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Self-Regulated Learning in Educational Technologies: Supporting, modeling, evaluating, and fostering metacognition with computer-based learning environments (SRL@ET)

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Preface

It is important that the educational system helps learners develop a general ability to get up to speed quickly in new domains. In order to do that students need to be able to manage their learning, for example, by setting goals, planning their learning, monitoring their progress, and responding appropriately to difficulties and errors. These general learning skills are often referred to as metacognition, or self-regulated learning (SRL). Bransford et al. [3] suggest focusing on metacognition as one of three principles that should be applied to educational research and design, as stated in the influential volume “How People Learn.” A similar recommendation is given also in Clark and Mayer's [4] book about e-learning design principles. Azevedo and colleagues have found that students who regulate their learning in a hypermedia environment are more likely to acquire deep understanding of the target domain [2]. A key question is whether instructional technology can be as effective in fostering metacognitive skills as it is in teaching domain-specific skills and knowledge. Numerous learning environments include metacognitive support in order to improve domain-level learning (e.g., [5] and [1] support self-explanation in order to promote learning of Physics and Geometry, respectively.) However, only a few systems actually attempt to help students to acquire or improve the metacognitive skills themselves (and not only the domain-level knowledge). Some work suggests that improving metacognitive and SRL skills can be done using educational technologies. Examples include the Help Tutor [6], Betty’s Brain [7] and MetaTutor [2]. However, a lot remains to be known about the fashion in which educational technologies can support the acquisition of metacognitive and SRL skills. The modeling, tutoring, and evaluation of metacognitive skills and knowledge poses a number of challenges:

Modeling metacognitive and SRL knowledge: Metacognitive knowledge is ill-defined by nature. While the correct answer to a problem at the domain level is usually independent of the learner or the context, this is not the case for metacognitive dilemmas, in which the appropriate metacognitive actions depend on the student, her capabilities, motivation, preferred learning style, the learning context, and her relevant domain knowledge. Traditional modeling may not be suitable to capture and adapt to the specific characteristics of the learner, task, and context. This difficulty influences the design of the systems as well as the methods for assessing students’ knowledge and actions.

Tutoring: Metacognitive tutoring is usually done within a context in which students are learning domain-specific skills. This setup requires that the two levels of instruction are integrated in a meaningful way. For example, the design of metacognitive tutors should add metacognitive content without overloading the students’ cognitive capacity, and relevant metacognitive learning goals should be set.

Evaluation: While students’ domain knowledge can be assessed using conventional tests, assessing students’ ability to plan, execute, and monitor their learning is much more challenging. First, this assessment should be independent of students’ domain knowledge. Second, the outcomes of productive metacognitive behavior are often not immediate. They contribute to the quality of the overall learning, but cannot be observed immediately in the solution to a specific problem.

Educational technologies have the potential to tackle these challenges successfully. They offer individual coaching, have the ability to monitor students' progress and learning parameters over extended time periods, and can adapt to individual students' needs. However, it remains largely unknown exactly how educational technologies can help students acquire better metacognitive skills and thereby become better learners with respect to domain-specific skills and knowledge.

This workshop follows earlier workshops on metacognition and SRL (at AIED 2003, AIED 2007, ITS 2008 and ITS2012). In this workshop we discuss the above and other related issues concerning the tutoring of metacognitive and SRL skills using Intelligent Tutoring Systems, focusing on the following: Social self-regulation skills, Scaffolding self-regulation skills and Domain focused self-regulation.

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Brief Overview of Social Deliberative Skills[1]

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Abstract. Social deliberative skill is the capacity to deal productively with heterogeneous goals, values, or perspectives, especially those that differ from ones own, in deliberative situations. In other papers we describe our team's initial results in exploring this domain, which includes evaluating software features hypothesized to support SD-skills in participants, using machine learning and text analysis methods to recognize SD-skills and other indicators of deliberative quality, and prototyping a Facilitators Dashboard to help third parties get a birds-eye-view of important aspects of an online deliberation so that they can better help participants bring SD-skills to bear within dialogues on controversial topics. In this paper we take the opportunity to expand upon the nature and importance of SD-skills as we currently understand them at a more theoretical level.

Keywords: social metacognition; deliberative dialogue; reflective reasoning; e-learning.

1. Introduction

For about three years our research team has been engaged in studying how to support "social deliberative skills" (SD-skills) in online dialogue (applicable to educational, civic, and workplace contexts). Though the construct of SD-skills overlaps with other skills and capacities, such as metacognition, critical thinking, collaboration skills, and reflective reasoning, it is its own construct, points to an important and understudied area of human capacity, and requires new research to understand it. In other papers we describe our team's initial results in exploring this domain, which includes evaluating software features hypothesized to support SD-skills in participants (Murray et al., 2013a), using machine learning and text analysis methods to recognize SD-skills and other indicators of deliberative quality (Xu et al. 2012, 2103), and prototyping a Facilitators Dashboard to help third parties (facilitators, teachers, mediators, etc.) get a birds-eye-view of important aspects of an online deliberation so that they can better help participants bring SD-skills to bear within dialogues on controversial topics (currently in the context of discussion forums) (Murray et al. 2013b).

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[1] Excerpts from a longer paper, in which there are many more references than fit in this extended abstract.

In the discussion section and also in the conference presentation we will summarize our research results, but in this paper we take the opportunity to expand upon the *nature* and *importance* of SD-skills as we currently understand them at a more theoretical level. We also reflect the indeterminacies inherent in defining such psychological constructs.

2. Social Deliberative Skills

The capacity to flexibly and productively negotiate differences of opinion, belief, values, goals, or world-views, is of critical importance in today's world. In the increasingly global world the economic productivity and security of nations can be linked to citizens' and leaders' capacity to understand and deal productively with diverse perspectives. King & Baxter (2005, p. 571) note that "in times of increased global interdependence, producing interculturally competent citizens who can engage in informed, ethical decision-making when confronted with problems that involve a diversity of perspectives is becoming an urgent educational priority…however [these skills] are what corporations find in shortest supply among entry-level candidates."

The capacity to engage skillfully in dialogue with conflicting opinions is important in all realms of social activity including international politics, civic engagement, collaborative work, and mundane familial squabbles. We have coined the term "social deliberative skill" to indicate *the capacity to deal productively with heterogeneous goals, values, or perspectives, especially those that differ from ones own, in deliberative situations.*

Many communication and collaboration interactions now take place on the Internet, which is becoming a ubiquitous global social communication medium. This research investigates how to support the use of social deliberative skills within online communication. Our focus is on supporting mutual understanding and high quality satisfactory outcomes between individuals and/or groups who are communicating with online tools, and much of what we find should be applicable to the support of more skillful deliberation in online work and communication generally. Our overall research goals are to better understand, assess, and support SD-skills in online contexts. We also believe that such skills honed in an online context will partially transfer to other aspects of life. We are interested in investigating online features, tools, and methods that afford, prompt, or gently support SD-skills, rather than teaching them outright.

We differentiate our research from others that focus on argumentation, which aims to help learners generate logical, well-formed, well-supported explanations and justifications. These are certainly important skills, but they are often framed in objective rather than intersubjective (or even ethical) terms. That is, they are about finding the right answer or the most efficient and effective solution to a technical or scientific question—but don't adequately address the specific moments of deliberation or collaboration where opportunities for mutual understanding and mutual recognition arise. They are often studied in the context of problem solving or collaborative work. We also differentiate our work from educational research on creativity, innovation, and collaboration that is framed in terms of pooling ideas and synergizing the best out of them, while often ignoring the skills needed to navigate the challenging straits of controversy, conflict, world-view unfamiliarity, and misunderstanding. We might call the context that we are interested in "difference-motivated social deliberation/inquiry" to highlight the starting point of intersubjective tension. For this research we focus on these social deliberative skills or capacities.

Both the literature on creative problem solving and the literature on civic deliberation emphasize the importance of having diverse perspectives represented in collaborative processes, but scholars on these fields do not always acknowledge the skillfulness needed to work productively with these differences. Meanwhile, in educational research (including educational technology research) there is significant focus on cognitive skills such as metacognition and argumentation, and also considerable research in collaboration, but little work in the specific area addressed by SD-skills.

For this research we will focus on the following social deliberative skills or capacities, which are seen repeatedly in the literature (described using a variety of terms):

1. Social perspective taking (includes cognitive empathy, reciprocal role taking)
2. Social perspective seeking (includes social inquiry, question asking skills);
3. Social perspective monitoring (includes self-reflection, meta-dialogue); and
4. Social perspective weighing (related to "reflective reasoning" and includes comparing and contrasting the available views, including those of participants and external sources and experts).

Capacities implied in the above include: tolerance for uncertainty, ambiguity, disagreement, paradox; and the ability to take first, second, and third-person perspectives on situations or issues (i.e. subjective, intersubjective (you/we/they), and objective).

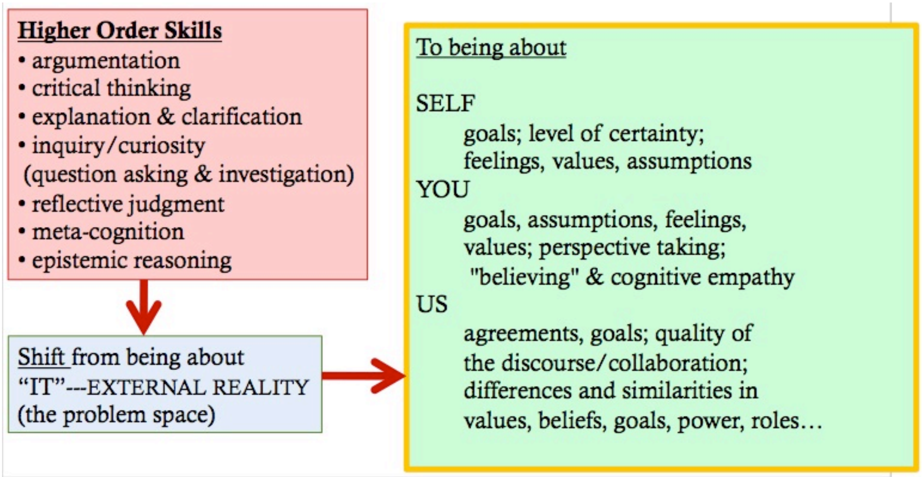

Figure 1: Conceptual Framework for Social Deliberative Skills

Our theoretical frame for these skills is that they involve the *application* of cognitively oriented higher order skills to thinking about the perspectives (or beliefs or arguments) of others (and consequently, of self as well). See Figure 1. When one turns the reflective lens from purely objective ideas about the world toward reflecting on the ideas of specific others (individuals or groups) that one is deliberating with, challenges arise that are beyond the purely cognitive/rational.[2] One is not only reflecting on disembodied ideas but upon *my*/*our*/*your*/*their* ideas. Yet, as forms of reflection, the skills involved are not purely emotional or social. These are critical yet under-explored (and under-supported) moments in collaborative learning, knowledge building, and deliberation in general. Social deliberative skills include reciprocal perspective taking (or cognitive empathy), active perspective seeking (e.g. question-asking skills), self-reflection (e.g. reflecting on one's biases), and meta-dialogue (corrective reflection into the quality of a deliberation or collaboration).

Table 1 illustrates the hand-coding scheme we have been using to code SD-skills.[3] Codes beginning with an underscore are meta-codes subsuming those hierarchically beneath them. Our research on dialogue quality focuses on the first two columns, though we may use codes from other columns as covariates. Though we have defined a number of Argumentation Codes (right column) we do not currently code for them individually (we code them all as ARG_GEN) because, as mentioned, we are interested in intersubjective and reflective skills rather than the argumentation skills per se.

SD-skill -- CORE Set	**Additional Delib. Quality Indicators**	**MISC CODES**	**ACTION NEGOTIATION**	**ARGUMENT CODES**
SELF_REFLection	_META_TOPIC	Q_TOPIC	(External actions)	_ARGument_GENeric
_INTERSUBictive	WEIGH	OTHERS_THNK	ActRequest	
Q_INTERLocutor	SYSTEMs_thinking		ActPropose	GENERAL_SOLUTN
REF_INTERLocutor		HELP	ActAccept	EXPER_OBSERV
PERSPECTIVE_taking	FACT_cite_SouRCe	REQ_HELP	ActDecline	ARG_OPINION
_META_Dialog	SOURCE_REFerence	PROCESS	ActNegot	SUPPORT
MEDIATE			(Dialogue_Actions)	SUM_MY-argumt
META_CONS	CHANGE_mind	AGREE	DI_ActRequest	EXAMPLE
META_CONFL	UNCERtainty	DISAGREE	DI_ActPropose	ELAB
META_SUM	APOLOGY		DI_ActAccept	
META_CHECK		_NEGative-emotion	DI_ActDecline	*low-skill:*
APPRECiation		NEGEMO_INTerloc	DI_ActNegot	OPINION_ONLY
		NEGEMO_Topic	(Facilitators only)	OVER_GEN
		_OFFTOPIC	WELCOMING	FACT_NOSRC
		TECHnical	PROC_EXPL	
		SOCIAL	MOTIVATE	

Table 1: Text Coding Scheme

This scheme synthesizes prominent frameworks found in the literature (Black et al., 2011; Klein, 2010; Stromer-Galley, 2007; Stolcke et al., 2000) and adds codes for dialogue quality specific to SD-skills. It is most closely related to what has been called "social metacognition" (Salonen et al., 2005; Lin & Sullivan, 2008; Joost et al., 1998; Mischel, 1998). We are in the process of comparing it to King and Kitchener's Reflective Judgment measurement (King & Kitchener, 1994).

[2] Studies of the HOSs in Figure 1 do sometimes include the intersubjective dimension, but the figure highlights how to focus exclusively on it.

[3] Cohen's Kappa Interrater reliability measure for this coding scheme is 71%, (76% agreement) averaged over five dialogue domains we have used it in (this level is considered "good" and is particularly good given the complexity of our coding scheme).

3. Discussion

In this paper (and more in the extended version) we have argued for the importance of studying social deliberative skills, we have differentiated this construct from related ones, and have illustrated how we measure it. We are applying this work to the study of deliberative dialogue in several online domains: classroom discussions of controversial topics, e-commerce and workplace disputer resolution, and civic engagement dialogue. In our studies of how scaffolding features support social deliberative skills we found that reflective tools showed a significant difference with large effect size (Murray et al. 2013a). We have made progress in using text analysis tools (CohMetrix, Graesser et al. 2010) and LIWC (Pennabaker et al. 2007) and machine learning algorithms to categorize social deliberative skill automatically (see Xu et al. 2012, 2013).

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Enhancing socially shared regulation in working groups using a CSCL regulation tools

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Abstract. Socially shared regulation of learning (SSRL) refers to processes by which group members collectively regulate activity within a balanced shared responsibility model. SSRL has shown to increase performance and learning when compared to other forms of regulating collaborative work (co-regulation). SSRL, however, is a relatively new concept which needs empirical study, especially in how to promote this it in real learning settings. This study is a major first step, studying the promotion of SSRL through an often used online collaborative work environment augmented with three SSRL tools (Radar, OurPlanner, OurEvaluator) to stimulate and enhance the four self-regulatory phases of learning: planning, monitoring, evaluating and regulating. Through the use environment and tools, students will be better able to share regulation of collaborative learning.

Keywords: Self-regulated learning, socially shared regulation, collaborative work, CSCL, regulation tools, scaffolding.

1 Theoretical framework

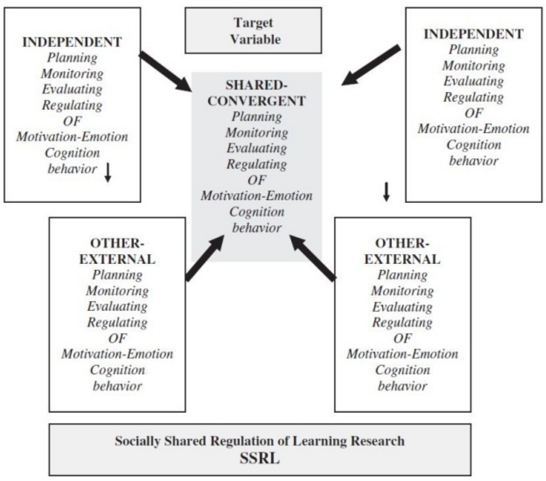
Regulation of learning has traditionally explored individual characteristics in various learning situations (self-regulation; [1]). However, new learning demands involving collaborative learning situations has shifted the focus towards the social aspects of regulated learning, namely co-regulation and socially shared regulation of

adfa, p. 1, 2011.

learning [4] [6]. Co-regulation of learning refers to processes where a group collaborates under unbalanced regulation (e.g. one of the members exerting power and deciding what to do). Socially shared regulation of learning (SSRL) refers to processes where group members collectively regulate activity; where decisions and regulatory activities are decided in shared ways. Research has shown that SSRL can produce better learning outcomes and enhance performance [5] [8]. Collaborative learning interventions, thus, should aim at promoting SSRL.

As can be seen in Figure 1, SSRL is reached through a number of iterations between the group members' individual self-regulation and the others self-regulation, until shared-convergent regulation is achieved [4]. As with individual self-regulation, the group's shared regulation is composed of four recursive phases: planning, monitoring, evaluating and regulating [9]. During the planning phase, the group establishes its goals and standards, and organizes the actions they will need to make to complete the task. While monitoring, group members compare the procedure they are following with the initial plan of action and the goals for the activity. Evaluating implies that the students compare the fit of their product to the standards determined in the planning phase. Finally, group members enter the regulating phase in which they make the changes needed to overcome an eventual gap between the standards set and the final product achieved.

Figure 1. Socially Shared Regulation of learning (extracted from [4]).



Research in the individual self-regulation field has found that interventions should aim to promote planning, monitoring and evaluating and that the most successful interventions are composed of an array of aspects: cognitive, motivational and emotional [3]. Research on promoting SSRL is limited necessitating building on research on individual learning [2]. The key aspect is that, to promote SSRL in the groups, a shared space is needed in which members can collaborate, creating and deciding how to regulate their efforts and actions. In a practical sense, this implies creating tools that target the phases of regulated learning such that students are able and stimulated to plan together, monitor how the group is performing, evaluate the final product against the standards set up at the beginning and, finally regulate/change accordingly to achieve their learning goals [6]. This is to say, prompt the aspects of socially shared regulation which often are salient for the students.

With these key aspects in mind, we tailored an operating online environment in which we could promote socially shared regulation. The Virtual Collaborative Research Institute (VCRI) (http://edugate.fss.uu.nl/~crocicl/vcri_eng.html) is an online tool to promote collaborative work, usually with group members work on their own computer, either synchronously or asynchronously [7]. In the PROSPECTS project (https://let.drupal.oulu.fi/en/node/10135), the VCRI environment was used as a platform to set up and promote SSRL by plugging in existing features of that environment such as Radar, Co-Writer and chat.

Radar is a tool with which group members report about aspects of their individual self-regulation relevant for the collaborative work (e.g., I know how to perform the task), and aspects related to the group work (e.g., I think the group is capable of performing the task). Students rate these aspects along six different axes in a five Likert scale yielding a radar-diagram. The six items in the axes are: (1) I understand the task, (2) I know how to do this task, (3) This task is interesting, (4) My feelings influence on my working, (5) I feel capable of doing this task, and (6) My is capable of doing this task. The idea behind Radar is that students will be aware of their strengths and weaknesses in a current situation and thus the group will be aware of their strengths and weaknesses that they might confront during the task assignment.

Co-writer, a shared writing space, was divided to promote collaborative planning (OurPlanner), serve as a platform for the students on-line task execution

(Task execution) and finally, promote collaborative evaluation of the regulated learning (OurEvaluator). OurPlanner is a shared new tool which prompts the students in their planning (e.g., describing the task, describing its purpose, creating a concrete plan). Task execution is the place where group members can collaboratively write and modify their course assignments. Finally, OurEvaluator allows group members together evaluate and regulate aspects of their collaboration. The idea behind these tools is to help students collaboratively clarify the goals and standards for the task, along with the procedure and strategies they will use. What they write in the Co-writer should be used to guide their monitoring and evaluating.

2 Procedure

First year teacher education students (N = 130) are participating in a 'Multimedia as a learning project' course. The course consists of nine sessions where the students worked collaboratively in 3-4 member groups. Each learning session is divided in two different parts: (1) a face to face part at the university computer class with teacher support, and then (2) an online part that students perform individually. In both phases the SSRL tools is actively used.

The face to face sessions have three phases. First, the instructor introduces the task. Then, the students individually complete the Radar and as a result see each other's Radars. This is followed by the groups collaboratively planning their work on the assignments (goals, strategies, etc.) using OurPlanner. The conversations during this planning are recorded. In the third phase, they work together performing the task.

The online sessions share the similar procedure as face to face sessions with one extra phase and with the students use the full SSRL regulation tool resources of the VCRI environment working synchronously on their own computer at home or at the university. First, the assignment is presented in VCRI. Then, teams plan their goals and the organization of the assignment using OurPlanner and negotiating through the chat. Third, they perform the task online using chat for negotiation during the task execution. Finally, they evaluate their work using the OurEvaluator.

In sum, the intervention promotes SSRL through the different phases. The planning of collaborative work is conducted during the planning phases in both face to face and online. Students monitor their progress during the working phases. Evaluating and regulating happens when students receive the online task instructions –being able to reflect about what they have achieved so far- and, of course, during the evaluation phase of the online session once the task is done. What VCRI adds is the collaboration tool: allowing the students to work together and regulate through its uses.

3 Results

The first notions of the data show promising findings dealing with the SSRL tool's prompting not only socially shared regulation, but also collaborative learning. The VCRI environment data will be analyzed looking for traces of SSRL to classify groups according to their regulation and performance. The data collection is currently ongoing, but the preliminary findings will be presented at the workshop.

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How should SE be supported – during problem solving or separately?

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Abstract. Self-explanation (SE) has proven to be an effective meta-cognitive strategy. However, some performance-oriented students tend to not take advantage of the SE opportunities provided as they are seen as extra work that does not directly contribute to problem solving. We focus on approaches that can be used to motivate such students to take advantage of SE support. As a first step, we analysed SE support provided in some systems and discuss their limitations. We also outline a study that compares the two approaches: separating SE support from problem solving versus interleaving the two.

1 Introduction

Self-explanation (SE) has proven to be an effective meta-cognitive strategy. Bransford et al. [1] suggest focusing on metacognition as one of three principles that should be applied to educational research and design, as stated in the influential volume "How People Learn". According to previous research studies, only a few students self-explain spontaneously, and therefore SE prompts have been used to encourage students to explain instructional material to themselves [2]. SE prompts can be of different types, according to the knowledge they focus on. For instance, Hausmann et al. [3] compared *justification-based prompts* (e.g. "what principle is being applied in this step?") and *meta-cognitive prompts* (e.g. "what new information does each step provide for you?") with a new type called *step-focused prompts* (e.g. what does this step mean to you?"). They found that students in the step-focused and justification conditions learnt more from studying examples than students in the meta-cognitive prompts condition. In another study, Chi and VanLehn [4] categorised SE as either procedural explanation (e.g. answer to "Why was this step done"), or derivation SE (e.g. answer to "where did this step come from?"). In [5], SE prompts are categorized into *procedural-focused self-explanation* (P-SE) prompts and *conceptual-focused self-explanation* (C-SE) prompts. P-SE prompts were given after examples to assist students to focus on procedural knowledge as the examples have shown to increase conceptual knowledge. On the other hand, after solving problems, students were given C-SE prompts in order to help the students to gain the corresponding conceptual knowledge covered in the problems they just completed.

adfa, p. 1, 2011.

SE has generally been supported in the context of a problem-solving environment. Even though many systems use the problem-solving context, they include additional steps to support SE. For instance, an enhanced version of Geometry Explanation Tutor expects students to explain every problem-solving step [6]. Asking students to explain each step is an additional task in the typical problem-solving process. How a student interacts with the learning environment depend on his/her attitude and learning goals [7]. If a student has a performance-oriented focus (i.e. attempting to demonstrate their ability by completing as many problems as they can without paying much attention to acquiring knowledge), it is possible that they may view this as extra work. In such situations, do we keep including such opportunities anyway to support SE as it is beneficial for students' leaning? This decision may have a negative impact as the student may be demotivated and likely to be disengaged from the learning. The other alternative is to provide only problem-solving support and support SE when they become more proficient; are students less likely to take advantage of SE opportunities when they are novices?

As a first step towards exploring these questions, we analysed the SE support provided by different systems. The way these systems support SE can be categorized as separating SE from problem solving vs interleaving the two. The systems in the first category provide SE opportunities immediately after a problem/step is completed. This may also result in disengagement from taking advantage of a learning opportunity as they have completed the problem/step and want to move to the next problem/step. Interleaving SE support with problem solving expect students to self-explain during problem solving. Will the students be more motivated if these opportunities to self-explain are integrated with problem-solving? What is the effect of each approach on student's mental model of process of problem-solving i.e. if the integrated approach is used, will the students feel that SE is a vital ingredient of learning by solving problems and vice versa. Exploring these issues will provide us with initial insights about students' behaviour towards SE support. This will enable us to design ITSs that dynamically adapt their pedagogical decisions such as SE support not only on the individual student's competency of the instructional task, but also on their learning goals.

In this paper we discuss some studies that use one of the two strategies (integrated approach vs. separation approach) and our plans to conduct an evaluation study that compares these two approaches.

2 Interleaving SE support with problem solving

We now discuss two systems that interleave SE support with problem solving. Both these systems expect students to provide self-explain during problem-solving.

2.1 Geometry Explanation Tutor

A new version of the Geometry Explanation Tutor was created to provide support for SE while students learn about the properties of angles in various kinds of diagrams [6]. In addition to solving problems, students were expected to explain all the steps for each problem. For example, a student could explain a step in which the triangle sum theorem was applied by typing "Triangle Sum". A Glossary of geometry knowledge was provided as a way of helping students to provide self-explanations. The Glossary lists relevant theorems and definitions, illustrated with short examples. It is meant to be a reference source which students can use freely to help them solve problems. Students could enter explanations by selecting a reference from the Glossary or could type their explanations. The tutor provided feedback on the students' solutions as well as their explanations. Further, it provided on-demand hints, with multiple levels of hints for each step. SE is supported via the additional task of explaining each problem-solving step: the students were expected to solve each step in a problem and provide explanations at the same time. Hence this system supports SE during problem solving, but support is provided using an additional task. As the SE is not adaptive, students may have to specify a theorem multiple times for a problem, if it has been used in several steps within the problem.

A study was conducted to compare the performances of students when they explain their problem-solving steps in their own words with their peers who did not. The students who explained the problem-solving steps learnt with greater understanding compared to their peers who did not. The explainers were also more successful on transfer problems.

2.2 NORMIT-SE

NORMIT, an ITS that teaches data normalization, was enhanced to support SE [8]. The enhanced system, NORMIT-SE, expects an explanation for each action type performed for the first time. For the subsequent actions of the same type, explanation is required only if the action is performed incorrectly. This approach would reduce the burden on more able students (by not asking them to provide the same explanation every time an action is performed correctly), and also that the system would provide enough situations for students to develop and improve their explanation skills.

Students provide explanations by selecting one of the offered options. The order in which the options are given is random, to minimize guessing. For example, if the specified candidate key is incorrect, NORTMIT-SE asks the following question "This set of attributes is a candidate key because……:"

If the student's explanation is incorrect, he/she will be given another question, asking to define the underlying domain concept (i.e. candidate keys). An example of such a question is "A candidate key is…………. ". In contrast to the first question, which was problem-specific, the second question focuses on domain concepts. If the student selects the correct option for a question, he/she can resume problem solving. If the student's answer is incorrect, NORMIT will provide the correct definition of the concept.

An evaluation study was conducted to investigate the effect of explaining problem-solving steps on both procedural and conceptual knowledge [8]. The students in the experimental group were expected to explain their problem-solving steps while their peers in the control group just solved problems. The experimental group acquired knowledge (represented as constraints) significantly faster than the control group. There was no significant difference between the two conditions on the post-test performance, and it might be due to the short duration of their sessions interacting with the system. Furthermore, the analysis of the self-explanation behavior shows that students find problem-specific question (i.e. explaining their action in the context of the current problem state) more difficult than defining the underlying domain concepts.

3 Separating SE support from problem solving

SQL-Tutor is an ITS that teaches database querying and was enhanced to provide SE support after each problem was completed [5]. The students were expected to solve the given problems as in the original version of SQL-Tutor which provided multiple levels of feedback. Upon completion of a problem, students were given an opportunity to self-explain. The student received a C-SE prompt with multiple options from which the correct one has to be selected. “What does DISTINCT in general do??” is an example of a C-SE prompt. There was only one SE prompt per problem. The prompts were non-adaptive and depended only on the problem. As the SE support focused only on conceptual knowledge, the problem-solving context does not have to be used to support SE.

A study was conducted to investigate the effects of such SE support on student learning. This was a part of a larger study and we report only the relevant results. Problems were provided in pairs. i.e. students solved two isomorphic problems in each pair. The participants were 12 students enrolled in an introductory database course at the University of Canterbury. Participants were informed that they would see ten pairs of problems, and that the tasks in each pair were similar. Providing this information to students may have motivated them to use problem pairs more efficiently. Analysis revealed that students performance on the post-test was significantly higher in comparison to the pre-test performance ($p<.01$).

4 Discussion and Future Work

The three research attempts discussed can be categorized using different criteria such as the type of approach used, the type of SE supported and the target instructional task. Both the enhanced Geometry Explanation Tutor and NORMIT-SE provide SE support during problem-solving. In contrast, SQL-Tutor provides SE support after problem solving. Furthermore, NORMIT-SE provides both conceptual and procedural SE. In contrast, the other two systems use only conceptual prompts.

The only system that provides adaptive SE support is NORMIT-SE. However, NORMIT-SE does not consider the learning goals of each student to customise SE support. However we believe that SE support could be more effective when it is customized based on both a learner’s knowledge and learning goals. Such customising has the potential to motivate students to take advantage of SE support instead of burdening them.

In order to explore how students utilise the different ways of SE support, we plan to conduct a study within the context of NORMIT-SE with four groups. All the groups will be asked to solve several problems while receiving typical feedback with multiple levels of help from NORMIT-SE. Groups 1 and 2 will be given conceptual SE-prompts and the other two (groups 3 and 4), procedural prompts. Groups 1 and 3 will be asked to self-explain after a problem is completed. The remaining two groups (groups 2 and 4) will self-explain when they submit their first attempt for a problem. We hypothesise that providing conceptual prompts at the end of each problem or procedural prompts after the first attempt are more beneficial than the other two scenarios. We also plan to identify measures related to a student's problem-solving behavior to infer learning goals for each student. Such measures can include the number of times a student access the full solution, number of times each help level is accessed and the number of times help is sought for a problem. Based on this analysis, we plan to classify students as having a performance-oriented or a learning-oriented focus. This classification will enable us to design ITSs that dynamically adapt SE support not only on the individual student's competency of the instructional task, but also on their learning goals

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An Investigation of Successful Self-Regulated-Learning in a Technology-Enhanced Learning Environment

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Abstract. Self-regulated learning (SRL) and metacognition are key in the context of 21st century education, adult training, and lifelong learning. For instructional strategies to foster metacognition and self-regulation it is crucial to know what are good metacognitive and SRL behaviors. We investigated this question in the context of a training simulator in a curriculum setting with 152 medical students. Learning behavior and personal attributes were examined in relation to metacognitive awareness. The results on characteristics of successful SRL confirm findings from traditional learning settings for a TEL context.

Keywords: self-regulation, metacognition, expert learner, training simulator.

1 Introduction

Broad interest in metacognition and self-regulated learning (SRL) can be identified in current research, as well as educational practice [1]. Often used synonymously, they are considered as mutual core components of learning. Learners highly skilled in those aspects are often referred to as ‘expert learners’ [2][3]. Given the demands of 21st century education, adult training, and lifelong learning; taking responsibility for one’s own planning, performing, monitoring, and regulating learning is crucial. In particular, for technology-enhanced learning (TEL), SRL and metacognition are recognized as having a key role [4]. It is acknowledged that SRL and metacognitive processes require the availability of appropriate knowledge and strategies. Learners need support in acquiring and applying these skills; accordingly, this area and related intervention programs are intensely investigated [5]. For sound instructional and scaffolding strategies an in-depth understanding of *good* metacognitive and SRL behaviors is crucial [3]. This paper investigates characteristics of successful SRL in the scope of learning episodes with an immersive experiential training simulator.

2 What is Good SRL Behavior?

Successful (and less successful) learning is not about the question of whether self-regulation and metacognition occur – all learners think about and try to regulate their learning in some way, but there are dramatic differences in how they approach it. A high quality and quantity of self-regulatory and metacognitive processes goes along with better learning performance and achievements [6][7]. Research has attempted to identify the differences between lower and higher achieving learners to draw implications for SRL and metacognitive scaffolding and strategy training [3][8]. Expert learners know, and successfully employ, more and better cognitive and metacognitive strategies [2][6]. A variety of personal attributes were found to characterize and distinguish students with high versus low metacognitive and SRL abilities (see *e.g.* [1][8] for an overview). Effective learning is related to higher levels of motivation and self-motivational beliefs [6]; whereas underachievers are known to be less efficacious about their learning and to have a lower self-esteem, to be more impulsive, and to give up earlier and more easily. In particular, they are also more anxious and fear failure [8]. The research aiming at explaining why some learners are more successful than others so far has been concentrated on traditional learning situations. TEL environments, such as web-based courses, impose additional demands on learners [9]. It is therefore important to examine the characteristics of effective metacognition and SRL more directly in a TEL context, to see whether the results confirm the state of the art from traditional learning settings and to identify whether there are any peculiarities for TEL. This paper presents an empirical investigation pursuing that goal. One main objective was to investigate SRL behavior and learner characteristics in relation to learners' general metacognitive awareness.

3 An Empirical Study in an Experiential Learning Environment

3.1 Method

Augmented Training Simulator. ETU's[1] RolePlay Simulation Platform offers simulation scenarios teaching student doctors about effective doctor-patient communication (see Figure 1). Users' main task is to select appropriate dialogues for clinical interviews with patients diagnosed with either mania or depression. The TEL environment embeds a range of features to support self-regulation. More specifically, the simulator provides learning triggers for delivering targeted in-context coaching, behavioral feedback and strategic reflections to reinforce learning and aid transfer to the job. The platform also doubles as a psychometric profiling, behavioral measurement and skill assessment tool. Metacognitive scaffolding was provided to learners within the ETU simulator using calls to a RESTful service developed as part of the ImREAL project[2]. The service utilizes a cognitive model to support self-reflection and presents items from the Metacognitive Awareness Inventory (MAI) [7],

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[1] www.etu.ie

[2] www.imreal-project.eu

e.g. “Have you focused your attention on the important information?”. It has previously been shown that providing this scaffolding within the ETU platform is beneficial [10]. Alongside the scaffolding thinking prompt is an open text box for collecting reflection notes which is consistently prefaced with a short text: “Reflect now on your learning: Was this last part of the simulation useful for you?” In addition, there is a place to reflect in the simulator’s note-taking tool, where learners can record and share notes.

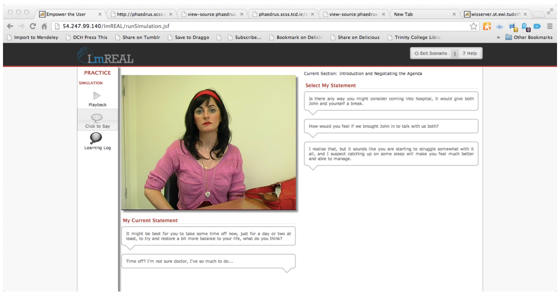

Figure 1. Screenshot of the ETU RolePlay Simulation Platform.

Participants, Instruments, and Procedure. In spring 2013, 152 third year medical students (M = 22.81 years old, SD = 3.79) from Trinity College Dublin participated in the study as part of their medical curriculum. A mixed-method approach capturing metacognition and SRL in terms of users’ general learning approach (self-report) and the actual activities during simulator usage (log data) was applied [11]. Students completed a cohort characterization survey before interacting with the simulator. Besides demographic questions and a personality questionnaire (SSP, Swedish Universities Scales of Personality [12]), a standard scale assessing metacognitive awareness (MAI [7]) was administered. Students could then use the simulator as long and often they wished. Interaction data and text entries from reflection notes and the note-taking tool were tracked by the simulator and served for investigating learning behavior. Self-predicted and objective learning performances based on an assessment of interview skills built into the simulator were also used. This trace methodology corresponded to the idea of examining SRL as a process [13]. After the learning episode students provided feedback on learning with the simulator in a survey covering the perception of reflection prompts, motivation, and SRL (QSRL, [14]).

3.2 Results

Log data from 152 students performing the training in the simulator was available, whereas subsamples of 76 (MAI) and 85 (SSP) filled out the *pre*-questionnaire and only 39 (prompts), 25 (QSRL) and 29 (motivation) students completed the *post*-survey. Samples sizes for filling out both the MAI (as grouping variable) and one of the other questionnaires (as dependent variable) were even smaller. To investigate differences with respect to learning activities and feedback on the simulator between users with high and lower metacognitive awareness (and thus SRL-abilities), the subsample that had completed the MAI *before* entering the simulator was split at the median into two groups. Focusing on SRL as a process [13], this was done using the regulation of cognition (ROC) subscales and scores ($Md_{MAI\text{-}ROC}$ =.69; $M_{low\text{-}ROC}$ =.56, *SD*=.13; $M_{high\text{-}ROC}$ =.83, *SD*=.08), which address the metacognitive strategies and subprocesses of learning [7].

Independent samples t-tests for high (high ROC) and low (low ROC) metacognitive awareness revealed significant differences (all p<.05) regarding participants' SRL-behavior, personality traits, motivation, as well the number of notes taken during the interview training (see Figure 2). More specifically, students with higher metacognitive awareness (as far as the regulation of knowledge is concerned) are also better in monitoring their own learning processes ($t_{(18)}$ = -2.15), have higher achievement motivation ($t_{(18)}$ = -2.26), attribute their successes more strongly to their abilities ($t_{(18)}$ = -2.88), and are more motivated regarding their current learning situation ($t_{(26)}$ = -2.83), especially to apply what they have just learned. Additionally they took more notes during the interview training (with *N*=14 and no equal variances: $t_{(9)}$ = -2.38), i.e. they reflected more explicitly on the decisions they made during the training. On the other hand, they show lower trait anxiety ($t_{(70)}$ = 2.04) and lower scores on lack of assertiveness ($t_{(70)}$ = 2.7). There was no difference regarding the perception of thinking prompts. Both groups rated them as helpful and appropriate on 5-pt scales (for 10 questions all *Md* = 4, overall *M* = 3.6, *SD* = .58).

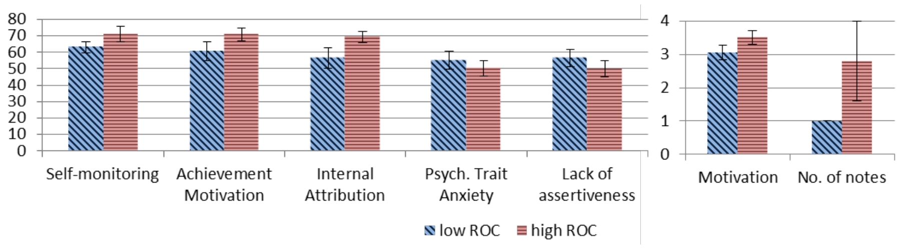

Figure 2. Mean SRL scores, personality traits, motivation, and number of notes for low and high metacognitive awareness.

4 Conclusion

The outcomes of the presented study argue for the transferability of known characteristics of good metacognition and SRL identified in traditional learning settings to a TEL context. Although comparisons are actually based on groups of high vs. medium metacognitive abilities, a range of distinguishing differences could be identified. In line with previous results that expert learners apply more metacognitive strategies, high ROC students were shown to more extensively monitor and evaluate their own learning and to take more notes in the simulator. Also a trend of higher learning performance (ETU score) being associated with higher SRL abilities was found: Results revealed higher SRL scores on all nine QSRL subscales for better performing students in the simulation (*N* = 25). However, since these differences are not statistically significant, further research with larger samples is necessary.

No difference was found in students' abilities of predicting their own performance. A general novelty effect of the learning setting might have mitigated an expected difference in persistence in terms of duration of simulator usage. Since achievement motivation refers to the desire to perform well on challenging tasks and is evidenced by effort and persistence, though, the higher scores identified for the high ROC group may be related to previous results on higher persistence of expert learners. This group also reported a higher motivation to transfer the just acquired skills to real world interviews. The lower internal attribution of success found for low ROC resembles existing results on lower self-efficacy for learners with low metacognitive abilities. In addition, low ROC students were shown to be more anxious, confirming previous results on higher anxiety for lower skilled learners. Follow-up investigations with samples featuring a higher range in metacognitive and SRL abilities are planned.

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Managing Ethical Thinking

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Abstract. The main set of reasoning tools needed for the Professional Ethics domain is metacognitive. Students need to be able not only to analyze case studies, commonly used in this kind of domain, but also be able to analyze their own analysis. We have developed a tool called Umka to implicitly support students in evaluating and regulating their ethical analysis. An experiment was carried out where computer science students studying professional ethics used Umka. Results of this experiment are shown, and further steps are discussed on how to make Umka's metacognitive support more explicit.

Keywords: ethical thinking, metacognition, case analysis

1 Introduction

Metacognition is defined as the ability to be aware of, monitor, and evaluate one's own thinking. In the context of Professional Ethics this translates into the learner's ability to be aware of, evaluate and, if necessary, regulate his or her own ethical thinking. Professional Ethics is commonly taught through the analysis of case studies, which present certain professional issues and dilemmas. Students are asked to provide solutions to resolve these dilemmas, and supply justifications for their judgment. The reasoning behind these justifications is a big part of what constitutes "ethical thinking".

Ethical thinking by itself involves many metacognitive activities such as recognizing the complexities of your circumstances, anticipating the consequences of actions, considering the effect of actions on others, the critical appraisal of message source, quality of appeal etc. The foundation researcher in metacognition Flavell [1] considered these activities to be metacognitive in nature, and important for making wise and thoughtful life decisions.

But besides these activities students also need to be evaluate and regulate their ethical thinking. Students have to be able to analyze their own arguments and motivations, to make sure they have covered all the facts, have not factored in their own beliefs or prejudices too strongly, have uncovered all the possible directions for analyzing the case, and have weighed their arguments against one another well in reaching their conclusion. Students need to have skills to articulately and consistently justify their moral judgements, skills for analysis and critique of others' and their own convictions, and skills for forming their own convictions. Developing all these skills in students are important goals of ethics education [2].

Several systems have been developed to support students in structuring their ethics case analysis. These systems walk students through the steps of ethical analysis by providing instructions and asking students to fill in predefined forms. Examples of such systems are Ethos [3] and the PETE system [4]. We have not found systems that support students beyond structuring their ethical analysis, and in particular there doesn't seem to be support for students learning the more complex processes of evaluating and regulating ethical analysis.

2 Umka as a Tool for Evaluating and Regulating Ethical Thinking

We have developed a computer tool Umka (screenshot in Figure 1) where students analyze a given case study both individually and through collaboration with one another by seeing each others' analyses and commenting on each others' arguments.

Umka also invites students to cognitively monitor their own ethical analysis, and adopt strategies for its improvement. This is done in Umka implicitly through an open group learner model of students' analysis. Bull and Kay [5] suggest that there is "potential to support metacognitive activity in a less explicit manner" though open learner models. And an important question that these researchers raise is "how to design and present a learner model that can best support reflection and particularly how to do it in ways that facilitate learning of the domain and of metacognitive skills".

If we consider the ethics domain, domain knowledge here is the formed convictions on important professional issues. Metacognitive skills are skills for evaluating one's own convictions, and strategies to form them such as looking at the issue from various points of view, exposure to the opinions of others, criticizing your own and others' convictions, overcoming criticism, or changing your convictions in response to the criticism.

The open learner model in Umka reflects how well-formed are learners' convictions or positions. The well-formedness of a learner position is determined by how broad it is in terms of different reasons the learner considered, and how well-argued it is in terms of how much the learner was able to persuade others in his or her reasoning. We have adopted the circle visualization for this (Figure 2). The size of the circle reflects the breadth of the student's position, which is determined by the number of different arguments the student has for and against a particular action in a case study. The darkness of the circle reflects the well-formedness of the student's position. The more the arguments and comments of the student are accepted by others, the more well-formed is the student's position, and the darker is the student's circle. [6] has more details on how the visualization is computed.

We expected that our open group learner model will trigger students to cognitively evaluate their convictions and adopt strategies for forming their convic-

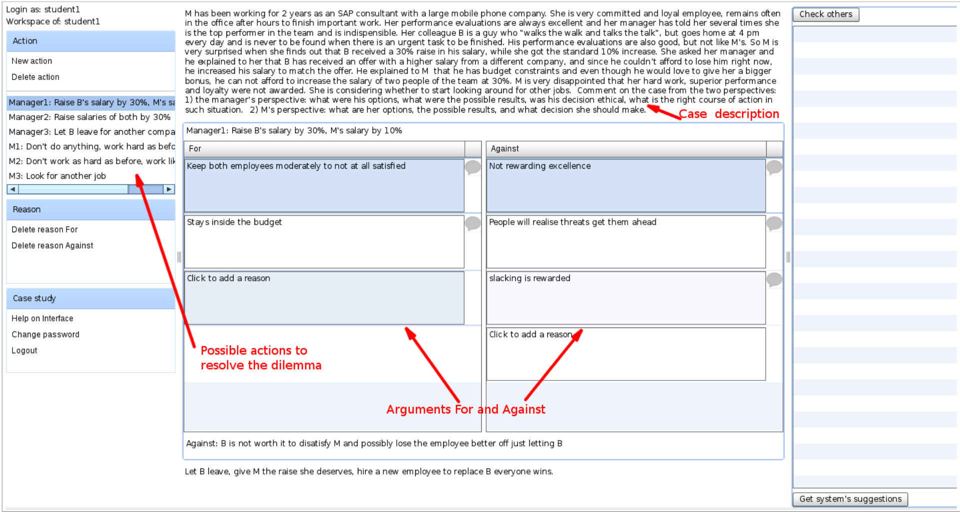

Fig. 1. A screenshot of the Umka system. Once logged in a student sees the case description in the top middle part, and possible actions to resolve the case dilemma in the left part. The student puts his/her arguments for and against every action in the middle.

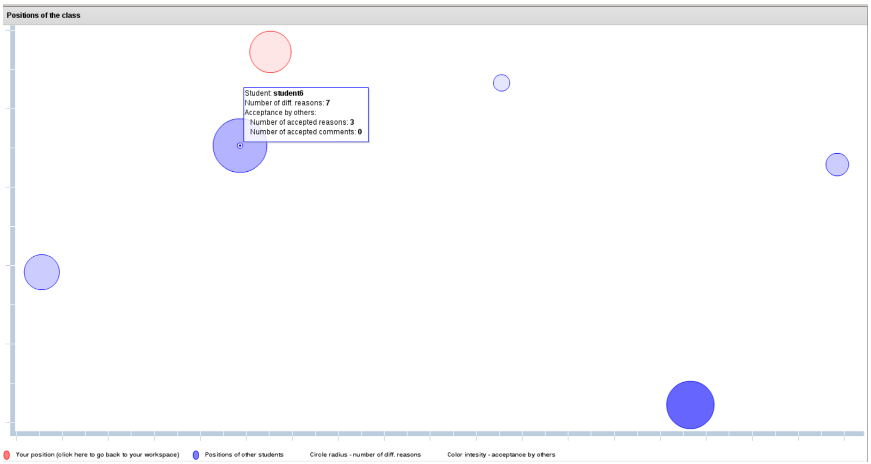

Fig. 2. Umka's visualization. A student sees his/her position as a red circle, and positions of others - as blue circles. The distance between the circles reflects the semantic distance between the corresponding positions.

tions. Our experiment described in the next section was designed to evaluate how effective was the proposed learner modeling in stimulating positive metacognitive behaviors in students, and how much students' own evaluation of their positions corresponds with the evaluation of their positions in our learner model.

3 Experiment and Results

In our two previous studies [6] we investigated the effect of Umka's support on students' behavior and the quality of students' analysis, and evaluated the accuracy of the learner modelling. The specific goal of our third experiment was more qualitative than the other two, essentially to probe more deeply into the effect of Umka on the cognition and metacognition of the students. In the third experiment we used the Umka tool for one of the assignments in an undergraduate course called "Ethics in Computer Science" at the University of Saskatchewan. Six students taking this class were analyzing a case study in the Umka tool concerning issues that may arise in the workplace. With only six students, the experiment is, of course, at best illuminative, not definitive, and there was no point in doing statistical analysis.

We were interested what students will do when they see their own learner models, and learner models of their classmates. The open learner model in Umka provoked in students certain behaviors for regulating their ethical thinking. After seeing the visualization of their learner models, students visited analyses of other students, commenting on the arguments of others, and revisited their personal analyses by adding more arguments into them. Thus, 54% of all students' arguments are arguments that have been added after seeing the visualization or analyses of other students. 55% of these added arguments were found to be good arguments by the instructor. All students except one were visiting analyses of others, and all students except one added new arguments after seeing their learner models or analyses of other students. There were 12 comments of the students on each others' arguments.

We compared these results with the results from the Wiki system that the students used for ethical analysis of another case study before they used the Umka system. In comparison, in the Wiki system the students didn't exchange any comments with each other, and the students didn't revise their own arguments.

In the post-study questionnaire we asked students to evaluate their ethical thinking and compare it with the Umka visualization, specifically asking how much the visualization was able to reflect the breadth and well-formedness of their positions. Unfortunately only one student out of six filled in the questionnaire. This student stated that the visualization didn't reflect much about his position because as he said ".. I feel that my 2 reasons were more detailed then 5 one sentance [sic] details that other students gave. Although if they expanded their reasons more I feel I would try [to] increase my position".

4 Conclusion and Future Directions

One of the goals behind Umka's development was to support students in managing their ethical analysis. This support is organized implicitly through Umka's interface, visual feedback on the breadth and depth of students' arguments, and encouragement to look at others' arguments. While our study was a small one, making definitive conclusions premature, the results were positive. Using Umka, students were motivated to actually argue and discuss with one another and to examine their own arguments; they were able to regulate their ethical analysis. There was not enough data to judge how well students were able to evaluate their ethical thinking and the degree they agreed with Umka's evaluation. A possible future direction is to organize Umka's visualization as an open negotiated learner model [7] to further stimulate metacognitive behaviors in students. Another possible direction is the introduction of explicit learner centered system suggestions on structuring and regulating ethical case analysis.

Metacognition plays an important role in learning Professional Ethics. The ability not just to analyze a case, but to analyze the analysis is fundamental to the ethics domain. Thus, the ethics domain is a perfect domain to explore metacognition, and further research is required to understand how it can be best supported by a computer environment.

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A Framework for Self-Regulated Learning of Domain-Specific Concepts

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Abstract. Research in self-regulated learning environments has focused on student motivation, development of metacognitive skills, learning strategies, and individual differences. Equally important is the modeling of domain-specific concepts and the ability for students to learn them under their preferred environment. In this paper, we present a general framework for modeling domain-specific concepts that support self-regulated learning across different domains. Our framework is motivated by a well-established pedagogical tool called the *concept map*.

Keywords: Concept map, self-regulated learning, individualized learning paths, performance monitoring, relevance perception

1 Introduction

One of the most important factors in course design is the development of a *concept map* [1], which is the overall picture of the relationship between the course concepts and the learning elements. As educators, we are often concerned with student performance regarding specific concepts and learning outcomes, and whether they understand the connections among the various course components. While we design assessments to help students achieve various learning outcomes, the interconnectedness of the concepts assessed in course activities make it hard for us to tease apart what students excel in and what they find difficult. In order to better help the students, ideally, educators should be able to point to an assessment piece, see the corresponding performance level, and know immediately which concepts students have trouble with and which learning outcomes may be in jeopardy. Likewise, students should have access to metrics about their own progress so that they can monitor and shape their own learning process. Much like the benefits that project management software offer to managers and employees, we wish to deliver analogous information in the context of a course that lets students and instructors manage the learning process. As such, we argue that an online course tool is needed to overcome these challenges by visually presenting key concepts and their connections to other elements. We present a general framework called the *Concept Navigator* for just this purpose. While its design is motivated by the needs of educators, this framework also supports students in a self-regulated learning environment. We believe that the

Concept Navigator will empower both students and educators by providing them with an explicit view of student progress with respect to a course concept map and the expected learning outcomes.

2 The Concept Navigator Framework

As new educational paradigms, such as flexible learning and flipped classrooms, become mainstream, there is a growing need to have the proper tools in place to support methods of student-initiated and student-directed learning [2]. The Concept Navigator is a general framework for visualizing course concepts, their relationships to each other, as well as their relationships to other course elements such as learning outcomes and assessment pieces. The backbone of this framework is driven by a course concept map, as concept mapping has been shown to support self-directed, experimental, and networked learning (see [2] for details). Although the concept map has long been available to educators for course design purposes, in our experience, most instructors do not use it in designing courses or in articulating the roadmap of a course to students. From a pedagogical standpoint, we believe that the development of a concept map is crucial to the successful delivery of a course. For this reason, our framework is designed to have instructor-defined concept maps of courses, rather than data-driven [3] or editable concept maps of learners [4] as proposed by alternative approaches.

The concept map alone is simply a set of concepts and their relationships. In our framework, we model additional entities and relationships as depicted in Figure 1. For example, a concept is associated with many learning outcomes, and can be included in an activity (e.g., reading) or exercised in a question (which belongs to either an assignment or a quiz). Also, note that a learning

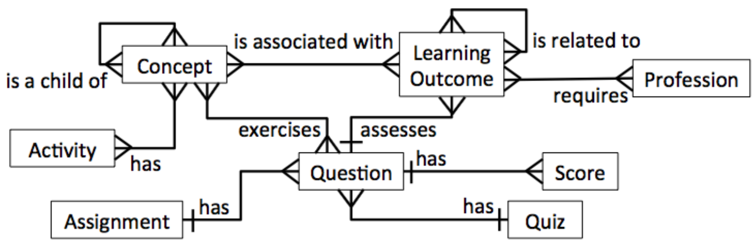

Fig. 1. The entity-relationship diagram for the Concept Navigator.

outcome is related to other learning outcomes because some outcomes may serve as prerequisite skills. Finally, a profession (e.g., Programmer, System Analyst, Project Manager) may require the mastery of different sets of learning outcomes. This relationship is of particular importance because it helps students see real-world relevance of what they are learning in class.

Overall, this model defines the structural content of a course from an the instructor's perspective. As such, one of our goals is to promote the use of concept maps in the process of course design. Since instructional content and style can vary, our framework is limited to supporting specific course development efforts rather than larger efforts such as degree program design (e.g., [5]). Unlike existing work in open learner models [6], we focus on the explicit communication of concepts and their interdependencies, as well as their relationships to learning outcomes and relevance to professions. Students with a good grasp of this knowledge will be able to personalize their learning experience by setting real-world driven goals and choosing their own paths based on what they want to achieve. Moreover, this framework is a concept navigation tool, without adaptive features and requiring minimal student configuration (see [7] for an alternative approach). In contrast to learning management systems such as Blackboard [8] and Moodle [9] that simply deliver course content digitally and perform simple software usage tracking, the Concept Navigator enables students to take control of their own learning process. Currently, Moodle also lets users tag course elements to learning outcomes, which is a step toward our overall design objectives.

3 A Course Prototype in the Concept Navigator

To illustrate our framework, we present a partial concept map of the course "Digital Citizenship" in Figure 2, where concepts are represented as nodes and relationships are represented as arrows. The small graphs shown on the top of the nodes indicate summary metrics of student performance, which we envision can be viewed per student or for a whole class. Student progress is implicitly shown in Figure 2 by a lack of available data in the remaining nodes.

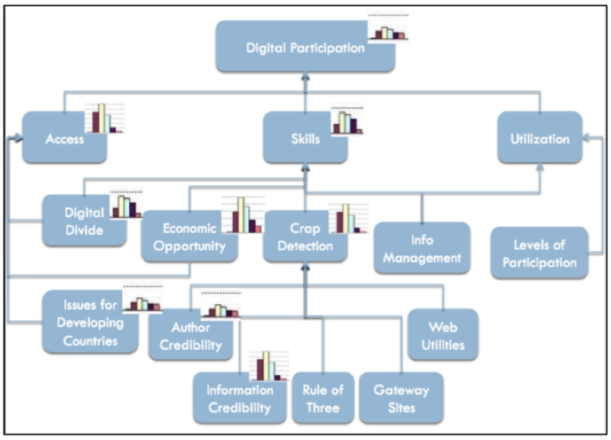

Fig. 2. A partial concept map for Digital Citizenship with summary metrics.

When a concept is selected, such as “Crap Detection”, a detailed view as in Figure 3 will be shown. Parent concepts based on Figure 2 and summary metrics are shown at the top, while related learning elements such as activities (e.g., readings, videos), questions (as part of exercises or assessments), and learning outcomes are displayed in the center. Details may be hidden or expanded.

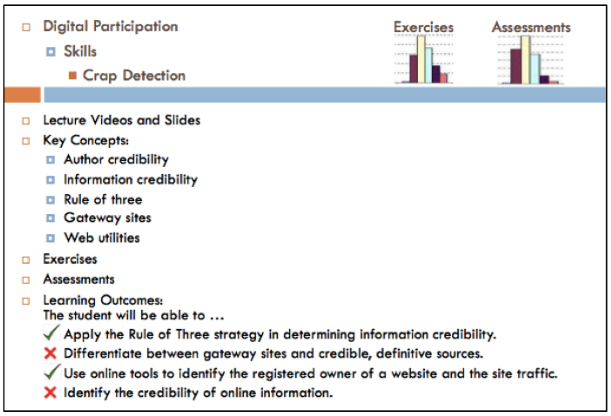

Fig. 3. Detailed view of Crap Detection, showing related concepts and summary metrics at the top and hidden and expanded learning elements in the center.

Of particular interest is the display of learning outcomes which serves as a constant reminder of why certain concepts are taught as part of the course and the expectations in applying them. Moreover, Figure 3 shows a visual status for each learning outcome to indicate how likely the student has achieved a learning outcome based on the current performance levels. These statuses can be determined based on predefined thresholds or automatically learned via a history of performance data. Usability feedback will be conducted to test whether a more fine-grained visual status (e.g., a percentage) will be more appropriate than a binary status (i.e., ✓ or ✗). These metrics are helpful in providing a formative assessment so that instructors may adapt learning activities accordingly.

4 Support for Self-Regulated Learning

The Concept Navigator is designed to support students in a self-regulated learning environment. A key aspect of the concept map interface (e.g., Figure 2) is the ability for students to pursue a course in a non-linear fashion. Given a visual map of the concepts and their dependencies, students may select the concepts of interest and acquire the relevant material via an individualized learning path. The ability to see the direct connections between concepts, learning outcomes, and professions not only enables students to set goals for themselves, but it also helps to foster a positive attitude in students by knowing the importance of each learning element at hand. With the metrics associated to each concept and learning outcome, students can monitoring their own progress and, thus, increase awareness of their own educational successes and needs.

Currently, our framework assumes students take full responsibility of their own learning. Opportunities to add social and intelligent features are left for future development, such as peer information sharing forums, monitoring alerts that trigger self-reflection, and adaptive assistance to support scaffolding.

5 Future Work

We presented a framework called the Concept Navigator which supports self-regulated learning of domain-specific concepts. This framework hails students as active agents in their own learning process. We instantiated this framework with a course prototype and discussed ways to support individualized learning, goal setting, performance monitoring, reflection, and relevance perception. Our immediate next step is to design the interface for visualizing the relationships among learning outcomes and between learning outcomes and professions. Thereafter, we will create a full instance of the Concept Navigator for a specific course and test it with student users. Controlled testing to debug usability issues will be conducted prior to assessing the utility of the system by testing it in the classroom. Finally, testing in different courses will be done to validate the feasibility of this framework across multiple domains.

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Evaluation of a meta-tutor for constructing models of dynamic systems

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Abstract. While modeling dynamic systems in an efficient manner is an important skill to acquire for a scientist, it is a difficult skill to acquire. A simple step-based tutoring system, called AMT, was designed to help students learn how to construct models of dynamic systems using deep modeling practices. In order to increase the frequency of deep modeling and reduce the amount of guessing/gaming, a meta-tutor coaching students to follow a deep modeling strategy was added to the original modeling tool. This paper presents the results of two experiments investigating the effectiveness of the meta-tutor when compared to the original software. The results indicate that students who studied with the meta-tutor did indeed engage more in deep modeling practices.

Keywords: meta-tutor , intelligent tutoring systems, empirical evaluation

1 Introduction

Modeling is both an important cognitive skill [1] and a potentially powerful means of learning many topics [5]. The AMT system teaches students how to construct system dynamics models. Such models are widely used in professions, often taught in universities and sometimes taught in high schools.

1.1 The modeling language, development tool and tutoring system

In our modeling language, a model is a directed graph with one type of link. Each node represents both a variable and the computation that determines the variable's value. Links represent inputs to the calculations. As in illustration, Figure 1 shows a model for the following system:

> The initial population of bacteria is 100. The number of bacteria born each hour is 10% of the population. Thus, as the population increases, the number of births increases, too. Model the system and graph the population over 20 hours.

Clicking on a node opens an editor with these tabs (and 2 others not described here):

- *Description*: The student enters a description of the quantity represented by the node.
- *Inputs*: The student selects inputs to the calculation of the node's value.
- *Calculation*: The student enters a formula for computing the node's value in terms of the inputs.

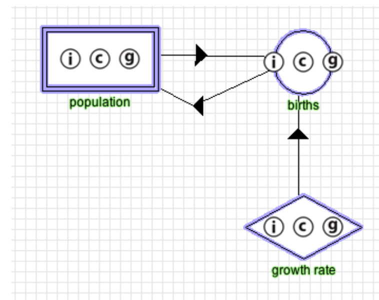

Fig. 1. A simple model.

There are three types of nodes in models:

- A *fixed value* node represents a constant value that is directly specified in the problem. A fixed value node has a diamond shape, never contains incoming links, and its calculation is just a single number. For instance, "growth rate" has 0.1 as the calculation of its value.
- An *accumulator* node accumulates the values of its inputs. That is, its current value is the sum of its previous value plus or minus its inputs. An accumulator node has a rectangular shape and always has at least one incoming link. For instance, the calculation tab of "population" states that its initial value is 100 and its next value is its current value + births.
- A *function* node's value is an algebraic function of its inputs. A function node has a circular shape and at least one incoming link. For instance, "births" has as its calculation "population * growth rate."

The students' task is to develop a model that represents a system described by a short text. They can create, edit and delete nodes using the node editor. When all the nodes have calculations, students can click the Run Model button, which performs calculations and draws graphs of each nodes' values over time. The system described so far is just a model development tool.

AMT has a simple tutoring capability. Each tab of the node editor has a *Check* button which turns its fields red if they are incorrect and green if they are correct. Each tab also has a *Give up* button that fills out the tab correctly. Thus, the system described so far is just a simple step-based tutoring system with minimal feedback on demand and only one kind of hint: a bottom-out hint.

1.2 The meta-tutor

Unfortunately, it is a rare for students to think semantically in terms of what the nodes, inputs and calculations mean actually mean. Students prefer to think of model elements syntactically, like puzzle pieces that need to be fit together. This shows up in a variety of ways, including rapid guessing, nonsensical constructions and the use of syntactic rather than semantic language to refer to model elements. The literature on model construction (reviewed in [5]) sometimes refers to these two extremes as Deep vs. Shallow modeling. The objective of the AMT system is to increase the relative frequency of Deep modeling.

A variety of methods for increasing the frequency of Deep modeling have been tried [5]. For instance, nodes can bear pictures of the quantities they represent, or students can be required to type explanations for their calculations. One of the most promising methods is *procedural scaffolding*, wherein students are temporarily required to follow a procedure; the requirement is removed as they become competent. This technique was used by Pyrenees [2], where it caused large effect sizes.

We adapted Pyrenees' procedure to our modeling language and called it the Target Node Strategy. The strategy requires students to focus on one node, called the target node, and completely define it before working on any other node. This decomposes the whole modeling problem into a series of atomic modeling problems, one per node. The atomic modeling problem is this: Given a quantity, find a simple calculation that will compute its values in terms of other quantities without worrying about how those other quantities values will be calculated. This is a much smaller problem than the overall challenge of seeing how the overall model can be constructed.

As an illustration, let us continue the bacteria population example and suppose that the target node is "number of bacteria born per hour." The ideal student might think:

> "It says births are 10% of the population, so if I knew population, then I could figure out the number of births. In fact, I could define a node to hold the 10%, and then the calculation would multiply it and population. But do I need initial population or current population? Oh. The number of bacteria born is increasing, so I must need current population, because it is also increasing."

This is one form of deep modeling. By requiring students to finish one node before working on another, the Target Variable Strategy encourages students to examine the system description closely because it is the only resource that provides relevant information. When they are allowed to work on any tab on any node, then they jump around trying to find a tab that can be easily filled in. This is a common form of shallow modeling, and the Target Node Strategy discourages it.

In addition to requiring the students to follow the Target Node Strategy, the meta-tutor nags students to avoid guessing and abuse of the Give Up button, just as the Help-Tutor [3] did. Because neither the strategy nor the advice on help seeking are specific to the domain (e.g., population dynamics), we consider them to be meta-cognitive instruction.

2 Evaluation

2.1 Experiment Design

The experiment was designed as a between-subject single treatment experiment with a control condition, where the meta-tutor was off, and an experiment condition, where the meta-tutor was on. The difference between the conditions occurred only during a training phase where students learned how to solve model construction problems. In order to assess how much students learned, a transfer phase followed the training phase. During the transfer phase, all students solved model construction problems with almost no help: the meta-tutor, the Check button and the Give-up button were all turned off, except in the Description tab where the Check button remained enabled to facilitate grounding. Because system dynamics is rarely taught in high school, no pre-test was included in the procedure. We conducted two experiments with 44 students participating in the first experiment and 34 students in the second experiment.

2.2 Hypotheses and Measures

Hypothesis 1 is that the meta-tutored students will use deep modeling more frequently than the control students during the *transfer* phase. We used the three measures below to assess it.

- The *number of the Run Model button presses* per problem.
- The *number of extra nodes* created, where extra nodes are defined as the nodes that can be legally created for the problem but are not required for solving the problem.
- The *number of problems completed* during the 30 minute transfer period.

Hypothesis 2 is that meta-tutored students will use deep modeling more frequently than the control group students during the *training* phase. The three dependent measures used to evaluate this hypothesis are described below:

- *Help button usage:* was calculated as $(n_{wc}+3n_{gu})/n_{rn}$, where n_{wc} is the number of Check button presses that yielded red, n_{gu} is the number of Give-up button presses, and n_{rn} is the number of nodes required by the problem.
- *The percentage of times the first Check was correct*.
- *Training efficiency:* was calculated as $3n_{cn} - n_{gu}$ where n_{cn} is the number of nodes the student completed correctly ($3n_{cn}$ is the number of tabs), and n_{gu} is the number of Give-up buttons presses.

Hypothesis 3 is that the experimental group students, who were required to follow the Target Node Strategy during training, would seldom use it during the transfer phase. To evaluate this hypothesis, we calculated the proportion of student steps consistent with the target node strategy.

2.3 Results

Table 1 summarizes the results of experiment 1 and experiment 2.

3 Conclusion and future work

Although we achieved some success in encouraging students to engage in deep modeling, there is much room for improvement. If the meta-tutor had been a complete success at teaching deep modeling, we would expect to see students supported by the meta-tutor working faster than the control students. The stage is now set for the last phase of our project, where we add an affective agent to the system [4], in order to encourage engagement and more frequent deep modeling.

Measure (predicted dir.)	*Experiment 1 (N=44)*	*Experiment 2 (N=33)*
Transfer phase (Hypothesis 1)		
Run model button usage (E<C)	E<C (p=0.31, d=0.32)	E≈C (p=0.98, d=-0.0093)
Extra nodes (E<C)	**E<C (p=0.02, d=0.80)**	E<C (p=0.47, d=0.26)
Probs completed (E>C)	E≈C (p=0.65, d=0.04)	E<C (p=0.09, d=−0.57)
Training phase (Hypothesis 2)		
Help button usage (E<C)	**E<C (p=0.04, d=0.68)**	**E<C (p=0.02, d=0.89)**
Correct on 1st Check (E>C)	Missing data	**E>C (p=0.015, d=0.98)**
Efficiency (E>C)	E<C (p=0.05, d=–0.70)	E>C (p=0.59, d=0.19)
Transfer phase use of Target Node Strategy (Hypothesis 3)		
Usage (E=C)	Missing data	E≈C (p=0.59, d=−0.19).

Table 1. Results of Experiment 1 and 2: E stands for the meta-tutor group, and C stands for the control group. Reliable results are bold.

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