Supporting Learner-Controlled Problem Selection in Intelligent Tutoring Systems

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Abstract

Many online learning technologies grant students great autonomy and control, which imposes high demands for self-regulated learning (SRL) skills. With the fast development of online learning technologies, helping students acquire SRL skills becomes critical to student learning. Theories of SRL emphasize that making problem selection decisions is a critical SRL skill. Research has shown that appropriate problem selection that fit with students' knowledge level will lead to effective and efficient learning. However, it has also been found that students are not good at making problem selection decisions, especially young learners. It is critical to help students become skilled in selecting appropriate problems in different learning technologies that offer learner control.

I studied this question using, as platform, a technology called Intelligent Tutoring Systems (ITSs), a type of advanced learning technology that has proven to be effective in supporting students' domain level learning. It has also been used to help students learn SRL skills such as help-seeking and self-assessment. However, it is an open question whether ITS can be designed to support students' learning of problem selection skills that will have lasting effects on their problem selection decisions and future learning when the tutor support is not in effect. ITSs are good at adaptively selecting problems for students based on algorithms like Cognitive Mastery. It is likely, but unproven, that ITS problem selection algorithms could be used to provide tutoring on students' problem selection skills through features like explicit instructions and instant feedback. Furthermore, theories of SRL emphasize the important role of motivations in facilitating effective SRL processes, but not much prior work in ITS has integrated designs that could foster the motivations (i.e., motivational design) to stimulate and sustain effective problem selection behaviors. Lastly, although students generally appreciate having learner control, prior research has found mixed results concerning the effects of learner control on students' domain level learning outcomes and motivation. There is need to investigate how learner control over problem selection can be designed in learning technologies to enhance students' learning and motivation.

My dissertation work consists of two parts. The first part focuses on creating and scaffolding shared student/system control over problem selection in ITSs by redesigning an Open Learner Model (OLM, visualizations of learning analytics that show students' learning progress) and integrating gamification features to enhance students' domain level learning and enjoyment. I conducted three classroom experiments with a total of 566 7th and 8th grade students to investigate the effectiveness of these new designs. The results of the experiments show that an OLM can be designed to support students' self-assessment and problem selection, resulting in greater learning gains in an ITS when shared control over problem selection is enabled. The experiments also showed that a combination of gamification features (rewards plus allowing re-practice of completed problems, a common game design pattern) integrated with shared control was detrimental to student learning. In the second part of my dissertation, I apply motivational design and user-centered design techniques to extend an ITS with shared control over problem selection so that it helps students learn problem selection skills, with a lasting effect on their problem selection decisions and future learning. I designed a set

of tutor features that aim at fostering a mastery-approach orientation and learning of a specific problem selection rule, the Mastery Rule. (I will refer to these features as the mastery-oriented features.) I conducted a fourth classroom experiment with 200 6^{th} – 8^{th} grade students to investigate the effectiveness of shared control with mastery-oriented features on students' domain level learning outcomes, problem selection skills and enjoyment. This experiment also measured whether there were lasting effects of the mastery-oriented shared control on students' problem selection decisions and learning in new tutor units. The results of the experiment show that shared control over problem selection accompanied by the mastery-oriented features leads to significantly better learning outcomes, as compared to full system-controlled problem selection in the ITS. Furthermore, the mastery-oriented shared control has lasting effects on students' declarative knowledge of problem selection skills. Nevertheless, there was no effect on future problem selection and future learning, possibly because the tutor greatly facilitated problem selection (through its OLM and badges).

My dissertation contributes to the literatures on the effects of learner control on students' domain level learning outcomes in learning technologies. Specifically, I have shown that a form of learner control (i.e., shared control over problem selection, with mastery-oriented features) can lead to superior learning outcomes than system-controlled problem selection, whereas most prior work has found results in favor of system control. I have also demonstrated that Open Learner Models can be designed to enhance student learning when shared control over problem selection is provided. Further, I have identified a specific combination of gamification features integrated with shared control that may be detrimental to student learning. A second line of contributions of my dissertation concerns research on supporting SRL in ITSs. My work demonstrates that supporting SRL processes in ITSs can lead to improved domain level learning outcomes. It also shows that the shared control with mastery-oriented features have lasting effects on improving students' declarative knowledge of problem selection skills. Regarding using ITSs to help students learn problem selection skill, the user-centered motivational design identifies mastery-approach orientation as important design focus plus tutor features that can support problem selection in a mastery-oriented way. Lastly, the dissertation contributes to human-computer interaction by generating design recommendations for how to design learner control over problem selection in learning technologies that can support students' domain level learning, motivation and SRL.

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Chapter 1. Introduction

As an ancient Chinese proverb says, "*Give a man a fish; you have fed him for today. Teach a man to fish; and you have fed him for a lifetime*". Teaching people how to learn makes fundamental changes in their life-long learning experiences. My research centers on helping students become better self-regulated learners. Theories of Self-Regulated Learning (SRL) take a comprehensive view of the processes involved in academic learning, emphasizing the agency of the learner. For example, Zimmerman (1986) defines SRL as "the degree to which students are metacognitively, motivationally, and behaviorally active participants in their own learning process." Theories of SRL abound (Pintrich, 2004; Winne & Hadwin, 1998; Zimmerman, 2000); all tend to view learning as repeated cycles with broad phases such as forethought, execution, and evaluation, with learning experiences in one cycle critically influencing those in the next in intricate ways. A number of empirical studies have revealed that the use of SRL strategies (both cognitive and metacognitive strategies) accounts significantly for the differences in students' academic performance in different domains of learning (Zimmerman & Martinez-Pons, 1986; Pintrich & De Groot, 1990; Cleary & Zimmerman, 2000), such as reading comprehension, math problem solving, music learning, athletic practice, etc. Consequently, researchers have started to ask whether SRL strategies are teachable, so that we can help students to become better self-regulatory learners. Many studies have demonstrated that training of SRL strategies can enhance students' academic achievement and motivation (Schunk & Zimmerman, 1998). In a meta-review of intervention studies conducted in primary and secondary schools, Dignath and Büttner (2008) analyzed 84 studies and found the average effect size (standardized mean differences between treatment and control conditions) of the SRL interventions on academic performance to be 0.69. Furthermore, theories of SRL highlight the role of motivation in facilitating and sustaining SRL processes (Garcia & Pintrich, 1994; Zimmerman, 1995; Pintrich, 1999). In other words, it is critical that the students *want* to learn and apply the cognitive and metacognitive strategies in SRL. Pintrich (1999) emphasized that different motivations such as self-efficacy, perceived task values and mastery goal orientation are generally associated with effective self-regulatory strategies. Interventions on SRL can target fostering the positive motivations toward applying the SRL strategies, in addition to helping students learn the strategies.

My research studies SRL in the context of online learning technologies. In recent years, learning technologies have become pervasive in formal and informal learning environments. Many learning technologies offer great learner autonomy with respect to deciding what, when and how to learn in such environments, which imposes high demands on effective SRL processes. However, students are not always equipped with knowledge of self-regulatory strategies and the motivations to apply them in different learning technologies. Therefore, investigating how to support students' SRL in online learning technologies plays an essential role in helping the learners to succeed in such learning environments. Intelligent Tutoring Systems (ITS) are a type of adaptive online learning environment that supports "learning by doing" through scaffolded problem solving practice for individual learners. ITSs have a proven track record of supporting students' domain level learning in a wide range of domains (VanLehn, 2011). ITSs also intelligently track students' learning progress in the system with student models. Many ITSs have Open Learner Models which display students' learning progress through visualizations, e.g., skill meters (Bull & Kay, 2008). Furthermore, ITSs have also been designed to facilitate the learning of SRL skills, such as help-seeking, self-assessment, planning and monitoring (Roll et al., 2011; Aleven et al., 2006; Azevedo et al., 2009).

My dissertation work focuses on supporting a critical SRL process, i.e., making problem selection decisions, while learning with Intelligent Tutoring Systems. Appropriate problem selection that matches a student's knowledge level will lead to effective and efficient learning (Metcalfe, 2009). Prior research has also shown that it is challenging for students to make good problem selection decisions, especially young learners (Metcalfe & Kornell, 2003; Schneider & Lockl, 2002). Although ITS has been designed to support other SRL skills (Roll et al., 2011; Aleven et al., 2006; Azevedo et al., 2009), it is still an open question whether it can be designed to support students' learning of problem selection skills that will have lasting effects on their problem selection decisions and future learning when the tutor support is not in effect. ITSs are generally strongly system-controlled learning environments, where the system adaptively selects problems for students based on their learning status (how well the students are learning/have learned) and problem selection algorithms. It is possible, but unproven, that ITS can be designed to offer students some control over problem selection and help them learn the strategies to effectively select problems by taking advantage of its problem selection algorithms. Furthermore, theories of SRL emphasize the important role of motivations in facilitating effective SRL processes, but not much prior work in ITS has integrated designs that could foster the motivations (i.e., motivational design) to stimulate and sustain effective problem selection behaviors. Lastly, although students generally appreciate having learner control (Clark & Mayer, 2011), prior research has found mixed results concerning the effects of learner control on students' domain level learning outcomes and motivation. There is need to investigate how learner control over problem selection can be designed in learning technologies to enhance students' learning and motivation.

The dissertation combines user-centered design, classroom experimental studies and educational data mining to investigate how to support learner-controlled problem selection in ITSs. Chapter 2 to 6 describe the theoretical background of my work, the projects I have conducted to investigate the theoretical research questions, as well as the contributions of the dissertation. Specifically:

Chapter 2 – Discusses the theoretical background for making problem selection decisions in self-directed learning environments, the potential of using ITS to help students learn problem selection skills, the prior work on learner control in learning technologies, as well as the overarching research questions of the dissertation.

Chapter 3 – Describes my earlier work that focuses on creating and scaffolding shared student/system control over problem selection in ITSs by redesigning an Open Learner Model and integrating gamification features to enhance students' domain level learning and enjoyment. It includes three classroom experiments involved a total of 566 7^{th} and 8^{th} grade students to investigate the effectiveness of these new designs on students' learning outcomes and enjoyment.

Chapter 4 – Describes the user-centered motivational design process I went through to extend an ITS to help students learn problem selection skills with shared control. It also presents the new tutor features that aim at fostering a mastery-approach orientation and learning of a specific problem selection rule (I will refer to the features as the mastery-oriented features).

Chapter 5 – Describes the fourth classroom experiment with 200 6^{th} – 8^{th} grade students that investigated the effectiveness of the mastery-oriented features from Chapter 4 with shared control on students' domain level learning outcomes, problem selection skills and enjoyment. The experiment also measured whether there were lasting effects of the mastery-oriented shared control on students' problem selection decisions and learning in new tutor units.

Chapter 6 – Summarizes the main findings and conclusions of the dissertation, and discusses the contributions of the work.

Chapter 2. Theoretical Background

2.1 Why is making problem selection decision important?

Problem selection is an integral part of learning. Inappropriate problem selection will lead to inefficient learning, which diminishes students' learning outcomes. For example, working on problems that do not match with a student's current learning status (how much/how well has been learned for certain topics) will lead to under- or over-practice of the learning materials. Students should work on problems that are not too easy or too difficult, given their current learning status. Selecting problems generally encompasses three aspects, deciding on 1) what problem type to study; 2) with that type, what specific problem to study; and 3) when to finish studying that type. Decisions on the three aspects will result in different problems being practiced in varied sequences.

Making problem selection decisions is a critical metacognitive skill in Self-Regulated Learning (Zimmerman, 2000; Metcalfe, 2009; Thiede et al., 2003; Kostons, van Gog, & Paas, 2010). It plays an important role when students are learning in self-directed learning environments both online and offline. In traditional school learning environments, students need to decide when and what to review in order to achieve best learning outcomes. They also have to study for quizzes and exams, which requires careful selection of learning materials based on their learning status. On the other hand, online learning environments impose even higher demands with respect to good problem selection skills, as they generally offer students some degree of freedom for selecting their own problems. Some learning technologies try to deploy learning analytics to show students' learning status in the systems, for example, in the form of skill meters, progress charts, badges, etc. However, being aware of their learning status does not necessarily mean that the students are able to make the best decisions on what to learn next based on the information (Mitrovic & Martin, 2003). The students need to have the metacognitive knowledge and motivation to effectively select problems that fit with their learning status.

Cognitive and instructional theories have highlighted optimal ways to select problems to achieve the best learning outcomes efficiently. For example, the concept of mastery learning emphasizes that the learning targets can be decomposed into small components, and students can proceed to master all the components at their own pace (James, Robert, & Robert, 1990). Atkinson (1972) defines a simple learning model that specifies three transitional states of student learning, *P*, *T* and *U*. In state P, the unit is learned and is not easily interfered by other learning activities, in other words, the unit is "mastered". State T means a learning stage, the target unit is temporarily learned, but is still subject to forgetting. Lastly, the U state means the unit is unlearned. Learning and instruction should focus on helping students transition from the unmastered/learning states (U and T) to the relatively permanently mastered state (P), not focusing on the learning units that are already in the mastered state. The extra practice on mastered learning units is considered redundant. Furthermore, Vygotsky's Zone of Proximal Development (ZPD) argues that there is a zone that is just above students' current abilities, and can be reached via scaffolding (Metcalfe & Kornell, 2005). Atkinson's transitional states model (1972) also pointed out that students should be directed to focus on the learning units that are in the T (learning) state first rather than the U (unlearned) state, as the learning units in the T state is closer to mastery. Both theories advocate that students should practice the problem types from easier to more difficult relative to their abilities. Lastly, interleaved sequences are favored over blocked sequences of practicing problems according to the theory of "desirable difficulties" (Bjork & Bjork, 2006; Kapur & Bielaczyc, 2012). The difficulties caused by the interleaved practice (essentially encountering difficult problem types earlier in the learning process) are believed to cause tougher learning process, but produce greater learning outcomes at the end (Taylor & Rohrer, 2010). The superior benefits of interleaved over blocked practice have been demonstrated in various domains, such as learning of motor skills (Hebert, Landin, & Solmon, 1996), vocabulary learning (Cepeda et al., 2006), and math problem solving tasks (Rohrer & Taylor, 2007). It is likely that the tougher learning experiences caused by the interleaved problem sequence may diminish students' enjoyment during the learning process, but eventually foster significant learning gains.

The importance of making appropriate problem selection decisions has been supported by empirical studies as well, as researchers have found that learning with problem selections that are informed by cognitive and instructional theories lead to significantly more effective and efficient learning outcomes than learning with randomly selected problems (Metcalfe & Kornell, 2005). Thiede et al. (2003) found that when students strategically chose to re-study the items that they were not good at, they achieved significantly better performance on the post-test for reading comprehension. A number of studies compared the effects of adaptive instructions designed based on the theory of mastery learning to fixed curriculums, and found significantly better learning effectiveness and efficiency with the adaptive instructions (Kulik et al., 1990; Corbett, 2000). For example, Corbett (2000) compared the effects on student learning between adaptive problem selection to fixed curriculum in an intelligent tutoring system for Lisp. The study found that the students who learned with the system-selected problems based on cognitive mastery achieved significantly better learning outcomes than their counterparts who learned with a fixed curriculum.

2.2 Can students make effective problem selection decisions?

It is challenging for students to effectively select problems for themselves, especially for young learners. Studies conducted with college students on memory tasks and reading comprehension have shown that students are able to base problem selection decisions on their own self-assessed learning status (Metcalfe, 2009; Thiede et al., 2003). A negative correlation has been found between their Judgment of Learning (how well they have learned a certain item) and the allocation of study time, which means that adults tend to focus on problems that they judge to be not well learned (Metcalfe

& Kornell, 2005). However, making such reasonable problem selection decisions has been proven to be difficult for young learners (Metcalfe & Kornell, 2003). Studies have found that children tend to make random choices with respect to what they should study (Schneider & Lockl, 2002). Kostons, van Gog & Paas (2010) found that even high school students focused more on the surface features (e.g., the cover stories) than the structural features (e.g., the complexity of the solution paths to the problems) of the problems when they selected problems for themselves in a computer-based learning environment.

Research on adaptive learning technologies provides further evidence for this disadvantage of student-selected problems, in that the students are generally found to be unable to make problem selection decisions that are as good as those made by computer algorithms developed based on cognitive and instructional theories. In a classic experiment in which participants learned vocabulary in a second language, Atkinson (1972) found that the student-selected practice condition achieved better learning outcomes than the random-selected condition, but was worse than the computer-selected condition which adopted a mathematic algorithm that takes into account students' learning status and item difficulty to select practice items for students. In a study with an intelligent tutoring system for SQL, Mitrovic and Martin (2003) found that even college students with high prior knowledge of SQL were not able to effectively select problems to practice in the tutor. Both the high and low prior knowledge students selected problems that were largely different from what the system would have selected for them even when an Open Learner Model was presented to help them make decisions.

Prior research has also shed light on why it is challenging for students to make effective problem selection decisions in self-regulated learning. Firstly, students are typically not good at accurately self-assessing their own learning status (Dunlosky & Lipko, 2007; Metcalfe, 2009). Accurate self-assessment lays the foundation for adaptive problem selection. Problem selection based on inaccurate assessment of learning status will not result in efficient or effective learning. One study (Salden, Paas, van der Pal, & van Merrienboer, 2006) found that 67% of the participants learning with a flight management training system overestimated their performance during training. Problems selected based on the students' self-assessed learning status did not result in better learning outcomes than a fixed set of problems (Salden et al. 2006). Secondly, the students may lack the appropriate level of motivation to initiate an effective problem selection process. Kostons et al. (2010) found that the students' self-efficacy on their abilities would influence their problem selection decisions. Students tend to select problems that they feel confident with (Bandura 1994; Kostons, van Gog & Paas, 2010), which do not necessarily align with their knowledge level or can teach them new knowledge and skills. With respect to other motivational constructs, research has also found that a mastery orientation is positively related with metacognitive activities (Patrick, Ryan, & Pintrich, 1999; Ford, Smith, Weissbein, Gully, & Salas, 1998). Thirdly, the students' domain level knowledge affects their problem selection decisions. Lack of domain knowledge may prevent students from recognizing which problems fit their current knowledge level and offer the best opportunities for learning new knowledge. Clark and Mayer (2011) concluded that novices of the learning content were less likely to benefit from making problem selection decisions themselves. Gay (1986) found that the low prior knowledge students focused on areas that they were already familiar with, and thus could not make effective problem selection decisions. Lastly, students also need metacognitive knowledge of effective problem selection strategies in order to make correct decisions. Kostons et al. (2010) pointed out that the students may not be aware of the advanced rules and strategies implemented by computer algorithms for adaptive problem selection. Therefore, even with accurate self-assessment, positive motivation and enough domain level knowledge, students may still fail to make effective decisions without knowledge of problem selection strategies that are informed by theories and empirical studies from cognitive science, educational psychology, instructional design and advanced learning technologies.

To sum up, making problem selection decisions is a critical SRL skill that will benefit students' lifelong learning in different learning environments. However, lack of domain knowledge, metacognition or motivation poses challenges in making effective problem selection decisions in self-regulated learning. There is need to investigate how to support the different aspects that could affect making problem selection decisions by students. The interventions should address some or all of these aspects.

2.3 Making Problem Selection Decisions in Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITSs) are a type of adaptive online learning environment that supports "learning by doing" through scaffolded problem solving practice for individual learners. ITSs have a proven track record of supporting students' domain level learning in a wide range of domains (VanLehn, 2011). ITSs track students' learning progress in the system with a student model (Bull, 2004), and offers adaptive problem selection for individual students based on algorithms like Cognitive Mastery (Corbett, 2000).

On one hand, it is likely that ITSs have the potential to be designed to scaffold students' problem selection. ITSs can be designed or extended to integrate features that may foster learning of effective problem selection strategies, while maintaining its effectiveness on students' domain level learning. For example, a common feature of ITS is an Open Learner Model (OLM), which is a type of learning analytics that displays information about students' learning status tracked and assessed by the system's student model (Bull, 2004). An OLM may be designed to facilitate students' self-assessment and in turn support making problem selection decisions (Bull, 2004; Bull & Kay, 2007; Bull & Kay, 2008). Furthermore, the fact that ITS is good at selecting problems based on algorithms like Cognitive Mastery (Corbett, 2000) suggests that it may also be extended to provide tutoring on making problem selection decisions. Prior work has shown some successful examples of using ITSs to help students learn other SRL skills. The Help-Seeking tutor was found to improve students' help-seeking behaviors with metacognitive feedback (Roll et al., 2011; Aleven et al., 2006). Roll et al. (2011) designed a self-assessment tutor that scaffolded students' self-assessment at the start of each section of the tutor curriculum. They found that this tutor improved students' self-assessment on better-mastered problems and that students were able to transfer improved self-assessment in other tutor units (Roll et al., 2011). MetaTutor implements pedagogical agents to prompt and provide feedback on students' use of different metacognitive processes, such as planning, monitoring and self-assessing (Azevedo et al., 2009). Nevertheless, it is challenging to design interventions in ITSs that have lasting effects on SRL skills and domain level learning when the interventions are removed. Little if any work on SRL and ITSs has established improved future use of SRL strategies when the scaffolding is not in effect (Aleven, Roll, & Koedinger, 2012; Roll et al., 2014). There has also been less work focusing on fostering the motivation towards 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 (Tai, Arroyo & Woolf, 2013). It is still largely an open question whether and how ITSs can be designed to help students want to learn and use the SRL skills such as how to effectively make problem selection decisions.

On the other hand, ITSs can be viewed as a research platform to more objectively investigate students' problem selection behaviors. Harley et al. (2014) argues that intelligent hypermedia learning environments can provide different sources of data to study student learning, such as log files, eye-tracking data, and facial expressions. Self-report data has often been used in traditional metacognition research (Pintrich, 1999). The log files of trace data offer a new lens to examine students' objective problem selection behaviors, such as the problems selected by students during the learning process, and the time spent on learning different types of problems. Analyses of such data in combination with traditional self-report data will provide more in-depth insights with respect to how and why students make certain problem selection decisions, thus inform the future design of effective interventions.

2.4 Learner Control over Problem Selection in Learning Technologies

When intelligent tutoring systems are designed to support students' problem selection, it grants opportunities for students to select problems through enabling different levels of learner control. Learner control has generally been considered motivating to students. Clark and Mayer (2011) pointed out that students prefer more control over their own learning activities in learning technologies. ITSs generally are strongly system-controlled learning environments. Therefore, in addition to helping students learn the skill of making problem selection decisions, granting learner control may facilitate students' motivation and learning in the ITSs as well.

2.4.1 Effects of Learner Control on Students' Motivation and Learning

Although students generally appreciate having learner control in learning technologies (Clark & Mayer, 2011), empirical studies have found mixed results with respect to its effects on enhancing students' motivation and learning outcomes (Schnackenberg & Sullivan, 2000; Williams, 1996; Lawless and Brown, 2011). Learner control spans a spectrum from full system control to full student control, with different ways of shared student/system control in between. Shared control means that the system and learners each take some responsibilities to control part of the learning activities and learning resources. Learner control can be applied to different aspects of student learning in learning technologies, e.g., selecting instructional materials (Brusilovsky, 2004), deciding the characteristics of the interface (Cordova & Lepper, 1996), or selecting how the system should be personalized through different ways to integrate the algorithms for item recommendation (Parra & Brusilovsky, 2015).

Cordova and Lepper (1996) found that letting elementary school students make trivial choices on the interface of the system could lead to significantly better learning outcomes in mathematics. Schraw, Flowerday and Reisetter (1998) compared the effects between choice and no-choice on students' reading comprehension. The results revealed higher interests in the text with the choice group but no significant difference between the two groups on task performance. Young (1996) also did not find significant difference on learning between the learner-controlled and program-controlled conditions with middle school students. However, with students who had learner control, those with higher metacognitive skills performed significantly better than their counterparts how had lower metacognitive skills in the experiment (Young, 1996). Hannafin and Sullivan (1996) found that college students learning in learner-controlled condition performed worse on the learning tasks but reported higher satisfaction with the learning process.

Clark and Mayer (2011) summarized that learner control may only be beneficial to students who have higher prior knowledge or better metacognitive skills. Higher prior knowledge and better metacognitive skills may lead to better problem selection decisions. Vandewaetere and Clarebout (2011) also pointed out that the effectiveness of learner control may depend on students' prior knowledge, self-efficacy, self-regulatory skills, working memory capacity (which affects the cognitive load) and actual perception/satisfaction of control. Particularly, students' perceived sense of control is found to be positively correlated with their intrinsic motivation and enjoyment (Flowerday & Schraw, 2003).

In principle, the effects of learner control on students' motivation and learning needs further investigation. It is still an open question how learner control can be designed and supported in learning technologies to increase students' motivation and improve their learning outcomes.

2.4.2 Interventions on Learner Control over Problem Selection in Learning Technologies

Interventions have been designed in learning technologies to support learner control over problem selection, aiming to enhance students' problem selection decisions, motivation towards learning and domain level learning outcomes. The interventions targeted helping students make effective problem selection decisions in the systems with learner control, while enhancing the motivational benefits of the control. There are primarily two lines of work: 1) scaffolding students' problem selection decisions by offering assistance from the system; and 2) helping students learn the metacognitive strategies for how to make problem selection decisions with learner control. Some of the interventions also tried to enhance students' perceived sense of control to increase their motivations.

One approach to scaffold students' problem selection decisions is to utilize visual cues embedded in the designs of the systems. Adaptive navigation support in hypermedia learning environments is among the best examples (Brusilovsky, 2004). Effective designs that assist students in making correct decisions on what to attend to next include using headers and site maps, eliminating the links to irrelevant materials, highlighting important topics, etc. (Clark & Mayer, 2011). These designs could help lower students' cognitive load for monitoring their learning status and making the problem selection decisions. They may also help to make up for students' lack of domain knowledge and metacognitive knowledge that is required to make the correct decisions. Brusilovsky, Sosnovsky,

& Shcherbinina (2004) found that with adaptive navigation support (designs in the system that highlight the important topics and topics that need more practice based on students' current learning status) in QuizGuide (an adaptive hypermedia learning system), students' participation was increased in the system, as well as their final academic performance.

Another approach is to selectively limit the amount of control the students could have over problem selection, i.e., to create shared control over problem selection between students and the system. With shared control, the system can help prevent students from making suboptimal problem selection decisions due to lack of domain and metacognitive knowledge, as well as lack of appropriate motivation. Sharing the control may also help alleviate students' cognitive load. For example, Corbalan, Kester, and van Merriënboer (2008) implemented an adaptive shared control over problem selection in a web-based learning application for Health Sciences. The tutor pre-selected problem types for the students based on the task difficulty and available support that are adapted to the students' competence level and self-reported cognitive load. For each problem type, the tutor provided problems that only differed with superficial features (e.g., the species and traits in a genetics problem) to let the students choose from. This form of shared control led to the same learning outcomes as the full system-controlled condition in the experiment, although – contrary to expectation – it did not foster higher interests of using the system (Corbalan, Kester, & van Merriënboer, 2008). In another study, the same authors (Corbalan, Kester, & van Merriënboer, 2009b) manipulated the level of variability of the surface features of the problems, hypothesizing that higher variability of the surface features would enhance the students' perceived control (they would be easier to perceive the control when the surface features vary). The results of the experiment revealed that the shared control combined with high variability of surface features led to significantly better learning outcomes and task involvement than the shared control with low variability features. Nevertheless, overall the shared control conditions did not lead to significantly better learning outcomes than the system-controlled conditions.

Instead of scaffolding the students to make the correct problem selection decisions, efforts have been made to explicitly help students learn the metacognitive strategies for problem selection. In a study which comprises two experiments, students were shown videos of human models who demonstrated how to select problems based on a rule that takes into account past performance and mental effort (Kostons, van Gog, & Paas, 2012). In Experiment 1, the students who watched the video of human models showed significantly better problem selection decisions on the post-tests. However, the results were not replicated in Experiment 2. Mitrovic and Martin (2003) adopted another approach to teach the problem selection strategies through a scaffolding-fading paradigm. In an SQL tutor, the students with low prior knowledge first selected problems with feedback from the system with respect to what the system would have selected for them and why (an Open Learner Model was also shown to the students to help explain the system's decisions). After they had reached a threshold for learning SQL (i.e., attained certain level of domain knowledge), the scaffolding was faded, and the students selected their own problems without receiving any feedback. The results indicated that the students in the fading condition were more likely to select the same problems as the system would have selected for them when the scaffolding was in effect. However, whether or not these students kept making better problem selection decisions during the fading stage was not measured.

2.5 Conclusions and Research Questions

Making problem selection decisions in learning technologies is a critical yet challenging SRL process. Supporting learner control over problem selection may enhance both students' motivation and domain level learning outcomes. Advanced learning technologies such as intelligent tutoring systems (ITS) have the potential to be designed to scaffold students to make the correct problem selection decisions, so that the students may also benefit motivationally for having the learner control. Moreover, it is also likely that ITSs could be used to help students learn the skills for making problem selection decisions, as well as analyze students' objective problem selection behaviors. Prior work on supporting learner-controlled problem selection mainly focused on scaffolding students' problem selection with assistance from the system. Only a small number of studies aimed at explicitly helping students learn the skills for effectively selecting problems. Moreover, little if any work on SRL and ITS have established improved future use of SRL strategies when the scaffolding is not in effect (Aleven, Roll, & Koedinger, 2012; Roll et al., 2014). On the other hand, theories of SRL emphasize the important role of motivation in facilitating and motivating the use of metacognitive strategies (Zimmerman, 2000). Researchers have also highlighted the influence of motivations on students' problem selection decisions (Bandura, 1994; Kostons et al., 2010). Nevertheless, not much work has investigated how to foster positive motivations to promote good problem selection behaviors in learning technologies. Therefore, there are three main open questions in supporting learner-controlled problem selection in intelligent tutoring systems:

1. How can learner control over problem selection in ITS be designed so that it enhances both students' motivation and domain level learning?
2. How can ITS be designed to support the learning and transfer of effective strategies for making problem selection decisions with learner control?
3. How can motivational design be integrated in ITS design to support the learning and transfer of problem selection strategies?

My dissertation work addresses these open questions with user-centered design techniques, classroom experimental studies, and educational data mining. The early work focused on creating shared student/system control over problem selection in an ITS for equation solving through redesigning of the tutor's Open Learner Model and integration of gamification features. These new designs targeted enhancing students' domain level learning outcomes and enjoyment with scaffolding for making problem selection decisions with the shared control. The effects of the designs were evaluated through 3 classroom experiments with 566 7^{th} – 8^{th} grade students. The second part of the dissertation focused on helping students learn a problem selection strategy with shared control through the integration of motivational design in the equation solving tutor. I also conducted a classroom experiment with 200 6^{th} – 8^{th} grade students to evaluate the effects of the motivational design features. The experiment also measured the lasting effects of the interventions on students' problem selection and learning in new learning units.

Chapter 3. Scaffolding Shared Student/System Control over Problem Selection in Intelligent Tutoring Systems

Summary. This chapter describes my earlier work to create two forms of shared student/system control over problem selection in an ITS for equation solving. The experiments in this chapter focused on investigating how shared control over problem selection can be designed in combination with other tutor features (i.e., Open Learner Model in Experiment 1 and 2; integration of gamification features in Experiment 3) to enhance students' domain level learning outcomes and enjoyment of learning. Experiments 1 and 2 showed that an OLM that is redesigned to facilitate students' self-assessment can lead to significantly better learning outcomes when shared control over problem selection is offered. Experiment 3 identified a combination of gamification features integrated with shared control that may be detrimental to student learning. Specifically, when performance-based rewards were included with the freedom to re-practice completed problems, the combination led to significantly worse learning than the re-practice condition without the rewards. These results contribute to the literatures on effects of learner control on students' learning outcomes, by demonstrating effective and less effective ways of designing shared control over problem selection in ITSs. This chapter discusses the design, methods and results of the experiments and the equation solving tutor, as well as implications for future design of shared control in ITSs.

3.1 Experiments 1 & 2: Supporting Shared Control over Problem Selection with an Open Learner Model in a Linear Equation Tutor

3.1.1 Introduction and Research Questions

This experiment focused on redesigning an ITS for equation solving to offer shared control over problem selection to the students. We also redesigned the tutor's Open Learner Model to facilitate the students' self-assessment, so as to help the students to better benefit from the shared control on their learning outcomes and enjoyment of learning. As discussed in Chapter 2, it is still largely an open question how to design the ITS to enhance the design of learner control to result in better learning and motivation.

ITS researchers have long been interested in the potential of Open Learner Models (OLM) to prompt students' metacognitive processes (Bull, Dimitrova & McCalla, 2007). Many ITSs have a learner model that intelligently tracks students' learning progress or their skill mastery. An OLM affords students access to part/all of progress information, often in different formats, which may help them reflect on what they know well and not so well. Bull and colleagues (2010) found that first year college students were interested in viewing their misconceptions in an OLM, and believed that viewing such information could help them better assess their learning and allocate efforts. Hartley and Mitrovic (2002) compared students' learning gains when with or without access to an inspectable OLM, but found no significant effect on the learning gains due to the OLM. In our own prior work, we conducted surveys and interviews with experienced Cognitive Tutor users and found that they inspect the tutor's OLM (i.e., the Skillometer) quite frequently but do not actively use it to help them reflect or self-assess (Long & Aleven, 2011). Thus, as Bull et al. (2007) pointed out, more empirical studies are needed to investigate how we can design an OLM to effectively facilitate students' metacognition, such as self-assessment and making problem selection decisions.

In Experiments 1 and 2, we implemented a type of shared control that lets students select the sequence of the problem types to practice, while the tutor assigns specific problems from the chosen problem types and also decides on when the students have had enough practice for a problem type (i.e., locking the mastered problems for the students). We also redesigned the Open Learner Model of an ITS for linear equation solving so that it facilitates students' self-assessment. Specifically, we designed and implemented three new features for the Skillometer to support a brief self-assessment phase at the end of each tutor problem: self-assessment prompts, delaying the update of the skill bars (so that the updating of the skill bars can function as feedback on students' self-assessment) and showing students' progress on the problem type level in addition to on the skill level (to give students an overview of their progress in the tutor).

The main research question for the two experiments was: Will the shared control with the redesigned Open Learner Model lead to better learning outcomes and enhanced enjoyment of learning with the tutor? We hypothesized that the shared control over problem selection will lead to better learning outcomes and higher enjoyment than full system control over problem selection in the tutor. Also, the effects of shared control on learning and enjoyment will be further strengthened by the presence of the redesigned Open Learner Model (i.e., we expected to see an interaction between the redesigned Open Learner Model and the shared control). Lastly, the specific type of shared control in the experiments allowed us to investigate what problem sequences the students would select and how that would affect their learning and enjoyment.

3.1.2 *Lynnette 1.0* – An Equation Solving Tutor

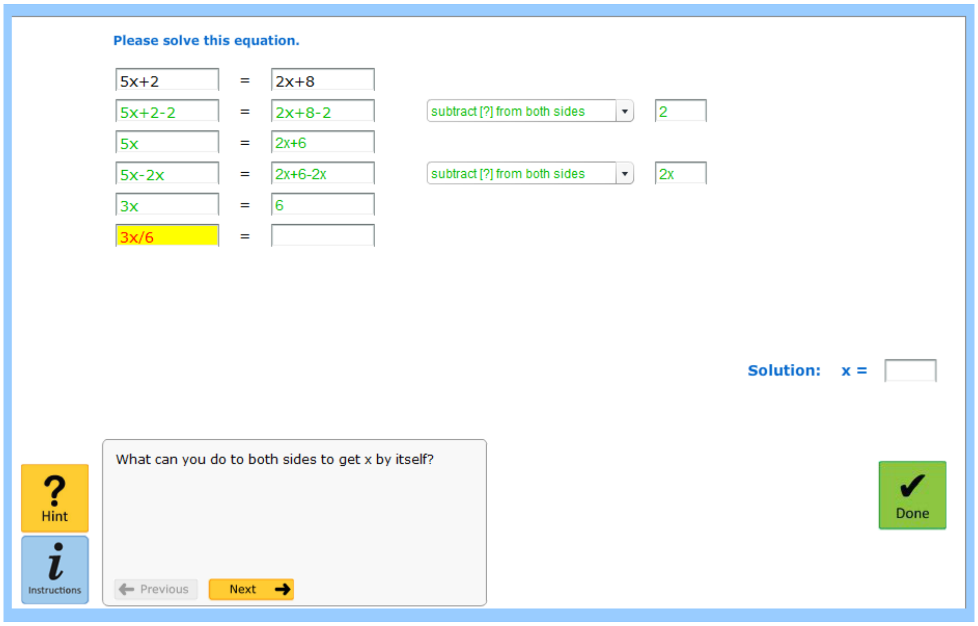


Figure 1. The problem solving interface of *Lynnette 1.0*

I used an ITS for equation solving as platform for the experiments. The tutor was first designed and built by Maaike Waalkens (it was not named *Lynnette* then), using the Cognitive Tutor Authoring Tools (CTAT, http://ctat.pact.cs.cmu.edu/), as an example-tracing tutor (Aleven et al., 2009). The tutor teaches five different types of linear equations (see Table 1). It was used in a classroom study and was found to be effective in improving student learning of equations (Waalkens, Aleven & Taatgen, 2013). The original equation solving tutor had a built-in Learner Model that kept track of students' learning status with respect to equation solving skills, but it was not opened to the students. The tutor was then redesigned and used in Experiments 1 and 2, as *Lynnette* 1.0. Figure 1 shows the main interface of *Lynnette 1.0*: in addition to solving the equations, students need to self-explain each main step. The tutor provides step-by-step guidance for each problem with hints and feedback.

Table 1. Five type of equations in *Lynnette 1.0*

Equations	Example	Level/Problem Type
One Step	x+5 = 7	Level 1
Two Steps	2x+1=7	Level 2
Multiple Steps	3x+1=x+5	Level 3
Parentheses	2(x+1)=8	Level 4
Parentheses, more difficult	2(x+1)+1=5	Level 5

3.1.3 Shared Control over Problem Selection in *Lynnette 1.0*

Table 2 summarizes the steps I went through to redesign *Lynnette 1.0*, including redesign of the built-in OLM (Long & Aleven, 2013a). The overall goals of the design process were to explore how much control we may give to the students over problem selection without impairing the effectiveness of the tutor on equation solving, and how we could redesign the OLM to enhance their experience of using the control. The supported shared control in the tutor should lead to better learning outcomes and higher enjoyment of using the tutor. Notably, the designs did not focus on teaching students to make effective problem selection decisions, only on helping students make effective problem selection decisions while having the support, unlike the research reported in the subsequent chapters.

Table 2. An overview of the design process for *Lynnette 1.0*

Design Processes	Research Approaches
1. Paper Prototyping with 3 8th grade students	HCI/User-centered design
2. High Fidelity Prototyping with 4 6th and 8th grade students	HCI/User-centered design
3. Building a working version of *Lynnette* for an initial classroom evaluation	N/A
4. Classroom Experiment 0 with 98 8th grade students	Experimental educational research, educational data mining
5. Building *Lynnette 1.0*	N/A
6. Classroom Experiment 1 with 62 7th grade students	Experimental educational research, educational data mining
7. Classroom Experiment 2 with 245 7th and 8th grade students	Experimental educational research, educational data mining

Results from the user-centered design process suggested that students needed scaffolding to make decisions on what to practice. All participants admitted during the prototyping sessions that they might keep selecting easy problems if they were completely free to select problems by themselves. As a result, I decided to let the tutor lock the mastered levels once it deems the students have reached mastery for all the skills in a level (as shown in Figure 2 for level 1 and level 2). Students could only select to get problems from unmastered levels, but they were free to select the levels in any order. Once the students selected a level, the tutor assigned a new problem to them from that level. All the problems in the same level entail the same set of skills for equation solving (e.g. add/subtract a constant from both sides), and would only be practiced once. Figure 2 shows the newly designed problem selection screen.

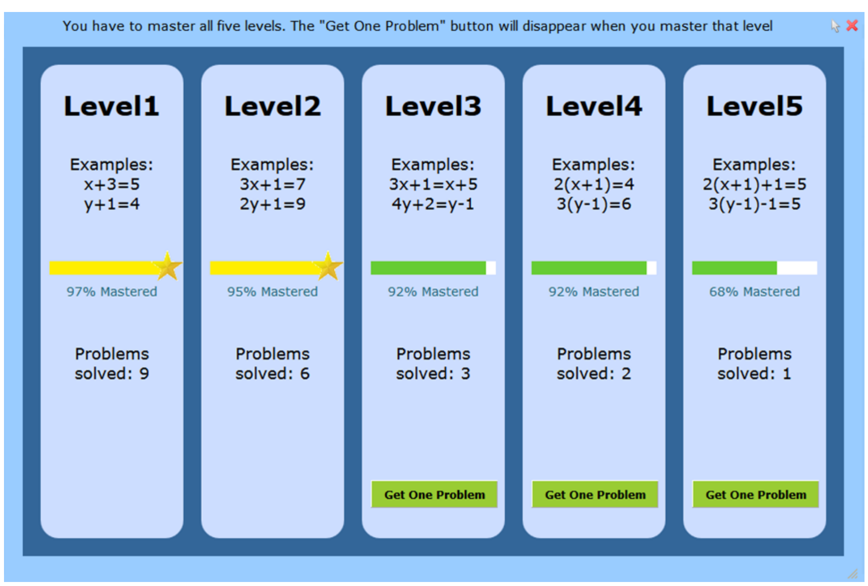


Figure 2. The problem selection screen of *Lynnette 1.0*

I redesigned the original OLM to support students' own decisions on how they would order their practice of the five types of equations. Prior literature has shown that students are not good at accurately assessing their own learning status (Dunlosky & Lipko, 2007; Long & Aleven, 2013b), which is arguably the foundation for making effective problem selection decisions. Alternatively, OLM can serve as a substitute for students' self-assessment, which offers accurate information regarding students' learning status assessed by the system. Figure 3 shows the new OLM in *Lynnette 1.0*. There were three main new features, compared to the original OLM: self-assessment prompts on learning progress, delaying the update of the skill bars until students have answered the self-assessment prompts, and showing overall progress on the problem type level. The OLM was shown on the problem solving interface at the end of each problem to create a short session for self-assessment with feedback (from the update of the skill bars) on their current learning status before the students proceeded to select the next level. The learning status on the problem type level was also displayed on the problem selection screen to assist their decision making. However, no instructions were provided to regarding how to refer to the OLM when they make problem selection decisions.

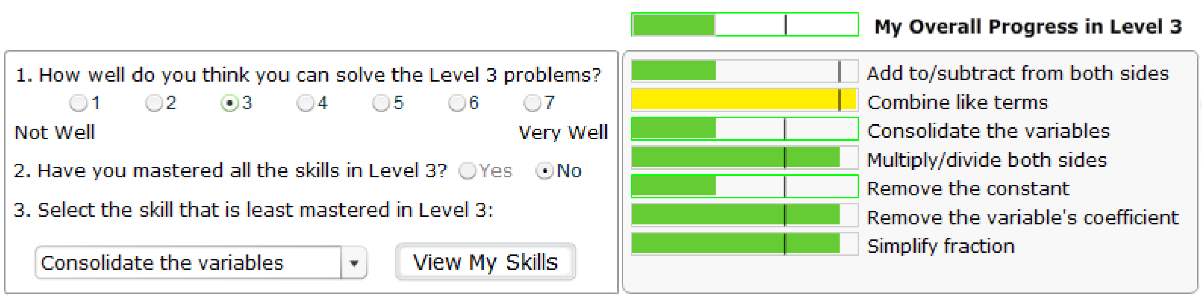


Figure 3. The Open Learner Model (OLM) in *Lynnette 1.0*

As stated earlier, Experiments 1 and 2 did not focus on helping students learn the rules for problem selection. Rather, the designs tried to scaffold their control through assistance from the redesigned OLM, and preventing them from making suboptimal decisions by letting the system lock the mastered levels. The purposes of the classroom experiments were to find out whether the inclusion of the redesigned OLM and the freedom of control over problem sequences would lead to better domain level learning outcomes and higher enjoyment of using the tutor.

3.1.4 Classroom Experiment 1

The experiment had a 2x2 factorial design, with independent factors OLM (whether or not the redesigned OLM was included) and PS (whether the students had shared control or full system-control over problem selection) (Long & Aleven, 2013c). 62 7^{th} grade students from 3 advanced classes taught by the same teacher at a local public school were randomly assigned to one of four conditions: 1) OLM+PS; 2) OLM+noPS; 3) noOLM+PS; and 4) noOLM+noPS. For the two noPS conditions, there was only one "Get One Problem" button on the problem selection screen, and the tutor assigned problems to the students to reach mastery sequentially from level 1 to level 5. In other words, the two system-controlled conditions would follow sequentially blocked practice for the five levels, which is common practice for many ITSs. On the other side, the students in the two

PS conditions were free to select whether they would follow blocked or interleaved practice to reach mastery for the five levels. All participants completed a paper pre-test on their abilities to solve the five types of equations on the first day of the study. They then worked with one of the four different versions of *Lynnette 1.0* in their computer labs for five class periods on five consecutive days. Lastly all students completed a paper post-test to measure their learning gains on solving linear equations.

Overall the students improved significantly from pre to post-tests, affirming the effectiveness of *Lynnette 1.0* in supporting students' equation solving ($F(1, 58) = 35.239$, $p < .000$, $d = 1.65$). A two-way ANOVA with the two factors (OLM and PS) found a significant main effect of OLM on students' post-test scores ($F(1, 58) = 4.903$, $p = .031$, $d = .56$), suggesting that the inclusion of the OLM led to better domain level learning outcomes. However, no significant main effect was found for PS. Due to the small size of the sample in this experiment, I decided to run a replication experiment later in the same school year to further investigate the effects of the new designs, as well as to study how students would select their problem sequences with the control.

3.1.5 Classroom Experiment 2

Experiment 2 replicated the same procedure in Experiment 1, except that the pre and post-tests were shortened (they were too long for the students in Experiment 1) and a questionnaire on enjoyment was added to the post-test. 245 7^{th} and 8^{th} grade students from 16 classes (8 advanced classes and 8 mainstream classes) of 3 local public schools participated in Experiment 2. They were taught by 6 teachers.

Effects of the two factors on learning outcomes and enjoyment

This experiment also found, overall, a significant improvement on equation solving from pre to post-tests ($F(1, 236) = 81.066$, $p < .000$, $d = 1.17$). ANCOVA (using OLM and PS as two independent variables, and using Teachers as co-variate) analyses found no significant main effects for OLM ($F(1, 236) = .773$, $p = .380$, $d = .11$) or PS ($F(1, 236) = .466$, $p = .496$, $d = .09$) on students' learning gains from pre- to post-tests. Also, no significant main effects of the two factors were found on enjoyment of using the systems (OLM: $F(1, 236) = .606$, $p = .437$, $d = .08$; PS: $F(1, 236) = .020$, $p = .889$; $d = .02$). However, a significant interaction between OLM and PS was found on students' learning gains from pre to post-tests ($F(1, 236) = 7.535$, $p = .007$). Planned contrasts (as we had hypothesized, the presence of the OLM would enhance the effects of the shared control on learning and enjoyment) revealed that the OLM+PS condition learned significantly more than the noOLM+PS condition ($F(1, 236) = 6.401$, $p = .012$). In other words, when students were allowed to select the levels with the shared control, the students who had access to an OLM learned significantly more about equation solving than their counterparts who did not. This finding on domain level learning possibly indicates that when students were granted control over problem selection, the presence of the OLM helped reduce their cognitive load for monitoring and assessing their learning status and led to better learning outcomes. Although there were no instructions regarding how to use the information from the OLM to help make problem selection decisions, the students might naturally try to look for such information when they were required to make choices. The absence of the OLM meant that they had to recall and self-assess their learning status, which might be frustrating and consequently diminished their learning. It is also likely that having control over problem selection nudged students to pay more attention to the OLM, which led to deeper reflection at the end of each problem with the self-assessment prompts and update of the skill bars that in turn lead to enhanced learning outcomes. This result is also a novel empirical finding with respect to using OLM to enhance students' domain level learning outcomes in ITSs.

In addition, pairwise contrasts with Bonferroni Corrections revealed that the noOLM+noPS condition learned significantly more than the noOLM+PS condition ($F(1, 236) = 6.056$, $p = .015$; with corrections: $p = 0.03$). Put differently, when the Open Learner Model was not in effect, the full system controlled condition learned significantly more than the shared control condition. This result is consistent with prior literatures which generally found superior learning outcomes with system-control (Atkinson, 1972; Niemiec, Sikorski, & Walberg, 1996). Without appropriate scaffolding (e.g., the OLM), students might be overwhelmed by the cognitive load engendered by making problem selection decisions, or could not make as good decisions as the system, which could diminish the motivational benefits of having learner control and lead to worse learning outcomes than the system-controlled conditions.

In short, the results indicate that OLM is an important tool for supporting self-assessment and problem selection and enhancing domain level learning in a learning environment where students are granted shared control over problem selection. Nevertheless, we did not find superior learning outcomes with the OLM and shared control condition when compared to the system-controlled conditions. Without the OLM, the system-controlled condition learned significantly better than the shared control condition.

Student-selected interleaved versus blocked practice

Experiment 2 also affords opportunities to study how students would freely select their own problem sequences with shared control without any instructions regarding effective problem sequences. Of the 245 students in Experiment 2, 120 students were in the two PS conditions. Tutor log data revealed that 61 out of the 120 students (50.8%) selected the same blocked sequence from level 1 to level 5 exactly as what was implemented in the two noPS conditions with full system control. This might be partly due to the design of the interface, which positions level 1 to level 5 from left to right sequentially (as shown in Figure 2). It is also likely that the students were more familiar with the blocked sequence that is commonly seen in their textbooks. On the other hand, 59 out of the 120 students (49.2%) selected interleaved sequences with varying ways of interleaving. I measured the degree to which these interleaved sequences differed from the system-selected blocked sequence by counting the number of reverse orders they had as compared against the blocked sequence. The results revealed that the degree of differences were generally small for the 59 students. In other words, the students still by and large followed the same blocked sequence. Most of the time, what might have happened was that the student tried to get one or two problems from higher levels, realized those problems were hard and went back to follow the more intuitive blocked sequence from lower to higher levels. In general, the students were much more inclined to select a blocked practice schedule in *Lynnette 1.0*.

I also investigated whether the student-selected interleaved sequences led to different effects on student learning and enjoyment as compared to the student-selected blocked sequence. ANCOVA (using Teachers as co-variate) analyses with the factor as whether the students selected a blocked or interleaved sequence revealed no significant main effect of this factor on their learning gains from pre to post-tests ($F (1, 113) = .003$, $p = .960$, $d = .01$). This could be largely due to the fact that the interleaved sequences did not differ much from the blocked sequence. However, a significant main effect was found for the self-reported enjoyment on post-test ($F (1, 113) = 14.392$, $p < .000$, $d = .69$), as the students who selected the blocked sequence reported significantly higher enjoyment. This is consistent with the theories and prior findings about interleaved practice, which argue that it causes a tougher and more frustrating learning process for the learners. The students who selected an interleaved sequence might encounter more difficulties when they were practicing the higher level problems early in the learning process, and the frustrating experience led to lower enjoyment. This is supported by the log data analyses, as on average, the students who selected interleaved sequences made more errors per step ($F (1, 113) = 1.848$, $p = .177$, $d = .25$), spent more time on each step ($F (1, 113) = .004$, $p = .952$, $d = .01$), and requested more hints per step ($F (1, 113) = 4.031$, $p = .047$, $d = .37$). The difference on the number of hints requested was statistically significant, which was consistent with our informal observations in classrooms. When students got to a new level and encountered difficulties when solving a new type of problems, they relied on the hints. In short, the interleaved sequences selected by the students did not lead to significant difference on domain level learning outcomes. On the other hand, the tougher experiences that resulted from the interleaved sequences still appeared to cause lower enjoyment of using the tutor.

In short, these results shed light on how students would select problem sequences with shared control in an ITS. They were more inclined to select blocked rather than interleaved practice. The fact that no significant difference on learning outcomes was found for whether students practiced with a student-selected blocked or interleaved practice does not convincingly conclude that interleaved practice was not more effective, given the student-selected interleaved sequence did not differ much from the blocked practice. An alternative explanation could be that the sequences selected by students were by and large the same as the system-controlled condition, thus they might not have experienced much difference in terms of sense of control, which might have contributed to the same learning outcomes achieved by the shared control and system control conditions.

3.2 Experiment 3: Gamification of Shared Control over Problem Selection in a Linear Equation Tutor

3.2.1 Introduction and Research Questions

Experiment 3 investigated whether gamification could be integrated with ITS to boost students' motivation and learning outcomes when they were granted shared control over problem selection (Long & Aleven, 2014). This experiment mainly focused on the motivational benefits of gamification. Therefore, I restricted the amount of control students could have to ensure the same practice sequence of the problem types, and studied the effects of two gamification features on student enjoyment and learning outcomes with the ITS.

In recent years, ITS researchers started to investigate how to integrate game elements with the tutoring environment to make the system more engaging for the students, while still maintaining its effectiveness on learning. Empirical studies have also been conducted to evaluate the effects of gamifying the tutors on students' learning and motivation, as well as to explore the best design to incorporate the game elements in tutors. Some studies have found that game-based learning environments could significantly enhance students' learning outcomes (Boyce & Barnes, 2010; Meluso et al., 2012), and produced the same learning effects as nongame tutors (Jackson & McNamara, 2013). However, gamification of ITSs is not always successful. One study (Easterday et al., 2011) found that tutor-like assistance led to better learning and interest as compared to game-like assistance in an educational game of policy argument. Therefore, gamification of ITSs should be done with care, where possible informed by empirical studies.

In Experiment 3, we focused on gamifying the shared control over problem selection in an ITS. With the shared control, the system adaptively selected problem types and also decided on whether students had mastered each problem type and might go on to the next, while the student selected individual problems from a certain problem type. We tried to improve on this simple form of shared control by adding gamification features, and investigate whether the gamified shared control will lead to higher enjoyment and better learning.

Commercial games provide plenty of ideas for gamification of problem selection. A feature found in many popular games (e.g., *Angry Birds*, *DragonBox*) is the possibility to re-do problems after they have been completed. This feature is often combined with rewards (such as a number of stars) that reflect performance on the given problem, which often are displayed prominently on the problem selection screen. One reason players may elect to re-do a problem is to increase the rewards (e.g., earn more stars). According to theories of autonomy in learning (Grolnick & Ryan, 1987), allowing re-practice gives students more freedom, which could possibly enhance their engagement in learning. Moreover, re-practicing could lead to more efficient acquisition of problem-solving skills, although to the best of our knowledge that has not been established definitively in the cognitive science literature. On the other hand, frequent re-practice may reduce problem variability and therefore be detrimental for learning (Paas & van Merriënboer, 1994). Empirical investigation of the effectiveness of these gamification features is therefore warranted.

Similar to Experiments 1 and 2, we investigated the effects of gamifying shared student/system control in our linear equation tutor, *Lynnette*. We investigated two gamification features: giving students the freedom to access and re-practice completed problems (not allowed e.g., in standard Cognitive Tutors) and rewards (stars) for each problem based on students' performance. These features are similar to *Angry Birds'* or *DragonBox's* problem selection and rewards systems. We hypothesized that 1) shared control with re-practice would enhance students' learning and enjoyment; 2) rewards based on students' performance on individual problems would also lead to better learning and enjoyment.

3.2.2 *Lynnette 2.0* – A Tablet based Equation Solving Tutor

Figure 4. The problem solving interface of *Lynnette 2.0* on a Samsung Galaxy Tablet

We (the CTAT team and I) designed and implemented *Lynnette 2.0* as a rule-based Cognitive Tutor that runs on Android tablets, implemented with CTAT. The problem-solving interface (as shown in Figure 4) was redesigned from *Lynnette 1.0* to fit the use on tablet computers. An additional "Undo" function was implemented to allow students to undo their steps. The students could undo the correct steps that have already been accepted by the tutor, in case they wanted to use a different strategy in the midst of solving a problem. Overall, as a rule-based tutor, *Lynnette 2.0* was very flexible in terms of allowing alternative strategies and skipping intermediate steps. Moreover, based on the results from Experiments 1 and 2, the five levels of equations were slightly reorganized. As shown in Table 4, the former Level 3 was separated into two levels (the new Level 3 and Level 4), given it was shown from the data that the students had particular difficulties with equations that have variables on both sides. Former Level 4 and Level 5 were combined into a new Level 5.

Table 3. New five types of equations in *Lynnette 2.0*

Equations	Example	Level/Problem Type
One Step	x+5 = 7	Level 1
Two Steps	2x+1=7	Level 2
Multiple Steps 1	3x+4=x	Level 3
Multiple Steps 2	3x+1=x+5	Level 4
Parentheses	2(x+1)+1=5	Level 5

3.2.3 Shared Control over Problem Selection in *Lynnette 2.0*

In Experiment 3, the student control was restricted in the sense that they were not allowed to select the levels which decided their practice sequence of the problem types. Rather, with the new shared control in *Lynnette 2.0*, they needed to complete the lower levels to unlock the higher levels, and the tutor locked the lower levels once they were mastered (there would always only be one unlocked level on the interface). Therefore, the shared control enforced the same full system-controlled problem type sequences as in Experiments 1 and 2, which was the blocked sequence. On the other hand, students had control over which specific problems they could select within a problem type (or level). As shown by the right image in Figure 5, the students were presented with a list of problems that they could select from. The problems within any given level required the same set of skills. Two gamification features were integrated with the shared control, re-practice and rewards. The left image in Figure 5 shows the rewards students could earn at the end of each problem, depending on whether they had completed that problem, the number of errors they made and the number of hints requested. The rewards were also displayed next to the problems on the problem selection screen (as shown on the right of Figure 5). Student could earn an extra trophy for perfect problem solving. Re-practice means that the students were allowed to re-do the problems they had completed before, and the rewards could be updated based on their re-practice performance.

Figure 5. Problem summary screen with rewards (left) and problem selection screen (right) in *Lynnette 2.0*

3.2.4 Classroom Experiment 3

Experiment 3 was conducted to investigate whether the gamified shared control could lead to enhanced enjoyment and learning outcomes. 161 7th and 8th grade students from 15 classes (3 advanced classes and 12 mainstream classes) of 3 local public schools participated in the experiment. They were taught by 5 teachers. Experiment 3 had a 2x2+1 design, with two independent factors as 1) whether or not the students were allowed to re-practice the completed problems, and 2) whether the students were shown performance-based rewards. I also included an ecological comparison condition, which was a standard version of *Lynnette 2.0* that had full-system control (no in-between screens as shown in Figure 5). With the standard tutor, students just kept receiving problems from the system, as is common practice in Cognitive Tutors. All five conditions followed the same procedure as Experiments 1 and 2. They all completed a paper pre-test on the first day of the study, learned with one of the five versions of *Lynnette 2.0* for 5 class periods, and took a post-test and an enjoyment questionnaire on the last day of the study. We analyzed the data using ANCOVAs, with the two independent factors Rewards and Re-Practice, as well as the Teachers as co-variate.

Overall the five conditions improved significantly on equation solving from pre- to post-tests (F (1, 155) = 28.203, $p < .000$, $d = .85$). However, the results revealed no significant difference on equation solving or self-reported enjoyment between the four gamified *Lynnette 2.0* versions and the standard

Lynnette 2.0. In other words, the gamified shared control led to comparable learning outcomes as the system-controlled tutor, but did not foster greater learning or greater enjoyment of using the tutor. Among the four gamified *Lynnette 2.0* versions, the main effects of Re-Practice and Rewards were also not significant for equation solving or enjoyment. However, an interesting significant interaction was found between Re-practice and Rewards on equation solving ($F(1, 120) = 8.173$, $p = .005$). When students were allowed to re-practice the completed problems, those who were given rewards did significantly worse on the post-test than their counterparts who did not see the rewards ($F(1, 120) = 6.944$, $p = .01$; with Bonferroni corrections, $p = .04$). Further tutor log data analyses revealed that the students who were given rewards revisited significantly more completed problems ($F(1, 57) = 8.195$, $p = .006$, $d = .72$), and the ratio of revisited problems correlated negatively with their post-test performance (Corr = -.277, $p = .028$). These findings suggest that the performance-based rewards encouraged students to re-practice completed problems to earn more stars and trophies, but the re-practice of previously completed problems was detrimental to learning.

3.3 Conclusions and Design Implications of Chapter 3

Experiments 1, 2 and 3 aimed at designing tutor features to assist students in making good problem selection decisions while enhancing their experience of using the shared control, but did not focus on explicitly helping students learn problem selection skills. Therefore, the experiments did not measure whether students learned to make good problem selection decisions on their own, after the scaffolding was removed, which would be addressed in the second part of my dissertation work.

Experiment 2 demonstrates that Open Learner Model could be an important tool for supporting problem selection and domain level learning in environments with shared student/system control. Little prior empirical work has investigated whether an OLM can improve students' domain level learning (Mitrovic & Martin, 2007). Experiment 2 establishes that an OLM can enhance learning outcomes in ITSs when shared control is enabled, although the shared control with the OLM did not lead to significantly better learning outcomes than the full system control over problem selection. The information regarding learning status offered by an OLM may help reduce the cognitive load for students when they have to monitor their learning and make decisions on problem selection, and also mitigate the detrimental influence on problem selection decisions due to inaccurate self-assessment on learning status. However, the student control in Experiment 2 was restricted to deciding the sequence of the problem types only, while the system decides when to lock the levels from practice. It is possible that the students need to be taught how to base their problem selection decisions on the learning status displayed by the OLM when given more control (e.g., deciding when they have had enough practice for a certain level) over problem selection in the tutor.

Although gamification in Experiment 3 did not lead to significant difference on students' enjoyment, it illustrates the effectiveness of using rewards as simple as stars and trophies to nudge middle school students' decisions on problem selection. However, the use of rewards in Experiment 3 encouraged a suboptimal strategy (re-practice the completed problems) for problem selection, which impaired student learning. Therefore, the use of rewards needs to align with the instructional goal to encourage desirable problem selection behaviors. With well aligned designs, gamification such as rewards has great potential to guide students into desirable behaviors. In Chapters 4 and 5, motivational features including gamification were explored and integrated to support students' learning and application of problem selection strategies in the tutor.

Notably, the shared control in all three experiments in this chapter was designed to scaffold problem selection by only granting limited amount of control to students. Arguably, the system still made decisions on the most critical aspect of problem selection, i.e., deciding when the students have had enough practice for a certain problem level. As discussed in Chapter 2, it is critical for students to learn the effective problem selection skills that can be applied in different learning technologies. Therefore, in Chapter 4 and Chapter 5, *Lynnette* was redesigned again to let students have more control than the system to make problem selection decisions, so that they can practice and learn the problem selection skills with the ITS.

Chapter 4. Motivational Design that Helps Students Make Good Problem Selection Decisions with Learner Control in Intelligent Tutoring Systems

Summary. This Chapter and Chapter 5 describe the part of my dissertation work that focuses on helping students learn an effective strategy for making effective problem selection decisions with the integration of motivational design. In this Chapter, I first describe the user-centered research and evaluations we went through to investigate how students naturally select problems in an Intelligent Tutoring System, what knowledge they have for a specific problem selection strategy, i.e., the Mastery Rule, as well as their motivations for actively applying the rule to select problems in ITS. I also present the iterative design and implementation process we went through to design and refine tutor features that may foster a mastery-approach orientation and learning of the Mastery Rule.

4.1 Introduction and Research Questions

The prior work, including my own 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. Therefore, in this project (Long, Aman, & Aleven, 2015), I focused on extending *Lynnette*, so that it may 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 (I will refer to this as the "Mastery Rule"). The Mastery Rule is based on theories of mastery learning (Kulik, Kulik, & Bangert-Drowns, 1990). System-controlled problem selection in an ITS based on this rule has been shown to significantly enhance student learning (Corbett, 2000). As a first step towards helping students learn problem selection skills, we keep the Mastery Rule simple by not taking into account any spacing effects (Anderson, 1994). 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 (Zimmerman, 1995). Scaffolding for SRL processes in ITSs often aims at helping students correctly apply relevant metacognitive strategies (e.g., Aleven, Roll, & Koedinger, 2012; Azevedo et al., 2009). Very little research has tried to foster students' motivation for applying 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 (Tai, Arroyo, & Woolf, 2013). However, it is still largely an open question how we can use motivational design (i.e., design to foster motivations) in ITSs to help students want to use the metacognitive strategies.

We emphasize motivational design in *Lynnette* to help students *want* to learn and 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 (Goodman, Kuniavsky, & Moed, 2012). 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 experimental studies, 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. Our user research was also informed by SRL theories. Next, we built prototypes of tutor features that aim to foster motivation and learning of the Mastery Rule based on results of our user research and grounded in motivation theories. Finally, we revised the tutor features from the prototyping process and implemented them in *Lynnette*.

4.2 Classroom Study

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). As mentioned, 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 claims that an OLM has the potential to support students' problem selection (Bull & Kay, 2008), but not much work has empirically investigated whether and how the presence of an OLM might influence students' problem selection decisions.

4.2.1 Methods

Lynnette 1.0 was slightly revised and used as the platform of the experiment. There were two conditions. Both conditions needed to select problems from a problem selection screen by clicking one of the "Get One Problem" buttons. As shown in Figure 6, 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. Hence the students had a broader shared control over problem selection, as compared to the old *Lynnette 1.0* (the system decides when a given student has completed a level and stops practicing that level in *Lynnette 1.0*). 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.

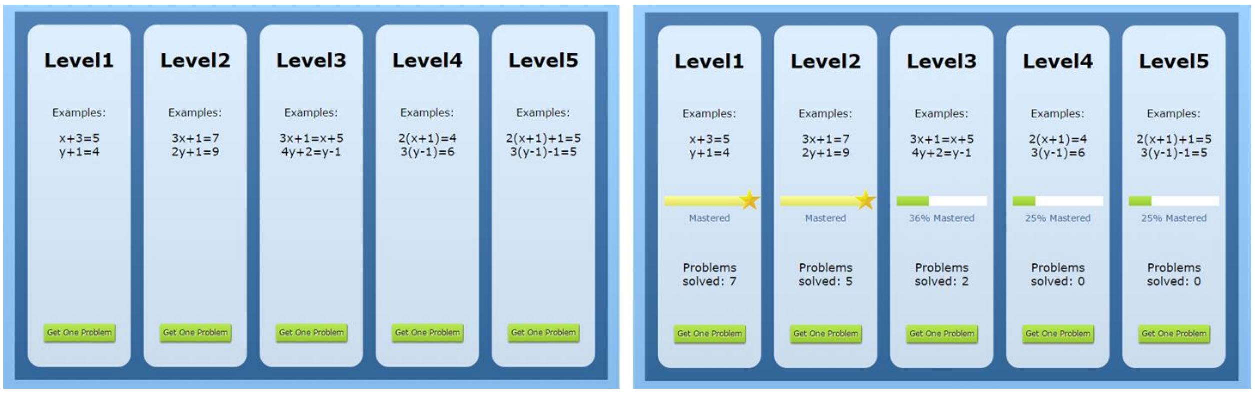


Figure 6. Problem selection screen for the noOLM (left) and the OLM condition (right)

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.

4.2.2 Results from the Classroom Study

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 4 shows the two conditions' average proportions (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 4. Means and SDs for proportions 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.) First, 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. Second, the OLM might have encouraged the students to work on 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.

4.3 Interviews and Storyboards

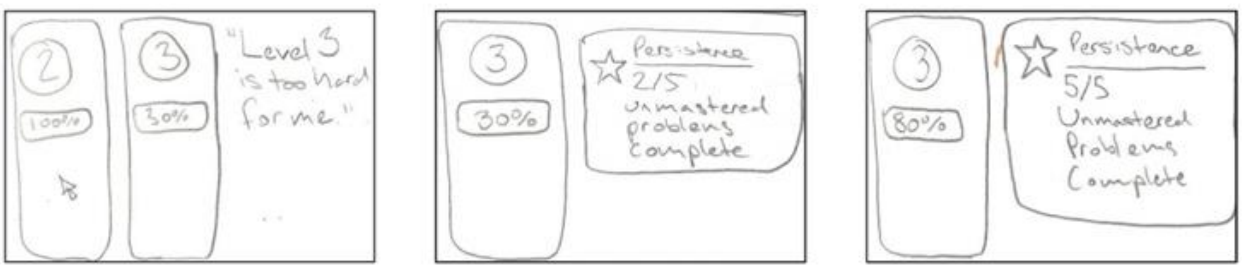
Our next step in the user-centered design process was to gather qualitative data to help explain and further investigate the quantitative results observed in the classroom experiment. Specifically, we conducted interviews and used storyboards to find out 1) how the OLM helps students make better problem 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.

4.3.1 Methods

12 6th – 8th grade students participated in the study in a lab at the Pittsburgh campus of Carnegie Mellon University. We recruited the participants from the participants' pool of Pittsburgh Science of Learning Center. 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 with storyboards. Each participant was compensated with 10 dollars for their effort. 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.

We designed interview questions (the interview script and procedure are included in Appendix X) that probe 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 6). 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 they selected. We also asked students who saw the OLM what they thought had led to the change of the mastery bars, displayed on the problem selection screens.



James is working through level 3 in Lynnette and having some difficulty. He is tempted to go back to level 2, which he has already mastered.

However, James can see that if he picks 5 unmastered problems in a row, he will receive an achievement badge.

James decides to persevere on level 3 and at least work through 5 of the level 3 problems.

Figure 7. A storyboard illustrates earning badges for persevering with a difficult level (Appendix XI shows all 18 storyboards)

We created 18 storyboards that reflect design ideas we brainstormed based on prior literature on supporting Self-Regulated Learning (the 18 storyboards are included in Appendix XI). Storyboarding is an effective technique in user-centered design for quickly identifying user needs and generating feedback on design ideas (Davidoff, Lee, Dey, & Zimmerman, 2007). 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 7 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 all 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 stories.

We had taken detailed notes of the interviews and storyboarding sessions with each participant. Two researchers collapsed and discussed the notes together to identify general themes from participants' responses. We tried to summarize responses regarding 1) students' understanding of the Open Learner Model (i.e., the mastery bars) and the Mastery Rule; 2) what factors may contribute to the difficulties of applying the Mastery Rule; and 3) what design features are motivating to these middle school students with respect to challenging themselves with new problem levels.

4.3.2 Results from the Interviews and Storyboards

The interviews and discussions of the 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 type of 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. These bars may encourage 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.

3) Avatars. Students generally liked individualized avatars and earning rewards for their avatars, but not all students were enthusiastic about the idea of having their avatars compete with each other. Likewise, the idea of social interactions between avatars was accepted only by some students.

4.4 Prototypes of Mastery-Oriented Tutor Features that Foster a Mastery-Approach Orientation and Learning of the Mastery Rule

We designed and created paper and HTML/Javascript prototypes of tutor features that aim to foster a mastery-approach orientation and learning of the Mastery Rule (I will refer to the features as the mastery-oriented features) based on results gathered from our user research. There were two main goals of our design: 1) to support students' motivation for applying the Mastery Rule; and 2) to support the learning of the Mastery Rule. We also have the ultimate goal to engender lasting effects of the mastery-oriented features on students' future problem selection decisions and future learning.

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 (Schunk, Pintrich, & Meece, 2008). These theories distinguish two types of achievement goals, mastery orientation and performance orientation (O'Keefe, Ben-Eliyahu, & Linnenbrink-Garcia, 2013). While a performance orientation focuses on demonstration of competence, a mastery orientation emphasizes developing competence (Schunk, Pintrich, & Meece, 2008). The orientations are further divided into approach and avoidance forms (Schunk, Pintrich, & Meece, 2008). 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 (O'Keefe, Ben-Eliyahu, & Linnenbrink-Garcia, 2013), 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 (O'Keefe, Ben-Eliyahu, & Linnenbrink-Garcia, 2013). Empirical study has also found that mastery goal orientation is correlated with positive motivational beliefs (e.g., task value, self-efficacy) and better self-regulatory behaviors (Wolters, Yu, & Pintrich, 1996). Therefore, we designed tutor features that may foster a mastery-approach orientation. Meanwhile, given math is uninteresting to some of the students, we included game elements (avatars, stars and badges) in some of the prototypes to make the tutor more fun.

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 8, one Achievement students can earn is by selecting three unmastered problems in a row.

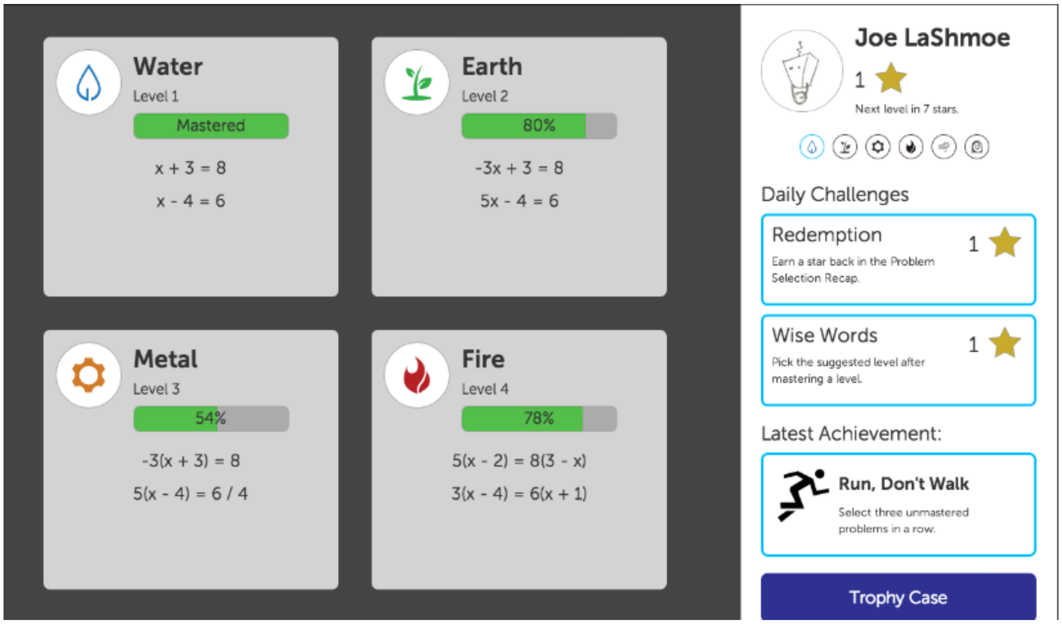


Figure 8. Prototype problem selection screen that also displays Daily Challenges and Achievements

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

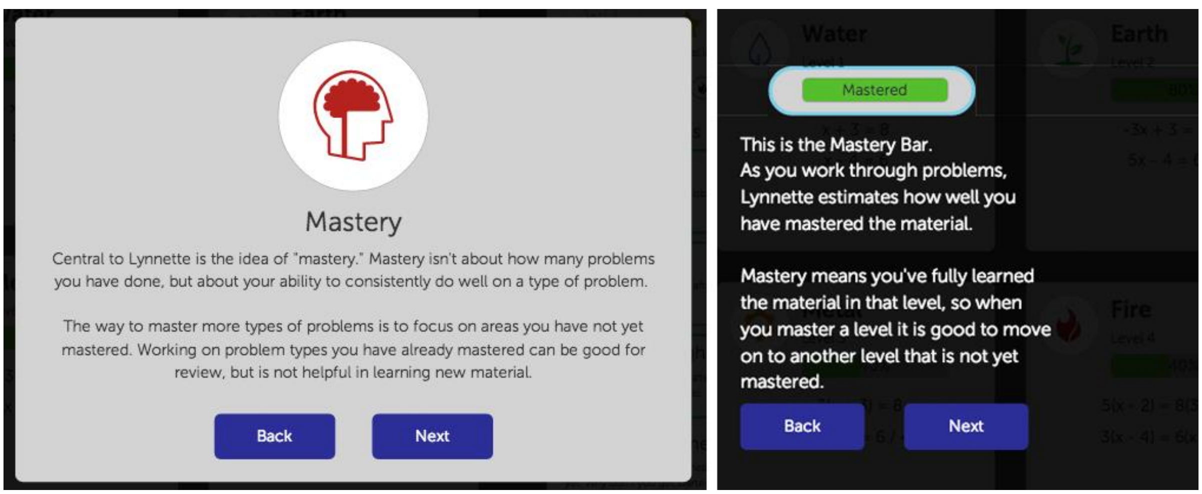


Figure 9. Prototype tutorial that shows the explicit explanations of mastery (left) and of the mastery bars (right)

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, namely, 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 9, 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 8.

Feedback Messages. We designed messages to serve as feedback on students' problem selection decisions. Figure 10 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."

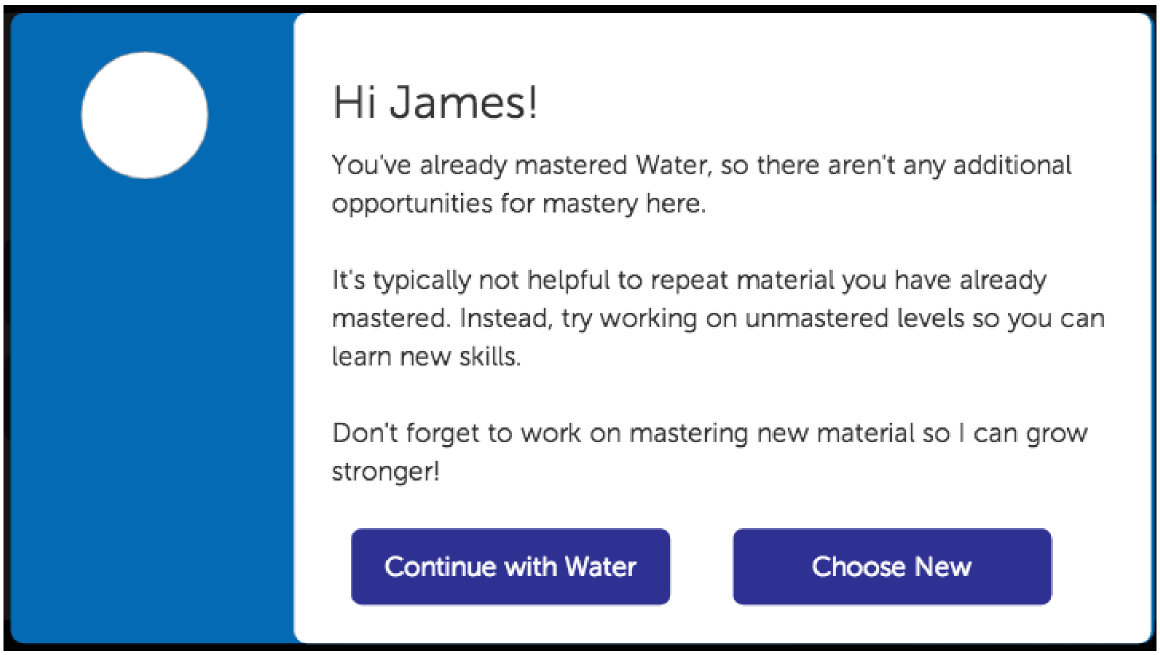


Figure 10. Prototype feedback message students receive after several ineffective problem selection decisions

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 on Figure 11).

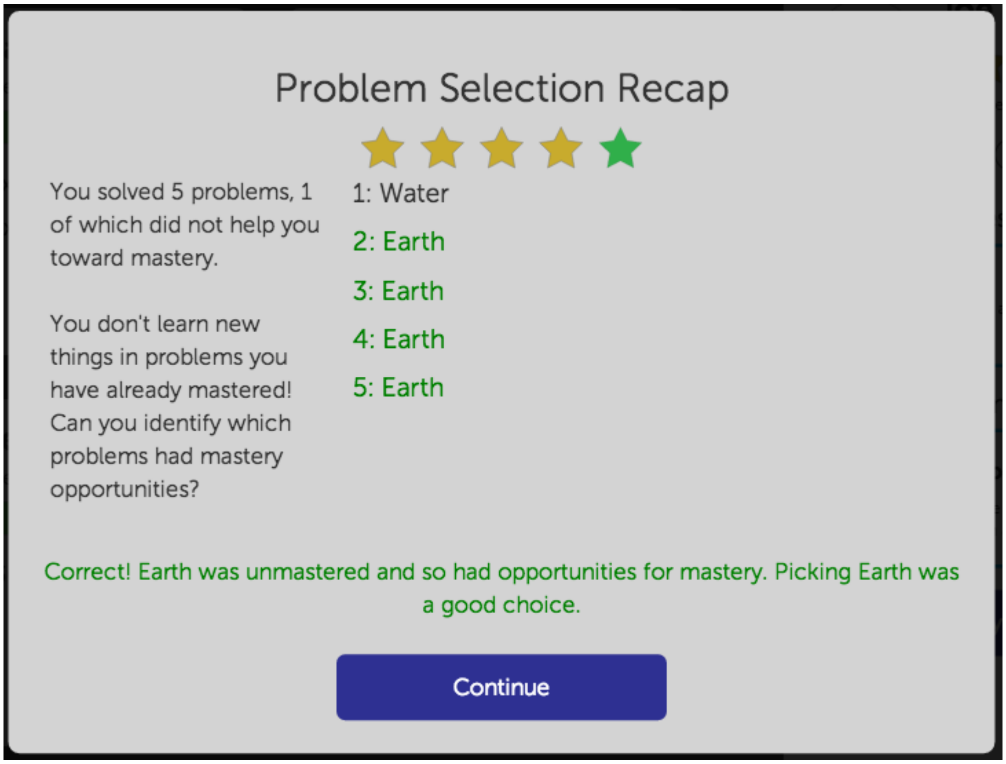


Figure 11. Prototype Problem selection recap screen

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 mainly 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.

4.5 Implementation of the Mastery-Oriented Features with Shared Control over Problem Selection in *Lynnette*

4.5.1 *Lynnette 3.0* and Its Shared Student/System Control over Problem Selection

We redesigned the shared control over problem selection in *Lynnette* to offer students more control so that they will have opportunities to practice the Mastery Rule. Specifically, in *Lynnette 3.0*, students select which problem type they want to practice, and also decide when they have had enough practice for that type (in previous *Lynnette* versions, Cognitive Mastery was implemented and the tutor controls how much practice is needed for each problem type). The system is only responsible for assigning a specific problem from a problem type chosen by the student. Figure 12 shows the problem selection screen of *Lynnette 3.0*. Students are free to select any levels they want to practice. Once the student selects a level, the tutor assigns a problem from the chosen level. Students are able to select problems even after they have fully mastered that level (as calculated by the tutor's Bayesian

Knowledge Tracing and displayed by the Open Learner Model, i.e., the mastery bars for each level). In addition, the previous *Lynnette* versions only provided practice for 5 levels of equations. *Lynnette 3.0* is extended to have 9 levels of equations (as reflected in Figure 12).

Figure 12. Problem selection screen in *Lynnette 3.0*; The Stars and Achievements displayed on the right panel reward students' good problem selection decisions

4.5.2 Mastery Oriented Features to Foster a Mastery-Approach Orientation and Learning of the Mastery Rule with the Shared Control over Problem Selection

We slightly revised the tutor features from the prototypes and integrated them with *Lynnette 3.0*. The features were more specifically defined and some features were dropped during the implementation process, based on their relevance to the research questions.

Tutorial. The interactive tutorial was kept the same as in the prototype. The students read through it when they log in to the tutor for the first time. It introduces the concept of Mastery, the mastery bars and how to apply the Mastery Rule to select problems in *Lynnette 3.0*.

Achievements and Stars as Rewards for Good Problem Selection Decisions. Two types of Achievements were implemented in the tutor to reward students' good problem selection decisions and perseverance with practicing new problems, as shown on the right panel of the screen in Figure 12. The students were able to earn a "Fast Runner" Achievement each time they selected 6 unmastered problems in a row. Similarly, the students could earn a "Mountain Climber" Achievement when they completed 6 unmastered problems in a row (the student could abandon a problem in the middle after s/he selected it). In addition, we added stars to more timely reward students' good problem selection decisions. The student could earn one star each time s/he selected an unmastered problem. The number of problem selection stars earned was also displayed on the problem selection screen shown in Figure 12. The Daily Challenge was not implemented in *Lynnette 3.0*. The participating schools have different schedules for their math classes. Some schools have double periods on a single day. Therefore, it is difficult to implement the same daily challenge for all the participating schools.

Feedback on Problem Selection Decisions. We implemented both positive and negative messages as feedback on students' problem selection decisions. Each time the student selected a problem, either a positive (as shown in Figure 13) or negative message (as shown in Figure 14) would pop out to provide instant feedback on her/his choice.

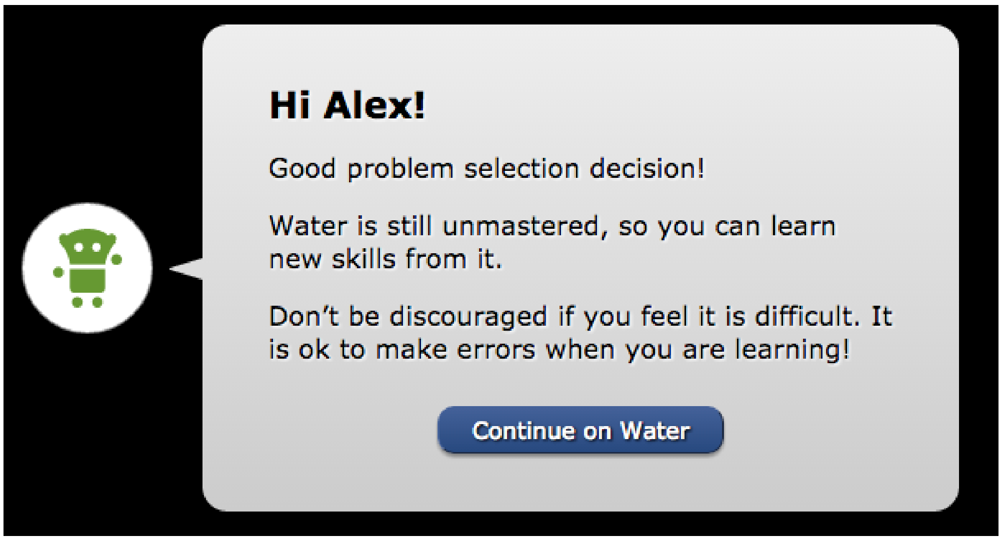


Figure 13. A positive feedback message on student's problem selection decision in *Lynnette 3.0*

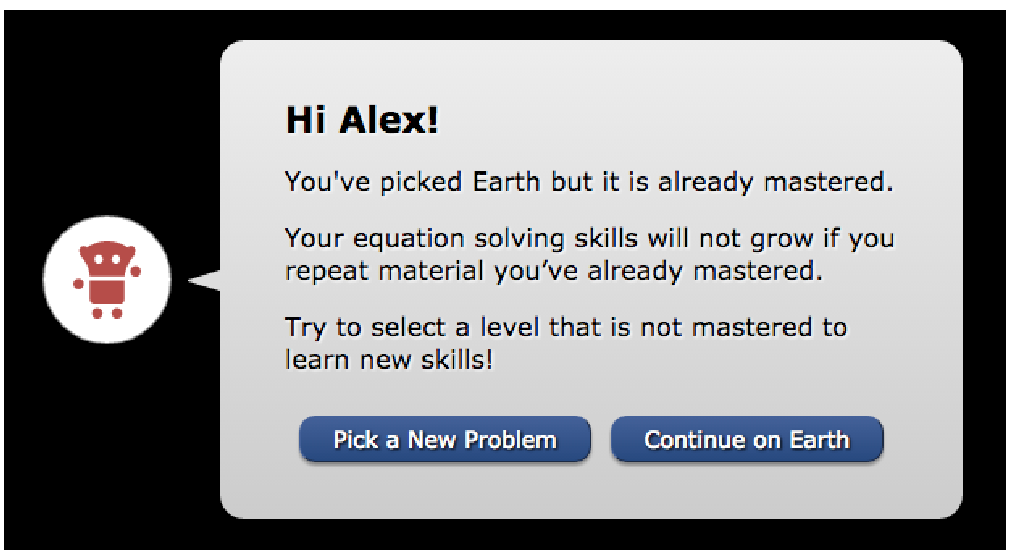


Figure 14. A negative feedback message on student's problem selection decision in *Lynnette 3.0*

Problem Selection Recap. The revised problem selection recap screen (as shown in Figure 15) was shown to the students after every 5th problem, in order to help students review and reflect on their recent problem selection decisions. It displayed the number of stars the student had earned for selecting their last five problems on the top of the screen. The specific problem levels the student had selected were displayed with corresponding mastery bars showing the percentages of mastery the time the student selected the levels. The student also received instant feedback on whether s/he had correctly clicked the unmastered levels (the levels that could help learn new skills). The name of the problem levels turned green or red when the student clicked. Green flagged a correct click.

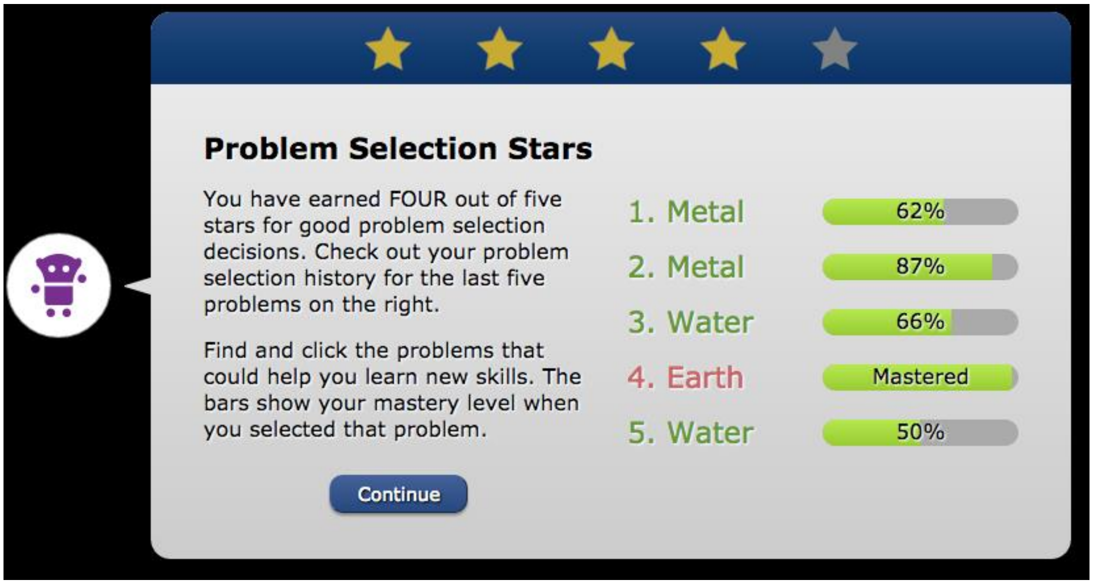


Figure 15. The problem selection recap screen in *Lynnette 3.0*; the "Continue" button appears when the student has clicked all the unmastered levels

All the tutor features described above focus on helping students learn the knowledge of the Mastery Rule, and fostering the mastery-approach goal orientation.

4.5.3 Gamification Features for Equation Solving to Make the Tutor More Fun

We implemented additional tutor features to make the tutor more fun, as we have found that math is uninteresting to some of our interview participants. As shown in Figure 12, each equation level was assigned an element, and a special badge was designed for that element. The student could earn the badge when s/he mastered a particular level. The problem selection screen shows which badges have been earned by the student. The badges were included simply to reward students' equation solving progress, rather than their problem selection decisions. They were present in all conditions in Experiment 4 which will be described in Chapter 5.

4.6 Discussion and Conclusions of Chapter 4

This project used a user-centered motivational 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 and implemented tutor features in *Lynnette* that may foster a mastery-approach orientation and learning of the Mastery Rule based on results and insights gained from our user research.

The 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 type they like and decide when to stop practicing it. 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. The classroom experiment helps empirically establish the beneficial 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.

The work contributes to the research of supporting self-regulated learning in ITS. The new tutor features are designed to foster a mastery-approach orientation that may have lasting effects on students' problem selection and future learning. Not much work in ITSs has investigated motivational design to help students *want* to apply SRL skills 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. The next chapter describes a classroom experiment we conducted to measure if mastery-oriented shared control will lead to better problem selection decisions and enhanced learning outcomes. The experiment also measures the mastery-oriented features' lasting effects on students' problem selection and learning when they are removed in a future learning unit in the same learning environment.

Chapter 5. Experiment 4: Mastery-Oriented Shared Control over Problem Selection in Intelligent Tutoring Systems

Summary. Chapter 5 describes the classroom experiment I have conducted to measure the effects of the mastery-oriented features with shared control over problem selection on enhancing students' problem selection decisions, domain level learning outcomes, enjoyment of the learning experience, and declarative knowledge about applying the Mastery Rule. This experiment also measured whether there were lasting effects of the mastery-oriented shared control on students' problem selection decisions and learning in new tutor units. The results of the experiment show that shared control over problem selection accompanied by the mastery-oriented features leads to significantly better learning outcomes, as compared to full system-controlled problem selection in *Lynnette*. Furthermore, the mastery-oriented shared control has lasting effects on students' declarative knowledge of problem selection skills. Nevertheless, there was no effect on future problem selection and future learning, possibly because the tutor greatly facilitated problem selection (through its Open Learner Model and badges).

5.1 Research Questions

We conducted a classroom experiment to empirically evaluate the effects of the mastery-oriented shared student/system control over problem selection described in Chapter 4 (specific hypotheses related to the research questions are presented in 5.4):

1) Can an intelligent tutoring system help foster students' learning of the Mastery Rule with mastery-oriented shared control over problem selection? **[Hypotheses 1 and 4]**
2) Does mastery-oriented shared control over problem selection lead to better domain level learning outcomes and greater enjoyment of learning, compared to full system control over problem selection in an ITS? **[Hypotheses 2 and 3]**

3) Does it have a lasting effect? That is, do students transfer the Mastery Rule of problem selection to a new tutor unit when the mastery-oriented design features are not in effect? **[Hypothesis 5]**
4) Will the transferred problem selection skill with shared control lead to better future domain level learning outcomes in the new tutoring unit, compared to full system control over problem selection? **[Hypothesis 6]**

5.2 Experimental Design

5.2.1 The Learning Phase versus the Future Learning Phase

The classroom experiment deployed a two-phase design, a Learning Phase and a Future Learning Phase. The Learning Phase addresses research questions 1 and 2, i.e., whether the students are able to correctly apply the Mastery Rule when the mastery-oriented features are present with the shared student/system control over problem selection; as well as whether the mastery-oriented shared control over problem selection will lead to enhanced learning outcomes and enjoyment of using the system. On the other hand, the Future Learning Phase tested whether the students will be able to apply the Mastery Rule with shared control when the mastery-oriented features are not in effect, and whether the shared control over problem selection will lead to better learning outcomes as compared to full system control over problem selection (research questions 3 and 4).

Table 5. Conditions of the Learning Phase and the Future Learning Phase

Learning Phase		**Future Learning Phase**	
Conditions	*Lynnette* Version	Conditions	*Lynnette* Version
Condition 1 (M-shared): Shared control over problem selection with mastery-oriented features	*Lynnette 3.0*	**Condition 1-1 (M-shared + Shared)**: Shared control over problem selection	*Lynnette 3.0-PSonly*
		Condition 1-2 (M-shared + system): System control over problem selection	*Lynnette 3.0-System*
Condition 2 (noM-system): System control over problem selection without the mastery-oriented features	*Lynnette 3.0-System*	**Condition 2-1 (noM-system + Shared)**: Shared control over problem selection	*Lynnette 3.0-PSonly*
		Condition 2-2 (noM-system + Shared): System control over problem selection	*Lynnette 3.0-System*

The experiment started with two conditions in the Learning Phase. In the Future Learning Phase, the first two conditions were split into four conditions. As shown in Table 5, only Condition 1 (I will also refer to it as the M-shared condition, standing for the mastery-oriented shared control) in the Learning Phase had the mastery-oriented tutor features that support students' learning of the Mastery Rule for problem selection. "noM-system" refers to no mastery-oriented design features and full system control over problem selection. For the four conditions in the Future Learning Phase, the first part of the condition name refers to whether they were split from the M-shared or the noM-system condition in the Learning Phase. The second part of the name stands for whether the condition had shared control or full system control over problem selection in the Future Learning Phase. For example, for Condition 1-1, "M-shared + Shared" means the condition was split from the M-shared condition and had shared control over problem selection in the Future Learning Phase. Such two-phase experimental design allows investigation of whether students are able to successfully apply the Mastery Rule when the mastery-oriented features are removed in a transfer of learning phase, compared to students who had been learning with full system-controlled problem selection in the Learning Phase.

We adjusted the interface of *Lynnette 3.0* to enable the two phases of learning. As shown in Figure 16, only the first six levels were unlocked in the Learning Phase. The students were free to select which level they wanted to practice. Once the students selected a level, the tutor assigns a problem from the chosen level. Students were able to select problems even after they have fully mastered that level (as calculated by the tutor's Bayesian Knowledge Tracing and displayed by the Open Learner Model, i.e., the mastery bars for each level). Level 7 to Level 9 were unlocked when the students entered the Future Learning Phase, and they would be able to freely select problems from all 9 levels by then.

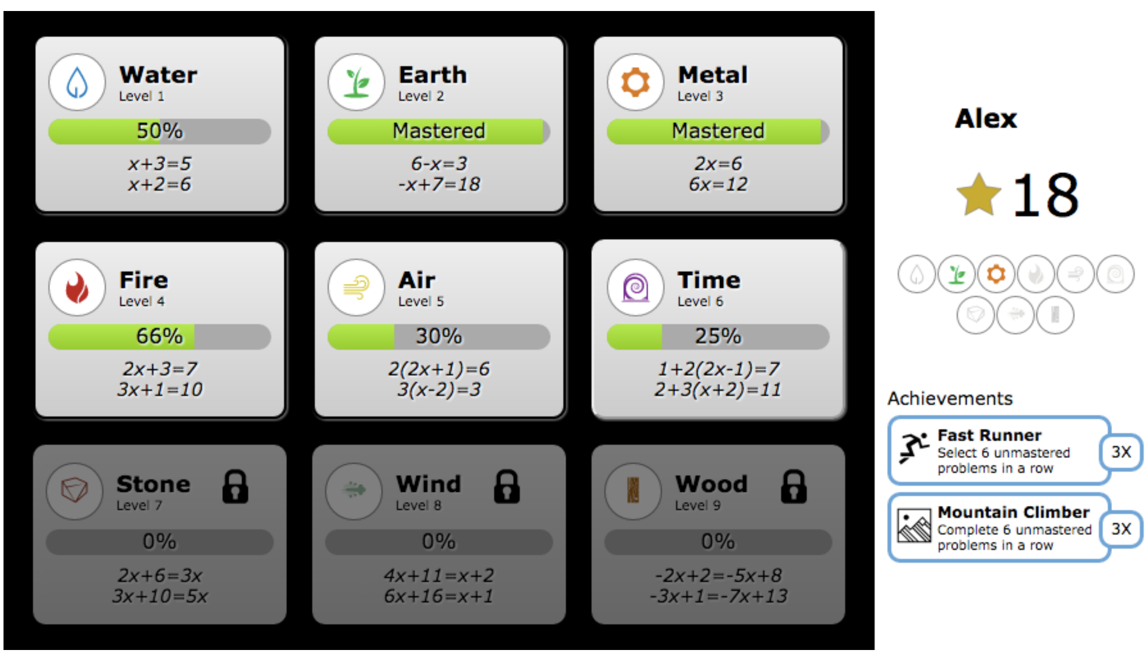


Figure 16. Problem selection screen in *Lynnette 3.0* during the Learning Phase

5.2.2 *Lynnette 3.0*, *Lynnette 3.0-System* and *Lynnette 3.0-PSonly*

We also created two variations of *Lynnette 3.0* for different conditions in the two phases, *Lynnette 3.0-System* and *Lynnette 3.0-PSonly*. Table 6 compares the main features of the three different versions of

Lynnette 3.0. Other than the control over problem selection and whether or not the mastery-oriented tutor features are included, the 3 versions share the same problem solving screen, which is the same as in *Lynnette 2.0*. In addition, all three versions have the gamification features that reward students' equation solving progress (i.e., the badges) and the Open Learner Model (i.e., the mastery bars).

Table 6. Comparisons of *Lynnette 3.0* versions in the experiment

***Lynnette* Version**	**Problem Selection**	**Mastery-Oriented Tutor Features to Foster the Learning of the Mastery Rule**
Lynnette 3.0	Shared Control	Included
Lynnette 3.0-System	Full System Control	Not Included
Lynnette 3.0-PSonly	Shared Control	Not Included

Lynnette 3.0-System implements full system control over problem selection. Figure 17 shows its home screen revised from the problem selection screen of *Lynnette 3.0*. Noticeably, the mastery bars always start from 25% instead of 0% (the same for all three *Lynnette* versions), assuming some prior knowledge of the students. The student clicks the "Next Problem" button to get problems from the tutor. Cognitive Mastery (Corbett, 2000) is implemented in *Lynnette 3.0-System*. The system assigns problems to students from Level 1 to Level 9 sequentially, and stops assigning problems from a level once it is mastered. All the mastery-oriented tutor features are not implemented in *Lynnette 3.0-System*.

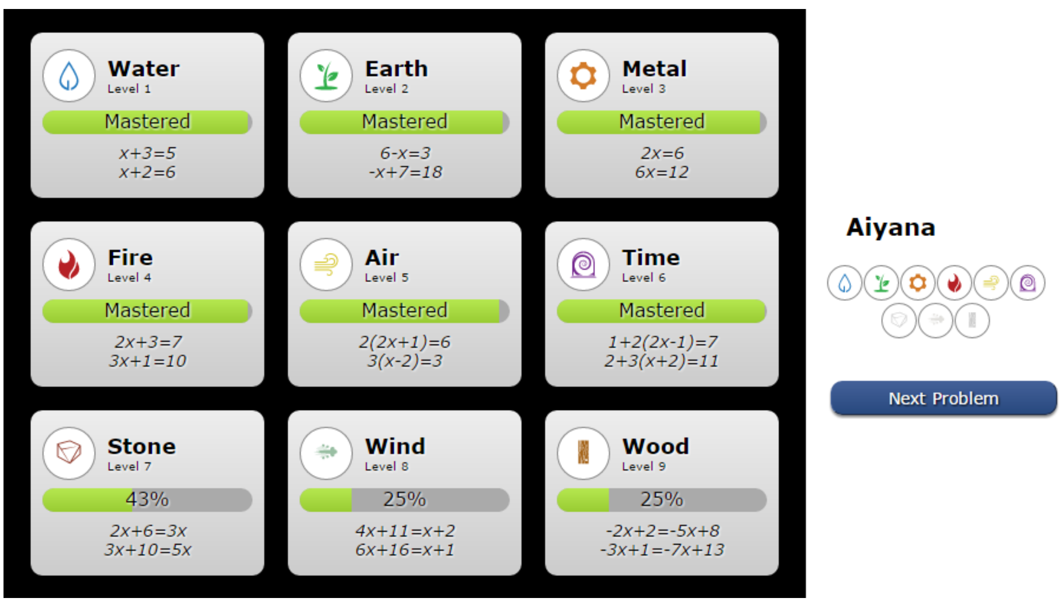


Figure 17. Home screen of *Lynnette 3.0-System* during the Future Learning Phase; Students click the "Next Problem" button to get problems assigned from the system; The badges and the OLM are also included

Figure 18 shows the problem selection screen for *Lynnette 3.0-PSonly*. Students have the same shared control over problem selection as in *Lynnette 3.0*. They are free to click any levels to get problems. However, none of the mastery-oriented tutor features are implemented in this version.

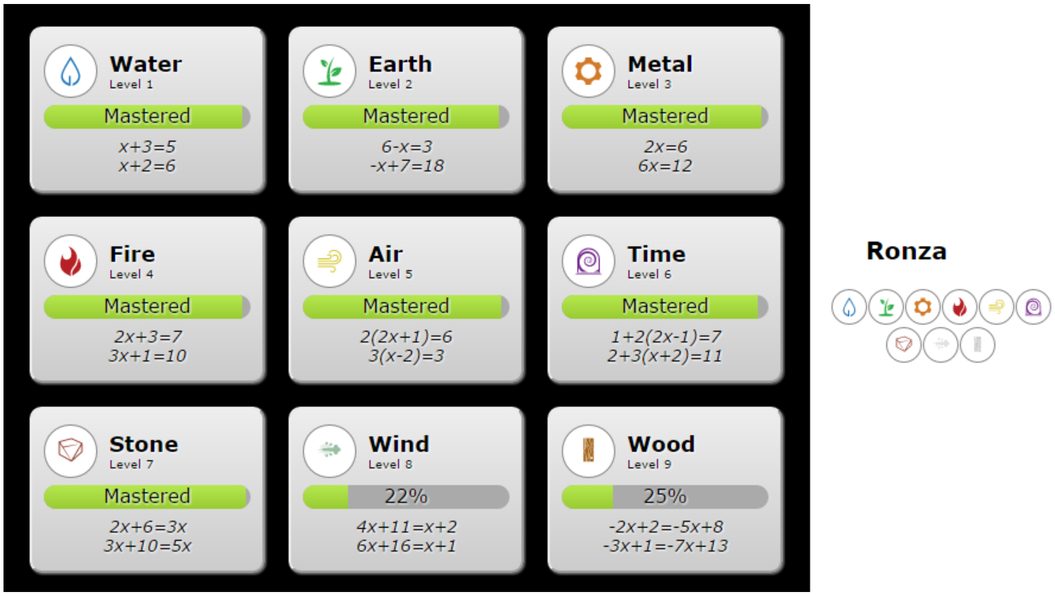


Figure 18. Problem selection screen in *Lynnette 3.0-PSonly* during the Future Learning Phase; Students click the levels to select problem types; The badges and OLM are included

5.3 Procedure and Measurements

All conditions followed the same procedure in the experiment. The participants took a paper pre-test on their equation solving abilities for equations of the first 6 levels that they would learn in the Learning Phase. Next, the conditions either learned with *Lynnette 3.0* or *Lynnette 3.0-System* for 4 class periods on the first 6 levels in their computer labs or using Chromebooks in classrooms. The participants took a paper mid-test after the Learning Phase, which included equations from all 9 levels, an enjoyment questionnaire and test items that measure the declarative knowledge of applying the Mastery Rule. After the mid-test, the participants learned with either *Lynnette 3.0-System* or *Lynnette 3.0-PSonly* for 2 class periods as the Future Learning Phase. Finally, they took a paper post-test on equations of all 9 levels. Table 7 summarizes the procedure of the experiment.

Table 7. Overview of the procedure of the experiment

Pre-Test	**Learning Phase**	**Mid-Test**	**Future Learning Phase**	**Post-Test**
• 15 minutes • Items on equation solving abilities on the first 6 levels	• Four 41-minute class periods	• 25 minutes • Items on equation solving abilities on all 9 equation types • Questionnaire on enjoyment • Items on declarative knowledge of applying the Mastery Rule	• Two 41-minute class periods	• 15 minutes • Items on equation solving abilities on all 9 equation types

Table 8 displays the target constructs and the corresponding measurements. The complete paper tests and questionnaires can be found in Appendix VII, VIII and IX.

Table 8. Measurements of the experiment

Constructs/abilities measured	Assessments	Assessments on Transfer
Equation solving abilities	• Items on pre-test • Items on mid-test • Items on post-test • Log data: process measures, e.g. number of errors and hints per step	• N/A
Problem selection skill (application of the Mastery Rule in the tutor)	• Log data: the problems students select in the Learning Phase	• Log data: the problems they select in the Future Learning Phase
Enjoyment of using the tutor	• Questionnaire on mid-test	• N/A
Declarative knowledge of applying the Mastery Rule	• Items on mid-test	• N/A

Test Items for Equation Solving. The pre-test had 6 equations, each from one of the six levels from the Learning Phase. The mid-test had 9 equation solving items, covering all 9 levels. The post-test had the same types of equation solving items as the mid-test, with different numbers.

Process Measures on Equation Solving. I also extracted process measures from the log data about students' equation solving in the tutor. I looked at the total number of problems and steps students completed in the tutor, as well as the total amount of time the students spent on solving the equation problems (not including the time they spent selecting/receiving problems or interacting with the mastery-oriented features). The process measures also included the average number of incorrect attempts the students made per step, and the average number of hints requested per step.

Questionnaires on Enjoyment. The enjoyment questionnaire was adapted from the Enjoyment subscale of the Intrinsic Motivation Inventory (IMI), which is the same as used in my prior experiments. The questionnaire had 7 items, all with a 7-point Likert Scale. The average score of the 7 items represent the students' self-reported enjoyment of using the system.

Test Items on Declarative Knowledge of Applying the Mastery Rule. There were three items on the mid-test to measure the students' declarative knowledge of applying the Mastery Rule. The first item tested the students' understanding of the concept of mastery, with three options that they could check (as shown in Figure 19). Figure 20 shows the second item, which described a scenario and tested whether the student would keep selecting problem levels that have been mastered. This item had four options. The third item also was scenario-based, and it tested whether the students were willing to challenge themselves with new problem types to learn new skills. It had 5 options (as shown in Figure 21). The students were instructed to check all the options that apply for each item.

If you are given a new unit in the Linear Equation Tutor, and you can select your own problems to practice:

1) What does it mean to have mastered a level in the Linear Equation Tutor

(check all that apply – write an "x" in the brackets):

[ ] I have completed all the problems in that level

[ ] I have learned all the equation solving skills in that level

[ ] I can consistently do well on problems in that level

Figure 19. The item that measures students' understanding of the concept of mastery

2) After you have mastered a level in the tutor, will you continue practicing

the level (check all that apply – write an "x" in the brackets)?

[ ] Yes, because I am good at the problems in this level.

[ ] Yes, because it will make me feel more confident.

[ ] Yes, because I do not want to fail.

[ ] No, because I want to learn something new.

Figure 20. The item that measured whether and why the students will keep selecting mastered levels

3) After you have mastered a level in the tutor, there are more levels that

are unmastered and more difficult. Will you select problems from these

unmastered levels (check all that apply – write an "x" in the brackets)?

[ ] Yes, because I want to learn new skills.

[ ] Yes, because I want to challenge myself with more difficult problems.

[ ] No, because the unmastered levels are difficult.

[ ] No, because I want more practice on the level I have mastered.

[ ] No, because I want to do easy problems.

Figure 21. The item that measures whether and why the students will practice new levels

5.4 Hypotheses

Table 9 summarizes the hypotheses of the experiment, the corresponding data analyses, and whether the hypotheses were confirmed by the data analyses.

Table 9. Hypotheses of Experiment 4

Hypotheses	**Data Analyses**	**Hypotheses Confirmed?**
H1 – Problem Selection Decisions in the Learning Phase: Mastery-oriented shared control over problem selection will help foster more consistent application of the Mastery Rule during the Learning Phase	• Check if the participants in the M-shared condition selected any mastered problems (i.e., violating the Mastery Rule) during the Learning Phase	**Confirmed**
H2 – Learning Outcomes in the Learning Phase: Mastery-oriented shared control over problem selection will lead to greater learning gains while it is in effect	• Test for significant difference between the M-shared and the noM-system condition on equation solving performance on pre-test and mid-test for the 6 levels of equations practiced in the Learning Phase • Test for significant difference between the M-shared and the noM-system condition on process measures of learning in the tutor	**Confirmed**
H3 – Enjoyment of Using the Tutor in the Learning Phase: Mastery-oriented shared control over problem selection will lead to higher enjoyment of using the tutor while it is in effect	• Test for significant difference between the M-shared and the noM-system condition on enjoyment ratings on the mid-test	Not Confirmed
H4 – Declarative Knowledge of Applying the Mastery Rule in the Learning Phase: Mastery-oriented shared control over problem selection will lead to better declarative knowledge of the Mastery Rule	• Test for significant difference between the M-shared and the noM-system condition on performance on the three items for declarative knowledge of the Mastery Rule on the mid-test	**Confirmed**
H5 – Problem Selection Decisions in the Future Learning Phase: The students exposed to the mastery-oriented shared control over problem selection in the Learning Phase will transfer the Mastery Rule of problem selection to the Future Learning Phase when the mastery-oriented features are not in effect	• Check if the participants in the M-shared + Shared and noM-system + Shared conditions selected any mastered problems (violating the Mastery Rule) during the Future Learning Phase • Compare the mastered/unmastered problems selected by the M-shared + Shared and the noM-system + Shared condition	Not Confirmed
H6 – Learning Outcomes in the Future Learning Phase: With good problem selection decisions, the shared control over problem selection will lead to better learning outcomes in the Future Learning Phase	• Test for significant main effects and interaction for two factors among the four conditions in the Future Learning Phase: 1) whether the condition is split from the M-shared condition of the Learning Phase, and 2) Shared versus System control in the Future Learning Phase	Not Confirmed

5.5 Participants

294 6^{th} – 8^{th} grade students from 5 middle schools in Pittsburgh participated in the classroom experiment. The participants came from 16 classes, taught by 8 different teachers. Among the 16

classes, 4 were advanced 6th grade classes, 9 were mainstream 7th grade classes, and 3 were mainstream 8th grade classes. The participants were randomly assigned to one of the four conditions within each class before the experiment started.

5.6 Results

I performed the analyses summarized in Table 9 to test the hypotheses. I report Cohen's *d* for effect sizes. An effect size *d* of .20 is typically deemed a small effect, .50 a medium effect, and .80 a large effect.

5.6.1 Defining Samples for Data Analysis

294 students from 5 local middle schools took the pre-test. 256 students mastered the first six levels or were present in all four class periods during the Learning Phase. 263 students mastered level 7 through level 9 or were present in both periods during the Future Learning Phase. The students mastered the levels at their own pace. Those who mastered the levels early in each phase were directed to practice non-algebra materials given by their teachers. For the 256 students from the Learning Phase and 263 students from the Future Learning Phase, Table 11 shows the total time a student spent on solving all the problems, the number of problems a student solved per minute, and the number of steps a student completed per minute, averaged by schools.

As shown in Table 10, School 1 was the most efficient, as on average students from this school spent least time solving the problems, and completed most problems and steps per minute. On the contrary, School 5 was the least efficient. The students completed much fewer problems and steps per minute than the other schools, indicating that they were not so active in the tutor. This is consistent with our informal classroom observations. I conducted the experiment in School 5 during the last week of the spring semester, and the teacher was absent. Informal classroom observations found that the students were frequently off-task (e.g., talking with peers, running around the computer lab, playing games on their computers) during both the Learning and Future Learning Phases, and did not take the paper tests seriously. The students logged in to the tutor, but did not complete much work. Therefore, I decided to exclude School 5 from the sample for data analysis.

Table 10. Participants' activities in the tutor summarized by schools

Schools	Learning Phase (SD in parentheses)			Future Learning Phase (SD in parentheses)		
	Total Time (minutes)	Problems per Minute	Steps per Minute	Total Time (minutes)	Problems per Minute	Steps per Minute
School 1	51.29 (29.12)	0.66 (0.20)	6.01 (1.79)	25.63 (16.06)	0.63 (0.17)	9.17 (2.39)
School 2	95.04 (38.27)	0.46 (0.17)	4.88 (1.47)	59.89 (20.85)	0.39 (0.19)	6.36 (2.66)
School 3	71.22 (34.15)	0.64 (0.32)	5.26 (2.33)	40.66 (26.97)	0.56 (0.29)	7.82 (3.83)
School 4	72.28 (30.82)	0.57 (0.24)	5.29 (2.26)	56.36 (18.51)	0.46 (0.19)	6.64 (2.16)
School 5	94.92 (29.13)	0.37 (0.13)	3.30 (1.88)	56.69 (29.08)	0.27 (0.14)	3.24 (2.49)

As a result, I defined two samples for the analyses with data from Schools 1 to 4. The first one is the *Learning-Phase-Sample*, which has 200 students who completed the pre-test and mid-test, and were present in all four class periods or mastered the first six levels during the Learning Phase. The second sample is the *Future-Learning-Phase-Sample*, which has 165 students who completed the pre-test, mid-test and post-test. These students were present during all 6 class periods (both the Learning and Future Learning Phases) or mastered all 9 levels. These two samples were used for the data analyses to investigate the research questions.

5.6.2 The Learning Phase: Problem Selection Decisions, Learning Outcomes, Enjoyment and Declarative Knowledge of the Mastery Rule

To address Hypotheses 1 to 4, I performed analyses on students' problem selection decisions, learning gains on equation solving from the pre-test to mid-test, enjoyment ratings on the mid-test, and their performance on the items for the declarative knowledge of applying the Mastery Rule. The Learning-Phase-Sample was used for all the analyses.

Problem Selection Decisions in the Learning Phase

To test Hypothesis 1, that mastery-oriented shared control over problem selection will help foster more consistent application of the Mastery Rule, I looked at the percentage of mastered problems the students selected in the M-shared condition during the Learning Phase (under perfect application of the Mastery Rule, the students should not select any mastered problems). (Selecting mastered problems is in violation of the rule.)

Twenty out of 102 students (19.61%) in the M-shared condition selected at least one mastered problems during the Learning Phase. The maximum number of mastered problems selected by any given student was 7. On average only 1.4% problems (SD=3.8%) selected by the students in the M-shared condition were mastered problems, indicating good application of the Mastery Rule when the mastery-oriented features were present.

Learning Outcomes on Equation Solving in the Learning Phase

To test Hypothesis 2, that mastery-oriented shared control over problem selection will lead to greater learning gains while it is in effect, I compared the two conditions' test performance on equation solving, as well as the process measures from tutor log data.

Each equation on the three paper tests was graded from 0 to 1, with partial credit given where appropriate. The pre-test only had items from Level 1 to Level 6. The mid-test had two parts: The Mid-Test-Equations1 includes equation types from Level 1 to Level 6, and the Mid-Test-Equations2 includes equation types from Level 7 to Level 9. Similarly, the Post-Test-Equations1 refers to the equation types from Level 1 to Level 6 on the post-test, and the Post-Test-Equations2 refers to the equation types from Level 7 to Level 9 on the post-test.

Table 11 shows the two conditions' average scores on pre-test and mid-test for the six types of equations practiced in the Learning Phase. Both conditions scored close to ceiling on the pre-test. An ANCOVA (with teacher as the co-variate to account for the variances reside within different teachers' classes) using the learning gain (Mid-Test-Equations1 minus Pre-Test) as the dependent variable revealed that the main effect of condition is significant ($F(1, 192) = 4.486$, $p = .035$, $d = .30$). In other words, The M-shared condition learned significantly more during the Learning

Phase than the noM-system condition. However, given the ceiling effect on pre-test for both conditions, the students did not improve significantly from pre-test to mid-test on solving the equations from Level 1 to Level 6 ($F\ (1, 192) = .011$, $p = .916$, $d = .02$).

Table 11. Means and SDs for test performance of Level 1 – Level 6 equations on pre-test and mid-test

	Pre-Test (SD)	Mid-Test-Equations1 (SD)
Condition 1 (M-shared)	0.81 (0.21)	0.85 (0.20)
Condition 2 (noM-system)	0.84 (0.19)	0.81 (0.21)

Given the ceiling effect on the pre-test, I split the sample based on the median of the pre-test score (median = .83) into two sub-groups: the Lower Performing Group and the Higher Performing Group. The Lower Performing Group had 102 students (mean pre-test score=0.67, SD=0.18), and the Higher Performing Group had 98 students (mean pre-test score=0.98, SD=0.05). Table 12 shows the average scores of the conditions within these two sub-groups. ANCOVAs revealed that overall the two conditions improved significantly from pre-test to mid-test on Equations1 within the Lower Performing Group ($F\ (1, 94) = 13.451$, $p < .000$, $d = .76$). The condition effect was marginally significant ($F\ (1, 94) = 3.490$, $p = .065$, $d = .37$), with the M-shared condition improving more than the noM-system condition on equation solving. On the other hand, there was a significant decrement of the two conditions' equation solving performance from the pre-test to mid-test with the Higher Performing Group ($F\ (1, 90) = 25.704$, $p < .000$, $d = 1.07$). No significant condition effect was found on the learning gains within the Higher Performing Group ($F\ (1, 90) = .019$, $p = .890$, $d = .03$).

Table 12. Means and SDs for test performance of Level 1 – Level 6 equations on pre-test and mid-test within the two aptitude sub-groups

		Pre-Test (SD)	Mid-Test-Equations1 (SD)
Lower Performing	Condition 1 (M-shared)	0.68 (0.20)	0.80 (0.22)
	Condition 2 (noM-system)	0.66 (0.16)	0.70 (0.22)
Higher Performing	Condition 1 (M-shared)	0.98 (0.04)	0.91 (0.14)
	Condition 2 (noM-system)	0.98 (0.05)	0.91 (0.15)

Furthermore, I looked at process measures from the tutor log data to compare how the two conditions performed during the learning process in the tutor. Table 13 shows averages of different process measures with the two conditions. The M-shared condition completed fewer problems and steps during the Learning Phase than the noM-system condition. ANCOVA tests (using teacher as co-variate) revealed that the difference was significant for the total number of steps ($F\ (1, 192) = 5.702$, $p = .018$, $d = .34$) and marginally significant for the total number of problems ($F\ (1, 192) = 2.950$, $p = .088$, $d = .24$). I also looked at the number of problems completed by problem levels, and there was no significant difference between the two conditions with respect to how many problems were completed in each level. Lastly, no significant condition differences were found for the total amount of time the students spent on the problems (F (1, 192) = .322, *p* = .571, *d* = .08), the incorrect attempts made per step (after log transformation: F (1, 192) = .027, *p* = .869, *d* = .02) or the hints requested per step (after log transformation: F (1, 167) = .169, *p* = .681, *d* = .06).

Table 13. Means and SDs (in parentheses) of the log process measures by the two conditions in the Learning Phase

	Total Number of Problems	Total Number of Steps*	Total Time on All Problems (mins)	Incorrect Attempts per Step	Hints per Step
Condition 1 (M-shared)	34.23 (10.73)	322.83 (120.03)	69.66 (36.07)	0.43 (0.24)	0.11 (0.16)
Condition 2 (noM-system)	37.17 (14.92)	366.45 (156.07)	71.94 (35.93)	0.44 (0.28)	0.11 (0.13)

* indicates significance of the condition effect at the .05 level

Table 14 displays the averages of the process measures within the Lower and Higher Performing Groups. For the Lower Performing Group, the students in the M-shared condition completed fewer problems (F (1, 94) = 1.786, *p* = .185, *d* = .27) and steps, but only the difference on the total number of steps was statistically significant (F (1, 94) = 6.228, *p* = .014, *d* = .50). The condition difference was not significant on other process measures within the Lower Performing Group either (Total time: F (1, 94) = .939, *p* = .335, *d* = .19; Log incorrect attempts: F (1, 94) = .088, *p* = .767, *d* = .06; Log hints: F (1, 87) = .485, *p* = .488, *d* = .14). On the other hand, the averages of the process measures within the Higher Performing Group had the same trend as the Lower Performing Group, but the condition difference was not statistically significant for any of the measures (Total problems: F (1, 90) = 2.433, *p* = .122, *d* = .32; Total steps: F (1, 90) = .779, *p* = .380, *d* = .18; Total time: F (1, 94) = .084, *p* = .773, *d* = .06; Log incorrect attempts: F (1, 90) = .045, *p* = .833, *d* = .04; Log hints: F (1, 72) = 1.716, *p* = .194, *d* = .30).

Table 14. Means and SDs (in parentheses) of the log process measures by the two conditions within the two aptitude sub-groups in the Learning Phase

		Total Number of Problems	Total Number of Steps	Total Time on All Problems (mins)	Incorrect Attempts per Step	Hints per Step
Lower Performing	Condition 1 (M-shared)	36.84 (12.07)	345.10 (127.19)*	80.20 (36.97)	0.48 (0.26)	0.12 (0.14)
	Condition 2 (noM-system)	40.64 (16.93)	418.20 (168.42)*	87.67 (37.45)	0.51 (0.28)	0.16 (0.22)
Higher Performing	Condition 1 (M-shared)	30.66 (7.28)	292.50 (102.43)	55.44 (29.68)	0.40 (0.31)	0.09 (0.12)
	Condition 2 (noM-system)	34.35 (12.52)	324.28 (132.39)	59.12 (29.18)	0.36 (0.19)	0.08 (0.09)

* indicates significance of the condition effect at the .05 level

Enjoyment of Using the Tutor in the Learning Phase

To test Hypothesis 3, that mastery-oriented shared control over problem selection will lead to higher enjoyment of using the tutor while it is in effect, I compared students' enjoyment ratings of using the tutors on the mid-test. As shown by Table 15, the M-shared condition reported higher enjoyment than the noM-system condition. However, an ANCOVA test found the difference between the two conditions was not statistically significant ($F\ (1, 192) = .450$, $p = .530$, $d = .09$).

Table 15. Means and SDs (in parentheses) of two conditions' enjoyment ratings on mid-test

	Condition 1 (M-shared)	Condition 2 (noM-system)
Enjoyment	4.63 (1.59)	4.52 (1.36)

I also compared the two conditions' enjoyment ratings within the Lower/Higher Performing sub-groups. Table 16 shows the two sub-groups' average enjoyment ratings. In general, the M-shared conditions in both sub-groups reported higher enjoyment of using the tutor, but the differences were not statistically significant according to the ANCOVAs (Lower Performing: $F\ (1, 94) = .059$, $p = .808$, $d = .05$; Higher Performing: $F\ (1, 90) = .599$, $p = .441$, $d = .16$). Also, overall the Higher Performing Group reported higher enjoyment ratings (mean=4.81, SD=1.39) than the Lower Performing Group (mean=4.35, SD=1.53). The difference was not statistically significant ($F\ (1, 192) = 2.327$, $p = .129$, $d = .22$).

Table 16. Means and SDs (in parentheses) of enjoyment ratings of the conditions by the two sub-groups

	Lower Performing		Higher Performing	
	Condition 1 (M-shared)	Condition 2 (noM-system)	Condition 1 (M-shared)	Condition 2 (noM-system)
Enjoyment	4.41 (1.60)	4.27 (1.44)	4.92 (1.54)	4.73 (1.27)

Declarative Knowledge of Applying the Mastery Rule in the Learning Phase

To test Hypothesis 4, I analyzed the students' responses to the three items measuring the declarative knowledge of applying the Mastery Rule. There were 3 options for Item 1 (measures the concept of mastery), 4 options for Item 2 (measures whether the students would keep doing mastered problems), and 5 options for Item 3 (measures whether the students would do new problems), with a total of 12 options for all three items. I coded the students' response to each option as 0 or 1. Table 17 shows the average scores for the two conditions with respect to each item and across all three items. The M-shared condition scored higher than the noM-system condition on all of the items. ANCOVAs revealed that the difference was statistically significant for Item 2 ($F\ (1, 184) = 4.175$, $p =.042$, $d = .42$) and all three items together ($F\ (1, 184) = 8.263$, $p =.005$, $d = .59$). It was also marginally significant for Item 3 ($F\ (1, 184) = 3.490$, $p =.063$, $d = .38$), but not significant for Item 1 ($F\ (1, 184) = .884$, $p = .348$, $d = .14$). In short, the M-shared condition showed significantly better declarative knowledge of the Mastery Rule on the mid-test after the Learning Phase.

Table 17. Means and SDs (in parentheses) of two conditions' average scores for the item of the declarative knowledge of the Mastery Rule on the mid-test; It also shows the Cronbach's Alpha for each item (among the options within each item) and all three items (among all 12 options)

	Cronbach's Alpha	Condition 1 (M-shared)	Condition 2 (noM-system)
Item 1 – Concept of Mastery (3 options)	0.150	0.63 (0.29)	0.59 (0.28)
Item 2 – Do Mastered Problems (4 options)*	0.719	0.70 (0.31)	0.59 (0.37)
Item 3 – Do New Problems (5 options)	0.516	0.88 (0.18)	0.83 (0.22)
All three items (12 options)*	0.474	0.76 (0.15)	0.69 (0.17)

* indicates significance of the condition effect at the .05 level

5.6.3 The Future Learning Phase: Problem Selection Decisions and Learning Outcomes

The Future Learning Phase was deployed to test whether there were lasting effects of the mastery-oriented features on students' problem selection decisions and learning outcomes when the features were removed with new problem levels in the tutor. I performed data analyses on students' problem selection decisions and equation solving performance to address Hypotheses 5 and 6. The Future-Learning-Phase-Sample was used for all the analyses in this phase.

Problem Selection Decisions in the Future Learning Phase

To test Hypothesis 5, that the students exposed to the mastery-oriented shared control over problem selection in the Learning Phase will transfer the Mastery Rule of problem selection to the Future Learning Phase when the mastery-oriented features are not in effect, I first compared students' problem selection decisions between the M-shared + Shared condition and the noM-system + Shared condition. The M-shared + Shared condition was exposed to the mastery-oriented shared control in the Learning Phase while the noM-system + Shared condition learned with full system control in the Learning Phase.

Table 18. Comparisons of the two shared control conditions' problem selection decisions in the Future Learning Phase

	Percentage of students who selected at least one mastered problem	Mean percentage of mastered problems selected over the total number of problems (SD in parentheses)
Condition 1-1 (M-shared + Shared)	30.61%	2.7% (7.8%)
Condition 2-2 (noM-system + Shared)	20%	1.6% (5.1%)

As shown in Table 18, fifteen out of 49 students (30.61%) selected at least one mastered problem in the M-shared + Shared condition during the Future Learning Phase, and the maximum number of mastered problems selected by any given student was 24. Seven out of 35 (20%) students from the noM-system + Shared condition selected at least one mastered problem. The maximum number of mastered problems selected by a student in this condition was 7. Therefore, more students in the M-shared + Shared condition selected at least mastered problem, compared to the noM-system +

Shared condition. Moreover, on average 2.7% of the problems selected by the M-shared + Shared condition was mastered, while 1.6% selected by the noM-system + Shared condition was mastered. An ANCOVA test revealed that the difference between the percentages of these two conditions was not significant ($F\ (1, 76) = .138$, $p = .711$, $d = .08$). In other words, although the M-shared + Shared condition selected more mastered problems than the noM-system + Shared condition, the difference was not statistically significant. Also, overall the two shared control conditions in the Future Learning Phase violated the Mastery Rule more often than the M-shared condition in the Learning Phase.

Learning Outcomes on Equation Solving in the Future Learning Phase

To test Hypothesis 6, that with good problem selection decisions, the shared control over problem selection will lead to better learning outcomes in the Future Learning Phase, I performed ANCOVAs to analyze students' learning gains from the mid-test to post-test. Two independent variables were used in the ANCOVA analyses: 1) whether the students had the mastery-oriented shared control or full system control over problem selection (M-shared versus noM-system) in the Learning Phase, and 2) what control the students had in the Future Learning Phase (Shared versus System). Teacher was also used as the co-variate.

Table 19. Means and SDs (in parentheses) for mid-test and post-test equation solving items

	Mid-Test-Equations1	Post-Test-Equations1	Mid-Test-Equation2	Post-Test-Equations2
Condition 1-1 (M-shared + Shared)	0.82 (0.23)	0.80 (0.24)	0.38 (0.40)	0.58 (0.40)
Condition 1-2 (M-shared + System)	0.86 (0.16)	0.85 (0.18)	0.36 (0.40)	0.59 (0.40)
Condition 2-1 (noM-system + Shared)	0.82 (0.20)	0.86 (0.16)	0.34 (0.41)	0.56 (0.43)
Condition 2-2 (noM-system + System)	0.84 (0.20)	0.86 (0.22)	0.46 (0.45)	0.59 (0.38)

Table 19 shows the four conditions' equation-solving performance on the mid-test and post-test. Both tests included two types of equations: Equations1 (Level 1 – Level 6) and Equations2 (Level 7 – Level 9). The averages show that the students' performance on Equations1 did not change much from mid-test to post-test. ANCOVAs revealed no significant improvement from the mid-test to post-test for Equations1 for the four conditions ($F\ (1, 155) = .002$, $p = .967$, $d = .01$). Also, no significant main effects or interaction were found for Equations1 with the two independent variables (M-shared or noM-system in phase 1: $F\ (1, 155) = 1.962$, $p = .163$, $d = .22$; Shared or system in phase 2: $F\ (1, 155) = .081$, $p = .776$, $d = .04$; Interaction: $F\ (1, 155) = .068$, $p = .795$). On the other hand, overall the four conditions improved significantly on Equations2 from mid-test to post-test ($F\ (1, 155) = 37.028$, $p < .000$, $d = .98$), as well as the whole test (with Equations1 and Equations2 together, $F\ (1, 155) = 16.839$, $p < .000$, $d = .66$). However, no significant main effects or interaction were found between the conditions for Equations2 (M-shared or noM-system in phase 1: $F\ (1, 155) = .510$, $p = .476$, $d = .11$; Shared or system in phase 2: $F\ (1, 155) = .269$, $p = .604$, $d = .08$;

Interaction: F (1, 155) = .786, *p* = .377) or the whole test (M-shared or noM-system in phase 1: F (1, 155) = .191, *p* = .663, *d* = .07; Shared or system in phase 2: F (1, 155) = .285, *p* = .594, *d* = .08; Interaction: F (1, 155) = .584, *p* = .446).

I also did a median split based on students' average performance on the mid-test (median=0.67, Equations1 and Equations2 together) for the Future-Learning-Phase-Sample. The Lower Performing Group had 81 students (mean mid-test score=0.49, SD=0.14) and the Higher Performing Group had 84 students (mean mid-test score=0.88, SD=0.12). Table 20 summarizes the four conditions' average test performance within the two sub-groups. For the Lower Performing Group, overall the four conditions improved significantly from mid-test to post-test on Equations1 (F (1, 71) = 1.669, *p* =.043, *d* = .24), Equations2 (F (1, 71) = 22.057, *p* <.000, *d* = 1.11), and the whole test (F (1, 71) = 16.664, *p* <.000, *d* = .97). However, no significant main effects or interaction were found due to the conditions for any of the three categories. On the other hand, for the Higher Performing Group, overall for the four conditions there was a significant decrement on Equations1 from the mid-test to post-test (F (1, 74) = 7.857, *p* =.006, *d* = .65). Nevertheless, there was a significant improvement on Equations2 (F (1, 74) = 12.696, *p* =.001, *d* = .83). No significant improvement was found for the whole test within the Higher Performing Group (F (1, 74) = 2.690, *p* =.105, *d* = .27). Also no significant main effects or interaction were found with the condition factors for any of the three categories of equations.

Table 20. Means and SDs (in parentheses) for mid-test and post-test within the two sub-groups

		Mid-Test-Equations1	Post-Test-Equations1	Mid-Test-Equation2	Post-Test-Equations2
Lower Performing	Condition 1-1 (M-shared + Shared)	0.68 (0.26)	0.67 (0.26)	0.07 (0.12)	0.36 (0.40)
	Condition 1-2 (M-shared + System)	0.74 (0.15)	0.74 (0.20)	0.04 (0.15)	0.27 (0.34)
	Condition 2-1 (noM-system + Shared)	0.71 (0.20)	0.80 (0.17)	0.07 (0.18)	0.34 (0.41)
	Condition 2-2 (noM-system + System)	0.71 (0.23)	0.76 (0.28)	0.04 (0.08)	0.34 (0.32)
Higher Performing	Condition 1-1 (M-shared + Shared)	0.96 (0.08)	0.93 (0.10)	0.70 (0.34)	0.81 (0.24)
	Condition 1-2 (M-shared + System)	0.96 (0.07)	0.94 (0.10)	0.63 (0.35)	0.85 (0.22)
	Condition 2-1 (noM-system + Shared)	0.97 (0.06)	0.93 (0.09)	0.71 (0.33)	0.87 (0.24)
	Condition 2-2 (noM-system + System)	0.95 (0.08)	0.93 (0.12)	0.79 (0.32)	0.78 (0.29)

Similar as for the Learning Phase, I looked at the process measures for the four conditions in the Future Learning Phase. Table 21 summarizes the averages of different process measures of the four conditions. I ran ANCOVAs with the same two independent variables as for the learning gains: 1) whether the students had the mastery-oriented shared control or full system control over problem selection (M-shared versus noM-system) in the Learning Phase, and 2) what control the students had in the Future Learning Phase (Shared versus System). The results revealed no significant main effects or interaction on any of the process measures shown in Table 22.

Table 21. Means and SDs (in parentheses) of the log process measures in the Future Learning Phase

	Total Number of Problems	Total Number of Steps	Total Time on All Problems (mins)	Incorrect Attempts per Step	Hints per Step
Condition 1-1 (M-shared + Shared)	18.63 (8.68)	285.88 (124.80)	46.84 (24.98)	0.30 (0.21)	0.07 (0.08)
Condition 1-2 (M-shared + System)	18.68 (7.98)	263.92 (118.53)	42.40 (25.12)	0.37 (0.49)	0.06 (0.08)
Condition 2-1 (noM-system + Shared)	18.03 (10.55)	283.03 (132.78)	45.08 (24.48)	0.27 (0.21)	0.07 (0.08)
Condition 2-2 (noM-system + System)	18.79 (7.50)	305.21 (135.03)	43.57 (24.28)	0.29 (0.18)	0.08 (0.11)

Table 22 shows the averages of the process measures within the Lower/Higher Performing Groups. No significant main effects or interactions were found with the two factors for any of the process measures within the two sub-groups.

Table 22. Means and SDs (in parentheses) of the log process measures in the Future Learning Phase

		Total Number of Problems	Total Number of Steps	Total Time on All Problems (mins)	Incorrect Attempts per Step	Hints per Step
Lower Performing	Condition 1-1 (M-shared + Shared)	20.20 (8.61)	320.04 (134.87)	60.59 (20.56)	0.41 (0.23)	0.11 (0.08)
	Condition 1-2 (M-shared + System)	21.35 (8.70)	293.82 (134.40)	56.81 (22.96)	0.53 (0.68)	0.11 (0.09)
	Condition 2-1 (noM-system + Shared)	21.60 (12.49)	337.45 (134.15)	57.95 (21.13)	0.34 (0.24)	0.10 (0.09)
	Condition 2-2 (noM-system + System)	22.16 (7.54)	376.26 (118.04)	59.73 (22.51)	0.38 (0.20)	0.12 (0.12)
Higher Performing	Condition 1-1 (M-shared + Shared)	17.00 (8.62)	250.29 (104.55)	32.52 (21.03)	0.19 (0.11)	0.03 (0.07)
	Condition 1-2 (M-shared + System)	16.52 (6.82)	239.71 (100.83)	30.75 (20.65)	0.24 (0.19)	0.02 (0.03)
	Condition 2-1 (noM-system + Shared)	13.27 (3.99)	210.47 (92.30)	27.93 (17.26)	0.17 (0.12)	0.02 (0.03)
	Condition 2-2 (noM-system + System)	16.13 (6.45)	248.96 (122.15)	30.79 (17.13)	0.21 (0.13)	0.05 (0.09)

5.7 Discussion and Conclusions of Chapter 5

This classroom experiment investigated whether mastery-oriented shared control over problem selection would foster the learning of an effective problem selection strategy, i.e., the Mastery Rule, as well as how the mastery-oriented shared control would affect students' learning outcomes and enjoyment. Furthermore, the two-phase design of the experiment allowed investigation of the lasting effects of the mastery-oriented features on students' problem selection decisions and learning outcomes when the features were not in effect.

First of all, I found that mastery-oriented shared control over problem selection, while it was in effect, led to better learning outcomes as compared to full system control in an ITS. Prior work has generally found that full learner control over problem selection leads to worse learning outcomes than the system control in computer-based learning environments (Atkinson, 1972; Niemiec, Sikorski, & Walberg, 1996). Some studies have found that scaffolding with shared student/system control can lead to comparable learning outcomes as system control (Corbalan, Kester, and van Merriënboer, 2008). Therefore, Experiment 4 contributes to the empirical literature on how learner control affects students' learning by demonstrating a benefit of shared control with mastery-oriented support over system control. It also sheds light on how an ITS that offers learner control can be designed to benefit students' domain level learning outcomes.

Specifically, during the Learning Phase, the mastery-oriented shared control condition improved significantly more than the system-controlled condition on equation solving from pre-test to mid-test, although overall the two conditions did not improve significantly due to the ceiling effects on the pre-test. However, when I split the sample by the median of the pre-test, I saw a significant learning gain from pre-test to mid-test within the Lower Performing Group, and the condition effect was marginally significant (the mastery-oriented shared control condition improved more). On the other hand, the Higher Performing Group had an almost perfect score on the pre-test and dropped significantly from the pre-test to mid-test, which might be interpreted as regression to the mean. Also, given the students were at ceiling, the standard deviation was really low, contributing to the drop being statistically significant. It seems reasonable to view this as an artifact of the very high scores, although other possible explanations cannot definitively be ruled out. Furthermore, when I looked at the process measures from the tutor log data, the students from the mastery-oriented shared control condition completed fewer problems and significantly fewer steps, indicating a more efficient problem solving process. I found the same results with respect to process measures within the Lower Performing Group. These results prove that shared control accompanied by the mastery-oriented features could significantly benefit students' domain level learning outcomes, especially for the students with low prior knowledge.

Based on the results, I discuss why the mastery-oriented shared control over problem selection led to significantly better learning gains. First, the students with the mastery-oriented shared control selected almost the same problems as the system control. They rarely violated the Mastery Rule, put differently, the students selected mostly unmastered problems as the Cognitive Mastery algorithm does for the system control. Therefore, we can mostly rule out the possibility that the difference in learning gains was due to the problems being practiced. Second, it is likely that the students with the mastery-oriented features were more concentrated on learning and growing their equation solving skills when they were constantly exposed to the messages from the tutorial, feedback, Achievements and problem selection recap screens that aim at fostering a mastery-approach orientation. These messages might also have encouraged the students to adopt metacognitive strategies such as reviewing, reflecting or summarizing, as a mastery-approach orientation has been found to be positively associated with use of such strategies (Wolters et al., 1996). Prior work has generally found that students with a mastery-approach orientation achieve better learning outcomes, compared to their counterparts who focused more on performance relative to others, i.e., students with a performance orientation (Schunk, Pintrich, & Meece, 2008).

Furthermore, Clark and Mayer (2011) pointed out that learner control may only benefit students when they have high prior knowledge or good metacognitive skills. There could primarily be two reasons for why I observed the opposite results in my experiment. First, the students in my Higher Performing Group were already at ceiling. They cannot improve with an average of 0.98 on the pre-test, unlike in cases in which even high prior knowledge students still have room to learn from the curriculum. To that end, the Lower Performing Group in my experiment might be fairly regarded as "high" prior knowledge students. They on average scored 0.67 on the pre-test, which is towards the higher end of the test score. Second, it may be that in my tutor design, cognitive load was not an issue, contrary to Clark and Mayer's observations. The reason for the claim that learner control may only benefit the students with high prior knowledge or good metacognitive skills is that the cognitive load brought about by the learner control could overwhelm and be detrimental to the lower performing students. However, the mastery-oriented features in my experiment provide explicit instructions, feedback and scaffolding to help students make problem selection decisions with the shared control, which might have effectively lowered the cognitive load for using the learner control. I also observed good application of the Mastery Rule of the students who had the mastery-oriented shared control. Therefore, the interventions might have helped the low prior knowledge students to use the learner control as easily as the high prior knowledge students, and thus significantly benefited the lower performing students who had more space for improvement on learning.

On the other hand, although the mastery-oriented shared control enhanced students' learning while it was in effect, no lasting effect on learning was found that carried over into the next unit without the mastery-oriented features but with shared control over problem selection. For the Future Learning Phase, I observed significant learning gains on the new equation types for all the students, as well as for the Lower Performing and Higher Performing Groups separately. However, no significant condition effects were observed for learning gains on solving the equations in the Future Learning Phase. In other words, there was apparently no carry into the next unit of a motivational effect on student learning. Additionally, the equations in the Future Learning Phase were more difficult than the Learning Phase, and the learning time was reduced to only 2 class periods. The students might experience higher cognitive load when learning more difficult equations within a shorter period of time, making it difficult to initiate metacognitive processes such as reviewing or reflecting that are related to a mastery-approach orientation.

A second main finding from the experiment was that the mastery-oriented shared control resulted in significantly better declarative knowledge of the Mastery Rule on the mid-test (the immediate paper test after the Learning Phase), as compared to the students from the full system control condition. The mastery-oriented features improved students' declarative knowledge about the Mastery Rule possibly through the explicit instructions and motivational messages from the tutorial, feedback messages, Achievements and the problem selection recap screens. The languages used in all those features aimed at fostering a mastery-approach orientation towards problem selection. This finding demonstrates that ITSs can be designed to help students learn the declarative knowledge for skills of problem selection.

A third finding from the experiment showed that the students with shared control exhibited good application of the Mastery Rule in both phases. The mastery-oriented shared control condition selected only about 1% of mastered problems during the Learning Phase. Similarly, the two shared control conditions in the Future Learning Phase selected around 2% of mastered problems regardless of whether or not they came from the mastery-oriented shared control condition in the Learning Phase. The results of the students' problem selection decisions were slightly surprising, given what I observed in the classroom experiment in Chapter 4. In Chapter 4, the students selected 34% mastered problems when no Open Learner Model was presented. My prior work (Long & Aleven, 2013c) also found students admitting that they would keep selecting easy problems if given control over problem selection. There may be two reasons that have resulted in the overall good problem selection decisions in both phases and in all shared control conditions: First, the gamification feature for equation solving, i.e., the badges with the elements, was extremely motivating to the students with respect to earning the badges and completing all the levels. The badges were initially designed and implemented to make the tutor more fun. They do not reward the students' problem selection decisions, but their equation solving progress (the student earns a badge for a level when it is mastered). However, my informal classroom observations revealed that the badges strongly encouraged the students to complete the levels without repeating already-mastered problems (their goal was to collect all the badges). A majority of students were competing with each other in terms of how many badges they had earned and which level they were at. Similarly, the presence of the Open Learner Model might have stimulated the students' desire for completing the levels as well. As we had observed in the studies presented in Chapter 4, the mastery bars are also motivating to students. In short, the inclusion of the badges and the OLM might have strongly encouraged the students to make problem selection decisions based on the Mastery Rule. A second reason that students in all conditions made good task selection decisions may have been that the classroom environments for this experiment were not entirely self-regulatory learning environments. The teachers sometimes told students to "finish" all the levels, or "now you should work on the newly unlocked levels". These informal instructions given by the teachers and the fact that the students were learning the materials in their math classes might have implied to the students that their task was to complete the levels within the given class periods. In other words, the students were practicing with a "goal" and supervision from their teachers, which might have influenced their problem selection decisions, instead of completely working on their own. Admittedly, this is also how ITSs are often used by teachers and students, making it hard to help the students develop their own SRL skills without scaffolding from the teachers and the classroom atmosphere. An alternative explanation for the consistent application of the Mastery Rule in the shared control condition by students who came from the full system control condition in the Learning Phase could be that these students, during the Learning Phase, might learn the Mastery Rule by observing how the tutor selected problems for them. The two phases and the conditions shared very similar problem selection screens. The students could have simply emulated what the tutor did in the previous levels when they were allowed to select the new levels for themselves. It is an open question whether the students would be able to internalize that implicit rule and successfully apply it when the tutoring environment changes though. In short, the experiment provides objective measures on students' problem selection behaviors, but the effects of the mastery-oriented features on the learning and transfer of students' problem selection skills need to be further investigated with self-regulated learning and transfer environments in which the students are not scaffolded by their teachers; the effects of the interventions should also be separated from other tutor features such as the badges and the Open Learner Model.

Lastly, the mastery-oriented shared control did not lead to significantly higher enjoyment of using the tutor as compared to the full system-controlled tutor. It is likely that the gamification feature, i.e., the badges, as well as the Open Learner Model implemented in the system-controlled condition also made it enjoyable to students. Prior literatures on learner control emphasizes its motivational benefits to students (Clark & Mayer, 2011; Flowerday & Schraw, 2003), but our finding suggests that enabling learner control does not necessarily enhance students' enjoyment of the learning experiences. In the future, we may measure other motivational constructs in addition to enjoyment (e.g., mastery orientation, self-efficacy, sense of autonomy). The mastery-oriented features might have more significant influence on these other constructs.

To sum up, the current experiment shows that shared control over problem selection accompanied by features that foster a mastery-approach orientation in an ITS leads to significantly better domain level learning outcomes, as compared to full system control over problem selection, which is standard practice in ITS. This is a novel contribution to the literatures on effects of learner control on student learning, which has generally found that pure learner control leads to worse learning than the system control (Atkinson, 1972; Niemiec, Sikorski, & Walberg, 1996). When the mastery-oriented features are removed, the shared control over problem selection still leads to comparable learning outcomes as the system control when (as we observed in the current study) students apply the problem selection rules correctly. The experiment also proves that ITSs can be designed to facilitate the learning of declarative knowledge of problem selection skills. Not much prior work on supporting SRL in ITS has investigated the lasting effects of interventions on SRL skills and future learning (Aleven, Roll, & Koedinger, 2012; Roll et al., 2014). My experiment has demonstrated some success of helping students learn problem selection skill that will have lasting effects on their problem selection decisions and future learning in the same learning environments, with improvement only on declarative knowledge of applying the rule on a paper test.

Chapter 6. Conclusions, Contributions and Future Work

6.1 Shared Control over Problem Selection in Intelligent Tutoring Systems

My dissertation consists of two main parts of work. The first part (Chapter 3) focuses on creating and scaffolding shared student/system control over problem selection in ITSs by redesigning an Open Learner Model and integrating gamification features to enhance students' domain level learning and enjoyment. Experiments 1 to 3 involved 566 7th and 8th grade students to investigate the effectiveness of these new designs. The second part of my dissertation (Chapter 4 and 5) addresses applying motivational design and user-centered design techniques to extend an ITS to help students learn problem selection skills with shared control and testing whether it has lasting effects on their problem selection decisions and future learning. I designed a set of tutor features that aim at fostering a mastery-approach orientation and learning of a specific problem selection rule. Experiment 4 with 200 6th – 8th grade students investigated the effectiveness of the mastery-oriented features with shared control on students' domain level learning outcomes, problem selection skills and enjoyment. It also measured whether there were lasting effects of the mastery-oriented shared control on students' problem selection decisions and learning in new tutor units.

6.1.1 Effects of Shared Control on Students' Domain Level Learning Outcomes

A key contribution of the dissertation is a demonstration (in Experiment 4) that shared control over problem selection, when accompanied by tutor features that target fostering a mastery-approach orientation and the learning of the Mastery Rule, can lead to significantly better domain level learning outcomes than full system-controlled problem selection with cognitive mastery in an ITS. This is a novel contribution to the literatures on learner control over problem selection in learning technologies. Research on learner control over different aspects of learning in computer-based learning environments has found mixed effects on student learning (Cordova & Lepper, 1996; Atkinson, 1972; Niemiec, Sikorski, & Walberg, 1996). However, with respect to learner control over problem selection, prior research has generally found that learner control leads to worse learning outcomes (Atkinson, 1972; Niemiec, Sikorski, & Walberg, 1996), when compared with system control informed by computer algorithms. Some studies found that shared control over problem selection can lead to the same learning outcomes as system control (Corbalan, Kester, and van

Merriënboer, 2008). In Experiment 4, I compared shared control with mastery-oriented features against a high bar control condition – System control with Cognitive Mastery has proven to significantly improve students' learning (Corbett, 2000), and found a superior effect on learning with shared control. It is likely that our mastery-oriented features fostered a mastery-approach orientation while students were learning with the shared control, which contributed to the greater learning gains. The mastery-approach orientation has generally been associated with positive metacognitive and cognitive strategies used by students during learning (Wolters et al., 1996). It may also be that the mastery-oriented features had enhanced the sense of control for the students, as the features constantly reminded students that they were making problem selection decisions for themselves. Increased sense of control has also been shown to improve learning outcomes in learner-controlled learning environments (Flowerday & Schraw, 2003).

Notably, my work does not establish, nor do I mean to argue, that pure learner control can lead to better learning outcomes than system-controlled problem selection. Across all four experiments, the students had only shared control over problem selection in *Lynnette*, and additional scaffolding for making good problem selection decisions (i.e., the Open Learner Model, gamification features, and mastery-oriented features) was provided. In fact, in Experiment 2, I found that when no OLM was offered, the system-controlled condition led to significantly greater learning gains than the shared control condition. Moreover, in the classroom study from Chapter 4, the students selected a significant number of mastered problems with the shared control but without access to the OLM, indicating that the students probably are not capable of making good problem selection decisions with pure learner control, without scaffolding features such as an OLM.

A second contribution of the dissertation is that I found an Open Learner Model, when combined with features to facilitate self-assessment, can benefit student learning in ITS with shared control over problem selection. Specifically, Experiment 2 found that the presence of the redesigned OLM resulted in significantly better learning outcomes than the no OLM condition when the shared control was provided. The field experiment conducted in Chapter 4 also showed that the inclusion of an OLM significantly improved students' problem selection decisions (students with the OLM selected significantly fewer mastered problems). Little prior empirical work has investigated whether an OLM can improve students' problem selection decisions and domain level learning outcomes. My work established that an OLM can enhance learning and SRL in ITSs when shared control is enabled, although the shared control with the OLM did not lead to significantly better learning outcomes than the full system control over problem selection in Experiment 2. The learning status shown by the OLM could aid students' self-assessment, which is necessary for making accurate problem selection decisions. As a result, the presence of the OLM may help reduce the students' cognitive load for monitoring and making problem selection decisions and thus lead to better learning outcomes with the shared control. Furthermore, the redesigned OLM in Experiment 2 with self-assessment prompts could facilitate students' reflection which may in turn have resulted in increased concentration on learning and greater learning gains.

A third contribution of the dissertation is the identification of a combination of gamification features with shared control that is detrimental to student learning. Experiment 3 has shown that using rewards to encourage re-practice of the completed problems led to significantly more revisits of the completed problems and worse learning outcomes than the condition with re-practice but no rewards. The combination of performance-based rewards and re-practice is commonly seen in commercial games, including serious games (e.g., *DragonBox*). My results caution that the integration of gamification features needs to align with the instructional goals and encourage desirable learning behaviors. This form of shared control over problem selection (with re-practice and rewards) should be avoided in systems that aim to foster better learning outcomes.

To sum up, my experiments have shown that shared control over problem selection can be designed to engender better learning outcomes than system-controlled problem selection, which is novel in research of learner control over problem selection in learning technologies. Nevertheless, Experiment 4 did not find lasting effects of the shared control in a transfer session when the mastery-oriented features were not in effect. It is also an open question whether the interventions will have lasting effects over longer period of time. Therefore, future research is warranted to further investigate the role of learner control over problem selection in ITSs.

6.1.2 Effects of Using ITSs to Help Students Learn Problem Selection Skills

A fourth contribution of the dissertation is that it shows that mastery-oriented shared control over problem selection improves students' declarative knowledge of the Mastery Rule. Experiment 4 found that the mastery-oriented features with shared control led to significantly better declarative knowledge of applying the Mastery Rule on a paper test. However, although the students selected good problems in the tutor with the mastery-oriented shared control, no superior effects on improving problem selection decisions were found during the Future Learning Phase due to the mastery-oriented features as compared to a condition that only learned with system-controlled problem selection in the Learning Phase. As discussed in Chapter 5, the overall good application of the Mastery Rule in Experiment 4 may be regarded as a ceiling effect on students' problem selection performance in the tutor. The design of other tutor features (i.e., the badges and the Open Learner Model) might have stimulated students' desires to complete all the levels as soon as possible, thus had contributed to the overall good problem selection decisions in all conditions. Future work will need to separate the effects of different tutor features and possibly study the effects over a longer period of time.

Another contribution of the dissertation is that it illustrates a way of integrating motivational design to extend the design of ITS to help students learn problem selection skills. Some prior work has developed metacognitive-tutoring that helps students learn SRL skills with ITSs (e.g., the Help-Tutor (Aleven et al., 2006), Meta-Tutor (Azevedo et al., 2009)). Mitrovic and Martin (2003) deployed a scaffolding-fading paradigm in a SQL tutor to coach students problem selection skills through feedback messages from the system. My work is the first study that aims at extending an ITS to help students learn the skill of making problem selection decisions with the integration of motivational design. The user-centered motivational design helped to identify mastery-approach orientation as important design focus to stimulate and sustain students' problem selection decisions based on the Mastery Rule. It also produced tutor features that can support problem selection in a mastery-oriented way. The combination of the mastery-oriented features and shared control led to superior learning outcomes as compared to system control in Experiment 4. Future research should explicitly measure students' goal orientations to investigate whether the mastery-oriented features could foster the mastery-approach orientation and whether that contributes to the improvement on domain level learning outcomes.

6.1.3 Effects of Shared Control on Motivation

Across all four experiments, I did not find significant effects of shared control on students' enjoyment of learning, compared to system control. This result is somewhat surprising given learner control has commonly been regarded as preferred by students (Clark & Mayer, 2011). Prior research has found correlations between perceived control and students' intrinsic motivation and enjoyment (Vandewaetere & Clarebout, 2011). It may be that the perception of control engendered by the shared control in my experiments was not strong enough to bring about higher enjoyment. It is also likely that the contrast between the shared control and system control in the systems was overshadowed by the similarities of the interfaces and other tutor features. For example, in Experiment 4, all conditions had badges (for completing the levels) and the Open Learner Model. Lastly, math is generally not liked by average middle school students. The students may still by and large perceive the tutors as formal learning environments for math, thus might not deem the tutors to be fun even with some amount of control in the system.

My results show that sharing the control over problem selection with the system does not always lead to higher enjoyment when learning with a math ITS. It is not guaranteed that learner control will always lead to more enjoyable learning experiences in learning technologies. One limitation of my work was that I did not measure other motivational constructs, such as goal orientation (Wolters et al., 1996), self-efficacy (Bandura, 1994), and sense of autonomy (Flowerday & Schraw, 2003). Although enjoyment is regarded as related to students' intrinsic motivation, it is probable that my interventions would have stronger influence on these other motivational constructs that are also related to self-regulated learning and learner control.

6.1.4 Effects of *Lynnette* on Improving Students' Equation Solving Abilities

My experiments have demonstrated the effectiveness of ITSs on improving students' domain level learning for an important topic in Algebra for middle school students, i.e., equation solving. As part of my dissertation work, I have worked with the CTAT (Cognitive Tutor Authoring Tools) team to iteratively improve the interface and the problem sets of *Lynnette*. So far, *Lynnette* has been used in 6 classroom experiments (four of them are included in this dissertation) with 823 6^{th} – 8^{th} grade students. All the experiments used a pre/post-test paradigm to measure students' learning gains on solving the equations being practiced in the tutor. The pre- and post-tests were given on paper, and the test items (equations) were graded from 0 to 1. Overall, all but one experiments observed significant learning gains on equation solving for the students from pre- to post-tests, with medium to large effect sizes.

The first experiment was conducted with 57 6^{th} and 7^{th} grade students (Waalkens, Aleven & Taatgen, 2013). The students worked with *Lynnette* on three consecutive days, two hours a day, during their summer holidays. The students improved significantly from pre- to post-tests on equation solving ($F(1, 55) = 6.623$, $p = .0103$, $d = .69$). In the second experiment, *Lynnette* was used by 98 8^{th} grade students from two teachers' four classes at the same public school (Long & Aleven, 2013a). They worked for three 41-minute class periods on three consecutive school days in a spring semester. A ceiling effect was observed in this experiment, in that the students performed fairly high on the pre-test (mean=0.91, SD=0.14), and did not improve significantly from pre- to post-tests. The third experiment (Experiment 1 in the dissertation) was conducted in a fall semester with 62 7^{th} grade students from one teacher's 3 classes at a public school (Long & Aleven, 2013b). The students worked with the tutor for five 41-minute class periods on five consecutive school days. There were significant learning gains on equation solving from pre- to post-tests ($F(1, 52) = 35.239$, $p < .000$, $d = 1.65$). The fourth experiment (Experiment 2 in the dissertation) conducted in a spring semester involved 245 7^{th} and 8^{th} grade students from 16 classes of 3 local public schools. They were taught by 6 teachers. All the students worked on the tutor for five 41-minute class periods on consecutive schools days. The learning gains were significant from pre- to post-tests for all the students ($F(1, 236) = 81.066$, $p < .000$, $d = 1.17$). The fifth experiment (Experiment 3 in the dissertation) was conducted in a fall semester with 161 7^{th} and 8^{th} grade students from 15 classes of 3 local public schools, taught by 6 teachers (Long & Aleven, 2014). Only in this experiment, the students worked with *Lynnette* on tablet computers instead of desktops. They still worked with the tutor for five 41-minute class periods on five school days in their computer labs. The pre- to post-test show significant improvements on equation solving ($F(1, 155) = 28.203$, $p < .000$, $d = .85$). Lastly, the sixth experiment (Experiment 4 in the dissertation) was conducted in a spring semester with 200 6^{th} – 8^{th} grade students from 13 classes, taught by 7 different teachers at 4 middle schools (as discussed in Chapter 5, one school was excluded from the data analysis). The students learned with *Lynnette* in two phases. Phase 1 comprised of 4 41-minute class periods, and the students did not improve significantly from pre- to the mid-test due to the ceiling effect on pre-test (mean=0.82, SD=0.20). On the contrary, with Phase 2 which lasted for 2 41-minute class periods, the students improved significantly on the equations covered in this phase from the mid-test to the post-test ($F(1, 155) = 37.028$, $p < .000$, $d = .98$).

6.2 Design Recommendations for Learner Control in Learning Technologies

My dissertation generates design recommendations for learner control in learning technologies. The dissertation focuses on how learner control can be supported effectively, not just on whether or not we should have learner control. My experiments have shown that with designs that are informed by theories and empirical studies, shared control can lead to better or at the minimum the same learning outcomes as system control. It also has the potential to engender positive motivation towards problem selection and learning. Nevertheless, my work also cautions the risks of granting students pure learner control over problem selection. Therefore, future design of learning technologies should consider offering learner control, with careful designs that support the related SRL processes (e.g., self-assessment, making problem selection decisions) as well as motivational constructs (e.g., mastery-approach orientation, self-efficacy, and sense of autonomy).

Including learning analytics similar to the Open Learner Model. Students have generally been found to be poor at self-assessing their learning status (Metcalfe, 2009), which might lead to inaccurate problem selection decisions. OLMs can afford information about students' learning status tracked by the systems, and thus offer support for self-assessment and problem selection. It can also reduce students' cognitive load for monitoring and making problem selection decisions. My experiments have empirically supported the beneficial role of OLM in this regard. Also, Experiment 2 illustrated designs that could be integrated with an OLM to facilitate self-assessment, i.e., the self-assessment prompts and delaying the update of the skill bars to serve as feedback on students' self-assessment. It will also be useful to explicitly explain how to apply problem selection rules based on the learning status offered by an OLM – in other words, highlighting the relations between the problem selection decisions and the learning status to help students use the OLM to make decisions, as had been explained in the tutorial of *Lynnette 3.0*.

Integrating motivational features that aim at fostering a mastery-approach orientation. Experiment 4 has demonstrated the effects of the mastery-oriented features with shared control on enhancing students' learning outcomes. Mastery-approach orientation has generally been associated with positive cognitive and SRL processes. Therefore, the design of learning technologies should consider integrating motivational features that emphasize the mastery-approach orientation, for example, as on boarding tutorials, feedback messages, or conversations with pedagogical agents.

Avoiding using performance-based rewards to encourage ineffective learning behaviors. Experiment 3 has found that the combination of rewards and re-practice was detrimental for student learning. It is likely that re-practicing the exact same problems does not contribute to abstracting the procedural skills for solving a certain type of equations. Therefore, the rewards were used to encourage an ineffective learning behavior in this case. Nevertheless, the experiment has illustrated that rewards are motivating for middle school students. The designs that involve rewards should be used with caution to facilitate effective learning behaviors.

Involving teachers to adaptively enable learner control in learning technologies. As discussed in Chapter 2, the effects of learner control over problem selection on learning and motivation could be affected by different factors such as students' domain level knowledge, self-efficacy, SRL skills, etc. The design of learner control could be made adaptive to students' characteristics and dynamically change as the students grow cognitively and metacognitively. Therefore, for future research, it may be helpful to let teachers take some responsibilities to help decide when and which students could have learner control in the system, provided that the system offers students' learning progress through a teachers' dashboard.

6.3 Summary of Contributions of the Dissertation

My dissertation work combines a user-centered design process, classroom experimental studies, and educational data mining to investigate how to support learner-controlled problem selection in Intelligent Tutoring Systems. Making problem selection decisions is important both theoretically and practically. Selecting problems that match a student's knowledge level will lead to better learning outcomes (Metcalfe, 2009). Learning technologies generally offer great learner autonomy and control which imposes high demands of effective problem selection skills to ensure effective and efficient learning. It is therefore critical for students to learn skills of making problem selection decisions that influence future learning in the same learning environment and ultimately in other environments, although the latter remains an ambitious goal for future research to investigate. The dissertation contributes to different strands of research.

First, my work contributes to the literatures on the effects of learner control on students' domain level learning in learning technologies. It demonstrates that shared control with mastery-oriented support can lead to greater domain level learning gains, as compared to system control over problem selection in ITSs. ITSs are effective at adaptively selecting problems for students (Corbett, 2000). Prior research has generally found that student-selected problems lead to worse learning outcomes than system-selected problems in computer-based learning environments (Atkinson, 1972; Niemiec, Sikorski, & Walberg, 1996). My work has proven that with careful designs that support students' SRL and motivation, shared control can be adopted in ITSs to facilitate domain level learning. Additionally, I have demonstrated that Open Learner Models can be designed to enhance student learning when shared control over problem selection is provided. Although researchers have long been interested in the potential of including OLM to facilitate student learning (Bull & Kay, 2008), few empirical studies have successfully illustrated the benefits of OLM on enhancing learning outcomes (Mitrovic & Martin, 2007). On the other hand, I have identified a specific combination of gamification features integrated with shared control that may be detrimental to student learning, which sheds light on the design of learning technologies that involve gamification features.

Second, my work contributes to research on supporting Self-Regulated Learning in ITS. First of all, my work has demonstrated that supporting SRL processes (i.e., making problem selection decisions) can lead to significantly better domain level learning outcomes, which has not been fully established in prior literatures on supporting SRL in ITSs (Aleven et al., 2006). Furthermore, I have shown that the shared control with mastery-oriented features have lasting effects on improving students' declarative knowledge of problem selection skills. Not much prior work on supporting SRL in ITS has investigated the lasting effects of interventions on SRL skills and future learning (Leelawong & Biswas, 2008; Roll et al., 2014). My Experiment 4 has demonstrated some success of helping students learn problem selection skill that will have lasting effects on their problem selection decisions and future learning in the same learning environments, with improvement only on declarative knowledge of applying the rule on a paper test. Lastly, my work is the first study to extend an ITS with features that might help students learn problem selection skill through the integration of motivational design. Although motivation has been identified as an integral part of SRL, not much prior work in ITSs has focused on fostering students' motivation to stimulate and sustain SRL processes. The user-centered motivational design identifies mastery-approach orientation as important design focus plus tutor features that can support problem selection in a mastery-oriented way.

Lastly, my contribution to human-computer interaction includes design recommendations for enabling learner control in learning technologies. Instead of focusing on whether or not we should offer students learner control, it is more useful to consider how to design the learner control so that it can facilitate students' learning, motivation and SRL processes. The design of learner control can be informed by user-centered research, cognitive and instructional theories, and results from empirical experiments.

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Appendix I: Pre-Test used in Experiment 1

The pre-test included items that measured students' procedural knowledge (items 1 – 4, 17 – 19), conceptual knowledge (items 5 – 16), and knowledge about the flexibility of using different strategies to solve the same equation (items 20-22). Chapter 3 only reported results concerning the procedural items. The other items answered research questions that are not addressed in the dissertation.

Solve the following equations (show your work please):

1) How well do you think you could solve "x–7 = 13"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: x–7 = 13

2) How well do you think you could solve "4x+3 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 4x+3 = 11

3) How well do you think you could solve "6 = 2(x+1)"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 6 = 2(x+1)

4) How well do you think you could solve "4x+2 = 3x+4"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 4x+2 = 3x+4

For each of the following, circle TRUE if the statement is true and circle FALSE if the statement is not true. Circle NOT SURE if you are not sure it is true or false.

5) 3–4x is equivalent to -4x+3 TRUE / FALSE / NOT SURE

6) 3x+2 is equivalent to -3x+2 TRUE / FALSE / NOT SURE

7) 4x-3 is equivalent to -4x+3 TRUE / FALSE / NOT SURE

8) 1+(-4x) is equivalent to -4x+1 TRUE / FALSE / NOT SURE

9) -x+3 is equivalent to -1*x+3 TRUE / FALSE / NOT SURE

For each of the following, circle TRUE if the statement is true for the equation "4=6+2x-7+x" and circle FALSE if the statement is not true. Circle NOT SURE if you are not sure it is true or false.

10) 2 is a constant term TRUE / FALSE / NOT SURE

11) 4 is a constant term TRUE / FALSE / NOT SURE

12) 4 and -7 are like terms TRUE / FALSE / NOT SURE

13) 2 and 6 are like terms TRUE / FALSE / NOT SURE

14) 2 is a variable's coefficient TRUE / FALSE / NOT SURE

15) 1 is a variable's coefficient TRUE / FALSE / NOT SURE

16) 2x and x are like terms TRUE / FALSE / NOT SUR

Solve the following equations (show your work please):

17) How well do you think you could solve "3(x+1)+2 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 3(x+1)+2 = 11

18) How well do you think you could solve "-2x+6 = 3x-4"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: -2x+6 = 3x-4

19) How well do you think you could solve "7 = 2(x-2)+1"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 7 = 2(x-2)+1

Peter has solved 3 equations, and he used two different ways to solve each equation. Below you see some parts of his work. For each of the following, select the CORRECT solution(s) he has done.

20) 2x+4 = 4x–6

Solution 1: x+2 = 2x-3 **Solution 2**: 4 = 2x-6

A. Solution 1 B. Solution 2 C. Both Solution 1 and 2 D. None

21) $3(x+5) = 6$

Solution 1: $x+5 = 2$ **Solution 2**: $3x+15 = 6$

A. Solution 1 B. Solution 2 C. Both Solution 1 and 2 D. None

22) $4(x-2)-1 = 5$

Solution 1: $4x-8-1 = 5$ **Solution 2**: $4(x-2) = 6$

A. Solution 1 B. Solution 2 C. Both Solution 1 and 2 D. None

Appendix II: Post-Test used in Experiment 1

The post-test included items that measured students' procedural knowledge (items 1, 2, 3, 10, 12, 21, and 22), conceptual knowledge (items 5 – 9, 14 – 20), transfer of knowledge (items 4, 11, 13, 23; these items were new equations that are not practiced in the tutor), and knowledge about the flexibility of using different strategies to solve the same equation (items 24 – 26). Chapter 3 only reported results concerning the procedural items. The other items answered research questions that are not addressed in the dissertation.

Solve the following equations (show your work please):

1) How well do you think you can solve "x-6=12"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: x–6 = 12

2) How well do you think you can solve "3x+5 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 3x+5 = 11

3) How well do you think you can solve "8 = 2(x-3)"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem:8 = 2(x-3)

4) How well do you think you can solve “0.2x+0.7 = 1.1”?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 0.2x+0.7 = 1.1

For each of the following, circle TRUE if the statement is true and circle FALSE if the statement is not true. If you are not sure about the answer, just circle NOT SURE.

5) 5x+3 is equivalent to -5x+3 TRUE / FALSE / NOT SURE

6) 3–2x is equivalent to -2x+3 TRUE / FALSE / NOT SURE

7) 6x-3 is equivalent to -6x+3 TRUE / FALSE / NOT SURE

8) 2+(-5x) is equivalent to -5x+2 TRUE / FALSE / NOT SURE

9) -x+4 is equivalent to -1*x+4 TRUE / FALSE / NOT SURE

Solve the following equations (show your work please):

10) How well do you think you can solve “5x+1 = 4x+3”?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 5x+1 = 4x+3

11) How well do you think you can solve “(3x+5)/2 = 2”?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: (3x+5)/2 = 2

12) How well do you think you can solve “5 = 3(x-2)+2”?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 5 = 3(x-2)+2

13) How well do you think you can solve “2x-3x+4 = 5+x+3”?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2x-3x+4 = 5+x+3

For each of the following, circle TRUE if the statement is true for the equation “3=6+4x-2+x” and circle FALSE if the statement is not true. If you are not sure about the answer, just circle NOT SURE.

14) 3 is a constant term TRUE / FALSE / NOT SURE

15) 4 is a constant term TRUE / FALSE / NOT SURE

16) 3 and -2 are like terms TRUE / FALSE / NOT SURE

17) 4 and 6 are like terms TRUE / FALSE / NOT SURE

18) 4 is a variable’s coefficient TRUE / FALSE / NOT SURE

19) 1 is a variable’s coefficient TRUE / FALSE / NOT SURE

20) 4x and x are like terms TRUE / FALSE / NOT SURE

Solve the following equations:

21) How well do you think you can solve "2(x+1)+3 = 11"?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 2(x+1)+3 = 11

22) How well do you think you can solve "-2x+7 = 4x+1"?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: -2x+7 = 4x+1

23) How well do you think you can solve "3(2x+2)+(2-x) = 23"?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 3(2x+2)+(2-x) = 23

Sarah has solved 3 equations, and she used two different ways to solve each equation. Below you see some parts of her work. For each of the following, select the CORRECT solution(s) she has done.

24) 2x+6 = 4x–4

Solution 1: x+3 = 2x-2 **Solution 2**: 6 = 2x-4

A. Solution 1 B. Solution 2 C. Both solution 1 and 2 D. None

25) $3(x+3) = -6$

Solution 1: $x+3 = -2$ **Solution 2**: $3x+9 = -6$

A. Solution 1 B. Solution 2 C. Both solution 1 and 2 D. None

26) $2(x-2) +3 \quad = 9$

Solution 1: $2x-4+3 = 9$ **Solution 2**: $2(x-2) = 6$

A. Solution 1 B. Solution 2 C. Both solution 1 and 2 D. None

Appendix III: Pre-Test used in Experiment 2

The pre-test included items that measured students' procedural knowledge (items 1 – 4, 15 – 17) and conceptual knowledge (items 5 – 14). Chapter 3 only reported results concerning the procedural items.

Solve the following equations (show your work please):

1) How well do you think you could solve "x–7 = 13"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: x–7 = 13

2) How well do you think you could solve "4x+3 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 4x+3 = 11

3) How well do you think you could solve "6 = 2(x+1)"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 6 = 2(x+1)

4) How well do you think you could solve "4x+2 = 3x+4"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 4x+2 = 3x+4

For each of the following, circle TRUE if the statement is true and circle FALSE if the statement is not true. Circle NOT SURE if you are not sure it is true or false.

5) 3–4x is equivalent to -4x+3 TRUE / FALSE / NOT SURE

6) 3x+2 is equivalent to -3x+2 TRUE / FALSE / NOT SURE

7) 4x-3 is equivalent to -4x+3 TRUE / FALSE / NOT SURE

8) 1+(-4x) is equivalent to -4x+1 TRUE / FALSE / NOT SURE

For each of the following, circle TRUE if the statement is true for the equation "4=6+2x-7+x" and circle FALSE if the statement is not true. Circle NOT SURE if you are not sure it is true or false.

9) 4 is a constant term TRUE / FALSE / NOT SURE

10) 2 is a constant term TRUE / FALSE / NOT SURE

11) 4 and -7 are like terms TRUE / FALSE / NOT SURE

12) 2 and 6 are like terms TRUE / FALSE / NOT SURE

13) 2 is a variable's coefficient TRUE / FALSE / NOT SURE

14) 2x and x are like terms TRUE / FALSE / NOT SURE

Solve the following equations (show your work please):

15) How well do you think you could solve "3(x+1)+2 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 3(x+1)+2 = 11

16) How well do you think you could solve "-2x+6 = 3x-4"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: -2x+6 = 3x-4

17) How well do you think you could solve "7 = 2(x-2)+1"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 7 = 2(x-2)+1

Appendix IV: Post-Test used in Experiment 2

The post-test comprised of two parts: An enjoyment questionnaire and the equation solving items. For equation solving, the test included items that measured students' procedural knowledge (items 1, 2, 3, 8, 9, 17, 18), conceptual knowledge (items 4 – 7, 11 – 16) and transfer of knowledge (items 10, 19; these items were new equations that are not practiced in the tutor). Chapter 3 only reported results concerning the procedural items.

Please read the following statements about your experience of using the *Linear Equation Program* for the past few lab days. For each statement, please indicate how true it is for you.

NOTE: You might also have done some extra Geometry exercises after you had finished using the Linear Equation Program. However, please answer the questions ONLY for your experience of using the *Linear Equation Program*.

1. I liked using the linear equation program.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

2. When I was using this linear equation program, I had trouble paying attention.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

3. I enjoyed using the linear equation program.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

4. Working with the linear equation program was fun.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

5. While I was using the linear equation program, I was thinking about how much I liked it.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

6. I thought using the linear equation program was boring.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

7. I thought using the linear equation program was very interesting.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

Thanks very much for answering the questions!

Now please go to next page and solve the following problems. Please try your best to solve each problem.

Solve the following equations (show your work please):

1) How well do you think you can solve "x-6=12"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: x–6 = 12

2) How well do you think you can solve "3x+5 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 3x+5 = 11

3) How well do you think you can solve "8 = 2(x-3)"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 8 = 2(x-3)

For each of the following, circle TRUE if the statement is true and circle FALSE if the statement is not true. If you are not sure about the answer, just circle NOT SURE.

4) 5x+3 is equivalent to -5x+3 TRUE / FALSE / NOT SURE

5) 3–2x is equivalent to -2x+3 TRUE / FALSE / NOT SURE

6) 6x-3 is equivalent to -6x+3 TRUE / FALSE / NOT SURE

7) 2+(-5x) is equivalent to -5x+2 TRUE / FALSE / NOT SURE

Solve the following equations (show your work please):

8) How well do you think you can solve "5x+1 = 4x+3"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 5x+1 = 4x+3

9) How well do you think you can solve "5 = 3(x-2)+2"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 5 = 3(x-2)+2

10) How well do you think you can solve "2x-3x+4 = 5+x+3"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2x-3x+4 = 5+x+3

For each of the following, circle TRUE if the statement is true for the equation "3=6+4x-2+x" and circle FALSE if the statement is not true. If you are not sure about the answer, just circle NOT SURE.

11) 3 is a constant term TRUE / FALSE / NOT SURE

12) 4 is a constant term TRUE / FALSE / NOT SURE

13) 3 and -2 are like terms TRUE / FALSE / NOT SURE

14) 4 and 6 are like terms TRUE / FALSE / NOT SURE

15) 4 is a variable's coefficient TRUE / FALSE / NOT SURE

16) 4x and x are like terms TRUE / FALSE / NOT SURE

Solve the following equations:

17) How well do you think you can solve "2(x+1)+3 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2(x+1)+3 = 11

18) How well do you think you can solve "-2x+7 = 4x+1"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: -2x+7 = 4x+1

19) How well do you think you can solve "3(2x+2)+(2-x) = 23"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 3(2x+2)+(2-x) = 23

Appendix V: Pre-Test used in Experiment 3

The pre-test included items that measured students' procedural knowledge (items 1 – 3, 13 –15) and conceptual knowledge (items 4 – 12). Chapter 3 reported results for the whole test.

Solve the following equations (show your work please):

1) How well do you think you can solve "4x+3 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 4x+3 = 11

2) How well do you think you can solve "8/x = 2"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 8/x = 2

3) How well do you think you can solve "2x+8 = 6x"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2x+8 = 6x

For each of the following, circle TRUE if the statement is true and circle FALSE if the statement is not true. Circle NOT SURE if you are not sure it is true or false.

4) 2x+3 equals 5 TRUE / FALSE / NOT SURE

5) 4x-3 equals -4x+3 TRUE / FALSE / NOT SURE

6) 3x equals 5x-2 TRUE / FALSE / NOT SURE

7) 3–4x equals -4x+3 TRUE / FALSE / NOT SURE

8) 4x/4 equals 1 TRUE / FALSE / NOT SURE

9) 3x+6-6 equals 3x TRUE / FALSE / NOT SURE

10) -x equals -1x TRUE / FALSE / NOT SURE

11) 3x+2 equals -3x+2 TRUE / FALSE / NOT SURE

12) 1+(-4x) equals -4x+1 TRUE / FALSE / NOT SURE

Solve the following equations (show your work please)

13) How well do you think you can solve "6 = 2(x+1)"?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 6 = 2(x+1)

14) How well do you think you can solve "5x+2 = 3x+10"?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 5x + 2 = 3x + 10

15) How well do you think you can solve "(2x+1)/5 = 3"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: (2x+1)/5 = 3

Appendix VI: Post-Test used in Experiment 3

The post-test comprised of two parts: An enjoyment questionnaire and the equation solving items. For equation solving, the test included items that measured students' procedural knowledge (items 1, 2, 3, 13, 15, 16), conceptual knowledge (items 4 – 12) and knowledge about the flexibility of using different strategies to solve the same equation (items 14, 17, 18). Chapter 3 reported results concerning both the procedural and conceptual items.

Please read the following statements about your experience of using the tablet *Linear Equation Tutor* for the past few days. For each statement, please indicate how true it is for you.

1. I liked using the linear equation tutor.

1 2 3 4 5 6 7

not at all true somewhat true very true

2. When I was using this linear equation tutor, I had trouble paying attention.

1 2 3 4 5 6 7

not at all true somewhat true very true

3. I enjoyed using the linear equation tutor.

1 2 3 4 5 6 7

not at all true somewhat true very true

4. Working with the linear equation tutor was fun.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

5. While I was using the linear equation tutor, I was thinking about how much I liked it.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

6. I thought using the linear equation tutor was boring.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

7. I thought using the linear equation tutor was very interesting.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

Thanks very much for answering the questions!

Now please go to next page and solve the following problems. Please try your best to solve each problem.

Solve the following equations (show your work please):

1) How well do you think you can solve "4x+3 = 11"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 4x+3 = 11

2) How well do you think you can solve "8/x = 2"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 8/x = 2

3) How well do you think you can solve "2x+8 = 6x"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2x+8 = 6x

For each of the following, circle TRUE if the statement is true and circle FALSE if the statement is not true. Circle NOT SURE if you are not sure it is true or false.

4) 2x+3 equals 5 TRUE / FALSE / NOT SURE

5) 4x-3 equals -4x+3 TRUE / FALSE / NOT SURE

6) 3x equals 5x-2 TRUE / FALSE / NOT SURE

7)	3–4x equals -4x+3	TRUE / FALSE / NOT SURE
8)	4x/4 equals 1	TRUE / FALSE / NOT SURE
9)	3x+6-6 equals 3x	TRUE / FALSE / NOT SURE
10)	-x equals -1x	TRUE / FALSE / NOT SURE
11)	3x+2 equals -3x+2	TRUE / FALSE / NOT SURE
12)	1+(-4x) equals -4x+1	TRUE / FALSE / NOT SURE

Solve the following equation (show your work please)

13) How well do you think you can solve "6 = 2(x+1)"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 6 = 2(x+1)

14) To solve equation 3x + 5 = 4x with FEWEST steps, what will you do first (circle one option):

a. Subtract 4x from both sides
b. Subtract 5 from both sides
c. Subtract 3x from both sides
d. Each of these choices is equally good
e. I want to do something else first: ______________________________(please write what you want to do)

Solve the following equations (show your work please)

15) How well do you think you can solve "5x+2 = 3x+10"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: $5x + 2 = 3x + 10$

16) How well do you think you can solve "(2x+1)/5 = 3"?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: $(2x+1)/5 = 3$

To solve equation 2x + 9 = -x, Sam did 2x = -x-9 as the first step.

17) Is what Sam did mathematically correct (circle one option):

a. Yes
b. No
c. Not sure

18) Sam is now stuck with the problem. To help him finish solving the equation with FEWEST steps, what will you do next, continuing from 2x = -x-9 (circle one option):

a. Add 9 to both sides
b. Add x to both sides
c. Subtract 2x from both sides
d. Each of these choices is equally good

e. I want to do something else next: ______________________________(please write what you want to do)

Appendix VII: Pre-Test used in Experiment 4

The pre-test included 6 items that measured students' procedural knowledge. Chapter 5 reported results for the whole test.

Please solve the following equations (show your work please):

1) How well do you think you can solve x + 1 = 6?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: x + 1 = 6

2) How well do you think you can solve 6 – x = 2?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 6 – x = 2

3) How well do you think you can solve 2x = 6?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2x = 6

4) How well do you think you can solve $2x + 1 = 5$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $2x + 1 = 5$

5) How well do you think you can solve $3(x+1) = 9$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $3(x+1) = 9$

6) How well do you think you can solve $2(x+1) – 1 = 7$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $2(x+1) – 1 = 7$

Appendix VIII: Mid-Test used in Experiment 4

The mid-test comprised of three parts: An enjoyment questionnaire, the equation solving items (procedural items from 1 to 9) and items for the declarative knowledge of applying the Mastery Rule (items 10 to 13). Chapter 5 reported results concerning the three parts.

Please read the following statements about your experience of using the *Linear Equation Tutor*. For each statement, please indicate how true it is for you (circle one number).

1. I liked using the linear equation tutor.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

2. When I was using this linear equation tutor, I had trouble paying attention.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

3. I enjoyed using the linear equation tutor.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

4. Working with the linear equation tutor was fun.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

5. While I was using the linear equation tutor, I was thinking about how much I liked it.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

6. I thought using the linear equation tutor was boring.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

7. I thought using the linear equation tutor was very interesting.

1	2	3	4	5	6	7
not at all true			somewhat true			very true

Thanks very much for answering the questions!

Now please go to next page and solve the following problems. Please try your best to solve each problem.

Please solve the following equations (show your work please):

1) How well do you think you can solve $x + 4 = 8$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $x + 4 = 8$

2) How well do you think you can solve $12 - x = 5$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $12 - x = 5$

3) How well do you think you can solve $5x = 10$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $5x = 10$

4) How well do you think you can solve $3x - 2 = 13$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $3x - 2 = 13$

5) How well do you think you can solve 5(x - 1) = 10?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 5(x - 1) = 10

6) How well do you think you can solve 3(3x - 3) – 1 = 8?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 3(3x - 3) – 1 = 8

7) How well do you think you can solve x – 6 = 7x?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: x – 6 = 7x

8) How well do you think you can solve 2x + 9 = 4x - 3?

Circle one number:

Not Well						Very Well
1	2	3	4	5	6	7

Now please solve the problem: 2x + 9 = 4x - 3

9) How well do you think you can solve -8x – 2 = -7x + 5?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: -8x – 2 = -7x + 5

Please answer the following questions about how to select problems:

If you are given a new unit in the Linear Equation Tutor, and you can select your own problems to practice:

10) What does it mean to have mastered a level in the Linear Equation Tutor (check all that apply – write an "x" in the brackets):

[ ] I have completed all the problems in that level

[ ] I have learned all the equation solving skills in that level

[ ] I can consistently do well on problems in that level

[ ] I don't know

11) After you have mastered a level in the tutor, will you continue practicing the level (check all that apply – write an "x" in the brackets)?

[ ] Yes, because I am good at the problems in this level.

[ ] Yes, because it will make me feel more confident.

[ ] Yes, because I do not want to fail.

[ ] No, because I want to learn something new.

[ ] I don't know what to do next.

12) After you have mastered a level in the tutor, there are more levels that are unmastered and more difficult. Will you select problems from these unmastered levels (check all that apply – write an "x" in the brackets)?

[ ] Yes, because I want to learn new skills.

[ ] Yes, because I want to challenge myself with more difficult problems.

[ ] No, because the unmastered levels are difficult.

[ ] No, because I want more practice on the level I have mastered.

[ ] No, because I want to do easy problems.

[ ] I don't know what to do next.

13) Please write down a good strategy to select problems to work on when you are doing your own practice:

Appendix IX: Post-Test used in Experiment 4

The post-test included 9 items that measured students' procedural knowledge for equation solving. Chapter 5 reported results for the whole test.

Please solve the following equations (show your work please):

1) How well do you think you can solve $x + 2 = 9$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $x + 2 = 9$

2) How well do you think you can solve $13 – x = 7$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $13 – x = 7$

3) How well do you think you can solve $16 = 4x$?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: $16 = 4x$

4) How well do you think you can solve 17 = 4x + 1?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 17 = 4x + 1

5) How well do you think you can solve 12 = 4(2x - 1)?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 12 = 4(2x - 1)

6) How well do you think you can solve 21 = 4(x - 2) + 5?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 21 = 4(x - 2) + 5

7) How well do you think you can solve 6x = 9x - 15?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 6x = 9x - 15

8) How well do you think you can solve 7x – 5 = 2x + 5?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: 7x – 5 = 2x + 5

9) How well do you think you can solve -3x – 2 = -7x + 10?

Circle one number:

Not Well						**Very Well**
1	2	3	4	5	6	7

Now please solve the problem: -3x – 2 = -7x + 10

Appendix X: Interview Scripts and Procedure used in Chapter 4

There were two versions of the interview scripts and procedures, one with the Lynnette version that had an Open Learner Model and one without.

Version 1 (*Lynnette* with the Open Learner Model):

1. The experimenter goes to https://equations.mathtutor.web.cmu.edu and logs in to *Lynnette*
2. Introduction from the experimenter: "This is a tutor program that helps you learn equations. It's called *Lynnette*. We built it here at CMU. "
3. The experimenter clicks "Get Started" on the home screen
4. Scripts for the experimenter:
   - "See there are five levels of equations that you can learn with *Lynnette*. (The experimenter points to the mastery bars of the Open Learner Model), what do you think these bars mean?"
   - "Now you can select a problem level on this screen. What level do you want to work on?"
   - "Can you tell me why you think you should work on that level?"
   - "Ok. Now you have selected this level. Let's do it."
5. Let the student work on the problem. The experimenter helps him/her if necessary.
6. After the student finishes the problem, the experimenter clicks "Done" and get back to the problem selection screen.
7. Scripts for the experimenter:
   - "Ok. Did you notice that the bar for the level has changed after you finish that problem? Do you know why it has changed?"
   - "Now what level are you going to work on next? Can you tell me why?"
   - After the student answers, "Ok. Thank you! Now let's answer one last question. What may be your goals if you are given 5 class periods to learn with *Lynnette*?"

Version 2 (*Lynnette* without the Open Learner Model):

1. The experimenter goes to https://equations.mathtutor.web.cmu.edu and logs in to *Lynnette*
2. Introduction from the experimenter: "This is a tutor program that helps you learn equations. It's called *Lynnette*. We built it here at CMU. "
3. The experimenter clicks "Get Started" on the home screen
4. Scripts for the experimenter:
   - "See there are five levels of equations that you can learn with *Lynnette*. What level do you want to work on now?"
   - "Can you tell me why you think you should work on that level?"
   - "Ok. Now you have selected this problem. Let's do it."
5. Let the student work on the problem. The experimenter helps him/her if necessary.

6. After the student finishes the problem, the experimenter clicks "Done" and get back to the problem selection screen.
7. Scripts for the experimenter:
   - "Ok. Now what are you going to work on next? Can you tell me why?"
   - After the student answers, "Ok. Thank you! Now let's answer one last question. What may be your goals if you are given 5 class periods to learn with *Lynnette*?"

Appendix XI: Storyboards used in Chapter 4

Part I: Help students know when they have had enough practice (Storyboards 1 – 4)

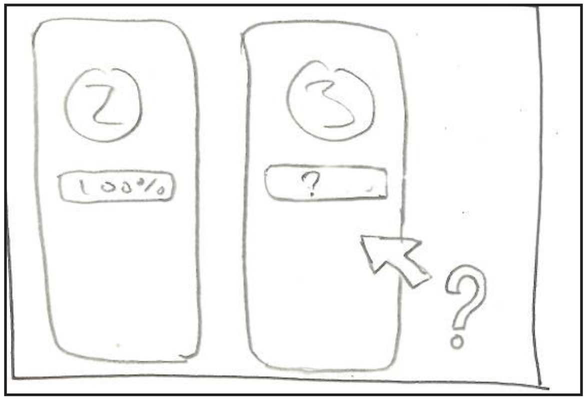
1. Pretesting
2. Are you sure you want to do that again?
3. Prompting to next level (badges)
4. Knowledge Components specific skill bars

Part II: Help students learn the metacognitive knowledge of the Mastery Rule, i.e., not repeating problem types that are mastered (Storyboards 5 – 10)

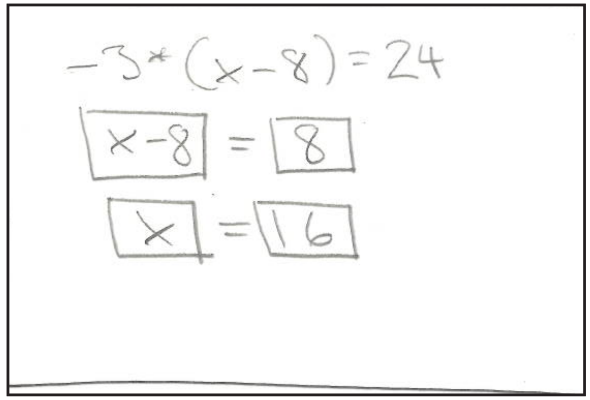
5. Path planning
6. Goal setting + recap
7. Success stories of other students
8. Message when not progressing toward your goals
9. Momentum / projected distance
10. Badges/rewards for streaks of good problem selection

Part III: Foster the motivation towards applying the Mastery Rule, i.e., motivate students to challenge themselves by selecting unmastered levels and persevere (Storyboards 11 – 18)

11. Special activities
12. Leaderboards (skill progress)
13. Leaderboards (avatars)
14. Worked examples
15. Explicit encouragement when making good problem selections but having difficulty
16. Remind students to use hints when having difficulty
17. Remind students to ask for help from peers or teachers
18. Working in the tutor as an alternative to taking quizzes

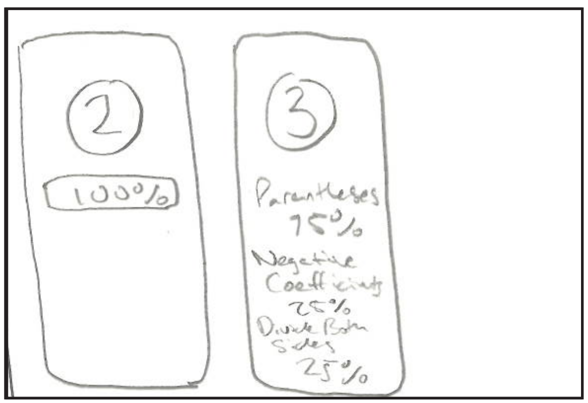


James is a student in the 7th grade. He just finished level 2 in the math tutor and is about to start level 3. However, he is unsure of how well he will be able to do in the new problems.

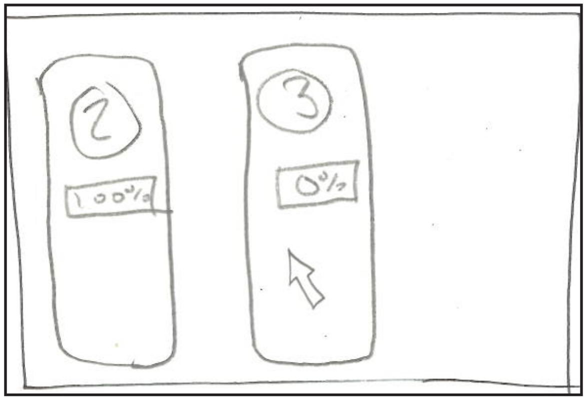


James does a set of placement problems for level 3. He doesn't get any feedback during the placement problems and fills in the answers the best he can.

When James is done with the placement problems he gets a skill graph back showing that he is 75% complete studying parentheses and 25% complete studying negative coefficients and divide by both sides.

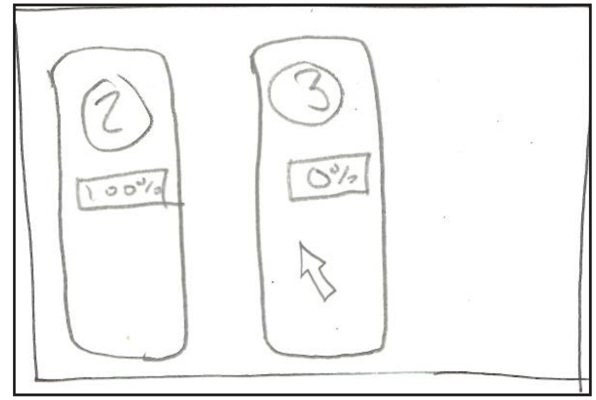


Because he already has some proficiency with one of the knowledge components and sees how far along he is in the rest, James thinks level 3 will be achievable and continues doing level 3 problems.

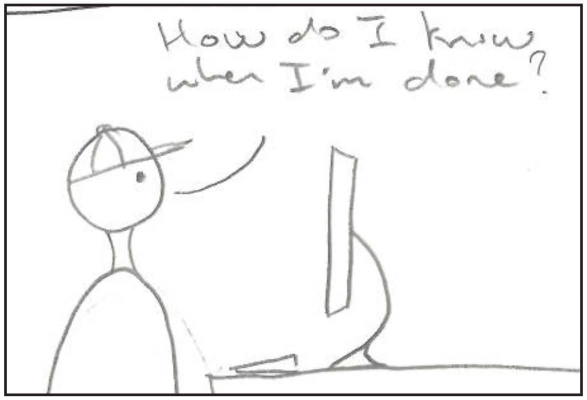


James has completed level 1 and level 2 in Lynnette. He selects and completes a problem from level 3, but feels it is a little too difficult for him.

James goes back to the problem selection screen and selects a level 2 problem again. He is presented with a pop up message asking if he is learning anything new in level 2.

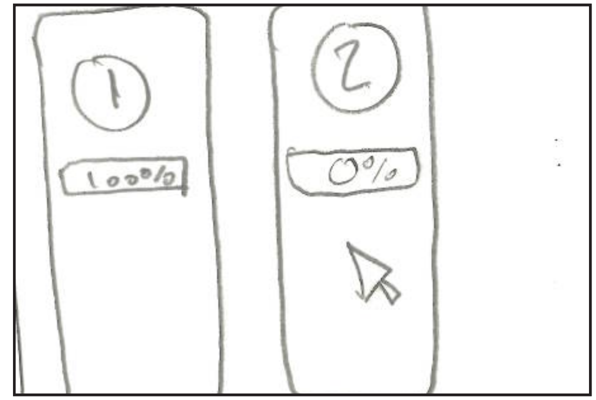


James pauses and decides that he is not going to learn anything new from practicing a level 2 problem again, so he goes back to the problem selection screen and selects a level 3 problem.

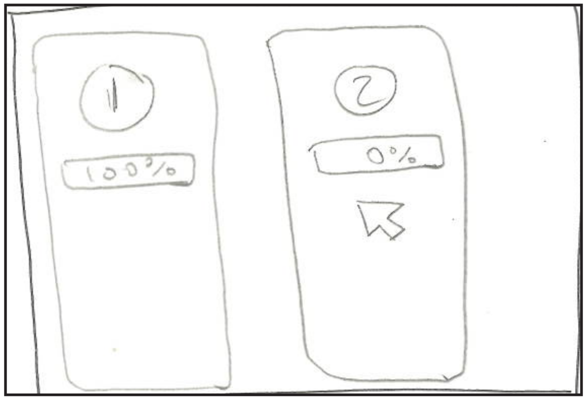


James is working through level 1 in Lynnette but he isn't quite sure when exactly he has achieved mastery of level 1 problems

When Lynnette thinks that James has achieved mastery, a popup screen appears congratulating him for completing level 1. He is given a badge for completing the level.



When James goes to choose his next problem, he knows that he has already completed level 1 and should move on to level 2.

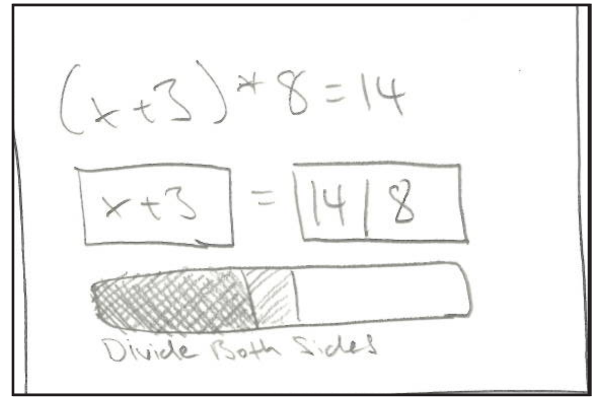


Sarah is a student in 8th grade studying algebra in her math class. She is starting level 2, which comes with its own set of skills and knowledge components. At the beginning, though, she does not know which steps correspond to which skills.

(x + 3) * 8 = 14

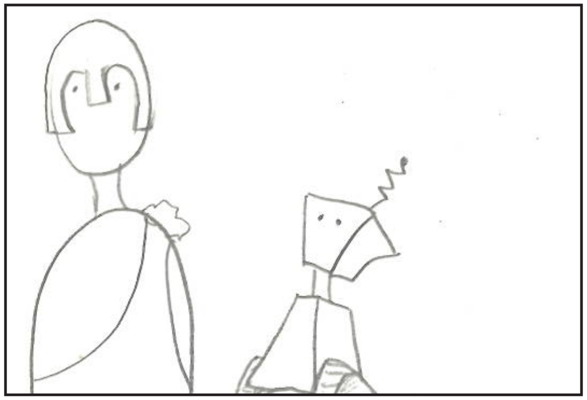
This problem uses:
- divide both sides
- parentheses
- fractions

When she starts a new problem she is able to see what components are present but not their order.

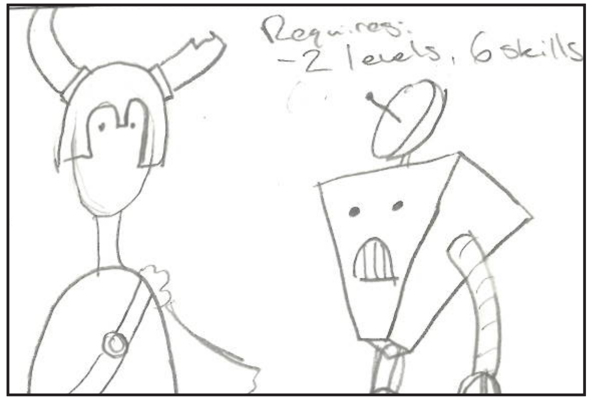


As she does each step in the problem, the skill bar for that component appears below the step and increases or decreases according to performance.

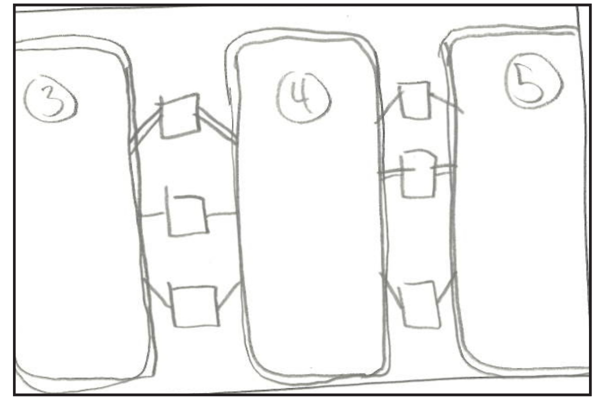
Because of the skill bar appearing next to the problem step, Sarah is able to give a name to which skills she is good at and which skills she needs more work on.



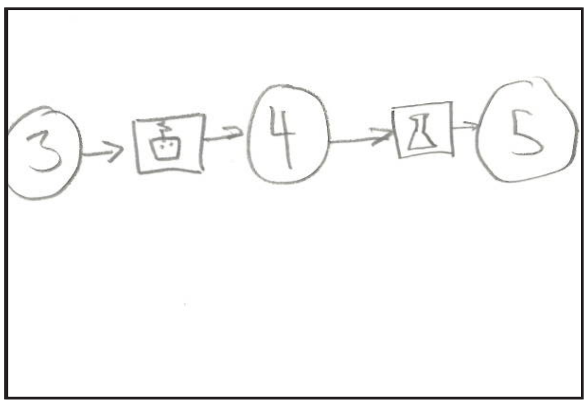
James is working through level 3 of the math tutor. He can see what his avatar looks like currently, but he has trouble understanding how doing more work will alter the look of his avatar.



At the beginning of the session, James is able to customize what he wants his avatar to look like

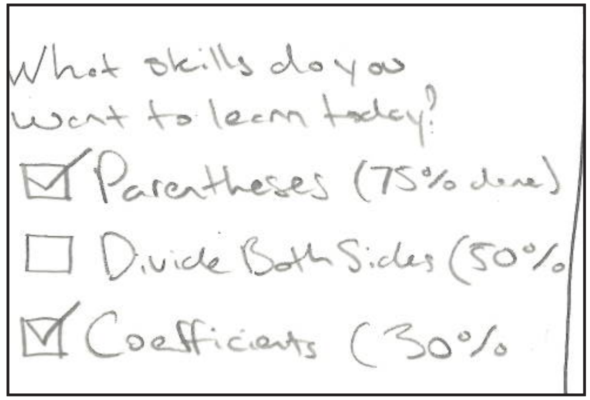


Lynette shows James what the best path through the tutor and how many skills he needs to complete in order to achieve his desired look.



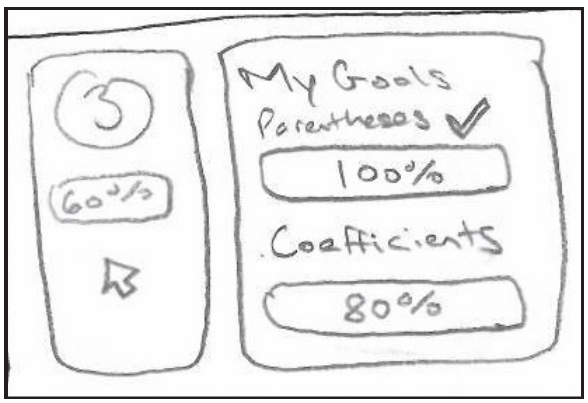
Seeing a tangible path through the tutor helps James plan out his learning goals for the session and motivates him to not stay on levels he has already mastered.

Sarah is just starting a session with the math tutor, but she has trouble setting goals for herself and knowing how much to reasonably expect to accomplish.

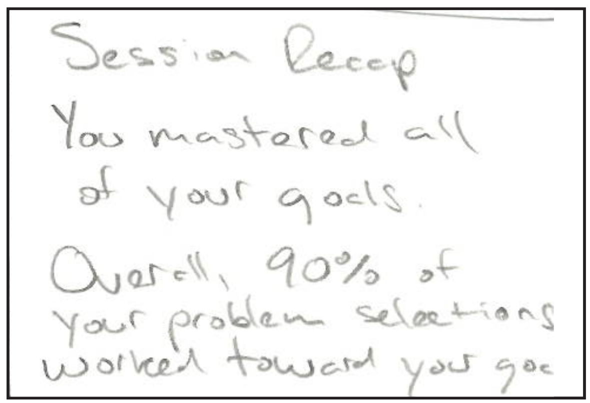


At the beginning of the session she is prompeted to set her goals by choosing 3 to 5 skills that she wants to master today.

She is also shown a graph of her previous mastery histroy so she can estimate how long it will take her to master each skill.

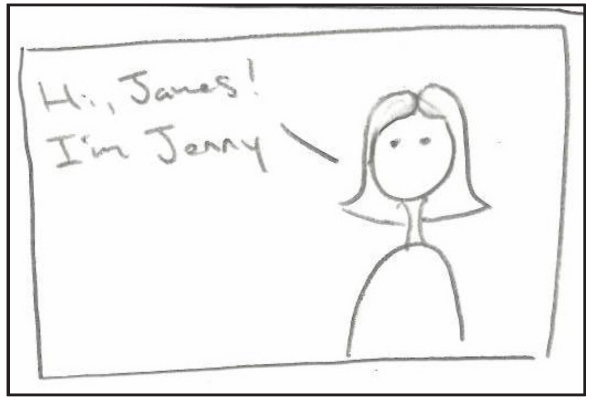


As she works through the problems she can see how much progress she is making towards her goals



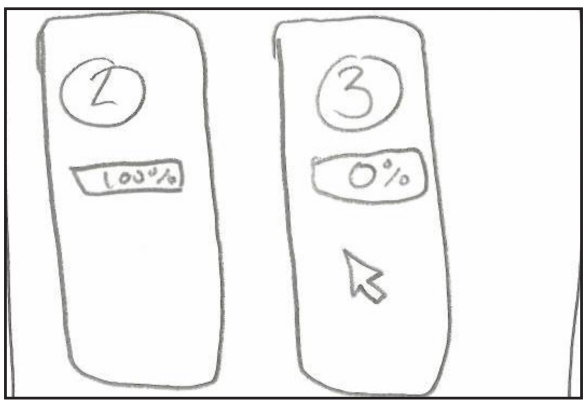
At the end of the session, she gets an overview on how well she picked problems that worked toward her goals and is rewarded if she picked appropriate goals.

James is a 7th grader. He starts learning to solve equations with his classmates using a math learning software called Lynnette. However, he is unsure of what the best way to select problems is.

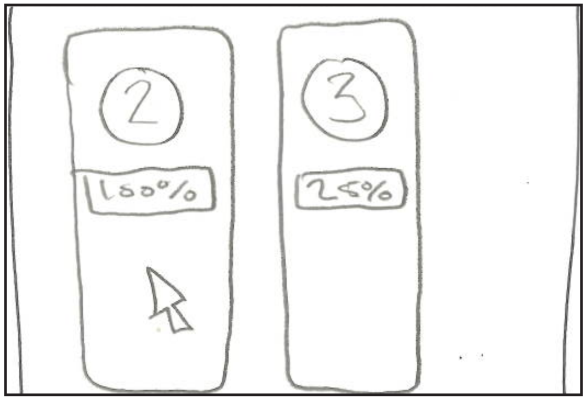


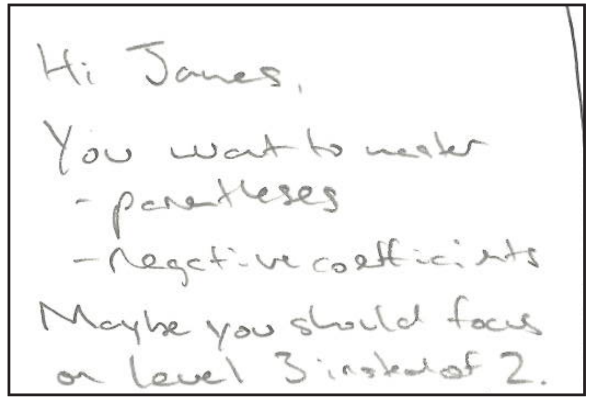
James logs in to Lynnette, and Lynnette starts telling James about a past student, Jenny.

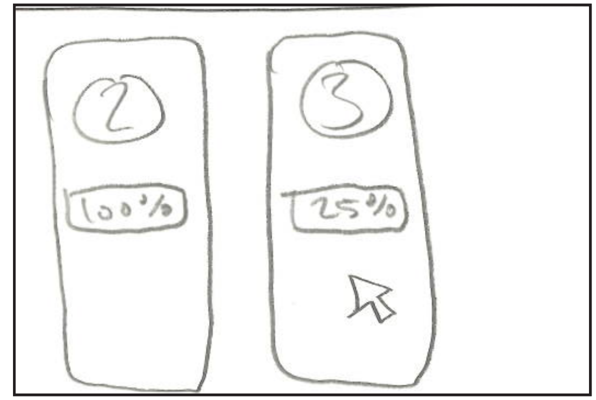
Jenny did really well in her PSSA math test last year, and she has some tips for learning Algebra. Jenny says that every time she finishes learning one type of problems, she moves on to new problems and that she enjoys challenging herself.



James reads through Jenny's story and decides to try out her tips when he learns equations in Lynnette.



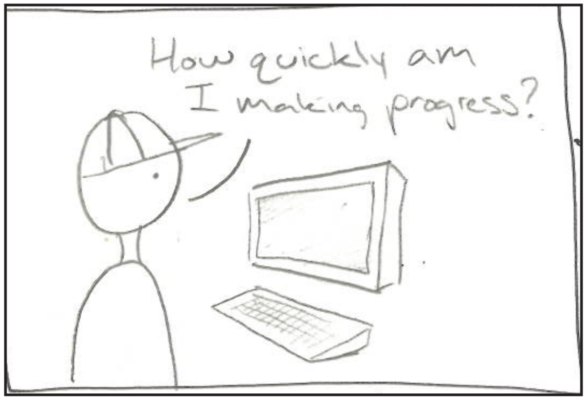




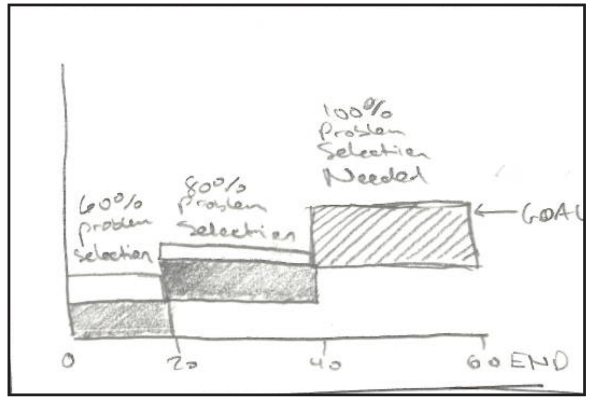
James has been working toward his goals he listed at the beginning of the session, but for the past few problems he has chosen levels that he has already mastered

He receives a pop up message reminding him of his learning goals and suggesting specific problem selections he could make that will help him toward his goals

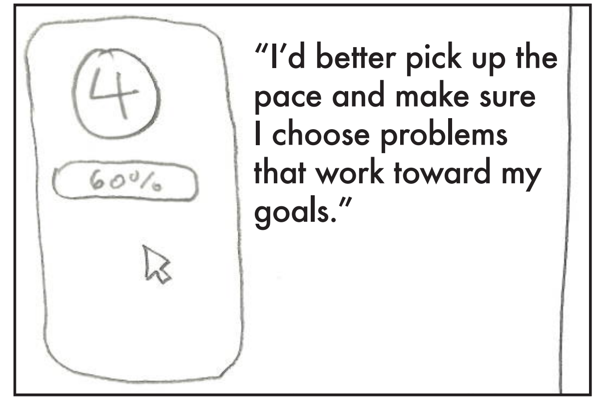
Reminded of his goals, James picks a problem selection that will help him progress and not something that he has already mastered.



James is working toward his goals, but is having trouble figuring out if he is on track toward them.



Lynnette provides James with a graph that shows his projected learning, based on his problem selection. The graph provides an extrapolation into the future at where he should expect to be at the end of the session and if he is on track to meet his goals.



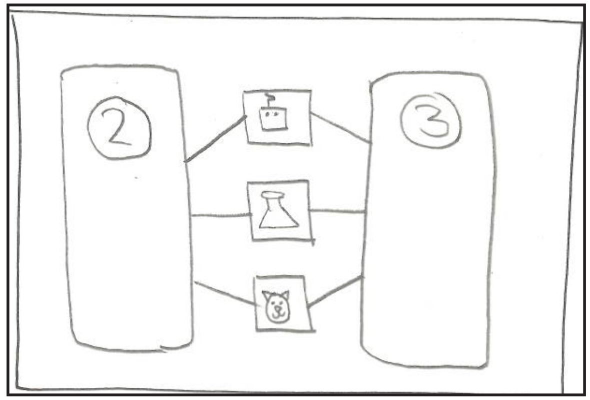
Seeing that he has been making some problem selections that do not help his learning, James adjusts his problem selection strategy to put him on better track for accomplishing his goals.

James is working through level 3 in Lynnette and having some difficulty. He is tempted to go back to level 2, which he has already mastered.

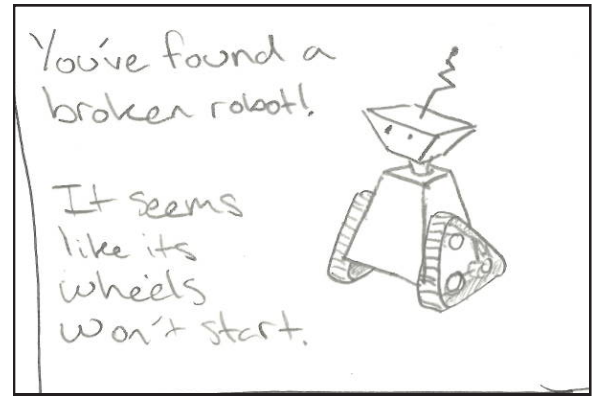
However, James can see that if he picks 5 unmastered problems in a row, he will receive an achievement badge.

James decides to persevere on level 2 and at least work through 5 of the level 3 problems.

James is 80% of the way through level 2 in the math tutor, but is starting to get bored of just doing equations over and over again without any real choice or application.

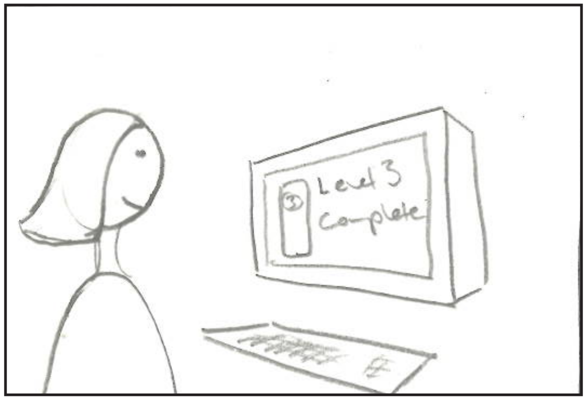


However, he knows that once he finishes level 2 he will be able to pick a special activity of his choosing that will add special items to his avatar.

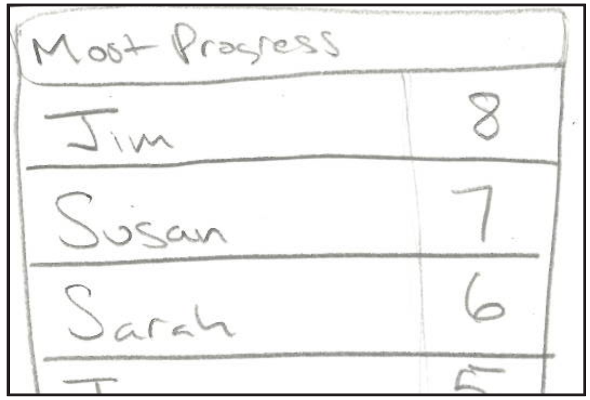


James chooses the robotics path.

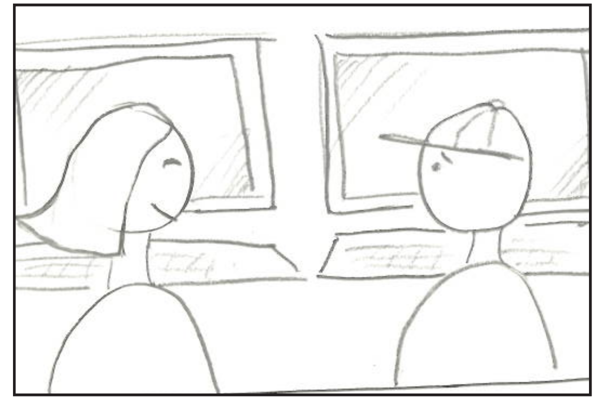
Once he finishes, James is rewarded with a robot pet. This allows him to diffferentiate his avatar from other students and highlights an area where math is applicable in the real world.



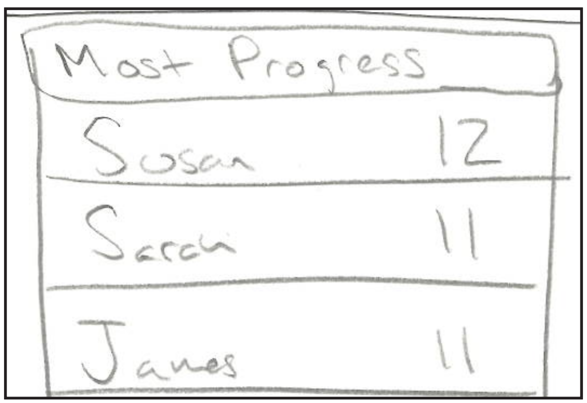
Sarah's class is doing a session with the math tutor today. She just finished level 3 and is proud of her progress and wants to know how her progress compares to other students in her class.



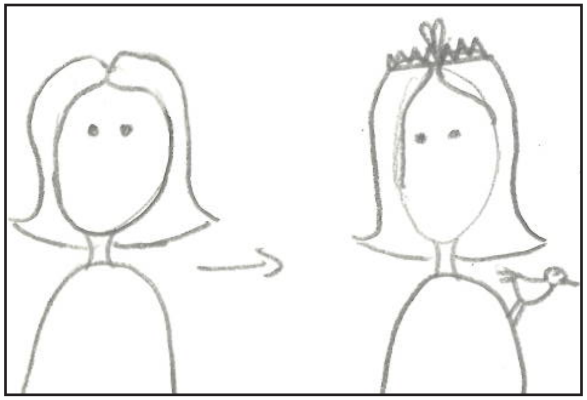
She posts her score to the leaderboard and sees that she has filled in the third most squares for today's session in her class.

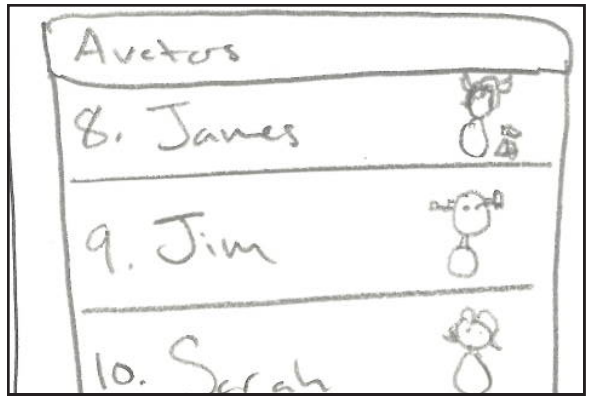


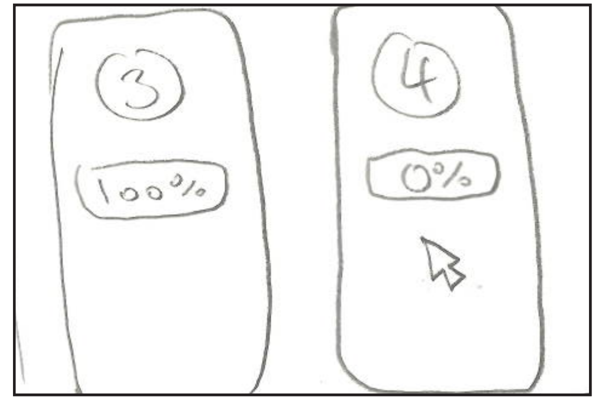
Sarah's friend James sees her score and tries to finish the skill he is on to catch up.



As a result of the competition, both Sarah and James complete more skills than they would have if working only by themselves.



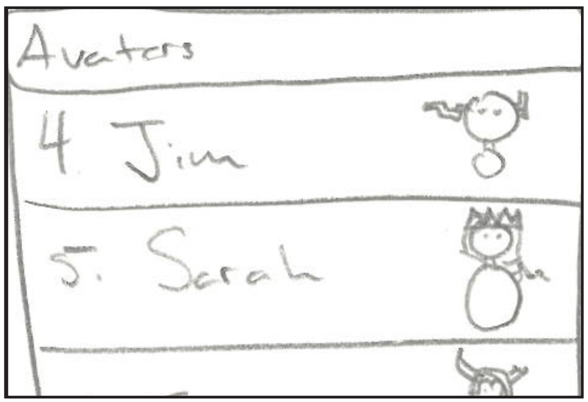




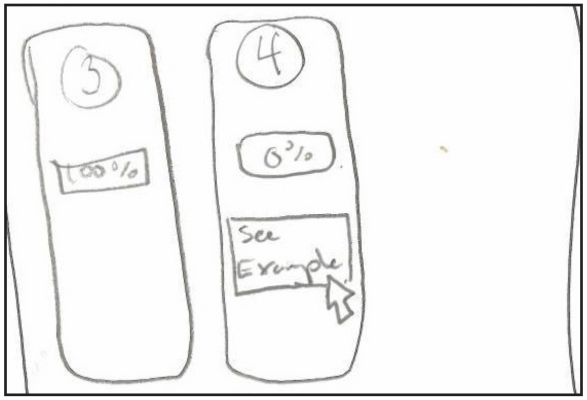
Sarah is a 7th grader. She is learning to solve equations with her classmates using a math learning software called Lynnette. Sarah creates an avatar for herself in Lynnette, and the skill of the avatar grows as Sarah learns more about equations.

Sarah notices that her avatar now ranks the 10th place among all the avatars in her class. She wants to get her avatar to a higher ranking.

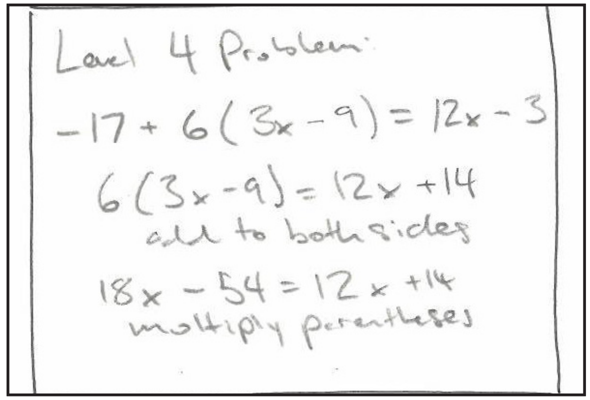
Sarah decides to learn a new type of equations so that she can increase her avatar's skills.



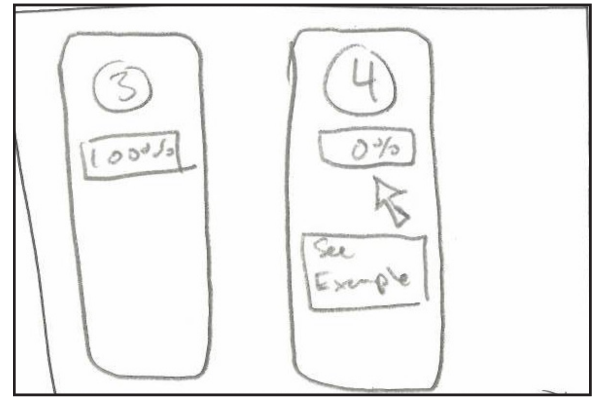
After learning to solve several problems in that new type, Sarah earns new skills for her avatar and sees that her avatar is promoted to the 5th place in the class.



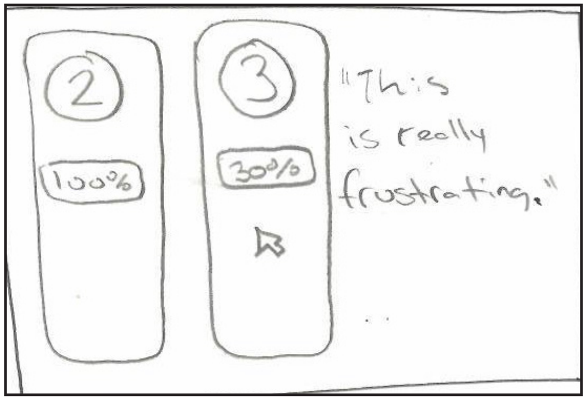
Sarah just finished level 3 in Lynnette and is about to start level 4. However, she isn't sure she has had sufficient instruction to be able to do the new types of problems.



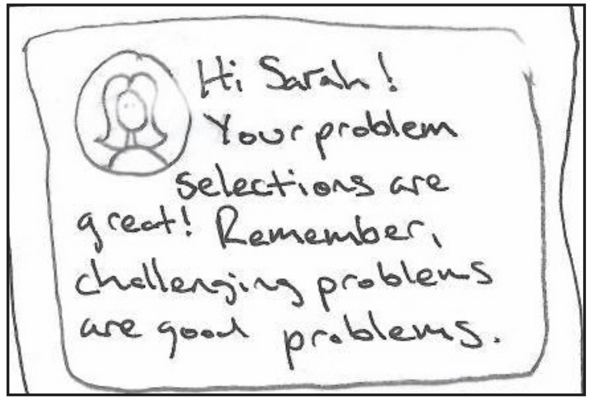
Before she starts, she examines the worked example for level 4, which shows each of the knowledge components contained in the level and an example of their application.



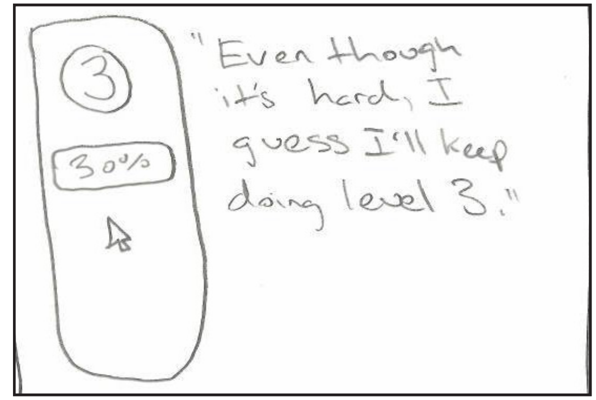
After studying the worked example, Sarah feels confident that she can attempt the level 4 problems.



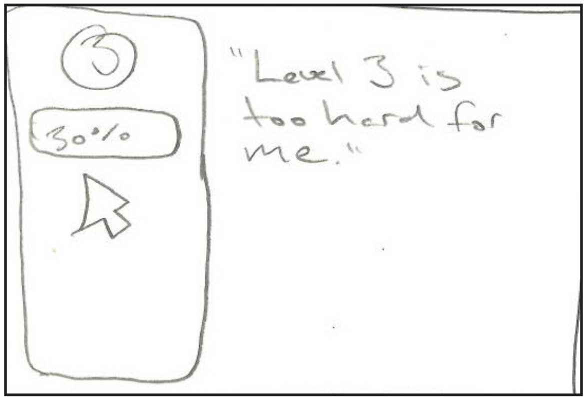
Sarah is making good problem selections, choosing unmastered levels, but is becoming discouraged by the challenging problems.



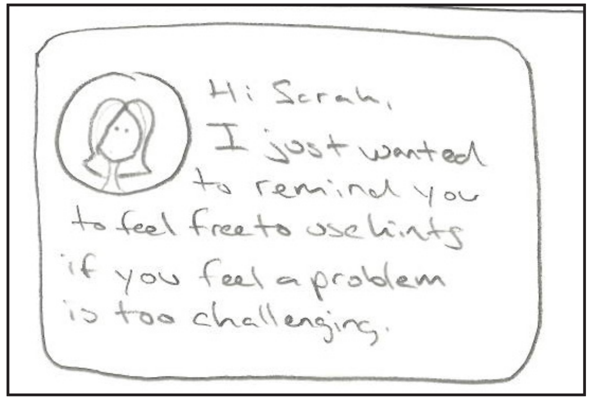
Lynnette presents a message to Sarah telling her to not be discouraged, that although the problems themselves are hard, her problem selection strategy is effective and she will learn if she keeps persevering the way she is.



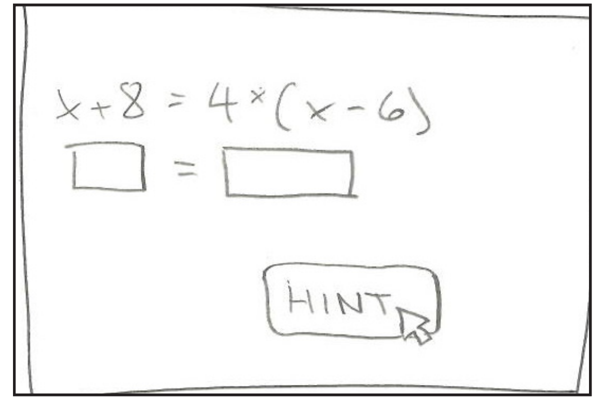
Sarah is encouraged that she is making good choices and continues to select challenging problems.



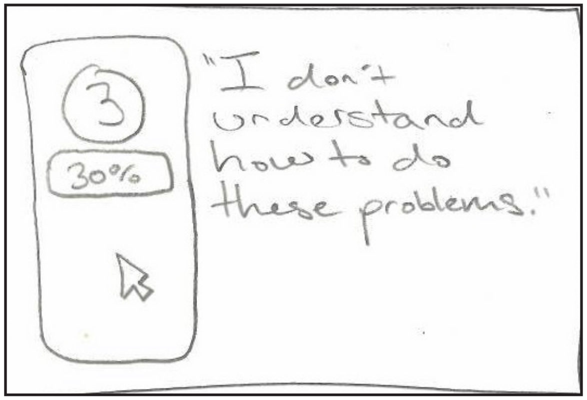
Sarah is picking challenging problems, but sometimes becomes discouraged by the difficulty.



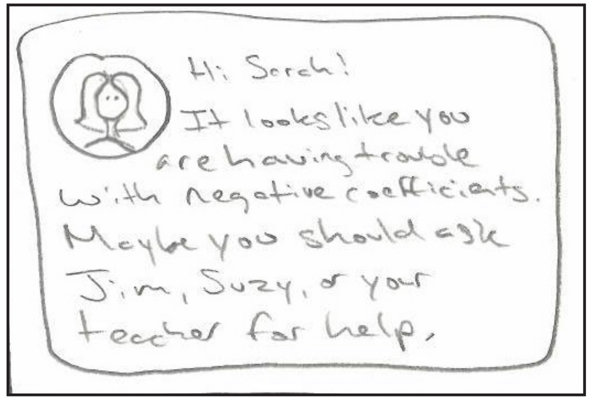
Lynnette shows a popup message reminding Sarah to use hints if she has to, and explains that these hints will help her focus on the problems that give her difficulty.



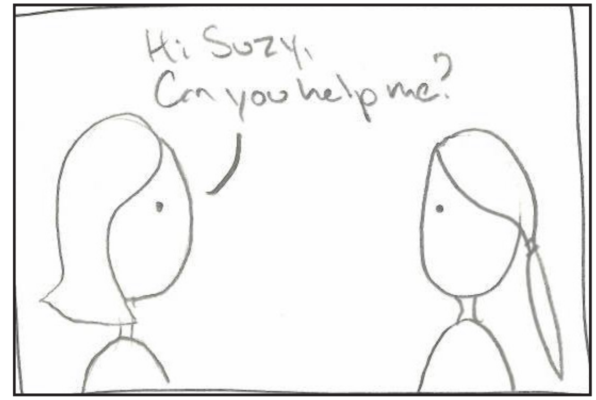
Sarah continues picking challenging problems, and uses hints when she encounters problems that are especially difficult for her.



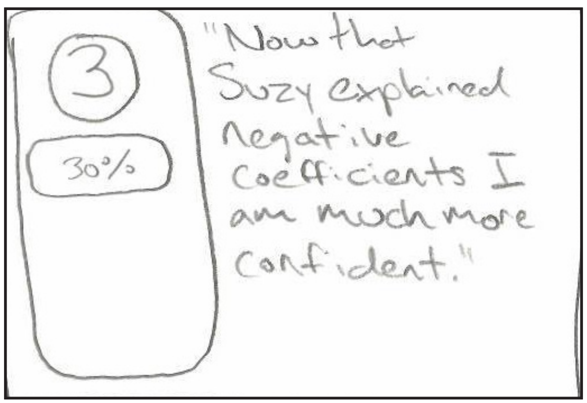
Sarah is picking challenging problems in level 3, but is having difficulty with understanding how to handle negative coefficients.



While in the problem selection screen, Lynnette shows a popup message pointing out that Sarah seems to be having some difficulty with the negative coefficients steps, and suggests that she ask for help from either her teacher, or from James and Suzy, who have already mastered the negative coefficient skill.

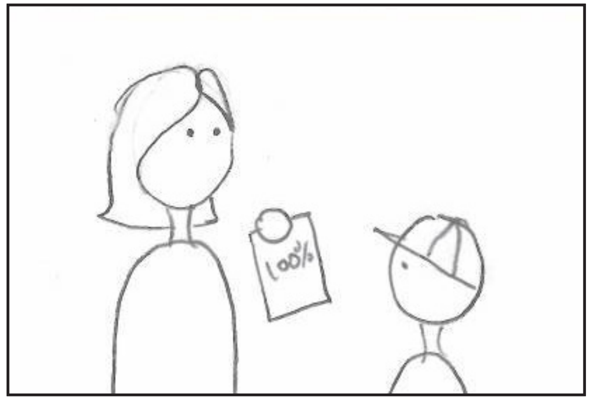


Before continuing on level 3, Sarah decides to ask Suzy to explain negative coefficients to her.

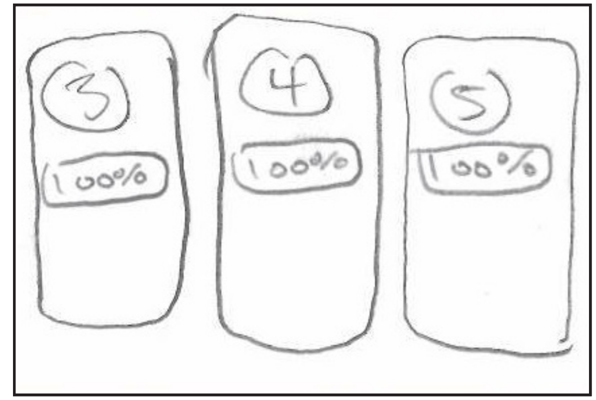


After hearing Suzy's explanation of how to handle the problem, Sarah feels more confident in her ability to finish level 3 problems and continues working on them.

James is working through level 2 of Lynette but doesn't see how completing the tutor actually matters.



James' teacher tells him that if he completes through level 5 of the tutor he will get an automatic 100% on the math quiz that week.



Not wanting to take the quiz, James focuses on making the most of his time in the tutor in order to finish all of the levels through level 5.