Motivational Design in an Intelligent Tutoring System That Helps Students Make Good Task Selection Decisions

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Abstract. Making effective problem selection decisions is an important yet challenging self-regulated learning (SRL) skill. Although efforts have been made to scaffold students' problem selection in intelligent tutoring systems (ITS), little work has tried to support students' learning of the transferable problem selection skill that can be applied when the scaffolding is not in effect. The current work uses a user-centered design approach to extend an ITS for equation solving, *Lynnette*, so the new designs may motivate and help students learn to apply a general, transferable rule for effective problem selection, namely, to select problem types that are not fully mastered ("Mastery Rule"). We conducted user research through classroom experimentation, interviews and storyboards. We found that the presence of an Open Learner Model significantly improves students' problem selection decisions, which has not been empirically established by prior work; also, lack of motivation, especially lack of a mastery-approach orientation, may cause difficulty in applying the Mastery Rule. Based on our user research, we designed prototypes of tutor features that aim to foster a mastery-approach orientation as well as transfer of the learned Mastery Rule when the scaffolding is faded. The work contributes to the research of supporting SRL in ITSs through a motivational design perspective, and lays foundation for future controlled experiments to evaluate the transfer of the problem selection skill in new tutor units where there is no scaffolding.

Keywords: Problem selection · Self-Regulated Learning · Mastery orientation · Motivations · User-centered design · Intelligent tutoring system · Open learner model

1 Introduction

Making problem selection decisions is an important self-regulated learning (SRL) process [17]. Strategic problem selection can lead to better learning outcomes as compared to randomly selected problems [13]. Although students generally prefer to have control over their own problem selection [7], studies have found that giving students control over which problems to solve often leads to worse learning outcomes than system-selected problems [3]. Therefore, researchers of intelligent tutoring systems (ITSs) have tried to design systems that have motivational advantages of student control while mitigating the downside of potentially poor problem selection decisions.

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For example, one ITS shares control over problem selection between students and the system, fostering student motivation through some student control while preventing the students from making decisions that are detrimental to learning [12]. Adaptive navigational support has also been designed and implemented in hypermedia learning environments to aid students in making effective problem selection decisions through visual cues [5]. However, the prior work has mainly focused on scaffolding making problem selection decisions during learning. Little work has investigated whether and how an ITS can be designed to help students learn the transferable skill of making problem selection decisions that can be applied when the scaffolding is not in effect.

The current work focuses on extending an ITS for equation solving, *Lynnette* [12], so that it can motivate and help students learn to apply an effective strategy for selecting problems in ITS, namely, to select problem types that are not fully mastered while avoiding problem types that are (we will refer to this as the “Mastery Rule”). The Mastery Rule is based on theories of mastery learning [11]. System-controlled problem selection in an ITS based on this rule has been shown to significantly enhance student learning [8]. As a first step towards teaching students problem selection skills, we keep the Mastery Rule simple by not taking into account the spacing effects [1]. Our goal is to help students become better at self-regulating problem selection in their own learning, so that they can actively apply the Mastery Rule later when there is no ITS support for problem selection.

Theories of SRL stipulate that effective self-regulation requires not only knowledge of metacognitive strategies, but also motivations that foster the active use of the strategies [17]. Scaffolding for SRL processes in ITSs often aims at helping students correctly apply the metacognitive strategies (e.g., [2], [4]). Very little research has tried to foster students’ motivation for applying the metacognitive strategies in ITSs. One study promoted a teammates relationship between students and the tutor, which motivated the students to engage in more effective help-seeking behaviors [16]. However, it is still largely an open question how we can use motivational design in ITSs to help students *want* to use the metacognitive strategies.

We emphasize motivational design (design to foster motivations) in *Lynnette* to help students *want* to apply the Mastery Rule when they are given control over problem selection, in addition to designs that help them correctly apply the rule. We adopted a user-centered design approach to solve the design problem: How to motivate and help students learn to apply the transferable skill of making problem selection decisions based on the Mastery Rule. The user-centered design approach entails conducting user research to uncover user needs and help generate design ideas [10]. Thorough user research will help ground our designs in empirical findings about the users’ knowledge, motivations and behaviors regarding selecting problems in ITSs.

Specifically, we combined user-centered design techniques including experimentation, interviews, and storyboards to study how students naturally select problems in the tutor, what knowledge they have for the Mastery Rule as well as their motivations for following the rule. Next, we built prototypes of tutor features that foster motivation and learning of the Mastery Rule based on results of our user research and grounded in motivation theories. We present and discuss results from our user research, as well as the final design prototypes.

2 Classroom Experimentation

As a first step in our user-centered design process, we conducted an exploratory classroom experiment to investigate how students naturally select problems in *Lynnette* with and without mastery information displayed by an Open Learner Model (OLM). OLM is a type of learning analytics that displays information about students' learning status (how much/how well they have learned for each type of problems) tracked and assessed by the system's student model, e.g., skill bars. Prior work highlights that an OLM has the potential to support students' problem selection [6], but no work has investigated whether and how the presence of an OLM might influence students' problem selection decisions.

Lynnette offers practice for five types of equations (categorized into five levels as shown in Figure 1), with increasing difficulty. *Lynnette* provides step-by-step feedback on students' equation solving, as well as on-request hint messages. There were two conditions in the experiment. Both conditions needed to select problems from a problem selection screen by clicking one of the "Get One Problem" buttons. As shown in Figure 1, for the OLM condition, the problem selection screen showed the student's progress towards mastery for the five levels, calculated by Bayesian Knowledge Tracing. For the noOLM condition, no mastery information was displayed on the problem selection screen – behind the scenes, the tutor still computed the mastery estimates so that they were available in the log data for later analysis. The levels were never locked and the students were able to keep selecting problems from a mastered level. Once the student selected a level, the tutor picked a problem from the chosen level and brought the student to the problem solving interface, which was the same for the two conditions.

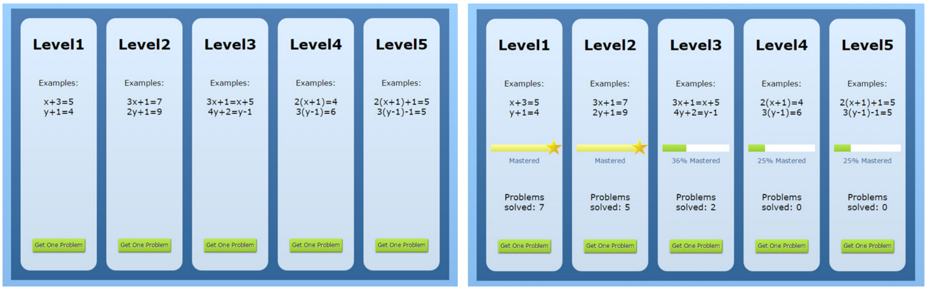

Fig. 1. Problem selection screen for the noOLM (left) and the OLM condition (right)

Twenty-five 7th and 8th grade students from 2 classes participated in the experiment. They were taught by 2 teachers at the same local public school. The students were randomly assigned within each class to one of the two conditions. There were 13 students in the OLM condition, and 12 in the noOLM condition. The students learned with the two versions of *Lynnette* for two 41-minute class periods on one school day. No instructions were given to the students with respect to how they should select problems in the tutor during the experiment. We analyzed the tutor log data to investigate what problems students selected to practice during the two class periods, especially whether the students selected problems from levels that had already been mastered, i.e., whether they violated the Mastery Rule.

On average, the OLM condition completed 21.08 (SD=7.65) problems, and the noOLM condition completed 28.75 (SD=14.32) problems. A 1-way ANOVA shows that the difference was not statistically significant. Table 1 shows the two conditions' average percentages (number of unmastered/mastered problems completed in a level/total number of problems completed) of problems completed in each level. (Note that under perfect application of the Mastery Rule, students practice unmastered problems only.) For both conditions, students selected most problems from level 1, 2, and 3. For the noOLM condition, on average, 34% of the problems completed by each student were from mastered levels, while only 8% of the problems were selected from the mastered levels for the OLM condition. A 1-way ANOVA shows that the difference of the percentages is statistically significant (F (1, 23)=7.207, *p*=.013, *d*=1.07).

Table 1. Means and SDs for percentages of problems completed in each level

	Unmastered Problems						Mastered Problems		
	L1	L2	L3	L4	L5	Total	L1	L2	Total
noOLM	.35(.26)	.12(.12)	.08(.08)	.04(.07)	.07(.09)	.66(.29)	.27(.27)	.06(.12)	.34(.29)
OLM	.27(.09)	.34(.12)	.26(.19)	.02(.04)	.03(.12)	.92(.17)	.06(.12)	.03(.05)	.08(.17)

The results of the classroom experiment shed light on how students select problems in an ITS that offers student-control over problem selection:

1) OLM helps students effectively select problems. Students in the OLM condition selected significantly fewer mastered problems as compared to the noOLM condition. (To recall, practicing mastered problems is considered to be redundant under the Mastery Rule.) On one hand, it is likely that the students have knowledge of the Mastery Rule, but are not capable of accurately assessing their mastery of the levels. The OLM aided the students by displaying their learning status, which in turn led to more effective problem selection. On the other hand, the OLM might have encouraged the students to work in new levels in order to fill all the mastery bars.

2) Students tend not to challenge themselves with new levels, and often fail to persevere in more difficult levels. We found some interesting patterns by examining the sequence of problems selected by individual students. For example, student H from the OLM condition kept alternating between level 1 and level 2 without trying any of the higher levels. Student M from the noOLM condition first tried to select one problem from each level, and then stayed in level 1 for the rest of the time. Student C from the noOLM condition selected one problem from level 1, 2, and 3 to start with, and then worked in level 1 for several problems even after reaching mastery, according to the system (though without mastery bars communicating that fact). In general, students often selected some problems from mastered lower levels after trying to solve a higher level problem, even with the presence of the OLM. Moreover, the classroom experiment only involved two class periods. It is possible that with longer practice time, the students in the OLM condition will more frequently violate the Mastery Rule when they encounter higher levels with more difficult problems.

3 Interviews and Storyboards

Our next step in the user-centered design process was to gather qualitative data to help explain and further investigate the quantitative results observed in the classroom experiment. Specifically, we conducted interviews and used storyboards to find out 1) how the OLM helps students make better problem selection decisions; 2) how much knowledge the students have about the concept of mastery and how to apply the Mastery Rule; and 3) what design features may motivate students to challenge themselves with unmastered problem types. 12 6th – 8th grade students participated in the study. The students participated either individually or with one or two friends/siblings. Each session took 45 – 60 minutes, starting with an interview followed by discussions on storyboards. All sessions were audio-recorded for later analysis. Two experimenters ran the sessions together, one serving as the interviewer/facilitator of the discussions, and one as the note-taker. None of the participants had used *Lynnette* before the study.

We designed interview questions that target students' understanding of mastery and the Mastery Rule, with and without the aid of the OLM. Specifically, the interviewer first introduced what *Lynnette* is, and brought up one of the problem selection screens (half of the participants saw the noOLM screen, and half saw the OLM one as both shown in Figure 1). The students were asked to select one level to start with and explain why they decided to pick that level. Next they solved one problem from the level they chose, and were brought back to the problem selection screen. Then they were again asked what level they wanted to select next and why, but were not asked to solve the problem again. For students who saw the OLM, they were also asked what had led to the change of the mastery bars.

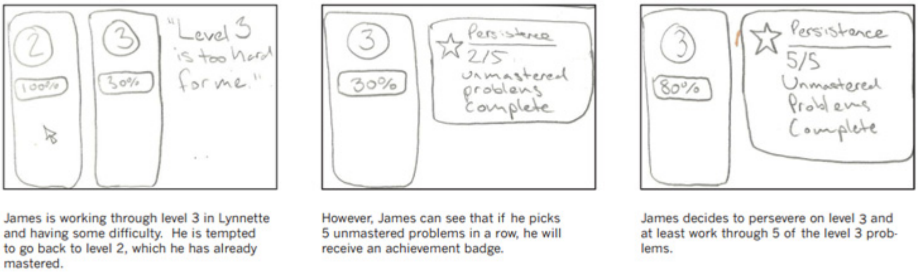

Fig. 2. A storyboard illustrates earning badges for persevering with a difficult level

We created 18 storyboards that reflect design ideas we brainstormed based on prior literature on supporting self-regulated learning. Storyboarding is an effective technique in user-centered design for quickly identifying user needs and generating feedback on design ideas [9]. Each storyboard contains one design idea, and consists of 3 to 4 frames, with explanatory text under each frame. The 18 storyboards reflect three main themes of design ideas of features in *Lynnette*: 1) Help students know when they have had enough practice (4 storyboards); 2) Help students learn the knowledge of the Mastery Rule (6 storyboards); and 3) Motivate the students to challenge themselves by selecting unmastered levels and persevere (8 storyboards). Figure 2 shows an example storyboard that illustrates the idea of using badges to motivate students to persevere in a new and difficult level. The students were given a copy of the storyboards, and then the interviewer read the storyboard aloud and led discussions with the students about their initial reaction to the idea and how they would react to the features if they were the student in the story.

The interviews and discussions with storyboards provide ample qualitative data:

1) The students do not understand the concept of mastery, and have misconceptions about the mastery bars in the OLM. In general, we found that mastery is a difficult concept for the students. When no OLM was present on the problem selection screen, a common answer to our question, "How many problems would you do for each level?" was, "I will do *5* problems in each level." On the other hand, when the OLM was present, almost all of the students perceived the mastery bars simply to mean how many problems they had completed in a level, instead of the degree to which they had mastered the skills to solve problems in that level.

2) It is not difficult to explicitly communicate the Mastery Rule to the students. Some of our participants were able to state the Mastery Rule when asked how they would select problems for themselves, such as "I know how to do level 1, so I will pick level 2." When we introduced the Mastery Rule in some of our storyboards, we also found that it was not difficult for students to understand and accept the rule. The Mastery Rule can be explicitly taught to the students.

3) Students have limited motivation with respect to why they should practice problems from unmastered new problem levels. Most of our participants admitted that they only would do what the teacher gives to them, and few mentioned they would learn new things in new levels. Also, math seems uninteresting to some of the students, and one of them said, "Sometimes I just feel lazy and just want to do easy problems." The lack of motivation may prevent the students from applying the Mastery Rule even if they are aware of the strategy.

We have also identified motivating design features for middle school students:

1) Mastery bars in the OLM. All of the participants expressed that they liked the mastery bars. The bars stimulate a desire for completion, and probably encouraged them to work on the new levels, as observed in the classroom experiment. However, as we found that the students had misconceptions about the meaning of the bars, it was clear that we needed to communicate the concept of mastery to them explicitly.

2) Rewards. The students liked all kinds of rewards, including badges, stars, achievements, and even positive messages from the tutor. One student commented, "Who wants to go out on a rainy cold night on Halloween if not for candies?" Therefore, well-designed rewards may encourage desirable problem selection behaviors.

4 Prototypes of Tutor Features That Foster Motivation and Learning of the Mastery Rule

We designed and created paper and HTML/Javascript prototypes of tutor features that foster motivation and learning of the Mastery Rule based on results gathered from our user research. There were two main goals of our design: 1) To support students' motivation of applying the Mastery Rule; and 2) To support the learning of the Mastery Rule. We also have the ultimate goal of enabling transfer of the learned rule when the scaffolding is not in effect, with the fostered motivation.

With respect to the goal of supporting motivation, we specifically focused on fostering a mastery-approach orientation. We found from our user research that the main obstacle for applying the Mastery Rule is lack of motivation to select new and challenging problems and to persevere when encountering difficulties, even with the presence of the OLM. Therefore, our designs need to help foster the motivation that will engender desirable problem selection behaviors. We decided to ground our design in motivation theories of achievement goals [15]. There are generally two types of achievement goals, mastery orientation and performance orientation [14]. While a performance orientation focuses on demonstration of competence, a mastery orientation emphasizes developing competence [15]. The orientations are further divided into approach and avoidance forms [15]. A mastery-approach orientation is generally associated with positive learning behaviors such as perseverance, willingness to take on challenges and desire to learn new things [14], which align with the desirable behaviors for applying the Mastery Rule. Research has also found that a mastery orientation can be fostered through interventions, and can last even after the interventions are faded [14]. Therefore, we designed tutor features that may foster a mastery-approach orientation. Meanwhile, given math is uninteresting to some of the students, we included some game elements (avatars, stars and badges) to make the tutor more fun.

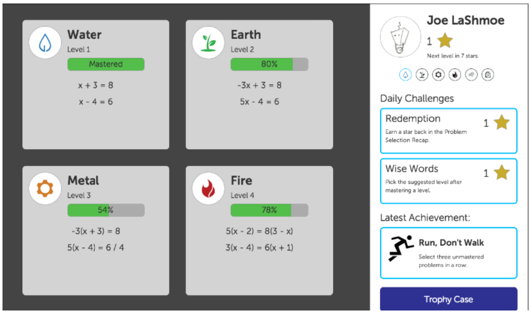

Fig. 3. The problem selection screen that also displays Daily Challenges and Achievements

Daily Challenges and Achievements. We designed Daily Challenges and Achievements to reward students for challenging themselves with new problem types and persevering when encountering difficulties, aiming to help them develop a mastery-approach orientation. For example, as shown in Figure 3, one Achievement students can earn is by selecting three unmastered problems in a row.

We also designed features aimed at helping students learn the Mastery Rule. Notably, all of these features also contribute to fostering a mastery-approach orientation.

The Tutorial. An interactive tutorial is presented to the students when they first log in to *Lynnette*. It explains to students that they are learning a separate skill of making problem selection decisions, in addition to learning to solve equations. We kept the mastery bars in the redesigned tutor, as our experiment suggests that *Lynnette*'s OLM can help students make significantly better problem selection decisions. However, we also found that explanations of the concept of mastery and the mastery bars needed to be presented to address students' misconceptions. Therefore, as shown in Figure 4, the tutorial explains the concept of mastery, the Mastery Rule, and the mastery bars. All of the explicit explanations and instructions from the tutorial emphasize the mastery-approach orientation. After going through the tutorial, the students start working with the tutor on the problem selection screen shown in Figure 3.

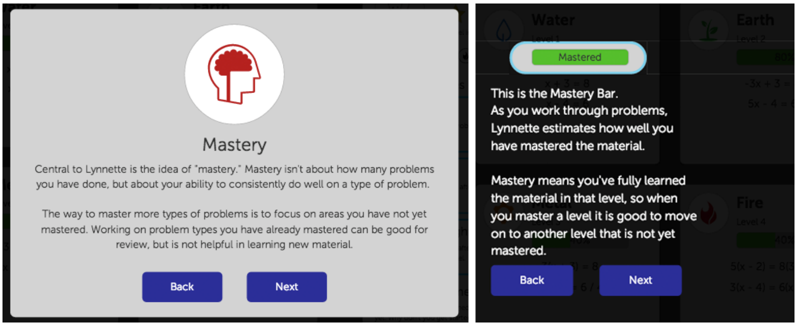

Fig. 4. Explicit explanations of mastery (left) and of the mastery bars (right) from the tutorial

Feedback Messages. We designed messages to serve as feedback on students' problem selection decisions. Figure 5 shows a message that a student could receive from his/her avatar after selecting several mastered problems. The message reminds the student of the ineffective problem selection decisions, and reinforces the mastery-approach orientation by saying, "Don't forget to work on mastering new materials."

Problem Selection Recap. We designed a problem selection recap screen to let students reflect on their problem selection history when they reach mastery for a level. The students are provided the levels they have selected before reaching mastery for that particular level (if they effectively apply the Mastery Rule, they should only have selected the current level or the levels above), and are asked to identify the mastered/unmastered levels they have selected. Students receive immediate feedback messages about whether they have correctly identified the mastered/unmastered levels, and the messages are also phrased to foster a mastery-approach orientation (as shown at the bottom of the left image in Figure 5).

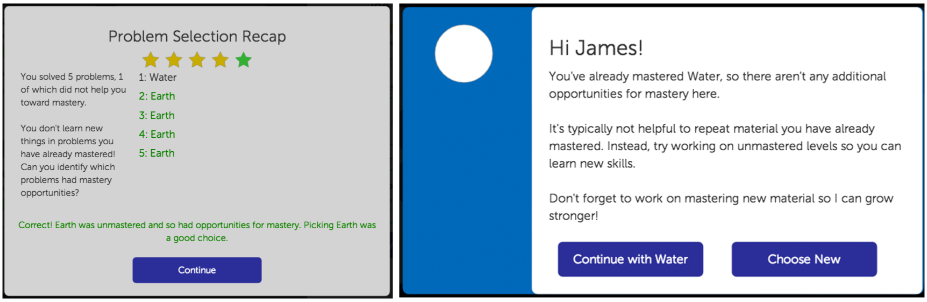

Fig. 5. Problem selection recap screen (left) and feedback message (right) students receive after several ineffective problem selection decisions

We conducted user testing using the HTML/Javascript prototypes (not yet integrated with *Lynnette*) with 10 6th – 8th grade students. The sessions were conducted either individually or in groups of two, and ranged from 40 to 45 minutes. All sessions were audio-recorded. The user testing helped us improve the usability issues of the interface and provided preliminary feedback on the effectiveness of the design features. In general, the participants perceived the redesigned tutor interface as fun and engaging. One student said, “Yes, I will definitely use it.” They also felt that the Daily Challenges, Achievements and feedback messages were motivating and helpful.

5 Conclusions and Future Work

The current paper uses a user-centered design approach to extend an ITS for equation solving, so that the new designs may motivate and help students learn to apply an effective problem selection strategy in a way that lasts, even when the scaffolding is no longer in effect. We started with a theoretically interesting question: How can an ITS help students learn to make good problem selection decisions? We conducted user research to identify user needs and help generate design ideas. Lastly, we designed prototypes of features in *Lynnette* that may foster the motivation and learning of the Mastery Rule based on results and insights gained from our user research. We also grounded our designs in motivation theories about mastery-approach orientation.

Our user research has produced interesting results that can inform future design of learner-controlled ITSs. We studied how an OLM influences students’ problem selection decisions when students are free to select any problem they like. We found that an OLM can help the students effectively select problems, as the OLM condition selected significantly fewer mastered problems than the noOLM condition; this is one reason why ITSs should include an OLM when students have control over problem selection. Our experiment helps empirically establish the significant role of OLM in supporting problem selection in ITS, which has not been addressed by prior work. We also investigated what may have caused the difficulty in applying the Mastery Rule. It appears that lack of motivation, especially the lack of a mastery-approach orientation, may be a stronger factor than metacognitive knowledge of the rule.

Our work contributes to the research of supporting self-regulated learning in ITS. Our prototypes are designed to foster a mastery-approach orientation as well as transfer of metacognitive knowledge when the scaffolding is not in effect (although with the OLM, as it is a common feature in ITS). Not much work in ITSs has investigated motivational design to help students *want* to apply metacognitive strategies needed for effective self-regulation, and little prior work has supported the transfer of SRL skills in ITSs. Lastly, the current work lays the foundation for future controlled experiments. We will conduct experiments and measure if our designs can successfully foster the mastery-approach orientation, and whether the motivation and knowledge of the Mastery Rule can transfer to new tutor units when the scaffolding is removed.

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