Vol. 18(4), pp. 54-62, April 2023
DOI: 10.5897/ERR2023.4313
Article Number: 537BE4470525
ISSN: 1990-3839

http://www.academicjournals.org/ERR

ACADEMIC JOURNALS
expand your knowledge

Educational Research and Reviews

Full Length Research Paper

An analysis of student decision making for educational recommender systems

Robert Wesley Songer[1*] and Tomohito Yamamoto[2]

[1]Department of Science and Technology, International College of Technology, Kanazawa, Japan.
[2]Department of Information and Computer Engineering, Kanazawa Institute of Technology, Kanazawa, Japan.

Received 8 February, 2023; Accepted 24 March, 2023

Recommender systems in education aim to help students make good decisions about the direction of their learning. The design of such systems in conventional research has treated the decision making process of students as a black box and assumes the best recommendations to be those that accurately predict student choices. Such an approach overlooks potentially valuable use cases for supporting optimal decision making, especially in self-directed learning contexts which present such challenges as identifying all available options, accurately evaluating the options against selection criteria, and selecting the best choice. This qualitative study aims to understand the areas where students struggle in the context of planning an open-ended project in order to inform the design of educational recommender systems. Data from interviews with 7 students at an international engineering school in Japan are analyzed to examine choice behaviors, influences on choice, and difficulty to choose in a self-directed learning context. The results illustrate considerations for designing educational recommender systems that can support the divergent thinking and convergent thinking demands of decision making. We provide case-based examples where the use of different recommender metrics, such as novelty and diversity, may provide value to users with different approaches to the decision-making process.

Key words: Decision making, self-regulated learning, educational recommender systems.

INTRODUCTION

In self-directed learning (SDL), learners are empowered to make their own decisions about their learning goals, assessment criteria, and resources while practicing self-regulation to achieve their goals (Robinson and Persky, 2020).

While SDL is often discussed in broad contexts that include non-traditional classroom settings, self-regulated learning (SRL) is studied in academic circles as the complex process in which students monitor and control their thoughts, feelings, and actions in pursuit of their learning goals. Throughout the process, students regularly consider multiple courses of action and must rely on their decision-making skills from planning to completion. Although there are several theoretical perspectives

*Corresponding author. E-mail: rsonger@neptune.kanazawa-it.ac.jp. TEL: +81-76-248-1080.

emphasizing different factors of the SRL process, it is generally assumed that students are aware of how their own self-regulatory processes affect their academic performance (Zimmerman, 2001). One might think that such awareness would lead students to act in their own self-interest and maximize their performance; however, they are regularly observed to make suboptimal decisions about what and how to study (Covington, 1992). Reasons for this may stem from their core values, beliefs about available options and decision-making strategies, or other factors influencing their performance (Byrnes et al., 1999). The task demands associated with self-regulation in open-ended learning contexts may also contribute to reducing learners' effective decision making (Baumeister et al., 1998). Thus, the ability to make well-informed and valuable decisions in open-ended, self-directed learning contexts is an essential but difficult skill to master.

In technology-enhanced learning (TEL), various decision-support systems have emerged from advances in big data and artificial intelligence. In particular, educational recommender systems (ERS) have emerged from the combination of digital learning environments that collect data on learner behavior with techniques for understanding and applying this data from learning analytics (Greller and Drachsler, 2012). Researchers studying the use of ERS in educational contexts are largely aware of the unique challenges they face compared to their commercial counterparts, and have made a number of useful observations to date. Some of the stated goals of ERS are to effectively and efficiently support the learning process, and thus their evaluation should measure such capabilities with user-centered studies (Manouselis et al., 2012). However, much of the ERS research continues to follow industry practices by focusing on algorithmic prediction accuracy and user satisfaction (Erdt et al., 2015). Relatively few recent studies evaluate domain-specific aspects of task support, learner motivation, and learning performance, or measure user perceptions of recommendation qualities such as usefulness, novelty, and diversity (Marante et al., 2020; Deschênes, 2020). This suggests that, rather than focusing on the learner's experience of interacting with the system, researchers continue to emphasize the system's ability to predict what the learner will choose. Treating decision making as a black box of inputs and outputs misses valuable opportunities to understand key behaviors that recommender systems aim to improve (Chen et al., 2013).

In response to this need for researchers to understand student decision making as they interact with the next generation of decision support technologies, we present this qualitative study as an attempt to better understand student decision making in self-directed, open-ended learning contexts. Specifically, we seek to identify students' decision-making behaviors in the planning phase of a self-directed learning project by examining (1) the extent to which they explore their options before selecting a learning goal, (2) the criteria they use when planning an open-ended, time-limited project, and (3) the areas where they struggle when selecting from their available options. The remaining sections are organized as follows. In the Literature Review section, we review relevant models and research on self-regulated learning, decision making, and ERS. The Methods section describes the approach of this qualitative study. In the Results and Analysis section, we relate our observations to our research questions and existing models, before summarizing our findings and their relevance to the design of an ERS in the Discussion and Conclusions section.

LITERATURE REVIEW

Self-regulated learning research has produced several models depicting the SRL process as cyclical, involving cognitive, motivational, and affective operations in three general phases (Panadero, 2017). These phases are: (1) the planning phase, which involves processes such as task interpretation, analysis, and goal setting; (2) the performance phase, in which learners enact and monitor their chosen strategies; and (3) the evaluation phase, which is characterized by feedback, reflection, and adaptation. One such model introduced by Winne and Hadwin (1998) specifically emphasizes the involved conditions, operations, products, standards, and evaluations called the COPES model. It identifies the information processing operations of searching, monitoring, assembling, rehearsing, and translating (collectively referred to as SMART) which are performed across the four stages of understanding, planning, performing, and evaluating.

SRL models assume decision making and goal setting to happen implicitly across the various phases rather than attempting to describe specific mechanisms for them. The COPES model is unique in that it includes the SMART operations as specific sub processes that may be used in the decision-making process itself. Winne (2001) further identifies AEIOU influences on learner choice as attributions, efficacy judgments, incentives, outcome expectations, and utility. Cases in which students intentionally choose suboptimal courses of action are then described as the results of weighing efficacy judgments and outcome expectations against utility and incentives.

Decision making

Decision-making involves making tradeoffs that are constrained by the limits of human cognition and influenced by personal and environmental characteristics. Personal characteristics include past experiences (Juliusson et al., 2005), biases (Kahneman et al., 1982), and emotions (Damasio, 1994). Environmental influences include perceived feasibility, expected outcomes, and social consequences (Grant, 2011). The limitations of human cognition require that effort be expended to identify and evaluate alternatives until the decision maker stops searching and makes a decision (Zopounidis, 2011). When faced with increasing search effort, decision makers may lower their standards for choice selection to reduce cost effort, even when aware that further search effort may lead to the discovery of better options (Payne et al., 1993). The term "satisfice" was coined by Simon (1957) to describe this act of choosing an option that may not be objectively the best, but is sufficient and satisfying to the decision maker. The extent to which they are willing to search for a good option can be determined by heuristics, which serve as computational models for choosing an option under certain circumstances (Gigerenzer et al., 2011). While heuristics may be useful for optimizing the use of limited cognitive resources, the ability of individuals to adhere to them is prone to error (Bhatia et al., 2021). In contrast to satisficing, maximizing involves considering all possible options before making a choice (Schwartz et al., 2002).

The decision maker's ability to maximize choice is strongly influenced by the conditions of the choice situation. In the rational model of decision making, the ideal choice situation is one in which the decision maker is fully aware of the desired outcome, has identified clear selection criteria, can evaluate each alternative to determine the optimal choice, and has the ability to implement the decision (Schoenfeld, 2011). Open-ended problems in self-directed learning rarely meet all conditions for being considered ideal decision situations. Here, the concept of bounded rationality may be more appropriate, as it recognizes that the decision maker must explore all options, has a limited ability to predict the outcomes of each choice, and selects options that are satisfactory within the given constraints (Simon, 1997).

Objectively rational decision making becomes largely impractical when the problem space is not well defined and an exhaustive list of options cannot be provided.

The tasks of searching for and selecting alternatives are accomplished by using divergent and convergent thinking (Runco, 2014; Lee, 2017). Divergent thinking is the cognitive process of generating or identifying multiple possible solutions to a question, while convergent thinking is the process of evaluating each solution and eliminating those that have no value with respect to the goals of the problem (Kim and Pierce, 2013). The SMART operations from the COPES model of self-regulated learning are similar to the concepts of divergent and convergent thinking. That is, the operations of searching and translating can be used to discover or create new information, while the operation of assembling creates new relationships between existing information. Once information is known, the rehearsing operation holds it in mind while the monitoring operation evaluates its qualities. Research shows that the practice of divergent and convergent thinking has several potential benefits for SRL, such as fostering tolerance for ambiguity and encouraging experimentation (Coleman et al., 2020). As the ability to generate numerous, novel, and diverse ideas, divergent thinking is considered a facet of creativity (Treffinger et al., 2002) and has been associated with rational decision-making styles (Palmiero et al., 2020). Contextually, the freedom to explore possibilities has been linked to student motivation and self-regulating efficacy (Flum and Kaplan, 2006). Using divergent thinking and convergent thinking together is generally recognized as a best practice for generating creative solutions to open-ended questions (Lee, 2017). Without divergent thinking skills, students may become fixated on a limited set of options, focusing their attention on a narrow set of ideas rather than generating fresh concepts (Butler and Roberto, 2018).

Once all available options are identified, the precise mechanism by which a person chooses is described in the emotion-imbued choice (EIC) model, which integrates existing models and theories of rational choice with 35 years of research into the influence of emotion in judgment and choice (Lerner et al., 2015). The EIC model combines evaluations of expected choice outcomes, choice qualities, and individual qualities with emotions integral to the decision, incidental emotions, and anticipated emotions from choice outcomes. Inputs to the decision include the potential utility of an option, qualities of the option such as probability of success, and personal qualities such as risk aversion, while their weights are influenced by various emotions related to the characteristics of the decision maker, the anticipation of certain outcomes, and the difficulty of the decision effort itself.

Decision support technology

Given the natural complexity of human decision making, several incarnations of technology have emerged to simplify the process. Jameson et al. (2014) propose the ASPECT model for researching and designing decision support technologies in the field of human-computer interaction (HCI). The model describes six patterns of decision behavior that system designers should consider when planning decision-enhancing features. The six patterns are aspect-based choice, socially-based choice, policy-based choice, experience-based choice, consequence-based choice, and trial-and-error-based choice. Following these patterns, a second model, called the ARCADE model, summarizes strategic approaches for technologies to implement when supporting user choice. These strategies include: accessing information and experience; representing the choice situation; combining and computing; advising on processing; designing the domain; and evaluating on behalf of the user.

As a form of decision support technology, educational recommender systems provide learners with information in their search for alternatives and evaluate options on their behalf. The most common goal of educational recommender systems is to help learners find learning resources, such as content, activities, or sequences of items (Drachsler et al., 2015). Recent research on these methods and their usefulness to learners is sparse, as shown in a review of ERS that support learner agency (Deschênes, 2020). The majority of the studies reviewed report some form of prediction accuracy metric (e.g., precision and recall) to evaluate the recommendations they provide, while those that report user-centered measures tend to focus only on user satisfaction without exploring deeper qualities. In contrast to this trend, Fazeli et al. (2018) show that the user-centric attributes of usefulness, novelty, diversity, and serendipity are valuable for understanding the user side of the interaction.

Other systematic reviews covering a broader range of ERS research have looked for gaps in the areas of application and methods of recommendation, with the aim of providing directions for future research (Urdaneta-Ponte et al., 2021; da Silva et al., 2022). Their findings show that few studies investigate the hybrid use of intelligent techniques that combine information about the user; there is little evidence of pedagogical effectiveness; and no studies investigate known issues for recommender systems in general, such as those related to the presentation of recommendations. Besides the complexity of human decisions, learning processes are also shaped by learners' educational interests (Verbert et al., 2012) and individual characteristics (Buder and Schwind, 2012). For these reasons, understanding all the factors involved is essential to overcoming the challenges of designing an effective and trustworthy ERS.

METHODS

This qualitative study analyzes data from interviews with students aged 16-17 regarding their experiences in an individual self-directed learning project. The project took place over five weeks at a small engineering school in Japan called the International College of Technology, Kanazawa[1]. Students enter the school around the age of 15 and join an intensive educational program that combines general post-secondary education with specialized engineering topics over five years. The SDL project is positioned at the end of a series of computing courses that introduce students to a variety of computing topics such as animation, video editing, programming, and web design. After two years of these computing courses, students begin the project where they must choose new skills to learn, plan their activities, and practice self-regulation in a completely autonomous project. The project requires them to make several planning decisions, including their topic, tasks, and final goals; the software and technologies they will use; and the rubric items on which they will be assessed. The teacher's role, in addition to a final assessment based on the rubric items chosen by the students, is limited to providing guidance and approval of the topics chosen by the students. How students approached these decisions for planning their self-directed learning was the focus of the interviews.

The authors first observed a class of 12 students during two of the five class periods designated for the project— one period at the beginning of the project and one at the end. The first class period was devoted to a brief introduction of the project, followed by time for students to plan their learning goals and specific tasks. At the time, it was explained to the students that they needed to choose a new computer skill to learn and the tasks they will complete in order to learn it.

They were instructed to write 3-5 tasks and allocate to them points for the final project grade. Up to 75 points were free for the students to distribute while the remaining 25 were reserved for the teacher's assessment of difficulty. Students then shared their chosen approach and the results of their efforts in presentations during the final class period.

After the semester finished, we asked to conduct interviews at a time when all grades had been completed but not yet reported to the students. Of the 12 students in the class, 8 were selected for interviews based on their ability to communicate clearly and reflect on their process as observed in the final presentations. All but one of them agreed to participate in the study. The interviews were conducted in four separate sessions, each consisting of one interviewer with one or two participants. The sessions were 30 to 40 min in length and were audio-recorded for later transcription. The audio recordings were transcribed using pseudonyms to protect participant confidentiality following the interviews.

During the interviews, participants were asked to reflect on the reasons for their choices as well as perceptions of their final outcomes. Guiding questions for the semi structured interview format focused on various dispositional, situational, and contextual factors surrounding each participant's project decisions. These questions were developed according to Kaplan and Flum's (2010) shared perspective of achievement goal theory and identity formation style theory; however, a previous analysis of the interview data from the same theoretical perspective yielded few interesting results (Songer and Yamamoto, 2021 for this analysis of the interview questions and results).The present study adopts an alternative analytical approach that focuses on decision-making influences and behaviors. The new analysis reexamines the interview data for (1) influences on student choices based on models for SRL and emotion-imbued choice, (2) choice behaviors based on the ASPECT model, and (3) difficulties to choose in terms of divergent thinking skills, convergent thinking skills, and aspects of decision making in self-regulated learning.

RESULTS AND ANALYSIS

Data on individual project outcomes, including overall theme and specific tasks selected by the participants for assessment as rubric items, are presented in Table 1 with each participant identified by their assigned pseudonym. What follows is an analysis summarizing for each participant the influential factors and decision-making behaviors involved in their decision, the extent to which they explored their options in their search, their criteria for selection, and difficulties encountered in the process.

Kenta decided to build an entire model of a car from the ground up using Fusion 360 (Autodesk) and print it out on a 3D printer. His choice was influenced by a desire to avoid tasks that were either too difficult or so easy that they would, as he put it, make him feel lazy. He expected the car model to be an enjoyable task that would improve his skills with the software. Kenta was confident in his experience with Fusion 360 from previous classes and felt it would be easier than his perceived alternatives of desktop publishing ideas.

Kenta described his perceived choice as between 3D

[1]https://www.ict-kanazawa.ac.jp/

Table 1. Planning decision outcomes of each participating student.

Participant	Project theme	Specific tasks
Kenta	Car Model in Fusion 360	Create moveable parts and 3D print
Takeo	Name Logo in Photoshop	Use two filters, an AI feature, and layer masks
Aya	Music Video in Premiere and Animate	Add a lip syncing animation and produce video of a certain length
Kei	Reinforced Learning in Python	Complete textbook problems and create an original program
Kazu	Video in Premiere with After Effects	Create an After Effects file
Shin	Appearance Attributes in Illustrator	Use features in the appearance panel to create various effects
Sakura	Image Editing in Photoshop	Add or change effects on an image

Source: Author.

modeling in Fusion 360 or desktop publishing in Photoshop (Adobe) and Illustrator (Adobe). His interest and experience led him to choose the car model and create every part himself, including moving parts such as doors or wheels. In the end, he had difficulty estimating the amount of time and effort it would take, as well as assessing his own ability to complete the work. He was unable to print the model by the end of the project.

Takeo created a logo of his name in Photoshop using filters, layer masks, and an AI function. He cited a lack of interest in programming and 3D modeling as a reason for choosing Photoshop, a tool he was comfortable with. The freedom of choice allowed him to choose a software tool he found easy to use and to avoid what he called "teacher slave labor". Kenta and Takeo both exhibited primarily attribute- and experience-based decision making, influenced by an anticipated enjoyment associated with their choices.

Takeo did not report exploring options or considering alternatives before choosing Photoshop. As a result, he may have chosen a skill that has no expected benefit to his future goals due to his limited perspective of available options. He stated that he would like to apply his skills to business and innovation in the agricultural industry, but it was not clear how this project would contribute to that goal. However, this contradiction did not seem to affect Takeo much, as he was able to make a decision on the first day.

Aya decided to create a music video in Premiere Pro (Adobe) with the addition of a lip-syncing animated character created in Animate (Adobe). She described feeling like the project had to be something big or complicated, such as programming; however, she chose to follow her interests in multimedia as she claimed to lack the confidence for programming. She also reported feeling pressure from perceived social expectations about the difficulty of the project, as well as time pressure from the demands of other classes. As a result, Aya had numerous criteria for selecting a project idea: (1) the tool had to be one that she felt confident with; (2) the tasks had to be advanced enough to earn points for difficulty; (3) the idea had to be unique so that she would stand out from her peers and get a good grade; and (4) the tasks had to be easy enough to complete during class time. She consulted with a classmate and together they considered many other options, such as video editing, 3D, desktop publishing, and programming. However, they struggled to choose the one with the best balance of grading potential and time efficiency. In the end, Aya spent two of the five class periods considering her options before finally settling on a topic. She was unique among the participants in that she exhibited decision-making behavior based primarily on consequences of choice, social expectations, and personal policies.

Kei immediately saw the project as an opportunity to learn about the machine learning topic of reinforcement learning from a textbook he had previously purchased for club activities but never used. He was concerned only with the teacher's approval, not with his classmates' perceptions or their ability to understand his topic. His decision was based solely on his own personal interest in the subject matter of the book.

Kei just explored the programming problems in the textbook and chose the ones he liked. The teacher gave him additional criteria for creating an original program so that he would have to apply the concepts rather than just copying solutions from the book. Overall, Kei had no difficulty choosing the topic, but he experienced a challenge in designing the original programming task.

Kazu decided to create a video using Premiere Pro and After Effects (Adobe), although it was not his first choice. He reported an initial interest in 2D animation using Live2D (Live2D Ltd.), but his idea was rejected by the teacher on the grounds that it would be a repetition of another project he had already done. He wanted to avoid subjects he considered boring, such as programming and web design. Unfortunately, his desktop PC broke down early in the project and he was forced to do it on a tablet PC instead. His final choice was influenced by the qualities of technical feasibility, anticipated enjoyment, and the desire to learn After Effects.

Kazu's exploration of alternatives was limited to programming, web design, 2D animation, and video editing. He eliminated options that he did not find fun and new, while the teacher eliminated the 2D animation option for him. Kazu also had technical criteria that the tasks be feasible on his tablet PC's weaker hardware. After his

Table 2. Summary of factors influencing participant choices, their exhibited decision-making behaviors, and experienced difficulties (DT = Divergent Thinking; CT = Convergent Thinking).

Participant	Influences on choice	Choice behavior	Difficulties
Kenta	Anticipated emotions	Attribute-based Experience-based	DT; Time estimates; Efficacy judgments
Takeo	Personal experience Anticipated emotions	Experience-based	DT; Maximizing utility
Aya	Time pressure Social perceptions Current emotions	Consequence-based Socially-based Policy-based	CT; Maximizing cost (time) vs. benefit (scoring)
Kei	Expected utility Current emotions	Experience-based Socially-based	DT & CT for designing an original solution
Kazu	Technical restrictions Anticipated emotions Expected utility	Attribute-based	DT; Maximizing utility
Shin	Personal experience Current emotions Expected utility	Experience-based	CT; Evaluating rubric items
Sakura	Current emotions Social perceptions	Attribute-based Socially-based	DT; Evaluating rubric items; fixation

Source: Author.

original idea was rejected, he could only think of doing a video editing project instead. This proved to be slow and cumbersome on his tablet.

Shin chose to focus his project on Illustrator's appearance attribute settings, which he claimed to have an existing interest in before the project began. He had knowledge and experience with Illustrator and saw the project as an opportunity to learn the features he had not previously used. He reported being aware that his peers probably thought he would choose a programming topic, but claimed that this expectation did not affect his decision.

While planning his project goals, Shin explored various effects that could be achieved with appearance attributes and selected specific ones to learn. He initially wrote rubric items to match specific attributes, but soon discovered while performing tasks that he needed to use them all to achieve each effect. This lack of familiarity with the features, which led to inaccurate rubric items, was his only reported difficulty.

Sakura decided to edit an image for various effects in Photoshop. She said she was interested in the software and wanted to learn how to use it the way others did. She admitted that she was unfamiliar with many of the features and was just following her impressions of what other people were doing with them. Her choice was influenced by the anticipated enjoyment of using Photoshop as well as social perceptions of its usefulness.

Sakura admitted that she did not explore other topics such as programming because she thought they were boring. Instead, she searched online for Photoshop tutorials that could be completed within class time and wrote her rubric items according to the various effects covered in the tutorial. She ended up fixating on a preconceived notion of how to use Photoshop and struggled to judge each effect's appropriateness as a rubric item. Her choice was one she could enjoy, though she was unsure the skills acquired would help her future career in management or data science.

Overall, participants reported a variety of influences on their decisions, choice behaviors, and difficulties during the decision-making process, as summarized in Table 2. Attribute-based and experience-based choice behaviors were the most prominent, as many of the participants reported choosing their topic out of anticipated enjoyment based on previous experiences with the software. In addition, choice-related emotions such as confidence and interest played a role in many of their decisions.

Kenta, Takeo, Kazu, and Sakura each reported considering only a few options, indicating a perceived lack of variety in the options available. As a result, Kenta chose a time-consuming goal, while Kazu's choice struggled with technical limitations. Takeo and Sakura's projects could be considered missed opportunities, as their respective outcomes had little apparent relevance to their future goals. These four participants would likely have benefited from divergent thinking support in the form of brainstorming or prepared lists of different topics.

Aya's case is a good example of a student who needs help with the convergent thinking side of the decision-making process. She had numerous criteria for choosing project tasks and spent a lot of effort trying to find the best choice. Her ability to maximize her selection was ultimately successful, but took considerable time (a resource she had hoped to preserve) and required assistance from others. In this case of planning a self-directed learning project, participants' difficulties with divergent thinking skills outweighed those with convergent thinking skills.

DISCUSSION

This analysis integrates several existing models and theories to illustrate the multifaceted decision-making process in self-regulated learning contexts. SRL models attempt to link various factors from the learner and the learning environment with the cognitive, motivational, and emotional processes involved in self-regulation. While these models largely represent the SRL process as a feedback loop in which the results of students' performance and self-reflection are used to refine their strategies, they lack details about the acts of goal selection and decision making. The decision-making mechanism itself is addressed with models of rational, emotion-imbued choice and incorporates the sub processes of searching for available options, determining selection criteria, and evaluating alternatives to select the best one. Factors influencing the decision include expected outcomes, qualities of the choices and the decision maker, concurrent emotions felt at the time of the decision, and emotions experienced or anticipated while considering options and outcomes. When the psychological effort to process each option and maximize choice is too high, the decision maker will use satisficing criteria to make a decision before considering all options.

Educational recommender systems have the potential to support decision making in several ways as described in the ARCADE model (Jameson et al., 2014). For learners who struggle with using divergent thinking to discover new options, an ERS can provide information and present the choice situation to reveal options or aspects of the context that are beyond their perspective. Takeo, Kazu, and Sakura each had difficulty perceiving a wide range of options for their project topics, making them good target users for such a use case. In Takeo's case, recommendations for a wide range of topics would have increased his chances of finding something that met his criteria and also related to skills he would need in the future. Kazu would have benefited from novel recommendations to encourage more diverse thinking about fun project ideas that would work within the constraints of his computer hardware. Similarly, Sakura, who lacked confidence in her own decision-making ability, might have been more satisfied with her choices if they had been presented by an ERS she could trust. Such a system could process only some of the steps, leaving the rest to the user, or explain how the recommendations were generated to provide transparency and help engage the user in choosing (Jameson et al., 2015).

An ERS that aims to support discovery would need to compute metrics such as novelty and diversity to include items that the user has not previously considered. Novelty metrics could be global metrics calculated from the inverse of item popularity across all users or item unexpectedness relative to the user's previous experience (Castells et al., 2015). Aya, who believed that her grade depended on choosing a unique topic, would likely have benefited from recommendations generated using the global metric of inverse item popularity. On the other hand, users such as Kei and Kazu might have preferred user-specific unexpectedness, which is calculated by comparing an item's properties to those previously selected by the user. Such novel recommendations may have provided Kei with unique ideas for his original reinforcement learning problem. Similarly, Kazu might have discovered novel project ideas that he could enjoy without requiring a high-spec PC.

When users have specific selection criteria, the recommender system can incorporate them into knowledge-based and intelligent recommendation generation methods. Using these criteria, the ERS can evaluate items on behalf of the user and support convergent thinking by narrowing down a large subset of options. It could then present either a single optimized choice or a set of choices for consideration along with their relevant properties. These systems would use utility metrics that measure some benefit to the user as defined by their criteria. For example, in Aya's case, difficulty and effort rankings would allow her to quickly determine which topics might be the most efficient to achieve the highest score.

Even when the ERS evaluates options and presents a carefully tailored set to the user, the user may still struggle with the given size and diversity of the consideration set, depending on their tendency to maximize or satisfice their choice (Schwartz et al., 2002; Saltsman et al., 2021). The design of the ERS should consider adjusting the level of diversity in the option set (Willemsen et al., 2011) or presenting options that are clearly divided into categories and possibly marked for personalization (Mogilner et al., 2008). Since Aya spent two full class periods considering her options, it is clear that she was trying to maximize her decision. A consideration set for her would need to be organized with a variety of topics with high difficulty and low effort ratings.

As a qualitative study based on observations and interviews, these findings are limited by the nature of self-reported data. Participants may have been selective in how they answered the interview questions without being completely honest. Each participant had experience with the interviewer as a teacher prior to participating in the study, so their responses may have been influenced by this pre-existing relationship. In addition, self-report data are limited by the perspectives of the participants, who are likely unaware of the theoretical motivations behind each question. The effects of these limitations most likely reduced the potential degree of data coverage and, to a lesser extent, accuracy.

Nevertheless, the purposes of this study do not dictate that broad coverage or strict accuracy be achieved, and it was believed that the data we were able to collect sufficiently illustrate the panorama of emotions, motivations, and cognitive processes involved.

The evaluation of ERSs in support of student agency has been heavily weighted towards prediction accuracy and away from user perceptions of recommendations (Deschênes, 2020). This analysis highlights specific aspects of decision making that contribute to the value students place on their choices, while the discussion relates these aspects to the design of recommender systems in education. By approaching interviews with students from the perspectives of SRL models, divergent thinking, convergent thinking, and emotion-imbued choice, we uncovered several examples of participants' decision-making behaviors, their search processes, the types of criteria they use for selection, and areas where they may struggle along the way. This discussion used these examples to highlight aspects of ERS design that have been largely overlooked in previous research. The cognitive demands of divergent and convergent thinking in the decision-making process are shown to be worthy issues for ERSs to address. Future research should explore approaches to the quantity, variety, and presentation of recommendations in terms of how they relate to the different decision-making qualities and characteristics of the learner. Educational recommender systems are positioned to provide unique value to learners, so it is important that researchers chart their own course rather than follow the trends of consumer-based systems.

FUNDING

All funds for this research were provided by Yamamoto Laboratory at Kanazawa Institute of Technology.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

REFERENCES

Baumeister RF, Bratslavsky E, Muraven M, Tice DM (1998). Ego depletion: Is the active self a limited resource? Journal of Personality and Social Psychology 74(5):1252-1265.

Bhatia S, He L, Zhao WJ, Analytis PP (2021). Cognitive models of optimal sequential search with recall. Cognition 210:104595.

Buder J, Schwind C (2012). Learning with personalized recommender systems: A psychological view. Computers in Human Behavior 28(1):207-216.

Butler AG, Roberto MA (2018). When Cognition Interferes with Innovation: Overcoming Cognitive Obstacles to Design Thinking. Research-Technology Management 61:45-51.

Byrnes JP, Miller DC, Reynolds M (1999). Learning to make good decisions: A self-regulation perspective. Child Development 70(5):1121-1140.

Castells P, Hurley NJ, Vargas S (2015). Novelty and Diversity in Recommender Systems. In: Ricci F, Rokach L, Shapira B (eds), Recommender Systems Handbook (2nd ed.) pp. 881-918. Springer, Boston.

Chen L, de Gemmis M, Felfernig A, Lops P, Ricci F, Semeraro G (2013). Human Decision Making and Recommender Systems. ACM Transactions on Interactive Intelligent Systems 3(3):1-7.

Coleman E, Shealy T, Grohs JR, Godwin A (2020). Design thinking among first-year and senior engineering students: A cross-sectional, national study measuring perceived ability. Journal of Engineering Education 109:72-87.

Covington MV (1992). Making the grade: A self-worth perspective on motivation and school reform. Cambridge University Press. https://doi.org/10.1017/CBO9781139173582

Da Silva FL, Slodkowski BK, da Silva KK, Cazella SC (2022). A systematic literature review on educational recommender systems for teaching and learning: research trends, limitations and opportunities. Education and Information Technologies pp. 1-40.

Damasio AR (1994). Descartes' Error: Emotion, Reason, and the Human Brain. Putnam, New York.

Deschênes M (2020). Recommender systems to support learners' Agency in a Learning Context: a systematic review. International Journal of Educational Technology in Higher Education 17:1-23.

Drachsler H, Sanatos O, Manouselis N (2015). Panorama of Recommender Systems to Support Learning. In: Ricci F, Rokach L, Shapira B (eds), Recommender Systems Handbook (2nd ed.) pp. 421-451. Springer, Boston.

Erdt M, Fernandez A, Rensing C (2015). Evaluating recommender systems for technology enhanced learning: a quantitative survey. IEEE Transactions on Learning Technologies 8(4):326-344.

Fazeli S, Drachsler H, Bitter-Rijpkema M, Brouns F, Vegt WVD, Sloep PB (2018). User-Centric Evaluation of Recommender Systems in Social Learning Platforms: Accuracy is Just the Tip of the Iceberg. IEEE Transactions on Learning Technologies 11(3):294-306.

Flum H, Kaplan A (2006). Exploratory Orientation as an Educational Goal. Educational Psychologist 41(2):99-110.

Gigerenzer G, Hertwig R, Pachur T (eds) (2011). Heuristics: The Foundations of Adaptive Behavior, Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199744282.001.0001

Grant R (2011). Contemporary strategy analysis.Wiley, New York.

Greller W, Drachsler H (2012). Translating learning into numbers: A generic framework for learning analytics. Journal of Educational Technology & Society 15(3):42-57.

Jameson A, Berendt B, Gabrielli S, Gena C, Cena F, Vernero F, Reinecke K (2014). Choice architecture for human-computer interaction. Foundations and Trends in Human-Computer Interaction 7(1-2):1-235.

Jameson A, Willemsen MC, Felfernig A, de Gemmis M, Lops P, Semeraro G, Chen L (2015). Human Decision Making and Recommender Systems. In: Ricci F, Rokach L, Shapira B (eds) Recommender Systems Handbook. Springer, Boston. https://doi.org/10.1007/978-1-4899-7637-6_18

Juliusson EA, Karlsson N, Gärling T (2005). Weighing the past and the future in decision making. European Journal of Cognitive Psychology 17:561-575.

Kahneman D, Slovic P, Tversky A (eds) (1982). Judgment under Uncertainty: Heuristics and Biases. Cambridge University Press. https://doi.org/10.1017/CBO9780511809477

Kaplan A, Flum H (2010). Achievement goal orientations and identity formation styles. Educational Research Review 5:50-67.

Kim KH, Pierce RA (2013). Convergent Versus Divergent Thinking. Encyclopedia of Creativity, Invention, Innovation and Entrepreneurship. Springer, New York. https://doi.org/10.1007/978-1-4614-3858-8_22

Lee KH (2017). Convergent and divergent thinking in task modification: a case of Korean prospective mathematics teachers' exploration. ZDM Mathematics Education 49:995-1008.

Lerner JS, Li Y, Valdesolo P, Kassam KS (2015). Emotion and Decision Making. Annual Review of Psychology 66(1):799-823.

Manouselis N, Drachsler H, Verbert K, Duval E (2012). Recommender Systems for Learning. Springer, Berlin.

Marante Y, Silva VA, Gomes Jr J, Vitor MA, Martins AF, Souza JF (2020).

Evaluating Educational Recommendation Systems: a systematic mapping. In Anais do XXXI Simpósio Brasileiro de Informática na Educação pp. 912-921. SBC.
Mogilner C, Rudnick T, Iyengar S (2008). The mere categorization effect: How the presence of categories increases choosers' perceptions of assortment variety and outcome satisfaction. Journal of Consumer Research 35(2):202-215.
Palmiero M, Nori R, Piccardi L, D'Amico S (2020). Divergent Thinking: The Role of Decision-Making Style. Creativity Research Journal 32(4):323-332.
Panadero E (2017). A Review of Self-regulated Learning: Six Models and Four Directions for Research. Frontiers in Psychology P 422.
Payne JW, Bettman JR, Johnson EJ (1993). The adaptive decision maker. Cambridge University Press. https://doi.org/10.1017/CBO9781139173933
Robinson JD, Persky AM (2020). Developing Self-Directed Learners. American Journal of Pharmaceutical Education 84(3).
Runco MA (2014). Chapter 1 - Cognition and Creativity. In Runco MA (Ed.), Creativity (2nd ed.) pp. 1-38). Academic Press. https://doi.org/10.1016/B978-0-12-410512-6.00001-1
Saltsman TL, Seery MD, Ward DE, Lamarche VM, Kondrak CL (2021). Is satisficing really satisfying? Satisficers exhibit greater threat than maximizers during choice overload. Pyschophysiology 58(1).
Schoenfeld AH (2011). How we think: A theory of goal-oriented decision making and its educational applications. Routledge, New York.
Schwartz B, Ward A, Monterosso J, Lyubomirsky S, White K, Lehman D (2002). Maximizing versus satisficing: Happiness is a matter of choice. Journal of Personality and Social Psychology 83(5):1178-1197.
Simon HA (1957). Models of Man: Social and Rational. John Wiley & Sons, New York.
Simon HA (1997). An Empirically Based Microeconomics. Cambridge University Press.
Songer RW, Yamamoto T (2021). Towards Educational Recommender Systems for Self-Directed Learning: Profiling Student Achievement Goals and Identity Formation to Inform Recommendation Evaluation Metrics. 5th International Conference on Education and Multimedia Technology. Association for Computing Machinery, pp. 11-17.
Treffinger DJ, Young GC, Selby EC, Shepardson C (2002). Assessing Creativity: A Guide for Educators. National Research Center on the Gifted and Talented.
Urdaneta-Ponte MC, Mendez-Zorrilla A, Oleagordia-Ruiz I (2021). Recommendation Systems for Education: Systematic Review. Electronics 10(1611).
Verbert K, Manouselis N, Ochoa X, Wolpers M, Drachsler H, Bosnic I, Duval E (2012). Context-aware recommender systems for learning: A survey and future challenges. IEEE Transactions on Learning Technologies 5(4):318-335.
Willemsen MC, Knijnenburg BP, Graus MP, Velter-Bremmers LC, Fu K (2011).Using latent features diversification to reduce choice difficulty in recommendation lists. Recommender Systems 11:14-20.
Winne PH, Hadwin AF (1998). Studying as self-regulated learning. In Hacker DJ, Dunlosky J, Graesser AC (eds), Metacognition in educational theory and practice pp. 277-304. Lawrence Erlbaum Associates Publishers.
Winne PH (2001). Self-regulated learning viewed from models of information processing. In Zimmerman BJ, Schunk DH (eds), Self-regulated learning and academic achievement: Theoretical perspectives. Lawrence Erlbaum Associates Publishers, pp. 153-189.
Zimmerman BJ (2001). Theories of self-regulated learning and academic achievement: An overview and analysis. In Zimmerman BJ, Schunk DH (eds) Self-regulated learning and academic achievement: Theoretical perspectives. Lawrence Erlbaum Associates Publishers pp. 1-37.
Zopounidis C (2011). Handbook of multicriteria analysis. Springer, New York.