employed to advocate for an educational recommender framework with a theoretical base in self-regulated learning. This paper focuses on the qualitative evaluation of this approach to gain insights on students' perceptions of the resulting recommender when deployed to assist students when studying for an upcoming exam. Student perceptions are analyzed to obtain design themes that serve to aid future researchers and practitioners in the design of these systems.

Keywords: Recommender systems, self-regulated learning, education, design science.

1. Introduction

Recommender systems, or recommenders, are information filtering systems that enable users to find useful information online quickly and easily from a wealth of information. 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, healthcare, tourism, e-commerce, education, and social media (Roy & Dutta, 2022). Educational recommenders are a key component of web-based adaptive learning solutions that 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). These systems often make use of learning analytics.

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). As part of a student-facing solution, analytics can serve to close the feedback loop to "increase student awareness, reflection, and achievement" and ultimately improve student success (Bodily & Verbert, 2017b, p. 1). Recommenders present the opportunity to utilize these analytics to directly engage students and to impact student learning.

2. Statement of Problem

The field of education has seen rapid growth in learning analytics, but there is a need to strengthen the relationship between the design of such systems and learning theory (Mangaroska & Giannakos, 2019). Learning analytics solutions are often technocentric instead of considering student needs (Galaige et al., 2022). Also, many of these solutions only consider the educator's perspective and are viewed as passive applications of learning analytics such as those that predict performance or success.

Implementation 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). Wong et al. (2019) has cited Self-Regulated Learning (SRL) as an area where learning theory and learning analytics converge, making it an ideal choice of a theoretical base. SRL theory 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). 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,

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situations where students are more in control of their learning activities, learning autonomously, seeking assistance when needed, and reevaluating their own learning processes.

The goal of this research is to understand how this theory-based approach can best assist student learning when applied to recommender design by building on existing recommender design and information systems (IS) research. This research proposes the use of SRL as the theoretical lens by which to apply learning analytics in a recommender design. This paper addresses the question: *What factors best support learners in an SRL-guided recommender design?* In keeping with IS research, the results would be of benefit to both practitioners and researchers alike.

3. Related Work

Recommenders have applications in a variety of areas and are often differentiated by the way they filter items. Common filtering approaches include content-based, collaborative, knowledge-based, and hybrid filtering.

Content-based filtering systems determine recommendation candidates, such as items to recommend, based on similarities between candidates. They often use attributes that describe the candidates in determining the recommendation (Aggarwal, 2016, p. 14). This approach provides 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 approaches and found in many early recommenders (Ko et al., 2022).

Collaborative-filtering is based on the similarities between users and items simultaneously. This is found in more modern recommender approaches. 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). Model-based techniques 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.

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 is gathered for this approach. Recommendations can be constraint-based or case-based. 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). One common and popular type of knowledge-based recommender, ontology-based, provides a way to classify and structure (e.g. demonstrate relationships) the knowledge-based instances (Middleton et al., 2009).

The last approach, 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). Common limitations or issues include the lack of initial data needed to make recommendations (cold-start problem), distinctively unique users for which it is difficult to find similar users (gray sheep problem), inability of the system to surprise the user with a relevant item that otherwise would not be discovered (lack of serendipity) (Herlocker et al., 2004), inability to scale in real-time when users and/or items in the system increase, and overfitting or too closely aligning with other items liked (lack of diversity).

A variety of recommenders in education have been explored. Much of the existing research focuses on learning object recommendations (Dias & Wives, 2019; Jordán et al., 2021; Joy et al., 2021; Pereira et al., 2018; Wan & Niu, 2018; Zheng, 2021). 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. The filtering methods used to recommend these learning objects vary. In a systematic literature review on adaptive learning content recommenders (Raj & Renumol, 2021), a variety of recommendation methods were found. Content-based recommenders such as Albatayneh et al.'s (2018) recommendation architecture uses semantic filtering of negative ratings to provide content-based recommendations to learners. 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. Some researchers used a hybrid approach by combining both content-based and collaborative filtering techniques, such as Jordán et al.'s (2021) video recommender. Kapembe and Quenum (2019) used 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.

Recommenders provide a student-facing application of learning analytics. One of the most reiterated problems in learning analytics research is the lack of a theoretical approach. Systematic literature reviews concerning learning analytics focused on the gap between theory and practice (Banihashem et al., 2018; Mangaroska & Giannakos, 2019). For this research, SRL is the theory considered as it 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). It provides how to compensate for learning differences. In a systematic literature review of educational recommenders deployed in traditional higher education environments (McNett & Noteboom, 2022), only one of the articles included in the study connected the approach to SRL theory.

4. Methodology

This research follows the Peffers et al. (2007) methodology for conducting design science research in IS. The first step of this process, identification of the problem and motivation for researching a solution has been discussed in previous sections. The second step, the objectives of the solution in the form of system requirements informed by prior research are discussed next (in Section 4.1). After this, the third step, design and development of the artifact is presented (in Section 4.2). This is followed by the demonstration of the artifact, a web application (in Section 4.3) and discussion of its evaluation (in Section 4.4). The results of the evaluation are then presented and discussed (in Sections 5 & 6).

4.1. Artifact Requirements

The major deliverable, the envisioned artifact, is a framework that consists of a reference model and methods for a recommender designed to support student study efforts. The reference model represents components of the recommender and their relationships while the method focuses on the algorithm utilized to provide recommendations. The target audience for this artifact is a traditional college environment (e.g. not massive open online courses).

It is advocated that requirements for design science artifacts be established (Braun et al., 2015). Existing research, including knowledge of the research gap and known problem, has driven the determination of the artifact's requirements. First, the artifact should be informed by pedagogy/learning theory as its infusion is the focus of this research. It is clear from existing research that there is a need for the artifact's framework to be grounded in learning theory and with an understanding of pedagogical implementation (Zawacki-Richter et al., 2019). Next, recommendations should be made with consideration for course learning outcomes. In aligning with the pedagogical focus, the recommendations presented should be derived from learning outcomes of the course, as suggested by Mangaroska and Giannakos (2019). Also, learning analytics are to be presented in a student-facing manner to facilitate SRL. 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) . The artifact should also consider student learning style. 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). The artifact should also use quality learning objects as the recommender candidates and consist of a simple and quick interface to promote usability as is common with IS system design to promote the fit of the task the system is designed to support (Goodhue & Thompson, 1995). And finally, it would be remiss to not also focus on the importance of student privacy when constructing adaptive learning systems. Students should know how their data is collected and used, and it is important to recognize that students expect to be the primary beneficiary of the data collected (Tsai et al., 2020). While the use of analytics may serve to benefit students, this data does carry an inherent privacy risk.

4.2. Artifact Design

In supporting the first artifact requirement, the design of the artifact model conceptually supports SRL by facilitating three phases as described by Zimmerman (2002): forethought phase, performance phase, and self-reflection phase. When considering the forethought phase, the recommender aids the learner's goals related to the learning outcome and supports strategies to meet those goals. The performance phase involves self-control activities that allow the learner to keep track of their progress. This is in the form of features that allow selection of study topics, and the flagging of a topic or concept that is difficult or misunderstood by the learner to enable help seeking activities. The self-reflection phase is facilitated by reporting analytics related to recommender use. Presenting a breakdown of items viewed with respect to the learning outcomes facilitates that reflection. While activities like these were done manually by students before, the recommender can better enable many SRL processes by automating selection of learning objects, tracking objects viewed, and reporting this data 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.

The model supports the SRL process using standard recommender components in an approach similar to Chrysafiadi et al.'s ICALM system (2019) and other educational recommenders (Eryılmaz & Adabashi, 2020; Joy et al., 2021; Sarwar et al., 2019; Wan & Niu, 2018). Three levels of recommendation adaption are the basis for the model: content, learner, and display mode. The content level is facilitated by the domain ontology. The learner and display mode are determined by user profile input. To populate the learner profile, learners are required to complete an initial survey before receiving learning object recommendations. The survey includes selected questions from the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1991) and VARK survey (Fleming, 1995). The MSLQ is a self-reported survey instrument for college students to assess academic motivation orientations and learning strategies used. It has been used by hundreds of researchers throughout the world (Duncan & Mckeachie, 2010). The VARK questionnaire was established in 1995 to better understand a learner's preference of information presentation mode. VARK was included to meet the artifact requirement that takes into consideration learning style while MSLQ serves to paint a clearer picture of the student motivation and strategies (such as goal orientation and time management).

The design focuses on the commonly found approach of recommending learning objects (e.g. videos, diagrams, assessments, and exercises). Each object is linked to learning outcomes in support of the artifact requirements. The learning object structure utilized is similar to that in existing research (Joy et al., 2021; Sarwar et al., 2019) in knowledge-based adaptive learning recommenders while also considering several attributes derived from the MSLQ. The knowledge base also maintains a learner log ontology that keeps track of each learning object visited by the learner. It additionally indicates if the item was flagged or liked. This aids the performance and self-reflection phases in SRL, and supports the artifact requirement that emphasizes student-facing use of the analytics.

A hybrid filtering approach consisting of a knowledge-based ontology with recommendations enhanced by collaborative filtering will avoid limitations of other techniques. A traditional college classroom presents both cold start and gray sheep difficulties. The use of the knowledge-based recommender 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. Additionally, ontology-based approaches have many benefits such as improved accuracy and quality of recommendations (Tarus et al., 2018). The goal of incorporating collaborative filtering is to diversify recommendations; to help learners find new learning objects that users with similar profiles also liked. The resulting algorithm for filtering learning objects is summarized as: (1) determine learner profile from survey; (2) filter learning objects by study topic selected; (3) apply MSLQ and VARK rules; (4) determine learning object scores; (5) take first N recommendations with the highest score to present to the learner; (6) find neighbor recommendations by using a machine learning algorithm (K-means); and (7) add additional recommendations to the original N recommendations.

4.3. Artifact Instantiation

The artifact instantiation is a web-based application 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). 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 address the artifact's privacy requirement, various security controls such as encryption and access controls were implemented to protect student privacy.

To utilize the system, participants create an account and then complete an initial survey needed to construct the learner's profile. Upon completing the profile, they are taken to the dashboard page (Figure 1) where they can choose from study topics and monitor their progress. When they click on a study topic, they are then taken to their recommended learning objects (Figure 2) for the given topic.

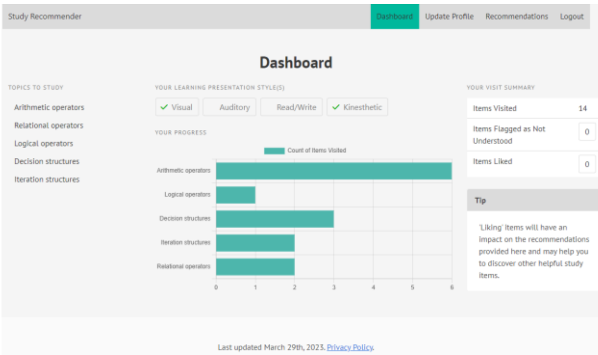

Figure 1. Study System Dashboard

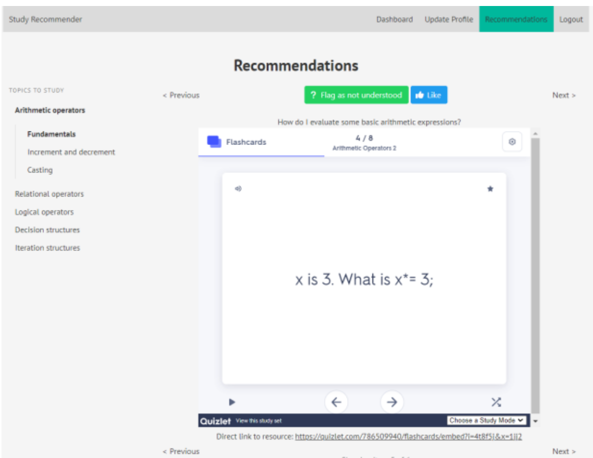

Figure 2. Example Learning Object

4.4. Artifact Evaluation

Existing recommender research (Bodily & Verbert, 2017a) has noted the need to explore student perceptions of these systems. The goal of the instantiation was to obtain this feedback given the novel SRL-influenced design. The demonstration for the evaluation was to be carried out at a single college in higher education. The study population consisted of college students most likely ranging in age from 18 to 22 years old. IRB approval was obtained and all participants, students in specific programming-based information technology courses, were volunteers.

Prior to agreeing to participate in the study, students received an email explaining the study and asking for their cooperation. The email explained the purpose of the research, included a consent document, incentive information, and outlined participant commitment. Consenting students then received an email with instructions on how to start using the system. Students had access to the system for a one- to two-week period as they prepared for an upcoming exam. After their exam, participants were distributed an online survey to complete anonymously. The survey included three open-ended questions: (1) what aspects of the system do you feel best supported your studying, (2) why or why not do you feel the system helped to improve your academic performance, and (3) why or why not would you consider using a system like this in the future to study.

Open coding techniques were applied to the open-ended survey questions to discover student perceptions of the system and to inform the evaluation. 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. Each response was evaluated one line at a time, often with at least one code recorded per line. QDA Miner Lite was used for coding. This was followed by axial coding in an effort to demonstrate relationships between the categories. Selective coding was used to unify the categories around a core category. Following standard grounded theory, coding of the open-ended question responses enabled identifying themes to address findings concerning the research question.

5. Results

In total, 114 possible participants were approached to participate in the study. From this pool of participants, 32 students completed the study, resulting in a 28% participation rate. One response was determined to be inconsistent and was removed, leaving 31 responses. The participants represent students from three different programming-based courses, each using the same system but different knowledge bases to support specific learning outcomes for their respective courses. However, because all participants were volunteers, volunteer bias may be present.

Coding results are shown in Table 1. From the selective codes emerged three key themes. Each theme is discussed next with detailed participant feedback.

5.1. Theme 1: Facilitate study efforts for improved outcomes

Self-motivation is an important quality of self-regulated learners (B. Zimmerman, 2002). Several participants noted that motivation to study was a challenge for them. As stated by participant 17, "… 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 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

Table 1. Coding Results

Axial Code	Code	Count
Selective Code: Facilitate study efforts for improved outcomes		
Individual Characteristic	Lack of motivation	4
Benefits of System Use	Encouraged studying	3
	Increased study efforts	1
	Improved academic performance	2
	Better prepared for exam	2
	Retained knowledge	3
Study Process Improvements	Focused studying efforts	7
	Provided study path	1
	Easier way to study	5
	Better way to study	3
	Faster way to study	4
Technology Expectations	Usability/Easy to use	5
	Needs more explanation	2
	Simple tool	1
	Quick response	1
	Needs dark mode	1
Selective Code: Provide a variety of quality relevant study materials		
Study Material Likes	Good and relevant examples	4
	Like practice problems	7
	Liked videos	7
	Liked self-assessments	7
	Liked documented practice problems	1
	Provided in-depth examples	1
	Different study material (from lectures)	5
	Multiple sources	3
Study Material Dislikes	Needs more assessments	1
	Needs more study material	1
Selective Code: Customize and support several study methods for every learner		
Study/Task Methods	Supported multiple study methods	5
	Combined study methods	1
	Tracked progress	1
	Helped student learn concept missed	2
	Helped learn independently	1
	Guided study process	1
	Easier access to study material	1
	Organized study materials	4
Personalized Learning	Personalization of study methods	10
	Helped variety of learners	1

their study efforts resulted in motivating some of the participants to study.

Several participants reported that the system served to encourage their study efforts as it helped them recognize not only the areas that they needed to study for the upcoming exam, but also helped them recognize areas of deficiency. Participant 3 stated that "[the system] helped [me] focus on the areas I did not know as well as others." It was also found that 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 the 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. It 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.

5.2. 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."

Participants noted that they considered the study material to be good, relative, and/or tangential to what they were learning in class, in addition to practical examples. 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."

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-based assessments.

The use of videos was also appreciated 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.

5.3. 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." 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 of concepts and reporting provided 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.

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 […] 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)."

6. Discussion

The three themes uncovered demonstrate factors that serve to support several facets of the SRL process. For example, the forethought phase of SRL sets the stage for learning, as learners consider what to learn and set learning goals. Here participants found organization of learning objects as key to guiding their learning process as it served to provide students with reflection concerning topics studied and choices when it came to selecting a topic to study. These aspects facilitated study efforts to help participants better identify knowledge areas where they may be weakest when studying and focus their efforts. Proper organization here is assisted by the use of ontologies.

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. The curation of knowledge bases is time-consuming but necessary. To best support student learning, the learning objects in the knowledge base need to be relevant and of high quality. 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).

Existing research in recommenders has supported considering the mode of learning object presentation, as this can improve engagement (El-Sabagh, 2021). Learning style or presentation preferences are prevalent learning parameters for learner modeling (Raj & Renumol, 2021). Here the use of MSLQ dimensions in addition to VARK survey responses helped to drive the selection of the most appropriate learning objects. For example, if a student favors organization strategies, learning objects that pull important concepts into table or charts may be preferred. In this study, students found the multiple modes refreshing and a good change of pace from how materials are normally presented during classes.

To support the self-reflection phase of SRL and its self-regulatory cycle, analytics should be reported back to the student. As noted by Zimmerman, "increases in self-satisfaction [of learning] enhance motivation." (2002, p. 68) 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 requires 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.

Lastly, 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.

7. Limitations and Future Work

This research sought to better understand factors that best support student learning when an educational recommender guided by SRL theory is employed. As an exploratory step in this cyclical design science research, the results of the qualitative evaluation were focused on perceptions of students. One of the most important directions for future works is to include a focus on other evaluation measures (e.g. precision, recall) of the recommendations and non-reported student measures such as grades to have a more complete picture of the effectiveness of this approach.

When considering SRL, future research opportunities include adding functionality missed by this research. One example is integrating support for the creation of student goals, and automated tracking and real-time reporting of activities supporting these goals. In addition, Viberg et al. (2020) noted that SRL environments tend to lack suggesting interventions that could improve student learning.

There are also opportunities to explore SRL-based recommender use outside of this one department and institution to support generalizability of results. This research also did not consider scalability factors as it focused on courses in a traditional environment.

8. Conclusion

This research builds upon existing educational recommender research with a design guided by SRL, an underexplored research area. Results from the qualitative analysis of the artifact stress three key design factors: the design of these systems should support overall goals, materials provided by these systems should be of high quality to support learning, and systems should be customized to support the needs of every learner. Future research that includes non-reported student measures and other disciplines may help shed additional insight on the effectiveness of this approach.

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