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Helping Students Manage Learning Behavior in Self-initiated Learning Scenarios

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2. Paul Salvador Inventado, Roberto Legaspi, Merlin Suarez, Masayuki Numao. Predicting Student Emotions Resulting from Appraisal of ITS Feedback, Research and Practice in Technology Enhanced Learning, Vol. 6, No. 2., pp. 107-133, 2011.

International Conference Papers

1. Paul Salvador Inventado, Roberto Legaspi, Koichi Moriyama, Ken-ichi Fukui, Masayuki Numao. Building Incremental Affect Models to Help Students Annotate and Analyze their their Behavior in Self -Directed Learning Scenarios. In Proc. of the 20th Conference on Computers in Education, pp. 170-172, Bali, 2013.
2. Paul Salvador Inventado, Roberto Legaspi, Koichi Moriyama, Ken-ichi Fukui, Masayuki Numao. Building Policies for Supportive Feedback in Self-directed Learning Scenarios. In Proc. Workshop on Computation: Theory and Practice, Manila, 2013.
3. Paul Salvador Inventado, Roberto Legaspi, Koichi Moriyama, Ken-ichi Fukui, Masayuki Numao. Modeling Affect in Self-directed Learning Scenarios. In Proc. 4th International Workshop on Empathic Computing, Beijing, 2013.
4. Paul Salvador Inventado, Roberto Legaspi, Koichi Moriyama, Ken-ichi Fukui, Masayuki Numao. An architecture for identifying and using effective learning behavior to help students manage learning. In Proc. Formative Feedback in Interactive Learning Environments, Memphis, 2013.
5. Paul Salvador Inventado, Roberto Legaspi, Koichi Moriyama, Ken-ichi Fukui, Masayuki Numao. Identification of effective learning behaviors. In Artificial

Intelligence in Education, volume 7926 of Lecture Notes in Computer Science, pp.670-673, Memphis, 2013.

6. Paul Salvador Inventado, Roberto Legaspi, Masayuki Numao. Sidekick Retrospect: A Self-regulation Tool for Unsupervised Learning Environments. In Theory and Practice of Computation, pp. 195-205, Manila, 2013.

7. Paul Salvador Inventado, Roberto Legaspi, Masayuki Numao. Student learning behavior in an unsupervised learning environment. In Proc. 20th International Conference on Computers in Education, pp. 730-737, Singapore, 2012. **(Best Technical Design Paper Award)**.

8. Paul Salvador Inventado, Roberto Legaspi, Rafael Cabredo, Masayuki Numao. Modeling affect and intentions in unsupervised learning environments In Proc. 3rd International Workshop on Empathic Computing, Sarawak, 2012.

9. Paul Salvador Inventado, Roberto Legaspi, Merlin Suarez, Masayuki Numao. Categorizing and comparing behaviors of students engaged in self-initiated learning online. Theory and practice of computation, Volume 5 of Proceedings in Information and Communications Technology, Chapter 11, pp. 133-144, Manila, 2012.

10. Paul Salvador Inventado, Roberto Legaspi, Merlin Suarez, Masayuki Numao. Investigating transitions in affect and activities for online learning interventions. In Proc. of the 19th Conference on Computers in Education, pp. 571-578, Chiang Mai, 2011. **(Best Student Paper Award)**.

11. Paul Salvador Inventado, Roberto Legaspi, Merlin Suarez, Masayuki Numao. Investigating the transitions between learning and non-learning activities as students learn online. In 4th International Conference on Educational Data Mining, pp. 367-368, Eindhoven, 2011.

12. Paul Salvador Inventado, Roberto Legaspi, Merlin Suarez, Masayuki Numao. Observatory: A tool for recording, annotating and reviewing Emotion-Related data. In 3rd International Conference on Knowledge and Systems Engineering, pp. 261-265, Hanoi, 2011.

International Conference Papers (co-authored)

1. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado , Masayuki Numao. Discovering Emotion Inducing Music Features using EEG Signals, Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 17, No.3, pp. 362-370, 2013.
2. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. An Emotion Model for Music Using Brain waves, In Proc. 13th International Society for Music Information Retrieval Conference, Portugal, pp. 265-270, 2012.
3. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. EEG-based Music Emotion Recognition using Regression Analysis, In Proc. 3rd International Workshop on Empathic Computing.
4. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. Discovering Emotion Features in Symbolic Music, In Proc. 26th Annual Conference of the Japanese Society for Artificial Intelligence, Yamaguchi, 2012.
5. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. Finding Motifs in Psychophysiological Responses and Chord Sequences, Proc. in Information and Communications Technology : Theory and Practice of Computation, Springer, pp. 78-89, 2012.
6. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. Discovering Emotion Features in Symbolic Music, In Proc. 26th Annual Conference of the Japanese Society for Artificial Intelligence, Yamaguchi, 2012.
7. Rafael Cabredo, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. Finding Motifs in Psychophysiological Responses and Chord Sequences, Proc. in Information and Communications Technology : Theory and Practice of Computation, Springer, pp. 78-89, 2012.
8. Yu Yamano, Rafael Cabredo, Paul Salvador Inventado, Roberto Legaspi, Koichi Moriyama, Kenichi Fukui, Satoshi Kurihara, Masayuki Numao. Estimating Emotions on Music Based on Brainwave Analyses, Proc. 3rd International Workshop on Empathic Computing, Springer.
9. Anh Mai, Roberto Legaspi, Paul Salvador Inventado, Masayuki Numao. Users Sitting Postures to Infer User's Learning and Non-learning States, Proc. 3rd International Workshop on Empathic Computing, Springer.
10. Anh Mai, Roberto Legaspi, Paul Salvador Inventado,Rafael Cabredo, Masayuki Numao. A Model for Sitting Postures in Relation to Learning and Non-learning Behaviors, In Proc. 26th Annual Conference of the Japanese Society for Artificial Intelligence, Yamaguchi, 2012.
11. Jocelynn Cu, Rafael Cabredo, Paul Salvador Inventado, Rhia Trogo, merlin Teodosia Suarez, Roberto Legaspi. The TALA Empathic Space: Integrating Affect

and Activity Recognition into a Smart Space Proc. 3rd International Conference on Human-Centric Computing, Philippines, pp. 1-6, 2010.

Book chapter

Ryan Baker, Paul Salvador Inventado. Educational data mining and learning analytics, In Lárusson, J. A. and White, B., editors, Learning Analytics: From Research to Practice, Computer-Supported Collaborative Learning Series. (to appear)

Abstract

Students engage in many learning activities outside of class such as doing homework, conducting research or simply investigating an interesting topic. Learning on one's own is not easy because apart from the learning task itself, students also need to identify what activities to perform, to decide how long to engage in them, to evaluate their progress, to shift to other activities if needed and to avoid distractions aside from others. In this research, we identified different processes that affect learning in self-initiated learning scenarios. We then designed and developed a methodology that added a retrospection phase after a students' learning session to help them analyze their behavior and adapt it based on their realizations. We implemented this methodology by developing a learning tool that collected information regarding students' learning behavior, asked them to annotate their behavior and provided them with policy-based feedback to help them evaluate the effectiveness of their activities. We conducted naturalistic experiments wherein students used the software and received automated feedback based on their learning behavior. The results from the experiment showed that retrospection can help students discover aspects of their behavior which they are unaware of and can help them adapt their behavior accordingly. We also observed that students who were more intrinsically motivated seemed to change their learning behavior faster and more systematically than students who were extrinsically motivated.

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Chapter 1

Introduction

1.1 Background to the Research

Students often learn on their own when they do their homework, projects or research papers. Due to the low cost and accessibility of information through the internet, more and more of these students have used this technology to search and acquire information faster. Although some would argue that it is easier to study now compared to the time when the internet was not yet accessible, we also have to consider that the internet has brought with it many distractions that make studying more challenging. Social networking sites, messaging tools, freely accessible multimedia and the like can serve as both good sources of learning and sources of hindrance to learning. Despite the changes in the medium used for learning, what have not changed are the challenges that students need to overcome when they learn on their own.

Research has shown that self-regulated students learn more effectively compared to other students because they are capable of managing the activities they do, monitoring their progress and adapting their behavior according to their performance [42]. Although self-regulation can be taught, it is difficult to learn and requires students to be highly motivated to learn. Some of the commonly cited causes of students' difficulty in self-regulation include the difficulty in monitoring their activities while learning, difficulty in selecting the appropriate strategy to perform in a given situation, difficulty in evaluating their performance and difficulty in carrying over learned strategies from previous learning sessions into their current activity [38, 39]. Research on self-regulated learning often focus on formal learning contexts wherein students engage in a specific learning task. However, this is not always the case when students would learn on their own because apart from their learning task-related challenges, they also need to perform other important but non-learning-related tasks as well as avoid distractions.

1.2 Research Objectives

This research intends to answer the question:

> **What kind of support can help students manage their learning behavior in self-initiated learning scenarios?**

The following questions will also need to be answered to address the main research problem.

1. How do students learn in self-initiated learning scenarios?
   Self-initiated learning scenarios differ from more formal learning scenarios because of the amount of control students have in selecting which activity they want to perform. It is also possible that students will also engage in non-learning related activities. It is important to understand how differently students learn in this environment to know how to support their learning.

2. How can students be encouraged to manage their learning behavior?
   Learning is a complex process requiring concentration and usually results in high cognitive load. It is important to consider a support methodology which adds minimal or no cognitive load to the students' learning task.

3. How can students' learning behavior in self-initiated learning scenarios be collected and represented?
   Students have full control over their learning when they decide to learn. Students decide what to learn, how to learn, how long to learn, and which applications to use aside from others. Thus, there is a need to define a methodology that will allow the collection of information regarding students' learning behavior in such an un-

controlled environment and define features that will be able to represent elements that affect students' learning behavior.

4. What kind of feedback will be helpful for students in managing their behavior?

   Despite the unstructured and uncontrolled environment in which the student is learning in, students' learning behavior needs to be analyzed automatically to identify what aspects of their behavior need to be changed. These changes then need to be suggested to the student so they can evaluate their behavior and decide to change it when needed.

1.3 Significance of the Research

Information grows every day at an enormous rate. Learners today need to be able to learn all the core concepts and theories that have been developed in the past as well as the information that is constantly being generated. By the time students graduate, they will most likely need to learn much more than what they have already learned in school. This makes learning on one's own an essential skill. Learning on one's own however, is not trivial and takes a lot of practice and experience to develop.

Systems have already been created to help students develop their self-regulated learning skills [5, 24, 38]. However, these systems bound students to the domain it was developed for and to the actions available in the system. This research proposes to investigate ways to help students manage or regulate their learning behavior without binding them to a domain and allowing them to learn in a naturalistic environment. This will allow students to more easily use and apply what they have learned about managing their behavior with less dependence on a system.

This research has four major contributions. First, we were able to observe that retrospection is an effective processes for helping students manage their learning behavior. We were able to develop a methodology and implement a system that allowed the automatic identification of effective learning behavior which we used for generating supportive feedback. The benefits of promoting retrospection were confirmed by the experiments we conducted.

Second, we identified a domain agnostic retrospective data collection methodology that allowed the retrieval of information regarding students' learning behavior in self-initiated learning scenarios using self-annotations with the help of desktop and webcam screenshots of their activity. According to the results of our experiments, this methodology did not disrupt nor add cognitive load to the actual learning task. Moreover, students reported that the annotation process helped them recall and evaluate their activities which are essential processes for effective learning.

Third, we were able to develop a reinforcement learning-based approach to automatically identify the effectiveness of learning behavior. The implementation is flexible such that other measures can easily be used to evaluate effectiveness.

Finally, our methodologies allowed us to retrieve information about students' learning behavior and provide them with customized feedback without binding their activities to a domain or system.

The approach we developed for identifying learning behavior effectiveness uses easily configurable parameters which can be modified to fit other measures of effectiveness. Changing this measure will also change the types of feedback generated by our approach. For example, using a learning gain-based parameter for measuring behavior effectiveness will result in feedback that promotes activities that help improve learning gain.

1.4 Methodology

The following activities were undertaken for this research.

- **Review of Related Literature.** Research on self-initiated learning, self-regulation, learning environments, data collection methodologies and data mining were surveyed to identify what has already been done and what approaches can be adapted to solving the research problems. Limitations of some of these systems were also considered in the development of the system to overcome such issues.

- **Software Development.** A system called *Sidekick* was developed for collecting students' learning behavior, encouraging students to recall their activities and helping students evaluate their learning behavior. The system was developed using Java and currently supports both Windows XP or later and Mac OS 10.6 or later. Two versions of the system were developed and tested by students in actual settings. Issues observed in the first version of the software were used to improve the succeeding version.

- **Data Collection.** Data was collected from students taking an actual course over the span of approximately one month. Students downloaded the system on their own computers and used it anytime and anywhere they wanted to learn. The researchers and the students entered into a privacy agreement regarding the use and distribution of data that was collected.

- **Analysis.** The effects of the different methodologies we developed and the relationships in the data were analyzed based on the results of the experiment we conducted.

- **Documentation.** The final document was written to describe the the basis of the research, the design and development of the system, the analysis of the results, the conclusions from the research and further recommendations. Conference papers and journal papers were also submitted to present the progress of the research to the international community.

Chapter 2

Review of Related Work

Majority of existing tutoring systems have been designed to address the cognitive aspect of learning in different domains and vary in the way they present content, the types of learning activities they provide, the measures they use for evaluating student knowledge and the types of feedback they give [1, 17, 26]. Although these systems help students learn, they do not help students identify what to learn, how to learn or how long to learn because they already provide students with their learning activities.

More recently, systems have been developed to address the metacognitive aspects of learning wherein systems helped students become more aware of how they learn. Self-regulated learning (SRL) is one of the important concepts used because it involves essential activities for defining and managing the learning task such as planning, goal setting, self-monitoring and self-evaluation [40]. In the past, majority of SRL research used self-report questionnaires and interviews to gather information regarding students' use of self-regulated learning [8, 29, 44] most likely because detailed information about students' behavior was difficult to gather. Recently however, the use of tutoring systems, learning environments and other learning tools have made it easier to retrieve learning related information at finer-grained levels, usually called trace data.

In SRL, the learning activities students perform and their effects on the learning task are important to consider because they affect students' decisions on what to do next. In the work of D'Mello and Graesser [14], students' emotions while interacting with a tutoring system were identified by first recording a video of the students and their desktop screen, then later asking the students to annotate the emotions they experienced. They used a likelihood function to analyze the probability of transitioning between emotions while students were studying. They discovered interesting transitions between students' emotions such as the high probability of transitioning from a confused state to a frustrated state and a frustrated state to a bored state among others. Apart from the design and verification of an affective model for learning, their results also highlighted important scenarios in the learning session wherein students need to be aware of their emotions so they can select the best action to maintain their learning productivity. Baker and his colleagues used similar approaches in analyzing the effects of performing certain activity types to students' emotions and the effects of emotions to certain activity types [6, 32]. Their annotation methodology was different wherein trained judges performed emotion annotation instead of the students. The relationship between students' activities and emotions can be used as a guide to maintain learning productivity and also for providing real-time feedback.

Hadwin et al. [18] investigated student learning behavior by processing trace data in students' interactions with elements of a learning environment (e.g., create a question note, link notes, update glossary). Their analysis of students' frequent actions, activity transition patterns, activity durations and viewed content within the learning activity revealed clear differences in the behavior of low performing and high performing students. They also mapped low level actions to self-regulatory processes (e.g., make questions, pull information across sources, outline concepts) and highlighted the value of trace data which gave more explanation about students' self-regulatory behavior compared to the more traditional SRL questionnaires. Students' actions or action transitions that mapped to good use of self-regulation processes have the potential of being used as guidelines for learning better as well as basis for real-time feedback.

Kinnebrew, Loretz and Biswas [21] introduced a differential sequence mining technique that distinguished frequent action sequences common to a group given two separate data sets. They used datasets taken from high-performing and low-performing students using a learning-by-teaching environment and were able to uncover behaviors common to a group but were either absent or infrequent in the other. High-performing students for example, were observed to spend more effort monitoring the understanding of the agent they were teaching (i.e., based on the sequence of low level actions) compared to low-performing students. Analyzing action sequences can uncover higher level relationships between actions and can also be used to identify effective learning strategies as they are shared by effective learners.

Results from the research we presented indicate that trace data can be used to distinguish effective and ineffective learning behaviors. Helping students become aware of these learning behaviors can help them evaluate and select better actions in future learning opportunities. Based on the aforementioned research, we designed a methodology that used a combination of self-reporting and trace data analysis to encourage students to analyze and evaluate their learning behavior. The novelty of our work is that unlike most research, our approach is domain agnostic so it does not require the creation of content specific to a particular domain. It also has minimal restrictions which allow students to learn in a naturalistic setting without forcing them to change their learning habits. Finally, the approach did not limit students to engage in learning activities alone so it also considers dealing with non-learning related activities and distractions.

Chapter 3

Theoretical Framework

In this chapter, we discuss the basis of our work which we used to design our methodology for analyzing student learning behavior and providing feedback to help students manage their learning behavior.

3.1 Self-initiated Learning

The term self-initiated learning is commonly associated with self-directed learning (SDL) which Knowles [22, p. 18] defined as "a process by which individuals take the initiative, with or without the assistance of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes." In this research, we were interested in a more simplistic definition of self-initiated learning wherein we simply considered learning tasks initiated by students regardless of the reason. We also scoped the research only to self-initiated learning activities outside of class which were related to an academic course taken by the students so we can easily analyze our findings. Regardless of these considerations, we expected students learning in this scenario to still either be motivated by their intrinsic desire to learn as in Knowles' definition of SDL, or by external factors, such as academic requirements, wherein they did not explicitly consider the need for improving their learning skills.

Self-initiated learning scenarios based on our definition fall under informal learning contexts, which are learning contexts that are less defined and unpredictable compared

Table 3.1: Differences of problem-solving components in formal and informal learning contexts [43]

Problem-solving components	Problem	Contexts
	Formal (structured)	Informal (unstructured)
Problem source	Socially presented	Personally anticipated/defined
Boundary conditions	Constrained	Open-ended
Solution resources	Necessary information given	Necessary information sought
Types of solutions	Formal cognitive	Practical behavioral
Solution process	Exact	Recursive
Motivation source	Intrinsic interest	Self-efficacy, outcome expectations, goal orientation, intrinsic interest
Behavioral competence	Preexisting	To be developed

to formal learning contexts like those conducted inside the classroom. For example, when students study at home, they may need to look for other information sources or seek help from others when they review topics in class which were unclear to them. They would also need to evaluate the correctness of their own understanding and evaluate when they have learned enough and move on to the next topic or stop studying.

Zimmerman and Campillo [43] identified eight differences between formal and informal learning contexts that students need to deal with while learning (see Table 3.1). They stated that students in informal learning contexts would need to anticipate issues, find missing information and solve issues that may arise while they solve a problem because of its open-ended nature. Students may also need to acquire new skills, implement their own solutions and evaluate their results recursively when they encounter problems which they have insufficient knowledge of. Informal learning contexts may require more motivation compared to formal learning contexts because it is more difficult for students to evaluate the correctness of their work and gauge how much effort or time they still need to spend before solving a problem. Apart from the differences identified by Zimmerman and Campillo, students may also do other non learning goal-related yet equally important tasks, less-important tasks or entertainment-related tasks. The addition of all these tasks on top of the learning task further increases students' cognitive load which they need to overcome to achieve their learning goal.

3.2 Learning Management

Despite the challenges that students encounter while learning, many of them exhibit proactive learning behavior in trying to accomplish their goals. These depict self-regulated learning behavior, wherein self-regulation is described as the self-generation of thoughts, feelings and actions that are planned and cyclically adapted for the attainment of personal goals [41]. Models of self-regulation can be used to help explain the reasons behind students' actions when they learn in environments that require self-initiative and self-direction [43]. In this research, we used Zimmerman's model of self-regulation [13, 42] to explain students' behavior in self-initiated learning contexts. The model consists of three cyclic processes namely the *forethought phase*, the *performance phase* and the *self-reflection phase* presented in Figure 3.1.

Forethought processes are categorized into task analysis and self-motivation belief processes. Task analysis processes help define the intended outcomes of the students' actions and identify which activities will be used to better achieve the goal. Self-motivational beliefs describe the factors that affect students' drive to learn such as belief in their abilities to accomplish the learning goal, their expected outcomes after accomplishing the learning goal, their interest in the learning goal and activities needed to accomplish it and whether they are interested in simply accomplishing the task or the experience they get from performing activities to accomplish the task.

Performance processes are grouped into self-control and self-observation processes. Appropriate self-control processes can be applied depending on the activity being performed in order to help students stay on track or improve their performance. Self-observation processes involve keeping track of previously performed activities and their outcomes to help identify the best activity to perform next or to track the current progress. The self-reflection process has two classes namely, self-judgement and self-reaction. Self-judgment involves students' self-evaluation of their learning outcomes by comparing it with their expected outcomes, their previous performance or the perfor-

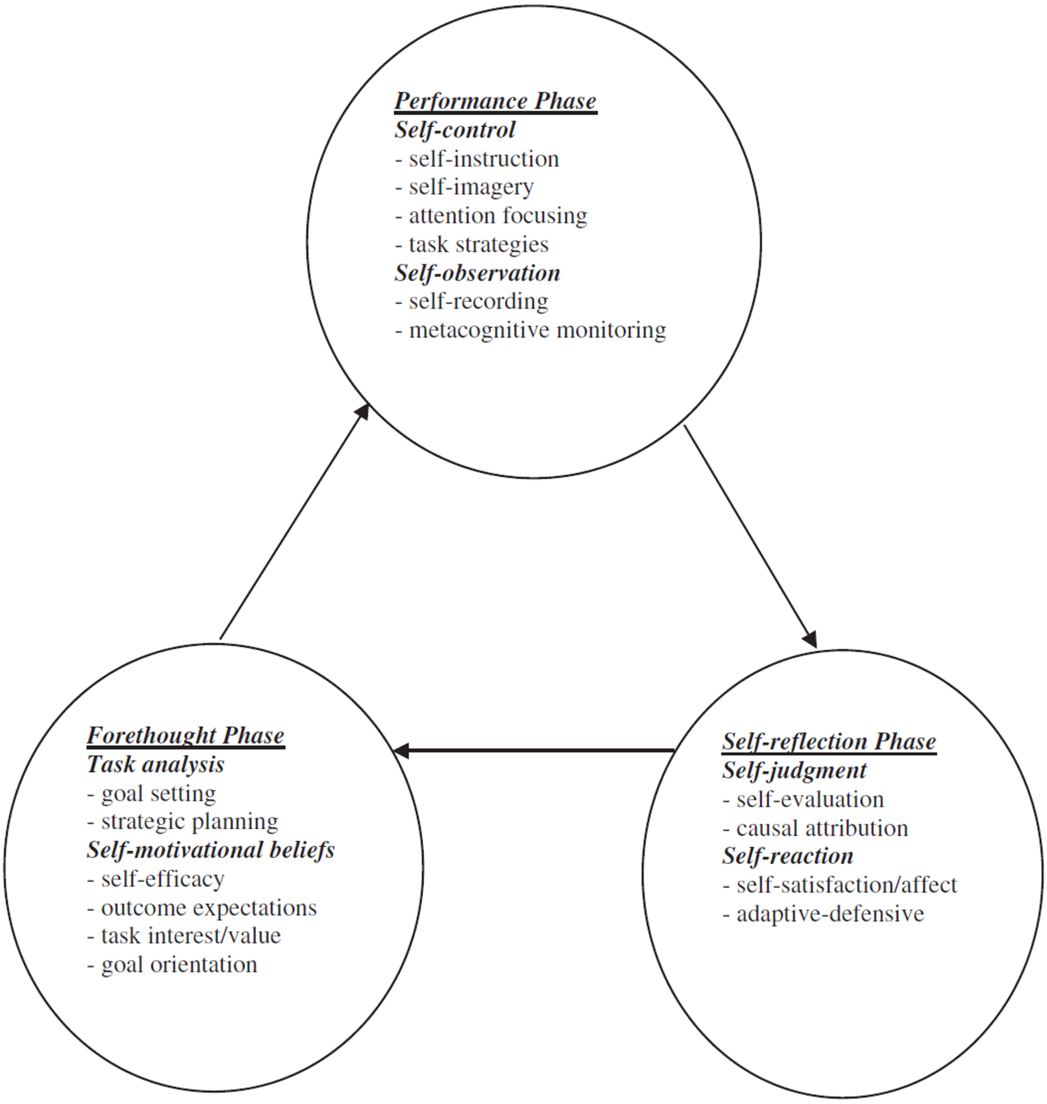


Figure 3.1: Zimmerman's three phases and subprocesses of academic self-regulation [13, 42]

mance of others and attributing causes to these outcomes such as their lack of ability or using a poor learning strategy. Results of self-judgements affect students' satisfaction and affective states which cause them to resort to defensive inferences (e.g., helplessness, procrastination, task avoidance, cognitive disengagement and apathy) or to adaptive inferences wherein students apply new solutions that may be more effective in achieving their learning goal.

Less self-regulated learners do not learn as well as self-regulated learners because they experience difficulty implementing SRL processes such as goal setting and planning [7], monitoring progress [4, 40], calibrating and evaluating performance [9, 30, 39, 38, 40], selecting appropriate strategies for given situations [16] and difficulty incorporating feedback into future behavior [16]. Although there is a need to help students address all these issues, for this research, we only focused on helping students evaluate their learning behavior.

Two of the reasons why students fail to evaluate their learning behavior correctly are deficiencies in calibrating their learning outcomes and calibrating their learning strategies [39]. Students are generally overconfident such that their perceived learning outcomes are higher than their actual learning outcomes. Similarly, at the end of a learning session, students' perception of the frequency and types of learning strategies they implemented are more than what they actually did. In effect, students are not able to identify which learning strategy was effective and how effective it was so they can not correctly adapt their behavior.

3.3 Self-reflection Features

Students' decisions for prolonging an activity or shifting to another activity are based on the features they consider during self-reflection. According to Zimmerman's SRL model, activity adaption is influenced by students' evaluation of the task's effectiveness and their satisfaction or affective experience while performing the task.

D'Mello and Graesser also highlighted the importance of affect in their model of affect dynamics during learning [14] which explains relationships between students' emotions

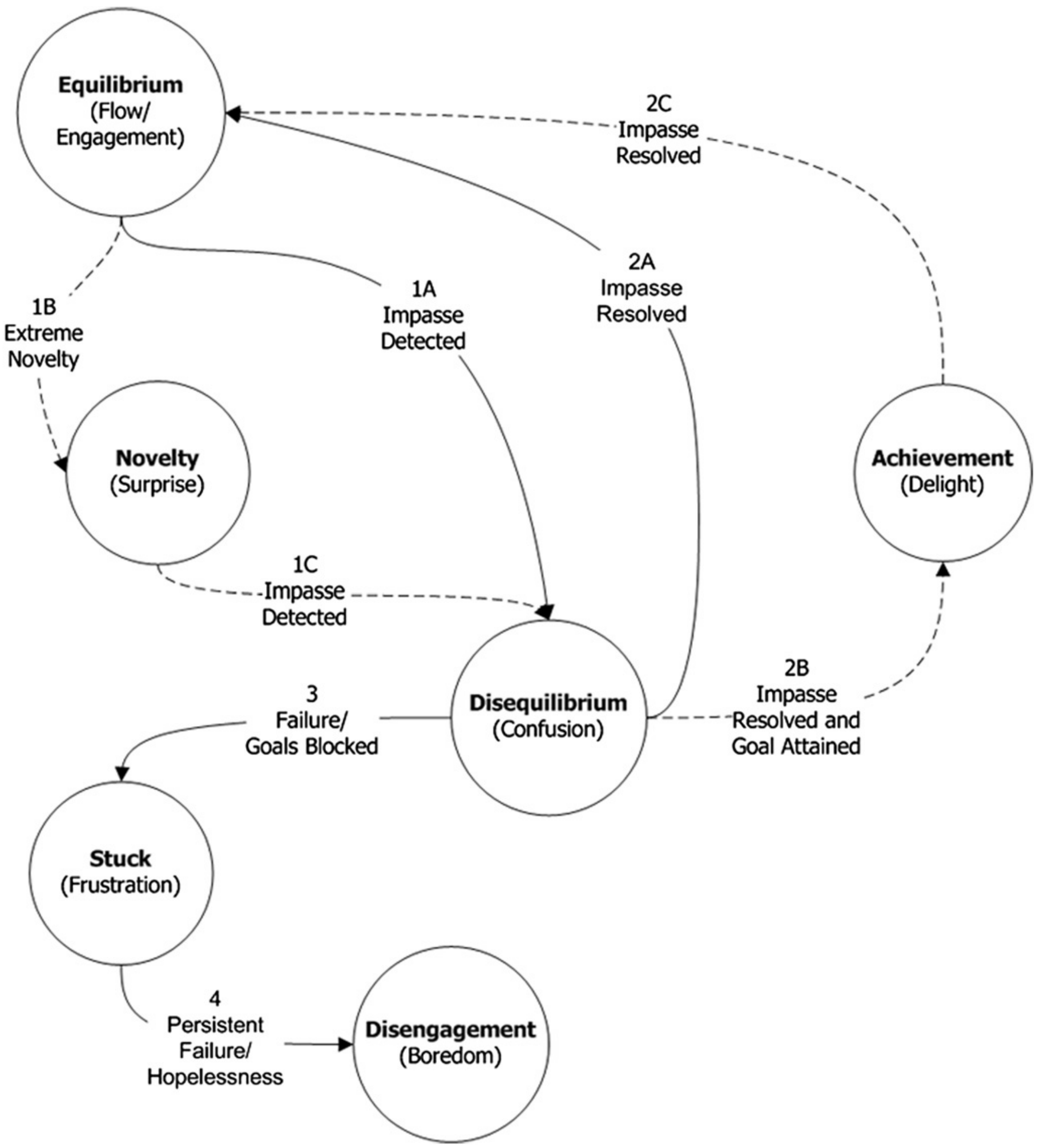


Figure 3.2: D'Mello and Graesser's model of affect dynamics during learning [14]

and events that occur while learning. Although their model, shown in Figure 3.2, focuses on events that cause changes in students' emotions, the model also indicates points wherein students may need to decide if they should either continue or adapt their current learning activity. For example, whenever students encounter impasses (i.e., inability to progress in the learning task because of lack of knowledge or misconceptions in knowledge) they become confused so they need to decide if they should continue performing the activity causing the confusion (e.g., reading lecture notes) or shift to another activity (e.g., read supplementary materials or seek help).

The affective states used in the model consist of engagement, surprise, delight, confusion, frustration and boredom which were commonly used by research looking into student learning while using computer-based learning environments [6, 10, 14, 15]. The neutral affective state is commonly added to handle special cases wherein students experience other emotions outside the set.

3.4 Learning Behavior Evaluation

Most learning-related research use learning gains to evaluate learning performance. However, learning gains may not always be the best measure for evaluating students' learning behavior in self-initiated learning scenarios. This is because it is possible, for example, that students may only partially achieve their learning goal, but they are able to discover ways to enjoy and become more engaged and motivated in their activities. The opposite may also happen wherein a student achieves the learning goal, but the amount of effort and stress leads him/her to become less motivated to continue learning in future learning tasks. It is also possible that in this situation, the student learns skills required for achieving the specific learning goals but doesn't invest time learning other related skills that would have been useful for solving other related problems in future learning sessions. Thus, in this work, we used motivation as a measure of performance instead of learning gains because we want to help students engage in activities that encourage them to continue learning and makes the learning task more meaningful to them. Motivation is an essential element in self-initiated learning and learning gains will not really mean much if the student is not motivated to initiate a learning activity.

In the context of learning environments, motivation can be encouraged by letting students engage in activities that promote *attention* to the activity, *relevance* to learning goals, *confidence* in achieving goals and *satisfaction* which are the elements of Keller's ARCS motivation model [20]. Attention refers to students' level of interest towards an activity, relevance refers to the usefulness of the activity to the current goal and possible future goals, confidence refers to students' perceptions of their capability to accomplish the activity and satisfaction refers to students' feelings of achievement or rewards they will gain after accomplishing the activity.

In a self-initiated learning scenario wherein it is the students who control the activities they perform, the ARCS motivation model can be used to instead measure students' level of motivation after engaging in activities they selected. This measurement can then be used to describe the effectiveness of activities wherein activities that lead to higher motivation will be preferred over those that do not.

According to the self-determination theory, motivation may either be perceived as having an internal or external locus of causality [11, 12, 33]. Autonomous behavior is controlled by an internal locus of causality (i.e., intrinsic motivation) such that actions are performed because they are important to the person. On the other hand, controlled behaviors are controlled by an external locus of causality (i.e., extrinsic motivation) such that actions are performed because of interpersonal demands such as satisfying the expectations of other people. Depending on students' locus of causality similar situations may have different effects on students' motivation. For example, it is possible for students who are intrinsically motivated to become more engaged when they encounter situations wherein they need to learn new skills compared to extrinsically motivated students.

3.5 Supplementing the SRL Process in Self-initiated Learning Scenarios

Our proposed methodology illustrated in Figure 3.3, assumes that students cycle through the three SRL processes described by Zimmerman within a learning session. We hypothesize that we can help students make better assessments of their performance and recall their learning strategies better by asking them to engage in a retrospection phase at the end of each learning session.

In the retrospection phase, students will be asked to recall what transpired over their learning session, evaluate the short term and long term effects of their activities and contrast the utility of different activities in a given situation. Students may need to use some tools to help them recall their learning session because relying on memory alone has been shown to be ineffective. In this research, we used desktop and webcam

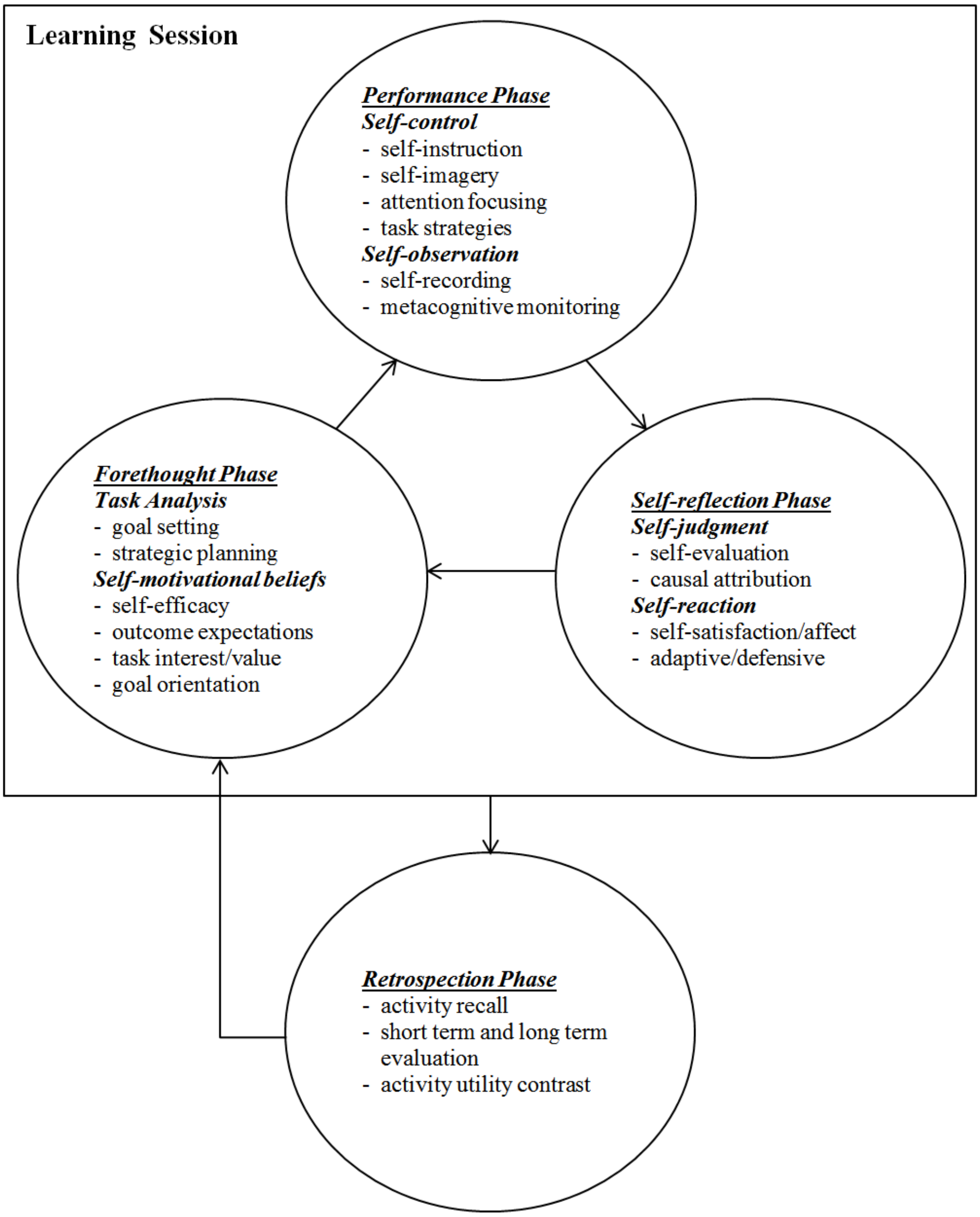


Figure 3.3: Proposed methodology for supplementing the SRL process

screenshot replays so students can see exactly what transpired over the learning session at a fine grained level. Evaluating learning behavior after the learning session has the benefit of allowing students not only to evaluate the immediate effects of activities they performed but also to observe its long term effects thereby leading to possibly more accurate evaluations. Lastly, students will be asked to contrast the use of different possible activities in a given situation (i.e., described by self-reflection features) to help them reflect further as well as identify other possibly more effective strategies.

Students can use the information they gained after the retrospection phase in succeeding learning sessions when they plan their strategies in the forethought phase, select actions and identify learning aspects to monitor in the performance phase and make evaluations in the self-reflection phase.

Chapter 4

Supporting SRL Processes in Self-initiated Learning Scenarios

In this chapter we discuss the development of a tool which implemented our proposed supplementary methodology and the data collection process we followed to gather results from students who received support through using the tool.

4.1 Sidekick

Sidekick is a learning support tool that we developed to help students analyze and evaluate their learning behavior so they can make better judgments when they select actions in future learning sessions. Sidekick is composed of three incremental stages illustrated in Figure 4.1, namely the *interaction stage*, the *analysis stage* and the *evaluation stage*.

4.1.1 Interaction Stage

The interaction stage involves both the forethought and performance phases in the SRL process. The goal of this stage is to encourage students to define an initial plan for the learning session, to record students' interactions within the learning session and to record desktop and webcam screenshots which will be used to help them recall what transpired during the learning session in the analysis and evaluation stages.

The first time students use the software, they are asked to create an account to get their profile consisting of their name, login information, age, gender, course enrolled in when they participated in the experiment, degree and year level. (see Figure 4.2(b)).

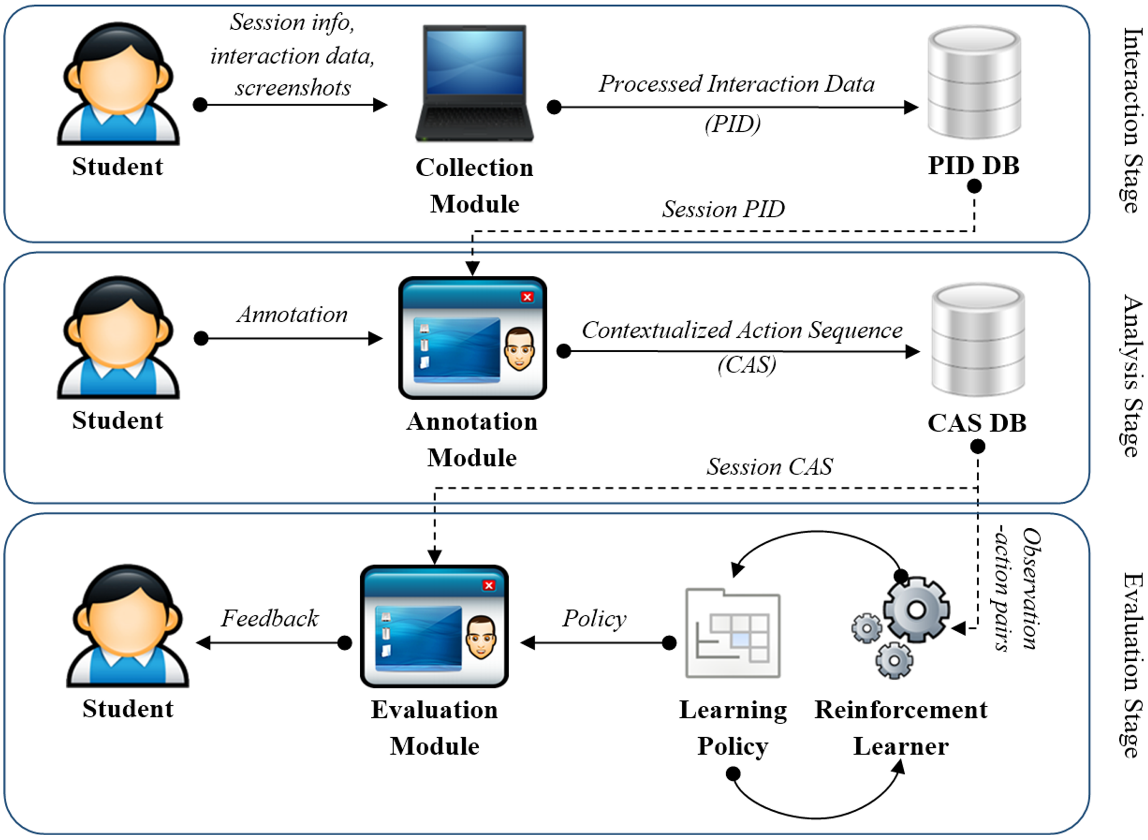


Figure 4.1: Architectural framework of Sidekick

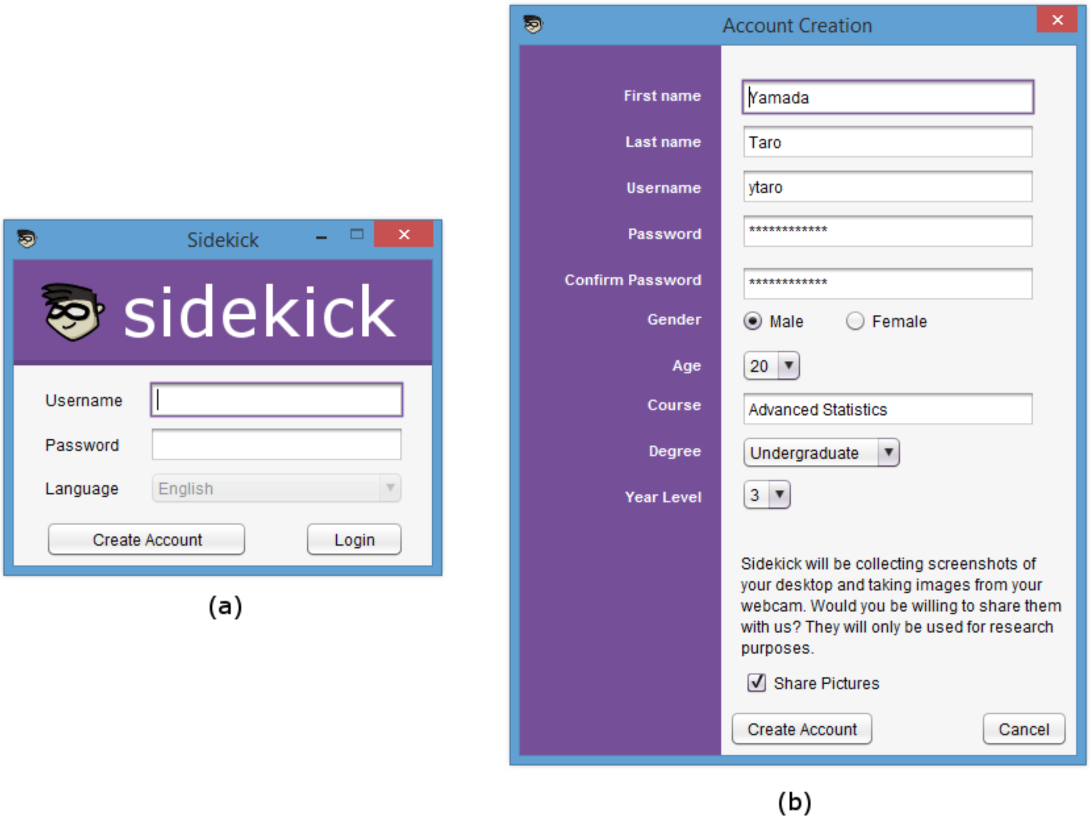


Figure 4.2: Screenshots of Sidekick's (a) login screen and (b) account creation screen

Students are then asked to answer a modified version of Black and Deci's Self-regulated Questionnaire for learning [8] which measures their level of autonomous and controlled behavior. The questionnaire was modified to fit the type of course that students were enrolled in and is listed in Appendix B.1. Students' profiles and their locus of causality can provide information regarding individual differences that can help explain their behavior.

After students provide their profile and at the beginning of every learning session, students are asked to think about their current learning task and answer questions about their perceptions of the task's importance, urgency, relevance and complexity using a 4-point scale (see Appendix B.2). Students' answers to these questions provide additional context when interpreting their behavior in the learning session. Students are then presented with the session management window (see Figure 4.3) where they can inform the system to start the learning session. Students can define their learning goals for the session using a simple text editor which they can update as they progress in the learning

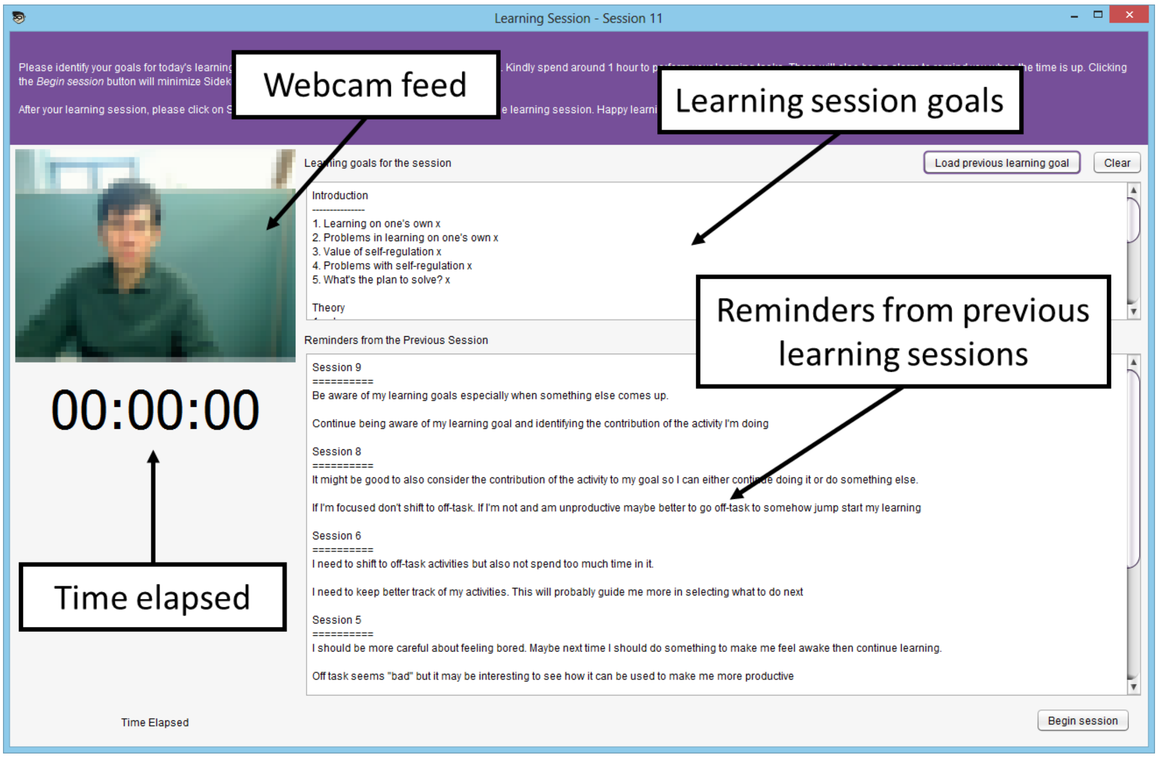


Figure 4.3: Sidekick's session management window

task. Students can also load their previous learning goals whenever they perform tasks that span more than one learning session. The window shows reminders based on their reflections from previous learning sessions so they get tips on how to go about their learning. Students' reflections will be discussed in more detail in the evaluation stage. The webcam feed shown on the window helps students check if the webcam is focused properly and the timer helps students keep track of how long they have been learning.

As soon as the student starts the session, the collection module starts logging interaction data and takes webcam and desktop screenshots every second. The screenshots are primarily used for facilitating the annotation process which will be discussed further in the analysis stage. The interaction data recorded by the system includes the filename of the currently running application, the title of the running application's window, the list of background applications, the number of key presses, mouse movement (i.e., the number of pixels and direction of the movement), the number of mouse clicks, the direction and distance moved by the mouse wheel and the timestamp. The collection module synchronizes data according to its timestamps, generates a single processed interaction data (PID) instance per second and stores it in the PID database.

4.1.2 Analysis Stage

The analysis stage encourages students to engage in the activity recall and short term and long term evaluation processes proposed in the retrospection phase of our methodology. The purpose of this stage is to help students recall in a finer grained detail what transpired during the learning session and and also observe the immediate and long term effects of their activities. The features which students are asked to provide are based on the self-reflection features discussed in sub section 3.3.

The stage begins by asking students to identify the first activity they performed and indicate its duration by clicking and dragging the mouse on the given time line as shown in Figure 4.4. The position of the mouse on the timeline corresponds to a particular timestamp during the learning session such that moving the mouse updates the webcam and desktop screenshots so students can see what they did at that point in time and accurately specify the activity's duration. This process more importantly addresses the problem of students' low calibration of task activities by showing them exactly what happened whenever they recall their activities.

Students indicate the activity they performed by choosing from a set of 11 pre-defined activities which best describe what they did. Pre-defined activities were used because we observed in our initial experiment that students performed similar activities but in slightly different ways. For example, students could read information from a webpage or read the same information from a print out. There are also subtle differences in activities performed such as using Google Chrome or Mozilla Firefox to browse information. Using activity categories also makes the data easier to interpret and less tasking for students to annotate. The pre-defined activities were based on research that investigated students' learning tasks [23], research that used activity categories within a learning system [3, 21], interaction data from initial data and an analysis of the domain our subjects were learning in. The 11 categories we identified together with their descriptions are presented below.

1. Make a learning plan - involves identifying, ordering and strategizing what tasks

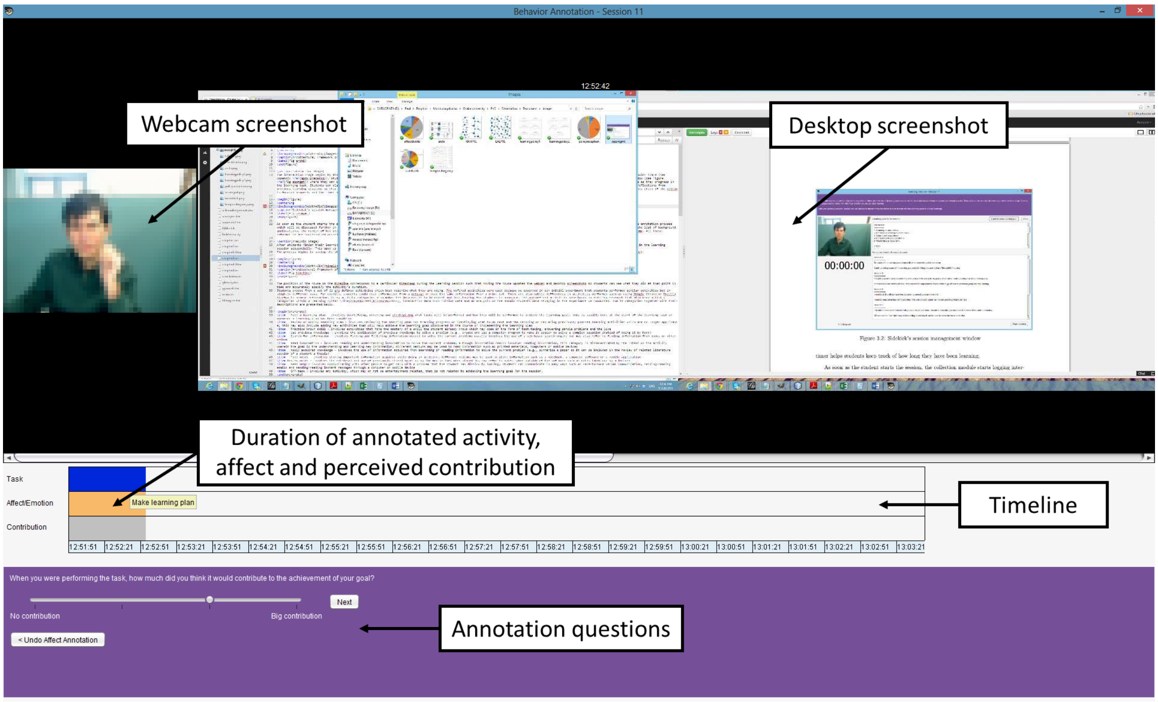


Figure 4.4: Screenshot of Sidekick's annotation interface

will be performed and how they will be performed to achieve the learning goal; this is usually done at the start of the learning task or whenever a learning plan has been completed

2. Review or modify learning plan - involves reviewing the learning plan for tracking progress or identifying what to do next and the removing or replacing previously planned learning activities which are no longer applicable; this may also include adding new activities that will help achieve the learning goal discovered in the course of implementing the learning plan

3. Practice known skill - involves activities that hone the mastery of a skill the student already knows which may come in the form of test-taking, answering sample problems and the like

4. Use previous knowledge - involves the application of previous knowledge to solve a problem (e.g., create and use a computer program to make it easier to solve a complex equation instead of doing it by hand)

5. Search for information - involves finding and filtering information needed to solve the current problem; usually involves the use of a web-based search engine but may also refer to finding information from books or other medium

6. Read information - involves reading and understanding information to solve the current problem; although information search involves reading information, this category is differentiated by the intent of the activity wherein the goal is the understanding and learning new information; different mediums may be used to read information such as printed materials, computers or mobile devices

7. Apply acquired knowledge - involves the use of information acquired from searching or reading information to solve the current problem (e.g., summarize a paper so it can be included in the review of related literature section of a student's thesis)

8. Take notes - involves storing important information acquired while doing an activity; different mediums may be used to store information such as a notebook, a computer software or a mobile application

9. Review notes - involves the retrieval and use of previously stored notes using the medium they were stored in; may refer to notes taken outside of the software such as notes taken during a lecture

10. Seek help - involves communicating with other people to get help with a problem that the student has difficulty solving; students can communicate in many ways such as face-to-face verbal communication, sending/reading emails and sending/reading instant messages through a computer or mobile device

11. Off-task - involves any activity, which may or not be entertainment related, that is not related to achieving the learning goal for the session.

Although off-task activities are not necessarily learning-related, we also keep track of them because the learning environment we consider gives students complete freedom over their activities. Research has also shown that off-task activities do not always serve as distractions because they may help alleviate stress and negative emotions [19, 35]. Observing transitions between learning and off-task activities may help describe cases wherein learning suffers or benefits from off-task activities.

The activities annotated by students are not bound by any software or limited to those done on the computer only like most existing research. The webcam screenshots help students to recall activities even if they were done outside of the computer.

After annotating the activity they performed, students are asked to describe their affective state while performing the activity. They are asked to select from delight, engagement, confusion, boredom, frustration, surprise or neutral which are emotions commonly experienced when learning [6, 10, 14, 15]. The interface allows students to indicate a sequence of affective states to handle cases wherein their affective states change over the course of performing the activity.

Lastly, students are asked to identify how much contribution they thought the activity had to their learning goal at the time when they performed it. This retrospective process allows students make immediate or short term evaluations about the activity. Students specified contribution using a 4-point scale ranging from no contribution to high contribution. This entire process is then repeated for the second activity until the last activity they performed in the learning session. While going through all the activities in the learning session sequentially, it will be possible for students to see the long term effects of their activities as well. Students' annotations are synchronized and attached to the PID which is then stored in sequence, called the contextualized action sequence (CAS) for the session, and is stored in the CAS database.

Although self-reports done after an activity are difficult to do because of the time that has elapsed, the interface will make it easier for students to observe their behavior because they can see the activities they performed, how they performed these activities and the sequence of their activities, thereby providing more contextual information. The retrospective self-reporting approach also minimizes cognitive load compared to asking students to do self-reports while learning and also encourages them to reflect on their activities at a finer grained detail which they might not do if only the timeline was presented.

The sequential annotation process was observed to be at least two times faster compared to when students were asked to freely annotate their learning session in the first version of the system.

4.1.3 Evaluation Stage

The evaluation stages encourages students to contrast two or more activities given a single situation. The purpose of the stage is to encourage students to reflect on factors that may make an activity better than another so they can make better decisions in future learning sessions based on their realizations.

One issue in behavior evaluation is that going over each activity doubles the effort done in annotation and many of those activity transitions happen repeatedly throughout the learning session. Moreover, some comparisons may be trivial if students already know the most effective activity in a given situation or when students know that some activities will surely not work in a given situation. Thus, it would be better for students to evaluate only the instances wherein they performed activities that were either ineffective or when they tried new activities that were effective so they can learn from it and decide to retain the behavior or adapt a new one.

We automated the identification of effective and ineffective activities using reinforcement learning (RL), which deals with the identification of rules for selecting the best action to take in a given state that will lead to the highest long term (i.e., cumulative) reward [37]. In the context of self-initiated learning scenarios, the goal would be to find the best activity to perform in a given situation that will lead to higher motivation in the long term.

As we have discussed in sub section 3.4, we consider activities effective when they lead students to become motivated. After the analysis stage, students will be asked questions regarding their perceived levels of attention, relevance, confidence and satisfaction using a 4-point scale (see Appendix B.4). The average of their four answers will be used as the cumulative reward value so that it favors activities that lead to a good balance between the four elements.

We identified effective activities from a student's historical learning behavior (i.e., contextualized action sequences) using profit sharing, a model-free RL approach that is capable of converging in domains that do not satisfy the Markovian property [2]. We decided to use this approach primarily because we deal with human behavior in a non-deterministic and uncontrolled environment and because its mechanism allows it to learn effective, yet sometimes non-optimal, policies quickly. Profit sharing takes as input a sequence of observation-action pairs (O_t, A_t), which means performing action A_t when O_t is observed. In our case, O_t refers to the state a student is in described by the student's activity, affective state and contribution annotations together with the duration of the activity. Activities performed for less than five minutes are considered short, activities performed between five to 10 minutes are considered medium and anything more than ten minutes are considered long. An episode n consists of a finite sequence of observation action pairs wherein the entire sequence is awarded the reward R based on the average of the student's ARCS ratings. After students perform annotation and give their ARCS rating, the CAS for the current session is converted into a series of observation-action pairs then the weights of the corresponding rule is updated using Eq. 4.1, where $W_n(O_t, A_t)$ refers to the current weight of the observation-action pair. $f(R_T, t)$ is a credit assignment function shown in Eq. 4.2, with t being the rule's position relative to the end of the episode, T. Note that it is possible for a rule's weight to be updated more than once if it appears more than once in a sequence. The set of all rules and their corresponding weights is called a policy. In profit sharing, a policy is rational or guaranteed to converge to a solution when the credit assignment function satisfies the rationality theorem presented in Eq. 4.3, with L being the number of possible actions in a state.

$$W_{n+1} \leftarrow W_n(O_t, A_t) + f(R_n^T, t) \tag{4.1}$$

$$f(R_t, t) = R\left(\frac{1}{L}\right)^{T-t} \tag{4.2}$$

$$\forall t = 1, 2, 3 \cdots, T. \quad L \sum_{j=0}^{t} f(R, j) < f(R, t) \tag{4.3}$$

Figure 4.5 illustrates an example of the the iterative process of the profit sharing algorithm wherein in the first state, O_t, the student felt engaged while making a learning plan time which the student felt had low contribution to the learning goal. After a short time, the student decided to perform action A_t, a search information activity. This changed the students' state to a search information state which caused the student to be confused and was considered to have a medium contribution to the learning goal. After a medium amount of time the student shifted to a seek help activity then continued to shift between different activities and states in the same way as previous transitions. The last activity the student performed was the apply information activity which made him/her feel delighted and was considered to have high contribution to the learning goal. After a long time, the student ended the learning session which he/she rated to have a relatively high performance value relative to the ARCS scale. This reward value is then propagated backward to each state in the session using the weight update function (Eq. 4.1).

Table 4.1 shows an example of a learning policy that may be generated by the example. In this representation, the policy can be interpreted from left to right. In the first rule of the policy for example, this could mean that when a student is feeling engaged while making a learning plan for a short time which he/she interprets as an unimportant activity, the student would benefit more when he/she searches for information according

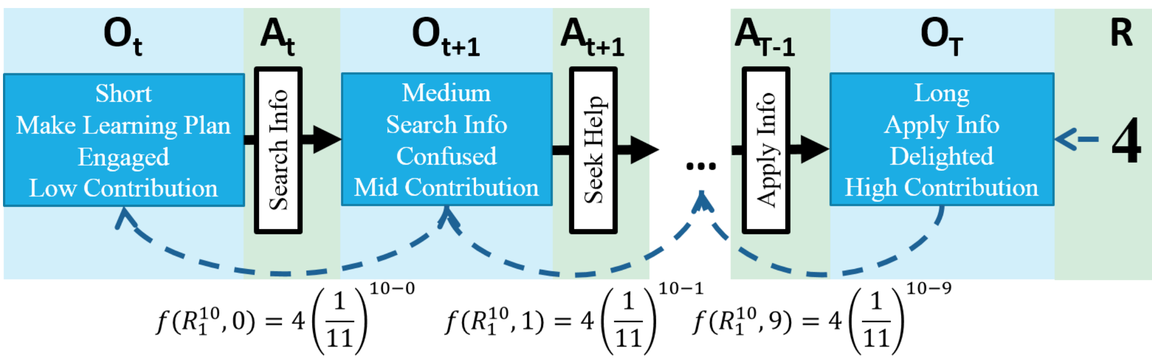


Figure 4.5: Updating observation-action pair weights using the profit sharing algorithm

Table 4.1: Sample policy that can be generated by profit sharing

	Action (Activity)			
Observation (State)	Search Info	Seek Help	Off-task	...
Short, Make Learning Plan, Engaged, Low Contribution	0.0346	0.0007	0.0000	...
Medium, Make Learning Plan, Confused, Low Contribution	0.1002	0.2544	0.0001	...
Medium, Seek Help, Delighted, High Contribution	0.0346	0.0007	0.0000	...
...	...	...	...	...

to the learning goals compared to seeking help or going off task. In the second rule of the policy, it shows that in this state the student would benefit more from seeking help rather than searching for information or going off task. This table is only a subset of a policy wherein policies may contain the combination of all possible observation and action pairs at the most. The size of the policy would be dependent on the states students experience and the activities they perform.

Although the weights of rules in the learning policy change over time, the current policy can be used as a reference to compare the current learning session and give feedback to the student. The rules with their corresponding utilities should first be filtered before they are used as feedback. Each rule found in the student's current learning episode can be compared to the rules in the learning policy and provide relevant feedback. The pseudo code presented below describes how three types of feedback can be given to the student.

Initialize set of weighted rules X

Copy old policy P into P'

For each (O_t, A_t) in the current learning episode

  Update $W(O_t, A_t)$ in P' using Eq. 4.1

  For each (O_p, A_p) in policy P

    If $O_t = O_{p,i}$

      Add $W(O_{p,i}, A_{p,i})$ into X

    End

End

End

For each (O_t, A_t) in the current learning episode

If (O_t, A_t) not in X

Unknown utility

Else if (O_t, A_t) not in P

If $W(O_t, A_t) < max(W(O_{p,i'}, A_{p,i'}))$ in X

Inform student that $A_{p,i'} > A_t$

Else

Inform student that $A_t > A_{p,i'}$

End

Else

If $A_t <> A_{p,i'}$ where $max(W(O_{p,i'}, A_{p,i'}))$ in X

Inform student that $A_{p,i'} > A_t$

End

End

End

The first type of feedback is given when students perform an action with a lower value based on the policy wherein the system asks the student if he/she thinks that the optimal action is a better option to take. In the second type of feedback, if the student performs an action which is not in the policy but has a lower value than the optimal action in the policy, the student is asked if he/she thinks that the optimal action is a better action to take. Lastly, if the student performs an action which isn't in the policy but has a higher value than the optimal action, the student is again asked if he/she thinks that the new action is the optimal action to take. The purpose of asking these questions is to encourage the student to re-evaluate his/her actions. This process may help the student identify the best action to perform in the situation presented. Whenever a student performs the optimal action according to the policy, feedback is no longer given because it is assumed that the student already knows this and is the reason

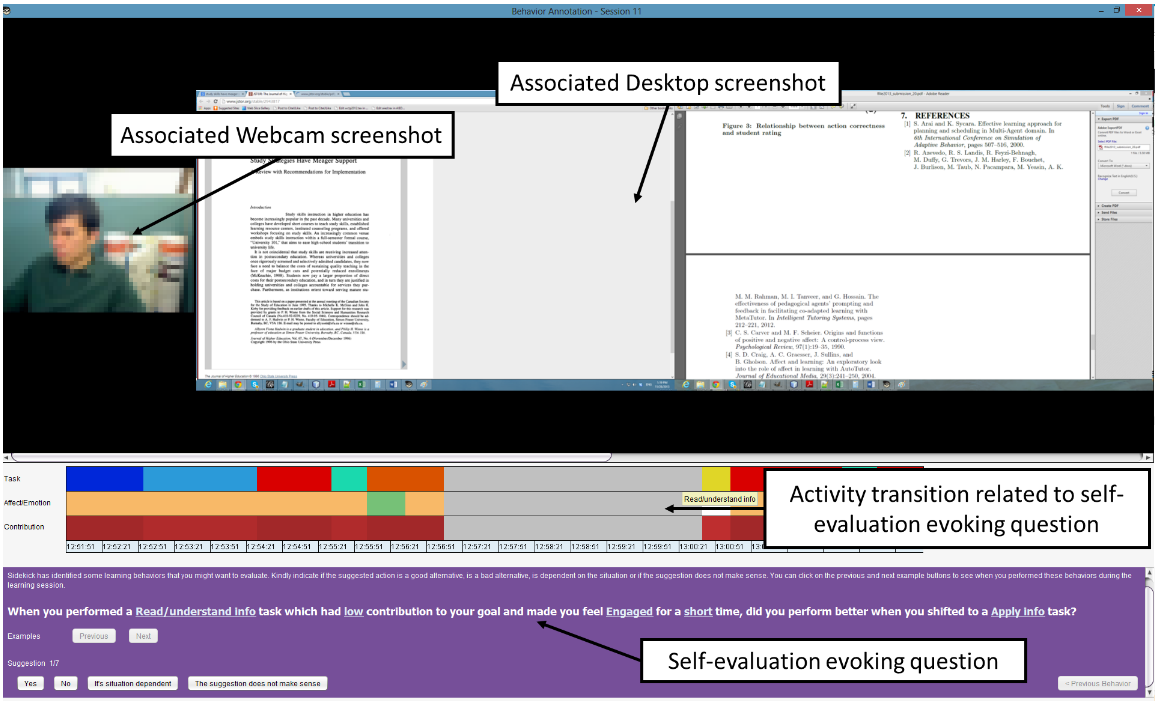


Figure 4.6: Screenshot of Sidekick asking students to evaluate their learning behavior

why the action was selected.

The actual questions shown to the student are generated using a template (see Appendix B.3). Whenever questions are presented, the instances in the learning session wherein the student performed such an activity transition are shown to the student using the timeline as seen in Figure 4.6. When available, the student can look at more than one example wherein he/she performed such a transition. Desktop and webcam screenshots are used to provide additional context and help students re-evaluate better. At this point, students can clearly see and compare which activity would have helped them better because they have also seen the long-term effects of their activities. Every time students are shown the feedback, they are also asked to indicate the correctness of the system's suggestion by indicating if it is right, wrong, dependent on the situation or if it doesn't make sense.

Every time students are given feedback regarding their choice of actions, students are evoked to contrast both activities thus inherently making them evaluate the situation. With the help of this methodology, there will be a lesser chance of calibration error because the student is able to review and see actual examples of the activities they performed and they can contextualize their evaluations with actual examples of such cases.

The last step in using the software involves asking students to write down realizations from their learning activity and use of the software. Specifically, they are asked if they discovered anything about their learning behavior and if they feel there is a need to change their behavior (see Appending B.5). This process makes their evaluation more concrete and the changes in behavior that they write down are stored so that they can be shown as reminders in the session management window of the interaction stage in succeeding learning sessions. The use of personal reminders may help students apply these behavior changes because the suggestions and reminders come from their own personal experience.

The continuous reflection and re-evaluation processes from the three stages in using the software will help students find the best activity to perform in given situations incrementally wherein as they learn more with the system, they may also find better ways to become more motivated to learn.

4.2 Data Collection Methodology

Our proposed methodology was tested by asking students to use the Sidekick tool and observe the effects of adding the retrospection phase into their learning task. The methodology was tested on an uncontrolled environment with the participation of undergraduate students taking an Advanced Statistics class at De La Salle University, Manila, Philippines. Students were given points in the course they were enrolled in as an incentive for participating.

All students attended a 30 minute presentation about Sidekick including its goals, which is to help them understand and improve their learning behavior. Students were asked to use the software whenever they did anything related to their course such as when they did homework, projects or studied for quizzes and exams. They were told that they could use the software anytime and anywhere they wanted. Students were asked to complete 10 one-hour learning sessions in a span of four weeks which coincided with their first major quiz for the course.

The software and its usage was also explained to the students so they would already be familiar with how to use it and what to expect when they use it. The different modules were explained to the students as well as the descriptions of the different annotations they would provide such as activities, affective states and contribution ratings.

Students were reassured that they could select or filter the data that was collected especially the desktop and webcam screenshots which may have been taken in personal environments (e.g., dorm rooms or houses). Students were asked to answer a privacy agreement form and were also reassured that their grades would not be affected by the activities they performed while using the software. Students were told that no information regarding their learning behavior would be shared with their professor except how many times they used the tool. After providing students with the necessary information about the experiment, their professor explained the details of the point system for participating in the experiment.

Chapter 5

Results and Analysis

5.1 Student Profiles

Our experiments were conducted with two undergraduate classes handled by the same instructor. Out of 47 students, only 11 participated in the study. They were aged between 18 to 20 years old ($\bar{x} = 18.909$, $\sigma = 0.899$, $n = 11$) and five of them were female while six of them were male.

All subjects volunteered to participate in the study so it is possible that they were more concerned about their grades compared to other students. Although all volunteers were willing to participate, they had varying levels of motivation. Based on students' answers to the learning self-regulation questionnaire [8], students' relative autonomy index ranged between $[-1.229, 2.000]$ with an average of 0.291 ($\sigma = 0.885$, $n = 11$) indicating that some were intrinsically motivated while others were extrinsically motivated.

5.2 Activity Recall

Students were encouraged to recall their activities by asking them to annotate their recently concluded learning session. Students spent an average of 61.181 minutes ($\sigma = 12.624$, $n = 110$) in every learning session which was acceptable given the instructions we gave to students for them to spend around one hour learning.

Students annotated an average of 12.550 transitions ($\sigma = 13.473$, min=4, max=90, $n = 110$) in each session. Looking deeper into the data, we can see in the histogram of the number of annotated transitions per session presented in Figure 5.1, students transitioned

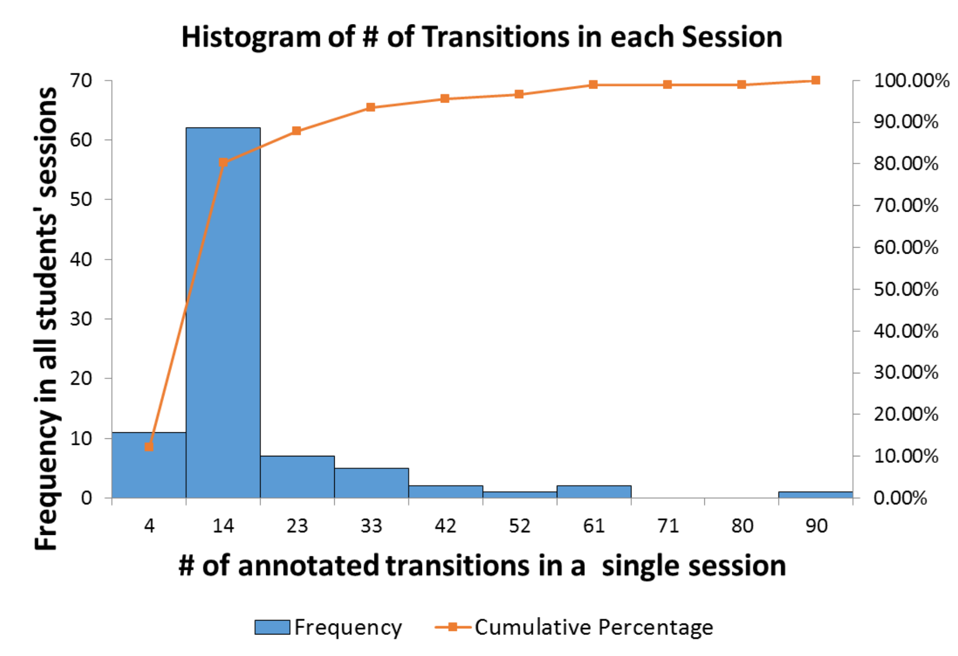


Figure 5.1: Histogram of the number of transitions students annotated for each learning session

four times within a session in 12.09% of all students' sessions and transitioned between five to 14 times within a session in 68.13% of all students' sessions. This indicates that in majority of the sessions from all students, students were able to analyze between four to 14 different learning situations which would have helped them to get a good idea of their learning behavior. The desktop and webcam screenshots would have also given students more contextual information regarding their behavior compared to simply recalling it by memory.

The time students spent performing each of the 11 activity categories were added then averaged to see which activities students commonly spent their time on. The results presented in Figure 5.2 show that among the 11 categories of activities, students spent the most time practicing their skills, reviewing their notes and performing off-task activities. Due to the nature of the course which involves mathematical computation, it is understandable why students spent most of their time practicing skills. Notes were presumably the students' major information source from their lectures which served as a primary resource and guide. Students spent more time off-task than other learning activities which mean that it is really important for students to manage this activity

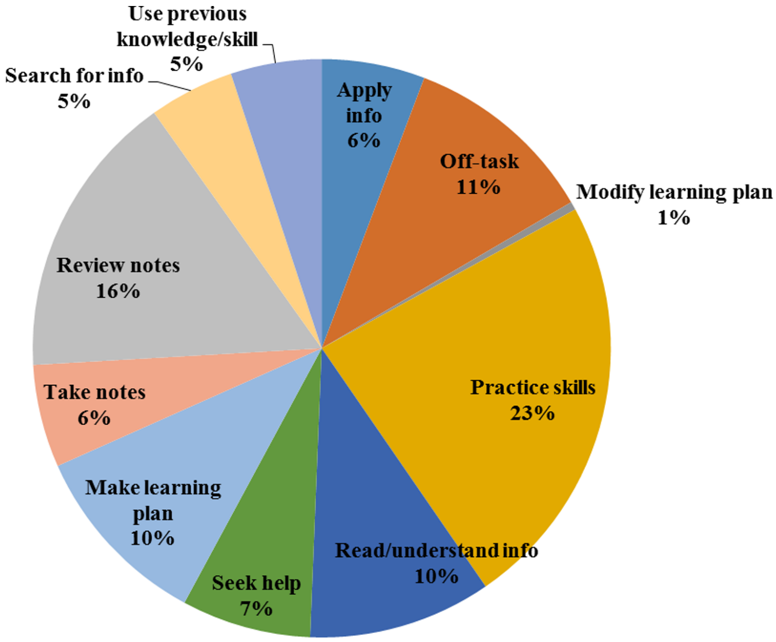


Figure 5.2: Average distribution of students' activities (based on duration)

as it seems to be prevalent in self-initiated learning scenarios. This also indicated that students did not purposely change their learning behavior during the experiment to hide their non-learning related activities so we can assume that the data we gathered was naturalistic.

The averages of each students' affective state durations were also added and averaged and is presented in Figure 5.3. Most of the time, students experienced non-negative emotions namely engaged and neutral indicating that the learning experience may have been worthwhile for them. However, it is interesting to see that students experienced more boredom than frustration or confusion. This may explain why students spent a significant amount of time in off-task activities. This may also indicate that students' choice of activities may have either been too easy so that there was no challenge, or too difficult causing them to disengage in the learning task.

A major concern for using annotation-based activity recall was the amount of time and effort students would need to exert. The results showed that students spent an average of 7.595 minutes ($\sigma = 13.511$, $n = 110$) annotating their behavior which does not seem too long relative to the benefit students could gain from observing their behavior. Furthermore, students' answers to an exit interview showed that 73% reported that the

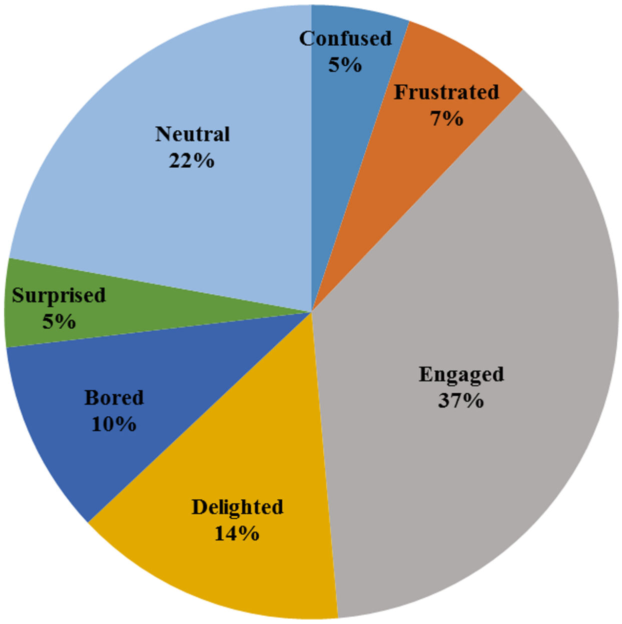


Figure 5.3: Average distribution of students' affective states (based on duration)

annotation process was easy to perform, 18% reported that it was difficult to perform and 9% reported that it was very difficult to perform. We observed from the data that students who had difficulty annotating their activities were those who usually performed many different activities in a single learning session. Although these students belonged to a minority of the group, it is still important to refine the current implementation or find other ways to evoke activity recall with lesser time and effort.

5.3 Learning Behavior Effectiveness

The effectiveness of the activities performed in a learning session were measured using students' ARCS ratings at the end of each learning session. These ratings were used to generate personalized learning policies wherein each policy consisted of rules describing the effectiveness (i.e., weight) of performing an action given a specific state. These effectiveness values changed in every learning session depending on which activities were performed and the ARCS ratings given at the end of the session.

Tables 5.1, 5.2 and 5.3 presents the policies generated incrementally by the profit sharing algorithm in the first, fifth and tenth session of an intrinsically motivated student (see Appendix A for the meanings of the activity acronyms). The observation column provides the features used to describe the state namely, the duration of the activity, the activity performed, the perceived contribution of the task and the affective state of the student when the activity was performed. The action column provides the predicted effectiveness or weight when a student would perform a particular action when the student is in a specific state. Whenever more than one action column contains a value, the column with the higher value is assumed to be the more effective action. All other columns labeled with a dash indicate that these transitions were not observed during the learning session or in previous learning sessions.

The tables show the changes in a student's learning policy over sessions based on his activities and ARCS ratings. In cases wherein a row contains only a single weighted action, for example the first row in session 10 (i.e., long, Off-task, low, Bored), it would mean that the student had only tried shifting to one activity (i.e., read information) from a given state. The student may have considered this to be the best action to perform which is why it was the only activity he performed or he simply has not tried out other possible activities from that state. In cases wherein rows contained more than one weighted action such as the sixth row (i.e., medium, Off-task, low, Bored), it indicates that the student has already tried different activities from the given state (i.e., read information and practice skill). Reading information from a bored state seemed to be more effective for the student based on the profit sharing algorithm's update function using ARCS ratings. In both examples, shifting to a read information state seemed to be a logical transition because students will benefit more from re-familiarizing themselves with the task they are supposed to perform after shifting from an off-task activity. Although this seems to be the best transition for the moment, it may still be possible for the student to find better alternatives when he tries out other activities. It is interesting to see that although the student constantly performed the same transitions, the student seemed to explore different activities when coming from an off-task state. Exploring other activities probably helped the student find a better way to get back to a learning state which also allowed the system to distinguish effective transitions.

Table 5.1: Intrinsically motivated student's learning policy generated from the 1st session

Session 1								
	Action (Activity)							
Observation (State)	MLP	SI	RI	AI	SH	OT	RN	PS
medium, Seek help, high, Engaged	-	-	-	-	-	1.5E-6	-	-
short, Apply info, low, Neutral	-	-	-	-	-	1.5E-2	-	-
short, Apply info, high, Engaged	-	-	-	-	-	1.5E+0	-	-
short, Make learning plan, low, Neutral	-	-	-	-	-	1.5E-8	-	-
short, Off-task, low, Bored	15.0E-10	-	-	15.0E-2	15.0E-8	-	-	-
short, Off-task, low, Neutral	-	-	-	15.0E-4	15.0E-6	-	-	-
short, Seek help, low, Neutral	-	-	-	-	-	1.5E-4	-	-

Table 5.2: Intrinsically motivated student's learning policy generated from the 5th session

Session 5								
	Action (Activity)							
Observation (State)	MLP	SI	RI	AI	SH	OT	RN	PS
long, Off-task, low, Bored	-	-	12.8E-2	-	-	-	-	-
long, Review notes, high, Neutral	-	-	-	-	-	35.0E-2	-	-
medium, Read/understand info, high, Neutral	-	-	-	-	3.0E-2	-	-	-
medium, Seek help, high, Confused	-	-	3.3E+0	-	-	-	-	-
medium, Seek help, high, Engaged	-	-	-	-	-	1.5E-6	-	-
short, Apply info, low, Neutral	-	-	-	-	-	1.5E-2	-	-
short, Apply info, high, Engaged	-	-	-	-	-	1.5E+0	-	-
short, Apply info, high, Neutral	-	-	-	-	32.5E-2	-	-	-
short, Make learning plan, low, Neutral	-	-	-	-	-	1.5E-8	-	-
short, Off-task, low, Bored	15.0E-10	-	-	15.0E-2	15.0E-8	-	-	-
short, Off-task, low, Neutral	-	-	-	15.0E-4	15.0E-6	-	-	-
short, Read/understand info, high, Bored	-	-	-	-	-	1.3E-2	-	-
short, Read/understand info, high, Neutral	-	-	-	-	-	1.3E+0	-	-
short, Seek help, low, Neutral	-	-	-	-	-	1.5E-4	-	-
short, Seek help, high, Confused	-	-	-	-	-	30.0E-2	-	-

Table 5.3: Intrinsically motivated student's learning policy generated from the 10th session

Session 10								
	Action (Activity)							
Observation (State)	MLP	SI	RI	AI	SH	OT	RN	PS
long, Off-task, low, Bored	-	-	12.8E-2	-	-	-	-	-
long, Off-task, high, Neutral	-	-	-	-	-	-	3.8E+0	-
long, Practice skills, very high, Engaged	-	-	-	-	-	3.3E-2	-	-
long, Review notes, high, Neutral	-	-	-	-	-	3.6E+0	-	-
long, Search for info, high, Neutral	-	-	-	-	-	32.5E-2	-	-
medium, Off-task, low, Bored	-	-	3.0E+0	-	-	-	-	32.5E-4
medium, Read/understand info, high, Neutral	-	-	-	-	3.0E-2	-	-	-
medium, Seek help, high, Confused	-	-	3.3E+0	-	-	-	-	-
medium, Seek help, high, Engaged	-	-	-	-	-	1.5E-6	-	-
short, Apply info, low, Neutral	-	-	-	-	-	1.5E-2	-	-
short, Apply info, high, Engaged	-	-	-	-	-	1.5E+0	-	-
short, Apply info, high, Neutral	-	-	-	-	32.5E-2	-	-	-
short, Make learning plan, low, Neutral	-	-	-	-	-	1.5E-8	-	-
short, Off-task, low, Bored	15.0E-10	3.3E-2	32.5E-2	15.0E-2	15.0E-8	-	-	-
short, Off-task, low, Neutral	-	-	-	15.0E-4	15.0E-6	-	3.3E+0	-
short, Read/understand info, high, Bored	-	-	-	-	-	1.3E-2	-	-
short, Read/understand info, high, Neutral	-	-	-	-	-	4.5E+0	-	-
short, Review notes, high, Bored	-	-	-	-	-	32.5E-4	-	-
short, Seek help, low, Neutral	-	-	-	-	-	1.5E-4	-	-
short, Seek help, high, Confused	-	-	-	-	-	30.0E-2	-	-

Tables 5.4, 5.5 and 5.6 presents the policies generated incrementally by the profit sharing algorithm in the first, fifth and tenth session of an extrinsically motivated student. Based on the data we collected, extrinsically motivated students seemed to shift to and from more states compared to intrinsically motivated students. They experienced more states while learning and also tried more alternative activities given a single state. This was the most likely cause of the big change in their policies given the same number of sessions as the intrinsically motivated students.

The learning policies generated for extrinsically motivated students seemed to have more information regarding which actions were better. The drawback however is that the variation of activities also meant lesser frequencies for each transition. Unlike the transitions of intrinsically motivated students which were more constant, it is highly possible that the weight values would still change until the system gets enough examples for the weights to stabilize. Also it may take students longer to understand the difference in an activity's effectiveness over another because of the number of transitions and examples that need to be taken note of.

The policies generated from extrinsically motivated students were also interesting. For example, note taking seemed to be an important activity for the student wherein it was beneficial to take down notes whenever the student had a positive outlook while performing activities that had high contribution to the goal. It was highly likely that she was able to use her notes whenever she performed other learning-goal related activities like practicing skills, searching for information and reading information as seen in the policy. Unlike intrinsically motivated students, it was also a bit uncommon for extrinsically motivated students to have a more constant rule regarding when to transition to off-task activities.

Table 5.4: Extrinsically motivated student's learning policy generated from the 1st session

Session 1								
	Action (Activity)							
Observation (State)	SI	RI	AI	PS	RN	TN	SH	OT
long, Practice skills, very high, Engaged	-	-	-	-	4.3E+0	-	-	-
medium, Practice skills, very high, Engaged	-	-	-	-	-	-	-	4.3E-2
short, Make learning plan, low, Neutral	-	-	-	-	4.3E-8	-	-	-
short, Off-task, very low, Neutral	-	-	-	42.9E-2	-	-	-	-
short, Practice skills, very high, Engaged	-	-	-	-	-	-	-	4.3E-4
short, Review notes, high, Confused	-	-	-	-	-	42.5E-8	-	-
short, Take notes, very high, Engaged	-	-	-		-	-	-	4.3E-6

Table 5.5: Extrinsically motivated student's learning policy generated from the 5th session

Session 5								
Observation (State)	SI	RI	AI	PS	RN	TN	SH	OT
long, Practice skills, very high, Engaged	-	-	-	-	4.3E+0	-	-	-
medium, Practice skills, high, Neutral	-	-	-	-	30.0E-4	-	-	-
medium, Practice skills, very high, Engaged	-	-	-	-	40.0E-12	-	4.0E-32	4.3E-2
medium, Review notes, high, Neutral	-	3.0E-2	-	-	-	-	-	-
medium, Search for info, high, Neutral	-	-	-	3.0E-4	-	-	-	-
short, Apply info, very high, Confused	-	-	-	4.0E-30	-	-	-	-
short, Apply info, very high, Engaged	-	-	-	-	-	-	-	4.0E-40
short, Make learning plan, low, Bored	-	-	-	-	-	-	-	40.0E-54
short, Make learning plan, low, Neutral	32.5E-48	-	-	-	4.3E-8	-	-	-
short, Make learning plan, high, Neutral	30.0E-6	-	-	-	-	-	-	-
short, Off-task, very low, Delighted	3.3E-26	-	-	-	-	-	-	-
short, Off-task, very low, Neutral	-	-	-	42.9E-2	-	-	-	-
short, Off-task, low, Delighted	3.3E-4	-	-	-	-	-	-	32.5E-28
short, Off-task, low, Neutral	40.0E-24	-	-	-	40.0E-6	3.3E-38	40.0E-40	3.3E-28
short, Off-task, high, Delighted	2.8E-56	-	-	-	-	-	-	-
short, Off-task, high, Neutral	27.5E-12	-	-	4.0E-46	-	-	-	-
short, Off-task, very high, Neutral	-	-	-	-	4.0E-34	-	-	-
short, Practice skills, low, Neutral	3.3E-6	-	-	-	-	-	-	-
short, Practice skills, high, Engaged	3.0E+0	-	-	-	-	-	-	-
short, Practice skills, high, Neutral	2.8E-24	2.8E-66	-	-	27.5E-72	-	-	-
short, Practice skills, very high, Confused	-	-	-	-	-	-	4.0E-16	-
short, Practice skills, very high, Engaged	4.0E-42	-	-	-	4.0E-2	-	40.0E-46	4.0E-6
short, Read/understand info, low, Confused	3.3E-30	-	-	-	-	3.3E-34	-	32.5E-46
short, Read/understand info, low, Neutral	3.3E+0	32.5E-32	-	-	-	3.3E-2	-	32.5E-40
short, Read/understand info, high, Bored	-	-	-	27.5E-84	-	-	-	-
short, Read/understand info, high, Engaged	-	-	-	-	-	-	-	27.5E-58
short, Read/understand info, high, Neutral	2.8E-8	2.8E-84	-	30.0E-2	2.8E+0	27.8E-42	-	2.8E-12
short, Read/understand info, very high, Confused	-	-	-	4.0E+0	40.0E-10	-	-	-
short, Read/understand info, very high, Delighted	-	-	-	-	4.0E-20	-	-	-
short, Read/understand info, very high, Engaged	-	-	-	-	4.0E-50	-	-	-
short, Read/understand info, very high, Neutral	-	40.0E-22	-	-	-	-	-	-
short, Review notes, low, Confused	-	-	-	-	32.5E-44	-	-	-
short, Review notes, low, Neutral	-	-	-	-	-	3.3E-42	-	-
short, Review notes, high, Confused	-	-	-	-	-	42.5E-8	-	-
short, Review notes, high, Engaged	-	27.5E-80	-	-	-	-	-	-
short, Review notes, high, Neutral	2.8E-50	27.5E-6	-	2.8E-70	-	27.5E-4	-	-
short, Review notes, very high, Confused	-	40.0E-2	-	40.0E-18	-	-	-	-
short, Review notes, very high, Engaged	-	40.0E-52	-	4.0E-12	-	40.0E-50	-	-
short, Review notes, very high, Neutral	-	4.0E-4	-	40.0E-20	-	-	-	-
short, Search for info, very low, Neutral	32.5E-26	-	-	-	-	-	-	-
short, Search for info, low, Neutral	-	32.5E-4	-	-	-	3.3E-10	-	32.5E-6
short, Search for info, high, Bored	27.5E-56	-	-	-	-	-	-	-
short, Search for info, high, Engaged	2.8E-48	-	-	-	-	-	-	-
short, Search for info, high, Neutral	27.5E-50	27.5E-2	-	27.5E-26	2.8E-10	27.5E-32	-	27.5E-78
short, Search for info, very high, Confused	-	4.0E-22	40.0E-42	-	-	-	-	-
short, Seek help, very high, Confused	-	40.0E-16	40.0E-32	-	-	-	-	-
short, Seek help, very high, Neutral	-	4.0E-44	-	4.0E-38	-	-	-	-
short, Take notes, low, Neutral	32.5E-12	32.5E-2	-	32.5E-8	-	-	-	32.5E-16
short, Take notes, high, Neutral	2.8E-2	27.5E-14	-	2.8E-72	2.8E-40	-	-	-
short, Take notes, very high, Engaged	-	-	-	4.0E-48	-	-	-	4.3E-6

Table 5.6: Extrinsically motivated student's learning policy generated from the 10th session

Session 10								
Observation (State)	SI	RI	AI	PS	RN	TN	SH	OT
long, Practice skills, high, Engaged	-	-	-	3.3E+0	-	30.0E-2	-	-
long, Practice skills, very high, Engaged	-	-	-	-	4.3E+0	-	-	-
long, Read/understand info, high, Neutral	-	-	-	-	-	-	-	30.0E-4
long, Read/understand info, very high, Engaged	-	-	-	32.5E-6	-	-	-	-
long, Search for info, high, Neutral	-	3.0E-4	-	-	-	-	-	-
medium, Practice skills, high, Neutral	-	-	-	3.0E-6	30.0E-4	-	-	-
medium, Practice skills, very high, Engaged	-	-	-	-	40.0E-12	3.3E-4	4.0E-32	-
medium, Read/understand info, high, Neutral	30.0E-6	-	-	-	3.0E-10	-	-	-
medium, Review notes, high, Neutral	-	3.0E-2	-	-	-	-	-	-
medium, Search for info, high, Neutral	-	-	-	3.0E-4	-	-	-	-
short, Apply info, very high, Confused	-	-	-	4.0E-30	-	-	-	-
short, Apply info, very high, Engaged	-	-	-	-	-	-	-	4.0E-40
short, Make learning plan, low, Bored	-	-	-	-	-	-	-	40.0E-
short, Make learning plan, low, Neutral	32.5E-48	-	-	-	4.3E-8	-	-	-
short, Make learning plan, high, Neutral	30.0E-6	-	-	-	-	-	-	-
short, Off-task, very low, Delighted	3.3E-26	-	-	-	-	-	-	-
short, Off-task, very low, Neutral	-	-	-	42.9E-2	-	-	-	-
short, Off-task, low, Delighted	3.3E-4	-	-	-	-	-	-	32.5E-28
short, Off-task, low, Neutral	40.0E-24	-	-	-	40.0E-6	3.3E-38	40.0E-40	3.3E-28
short, Off-task, high, Delighted	2.8E-56	-	-	-	-	-	-	-
short, Off-task, high, Neutral	27.5E-12	3.0E-2	-	4.0E-46	-	-	-	-
short, Off-task, very high, Neutral	-	-	-	-	4.0E-34	-	-	-
short, Practice skills, low, Neutral	3.3E-6	-	-	-	-	-	-	-
short, Practice skills, high, Bored	-	-	-	-	-	30.0E-6	-	-
short, Practice skills, high, Engaged	3.0E+0	-	-	-	-	-	-	-
short, Practice skills, high, Neutral	3.0E-4	30.0E-14	-	-	27.5E-72	-	-	-
short, Practice skills, very high, Confused	-	-	-	-	-	-	4.0E-16	-
short, Practice skills, very high, Engaged	4.0E-42	-	-	-	4.0E-2	-	40.0E-46	4.0E-6
short, Practice skills, very high, Neutral	-	3.3E-2	-	-	-	-	-	-
short, Practice skills, very high, Engaged	-	-	-	-	-	-	-	4.3E-4
short, Read/understand info, low, Confused	3.3E-30	-	-	-	-	3.3E-34	-	32.5E-46
short, Read/understand info, low, Neutral	3.3E+0	32.5E-32	-	-	-	3.3E-2	-	32.5E-40
short, Read/understand info, high, Bored	30.0E-24	-	-	27.5E-84	-	-	-	-
short, Read/understand info, high, Engaged	3.0E-12	-	-	-	-	-	-	27.5E-58
short, Read/understand info, high, Neutral	30.0E-2	2.8E-84	-	30.0E-2	2.8E+0	3.0E-2	-	2.8E-12
short, Read/understand info, very high, Confused	-	-	-	4.0E+0	40.0E-10	-	-	-
short, Read/understand info, very high, Delighted	-	-	-	-	4.0E-20	-	-	-
short, Read/understand info, very high, Engaged	-	-	-	-	4.0E-50	-	-	-
short, Read/understand info, very high, Neutral	-	40.0E-22	-	-	-	32.5E-2	-	-
short, Review notes, low, Confused	-	-	-	-	32.5E-44	-	-	-
short, Review notes, low, Neutral	-	-	-	-	-	3.3E-42	-	-
short, Review notes, high, Confused	-	-	-	-	-	42.5E-8	-	-
short, Review notes, high, Engaged	-	27.5E-80	-	-	-	-	-	-
short, Review notes, high, Neutral	30.0E-10	27.5E-6	-	3.0E-2	-	27.5E-4	-	-
short, Review notes, very high, Confused	-	40.0E-2	-	40.0E-18	-	-	-	-
short, Review notes, very high, Engaged	-	40.0E-52	-	4.0E-12	-	40.0E-50	-	-
short, Review notes, very high, Neutral	-	4.0E-4	-	40.0E-20	-	-	-	-
short, Search for info, very low, Neutral	32.5E-26	-	-	-	-	-	-	-
short, Search for info, low, Neutral	-	32.5E-4	-	-	-	3.3E-10	-	32.5E-6
short, Search for info, high, Bored	27.5E-56	-	-	-	-	-	-	-
short, Search for info, high, Engaged	2.8E-48	-	-	-	-	-	-	-
short, Search for info, high, Neutral	27.5E-50	3.3E+0	-	3.0E-14	3.0E+0	27.5E-32	-	27.5E-78
short, Search for info, very high, Confused	-	4.0E-22	40.0E-42	-	-	-	-	-
short, Seek help, very high, Confused	-	40.0E-16	40.0E-32	-	-	-	-	-
short, Seek help, very high, Neutral	-	4.0E-44	-	4.0E-38	-	-	-	-
short, Take notes, low, Neutral	32.5E-12	32.5E-2	-	32.5E-8	-	-	-	32.5E-16
short, Take notes, high, Neutral	32.8E-2	3.0E-4	-	2.8E-72	-	-	-	-
short, Take notes, very high, Engaged	-	-	-	4.0E-48	-	-	-	-
short, Take notes, very high, Neutral	-	-	-	3.3E+0	-	-	-	-
short, Take notes, very high, Engaged	-	-	-	-	-	-	-	4.3E-6

It is possible that because of the external motivation driving extrinsically motivated students, they considered off-task activities as distractions to learning and thus avoided it. Intrinsically motivated students on the other hand seem to have more defined instances when to shift to off-task activities such as when they spend a long time performing learning-related activities wherein they experience positive emotions which are indicative of success.

The rules generated in the learning policies of both intrinsically and extrinsically motivated students were both explainable and logical indicating that it was possible to identify effective learning behavior regardless of the student's locus of causality. The major difference between them was the state space covered by the learning policy and the number of examples that was needed before the weights of the rules in the policy would stabilize.

Regardless of a learning policy's accuracy, students still have control over which actions they will perform based on their own internal value systems. However, policy-based feedback was given to students after annotation to further encourage them to contrast the performance of different activities given a single state. The goal is for students to re-analyze the effective activities identified by the system so that students may consider adapting them and possibly improve their learning.

An example of the feedback generated by the policy-based feedback generator is presented in Table 5.7. Each row refers to the student's state and corresponding action ordered sequentially according to data from her 10th session. Her actions were compared to the updated policy (i.e., Table 5.6) wherein we can see that three of her actions were suboptimal. Feedback was presented to encourage her to contrast her action and the optimal action given a specific state. Her analysis would allow her to hypothesize which action would be more applicable which she can apply in succeeding learning sessions.

Table 5.7: Feedback generated for an extrinsically motivated student using the learning policy from the 10th session

Observation (State)	Student Action	Best Action	Feedback
short, Review notes, high, Neutral	Practice skills	Practice skills	
medium, Practice skills, high, Neutral	Practice skills	Review notes	Do you think it's a better idea to shift to a Review notes task instead of other kinds of tasks?
short, Practice skills, high, Bored	Take notes	Take notes	
short, Take notes, high, Neutral	Read/understand info	Read/understand info	
short, Read/understand info, high, Neutral	Review notes	Review notes	
short, Review notes, high, Neutral	Practice skills	Practice skills	
long, Practice skills, high, Engaged	Take notes	Practice skills	Do you think it's a better idea to shift to a Practice skills task instead of other kinds of tasks?
short, Take notes, high, Neutral	Review notes	Read/understand info	Do you think it's a better idea to shift to a Read/understand info task instead of other kinds of tasks?

On average, students were asked 3.790 evaluative questions per session ($\sigma = 2.388$, $n = 110$) which did not seem to require too much additional effort given the potential benefit of activity evaluation. Out of all the evaluative questions generated in the experiment, students considered its suggestions to be correct 47% of the time, correct given the right situation 41% of the time, incorrect 8% of the time and nonsensical 4% of the time. Examples of evaluative questions categorized by students' rating are presented in Table 5.8.

Evaluative questions rated by students as correct were mostly logical suggestions in improving behavior such as searching for relevant information when you are confused with what you are doing or applying information that you recently learned about to understand the concept better. Suggestions that were situationally applicable were useful in specific cases such as seeking help on what you are reviewing only when you have spent enough time understanding it first or searching for alternative sources of information only when you have given a good amount of effort understanding the current information source. Questions that were considered incorrect were usually those that seemed be counter productive or something that wasted time such as going off-task after seeking help wherein they could have continued learning or spending too much time making a learning plan instead of doing activities that could have helped achieve the learning goal. Although students considered these suggestions to be incorrect, they may actually serve as negative examples that students would avoid performing.

Although nonsensical questions were originally designed and explained to the students as a fallback for cases wherein the system gave unexpected results or errors, students classified questions under this category when they seemed unintelligent or foolish such as making a new learning plan when you have just modified the current learning plan or continuing to practice a skill despite the long amount of time you have already spent doing that. Students' negative rating of evaluative questions were usually targeted towards the questions and did not seem to be a reflection of the system's ability to generate questions. Also, regardless of the question, students were able to evaluate both effective and ineffective learning behaviors which promote evaluation. Moreover, even

Table 5.8: Sample evaluative questions asked after annotation

Student Evaluation	Question
Correct	When you perform a Practice skills task that has a high contribution to your goal and makes you feel Confused for a short amount of time, do you think its a better idea to shift to a Search for info task instead of other tasks?
Correct	When you perform a Search for info task that has an average contribution to your goal and makes you feel Neutral for a medium amount of time, do you think its a better idea to shift to an Apply Info task instead of other tasks?
Situational	When you perform a Review Notes task that has an average contribution to your goal and makes you feel Neutral for a short amount of time, do you think its a better idea to shift to a Seek Help task instead of other tasks?
Situational	When you perform a Read/Understand Info task that has a high contribution to your goal and makes you feel Confused for a short amount of time, do you think its a better idea to shift to a Search for Info task instead of other tasks?
Incorrect	When you perform a Seek Help task that has an average contribution to your goal and makes you feel Confused for a short amount of time, do you think its a better idea to shift to a Off-task task instead of other tasks?
Incorrect	When you perform a Make Learning Plan task that has a low contribution to your goal and makes you feel Frustrated for a medium amount of time, do you think its a better idea to shift to a Make Learning Plan task instead of other tasks?
Nonsensical	When you perform a Practice Skills task that has a high contribution to your goal and makes you feel Engaged for a long amount of time, do you think its a better idea to shift to a Practice Skills task instead of other tasks?
Nonsensical	When you perform a Modify Learning plan task that has an average contribution to your goal and makes you feel Neutral for a medium amount of time, do you think its a better idea to shift to a Make Learning Plan task instead of other tasks?

if the system's suggestions were incorrect it is already helpful to encourage students to self-reflect because they will eventually be able to discover a behavior's ineffectiveness as they utilize it [31].

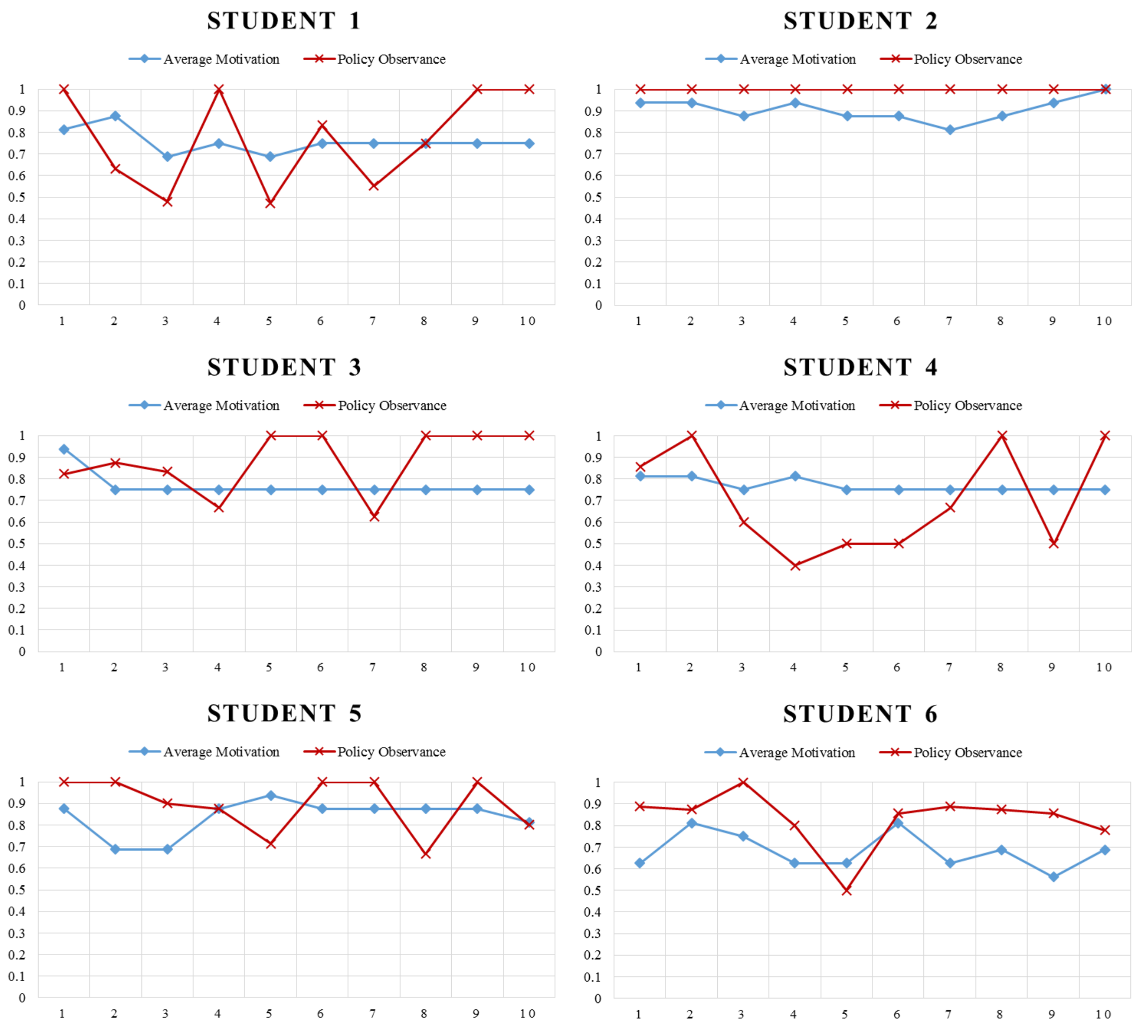
5.4 Effects of the Retrospection Phase

In this section we discuss the effects we observed from students when they performed retrospection after their learning session.

5.4.1 Activity Evaluation

Each student had a personalized learning policy based on their behavior and their motivation ratings. Differences in behavior resulted in a big difference between the number of rules generated in each students' learning policy as we have seen in section 5.3. Students' policy contained an average of 54 rules ($\sigma = 32.147$, $n = 11$) after the 10th learning session. The learning policy was used as basis for providing each student with feedback to help them maintain or increase their learning motivation. Other research using reinforcement learning algorithms usually build their policies by running the algorithm for thousands of iterations. In our case however, we did not work with simulated data and it would take a lot of time and effort to generate such data. Furthermore, we do not have control over the student's decisions so despite being able to find effective learning behaviors, these can not be tested and explored unless students themselves perform such actions. Instead of using simulations, we observed the relationship between students' motivation ratings and the number of times the optimal actions in the policy were followed. Following the policy is supposed to maximize students' motivation, so the more the policy is followed, the more the motivation should increase and vice versa. Figure 5.4a and 5.4b shows the difference between students' reported motivation values and the number of times they followed the policy in that session. Both values were scaled between zero and one to make them easily comparable.

We can see that some students' motivation ratings more closely correlated with their policy observance than others. Looking more closely into the students' profile, we were



(a) Students 1 - 6

Figure 5.4: Difference between students' motivation ratings and their policy observance

(b) Students 7 - 11

Figure 5.4: Difference between students' motivation ratings and their policy observance

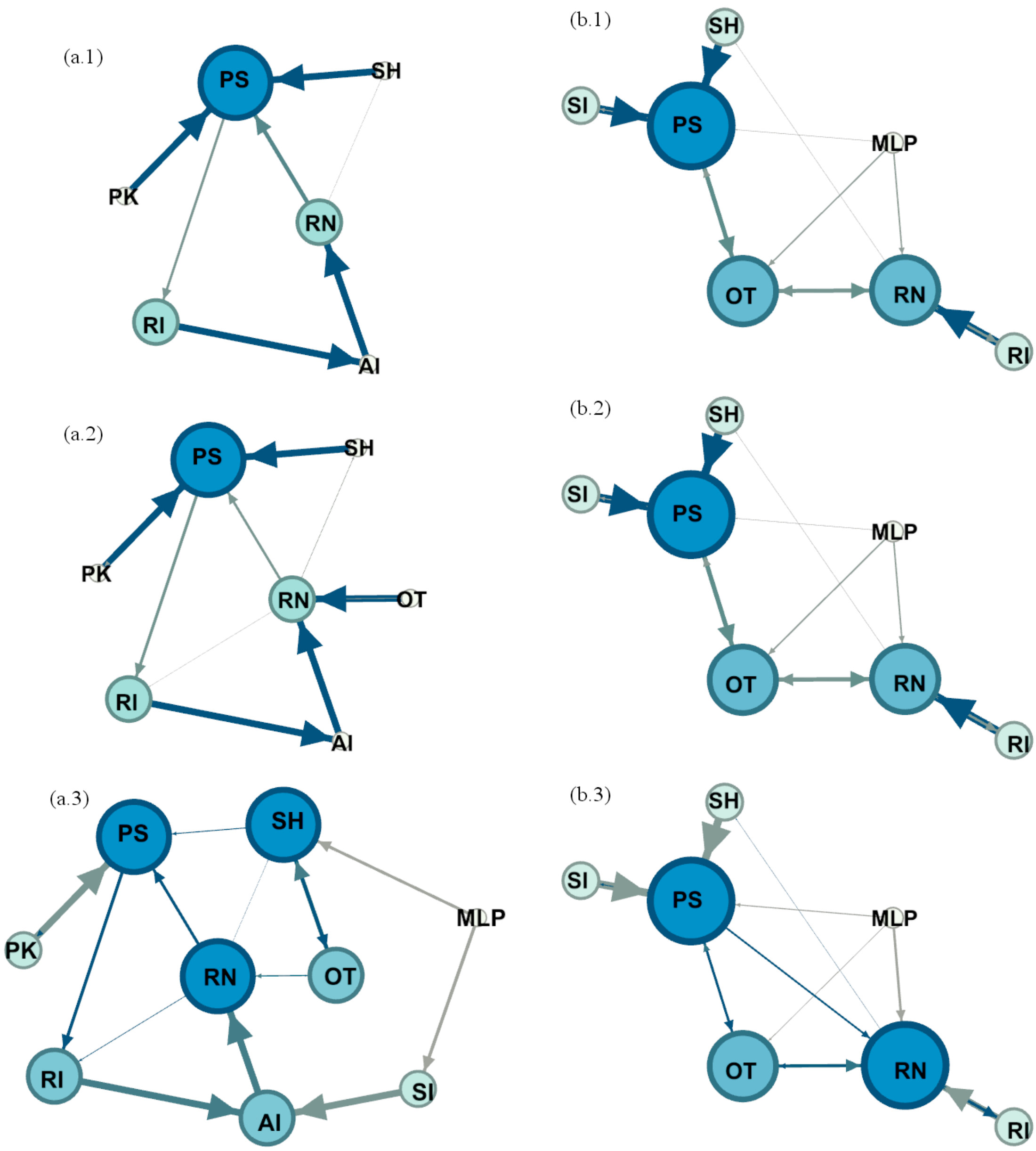
able to see that students 5 to 10 were intrinsically motivated while students 1 to 4 and student 11 were extrinsically motivated. In the succeeding section, we will be able to see that intrinsically regulated students tend to have more predictable behavior patterns. Despite the large search space of states and actions, having a more predictable behavior will bound the reinforcement learners exploration to a smaller subset of the space. This may also account for the reason why there seemed to be more correlation between these students' motivation rating and policy observance. Given more data it is possible for the reinforcement learner to exhaust more possibilities and thus improve its model of student behavior. We believe that the results are promising given the complex nature of learning behavior and the minimal number of examples for training (i.e., 10 iterations).

Moreover, according to students' evaluation of the feedback generated, which was useful around 88% of the time, we can consider that the policies generated were at least partially correct. However, because students have control over their own actions, they can easily decide not to follow the suggestions given to them. This is more likely to happen with extrinsically motivated students because they more commonly engage in surface level learning strategies and are more concerned about completing learning goals and not really learning more or maintaining motivation [34]. Intrinsically motivated students on the other hand are more likely to reflect and adapt their learning behavior because they can see the benefit it has on their learning.

5.4.2 Changes in Student learning behavior

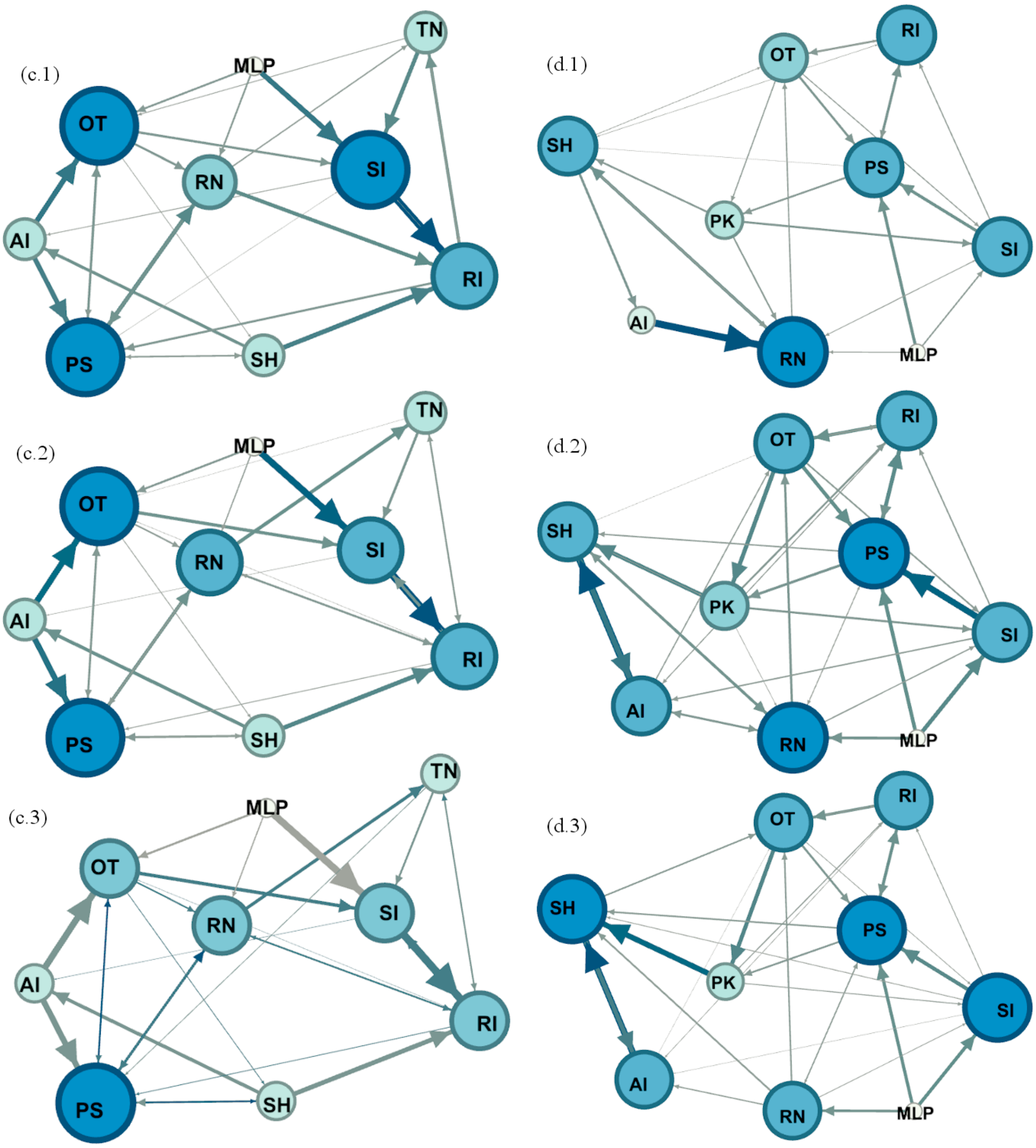
Changes in students' learning behavior were observed by looking at their transition likelihoods between states over the span of 10 learning sessions. The likelihood function we adapted was originally used in [15] to analyze transitions between students' emotions while learning. In our case however, we use the likelihood function to observe the transitions between students' activities. The function shown in Eq. 5.1 shows the computation of the likelihood of transitioning from an activity A_i to the next activity A_{i+1}. The likelihood value ranges between $(-\infty, 1]$ wherein a likelihood value that is greater than zero indicates an increasing likelihood value as it approaches one. A transition likelihood of zero indicates that the transition is equal to the base rate of transitioning into the target state and values below zero indicate that the transition is less likely to happen.

$$L(A_i, A_{i+1}) = \frac{P(A_{i+1}|A_i) - P(A_{i+1})}{1 - P(A_{i+1})} \tag{5.1}$$



(a) Student a - intrinsically motivated student and Student b - high performing student

Figure 5.5: Temporal transition likelihood graphs of students in the 4th, 7th and 10th session respectively (see Appendix A for category acronyms)



(b) Student c - extrinsically motivated student and Student d - low performing student

Figure 5.5: Temporal transition likelihood graphs of students in the 4th, 7th and 10th session respectively (see Appendix A for category acronyms)

Figure 5.5a and 5.5b presents temporal activity transition likelihoods of four students who used the system. The graphs shown are the transition likelihoods of student A - the most intrinsically motivated student, student B - the highest performing student in class, student C - the most extrinsically motivated student, and student D - the lowest performing student in class. Only the likelihoods in each students' 4th, 7th and

10th learning session are shown in the graph. The direction of the arrows in the graph indicate the transition from one activity to another. The thickness of the arrow indicates the likelihood of transitioning towards the target node and the size of the node indicates the frequency of transitioning into the node from other nodes. There are actually more transitions between activities than what is shown in the graph, but only transitions with probabilities higher than chance are shown (i.e., $L > 0$).

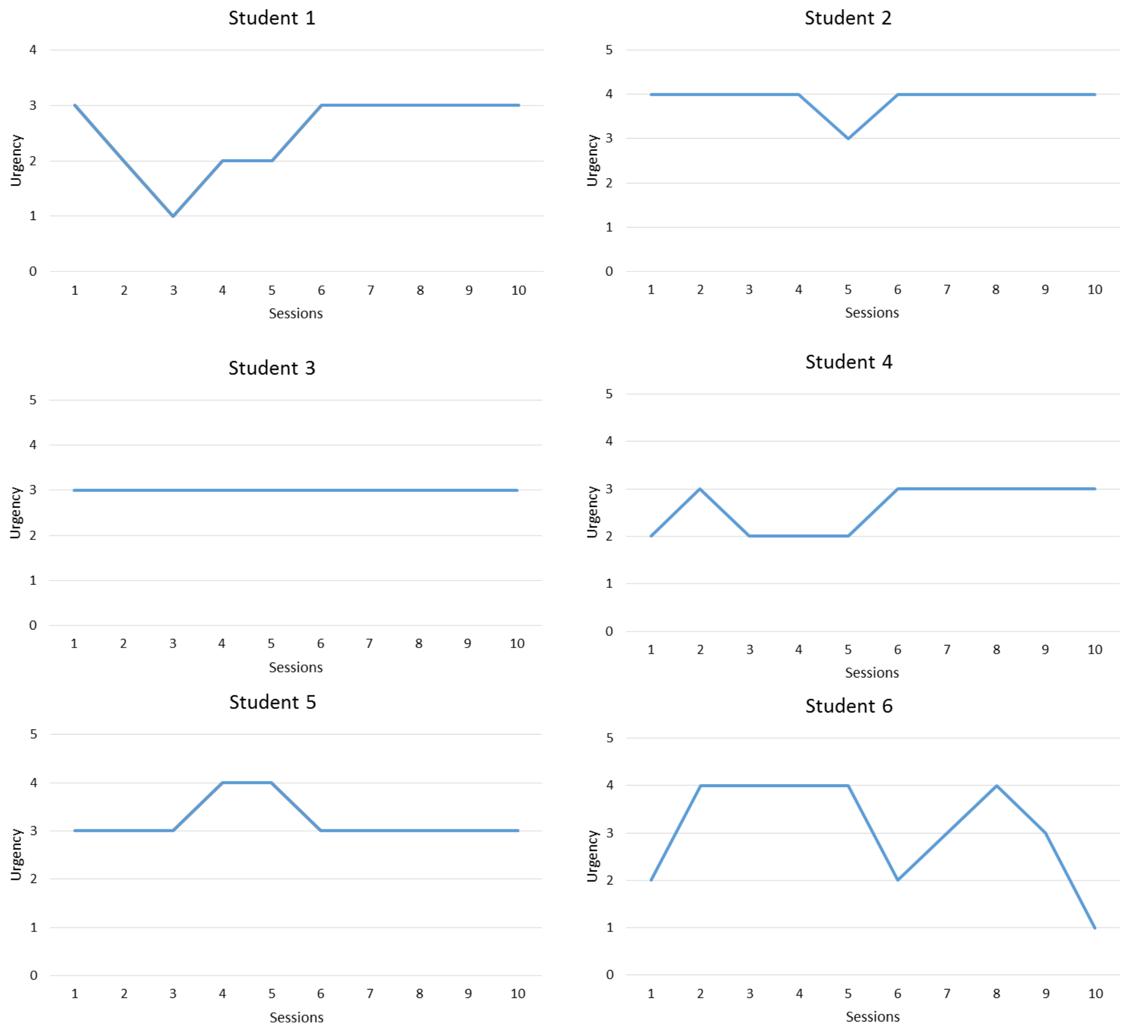
The graphs show that there were constant patterns in the behavior of student A and student B indicated by the few yet highly likely transitions between their activities. Student B was actually an intrinsically motivated learner as well but her knowledge of the subject may have caused her to change between a fewer number of activities. We notice that she mostly reviewed her notes while practicing her skills unlike student A who needed to find other sources of information and seek help. We also see very little change in student B's transition likelihood over time presumably because she has already found a good learning behavior. Student A on the other hand, engaged in supplementary learning activities like reading information and seeking help. We can see that student A seems to have a systematic way of improving his behavior wherein the frequency and likelihood of performing helpful activities increase over time. We can attribute these students' behavior to traits commonly attributed to intrinsically motivated learners wherein they often persist more in learning tasks, have deeper levels of learning and acquire knowledge in a more differentiated and coherent form [34, 36].

In the case of student C and student D however, who were both extrinsically motivated, their activities were more varied and the transitions between them were less likely. We may interpret this as their behavior in trying to find the best way to achieve the task. Their approach seemed to be less systematic because they spread out their effort instead of just focusing on one activity. Student D's behavior shows very little change in the frequency and transition likelihoods between his activities over time. This may indicate that this is the most effective learning behavior he has identified so far. An interesting case to consider is that although student C was extrinsically motivated, she had one of the highest scores among the group. Unlike student D however, her behavior changed over time wherein there was a significant decrease in the amount of off-task activities she performed and increase in the amount of time she practiced her skills. Both students' behavior can be attributed to traits common to extrinsically motivated learners wherein they were more concerned about completing the goal rather than learning from the task and used surface level strategies [34]. It is less likely for extrinsically motivated students to adapt their behavior because they are often less interested in the learning task however, Student C was able to adapt her behavior, albeit slowly. It is possible that the retrospection phase might have helped her improve her behavior despite being extrinsically motivated.

Extrinsically motivated students may have more difficulty adjusting their behaviors because they commonly try out different actions. However, encouraging them to engage in retrospection forces them to recall and evaluate more than they usually do. The annotation process may encourage them to practice and improve their skills in identifying their activities, affective states and perceived contributions as well as its effects on their learning which can help them them realize what may be wrong with their behavior and how they should change it.

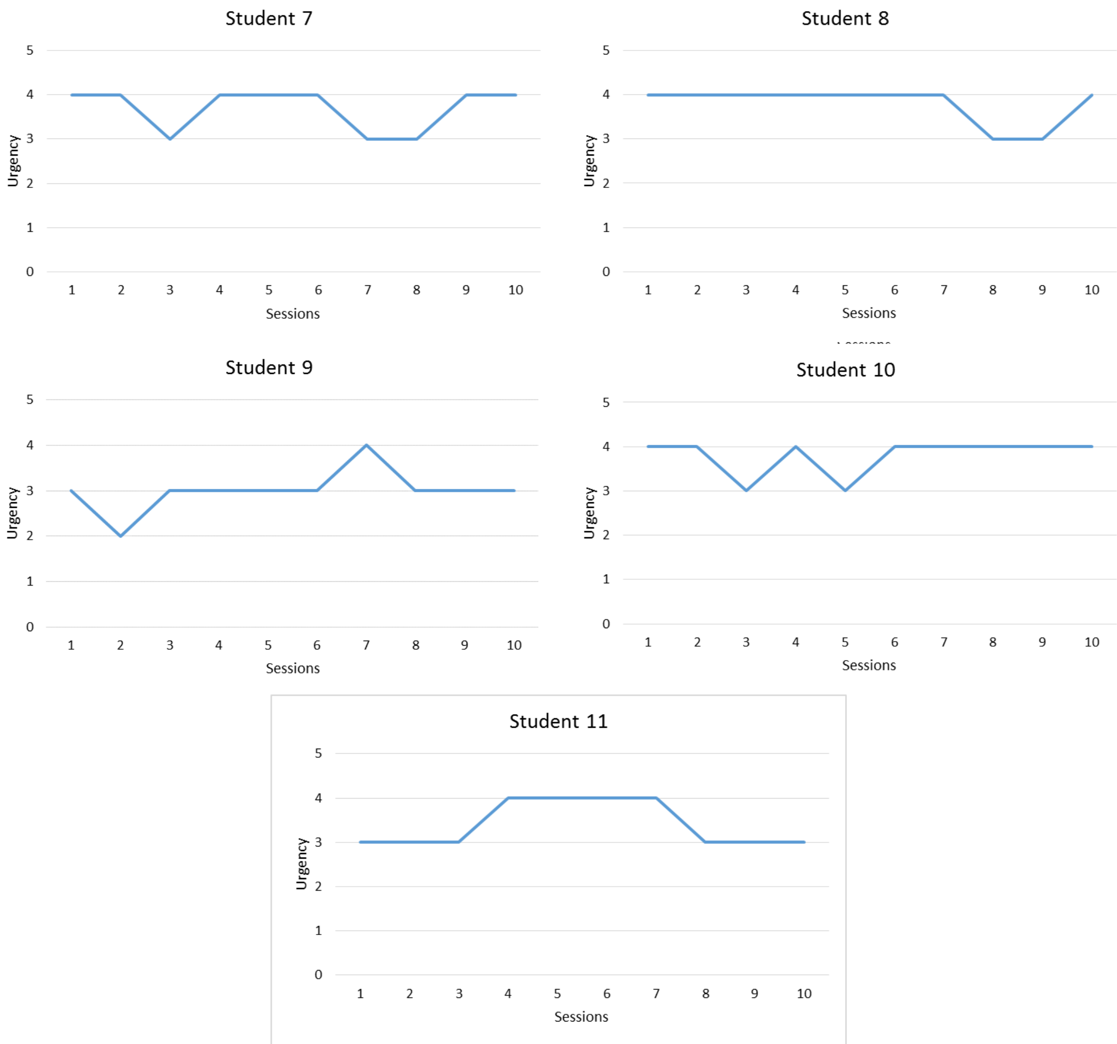
Intrinsic motivation has been found to influence self-regulation and cognitive strategy use but not necessarily performance [25, 27, 28]. This may indicate that the intrinsically motivated students were more self-regulated and explains why their behavior was more constant and changed more systematically compared to extrinsically motivated students. Furthermore, we did not find direct correlations between the students' performance according to their grades for the course and their locus of causality. Performance may be related to other factors which we did not consider in this study and warrants a more focused investigation in future research.

All students' behavior seemed to either improve or remain the same over the 10 sessions. It was unclear however, what caused this change in behavior. There are three possible causes we identified which would have changed students' behavior namely, a change in learning focus, a change in the urgency or need for learning and the self-reflection and self-evaluation activity from the use of the software. Transition likelihoods will definitely change focus when a different set of activities are performed. However, at the time students' data was recorded, all their activities were leading up to their first quiz so we can expect that they engaged in activities involving the understanding of the topics covered in the quiz. Moreover, the change in students' behavior did not involve the addition of new activities but instead changed in focus such as giving more attention to practicing skills or seeking help. Minimizing the amount of time spent in off-task activities for example would probably not be caused by a change in learning goals.



(a) Student 1-6

Figure 5.6: Direction of the change in students' learning task urgency over time



(b) Student 7-11

Figure 5.6: Direction of the change in students' learning task urgency over time

A change in urgency or need for learning, for example when the exam date is getting closer, would also affect students' behavior wherein we expect that off-task activities may decrease or help seeking would increase. However, if we look at students' descriptions of the urgency of their learning task, we observe that these ratings were not always increasing as shown in Figure 5.6a and 5.6b. This means that student behavior changed because of other factors apart from urgency.

Students' answer to a survey done after the learning session also showed that 7 out of 11 students (64%) commented that they were able to observe aspects of their learning behavior they were previously unaware of, to become aware of their learning habits and even change their learning behavior. We believe that based on our findings, we can say that software helped students improve their learning behavior or at least helped students not to engage in more ineffective learning behavior.

5.5 Software Usage Experience

We also asked students to evaluate the software itself wherein they generally had a good outlook towards the software. Around 91% of the students felt that the interface was appealing and 9% felt that the interface was very appealing. Students were also happy about the system's controls wherein 73% of the students felt it was easy to use and 27% felt it was very easy to use. Out of all students 36% found the software to be very helpful to their learning, 27% found it helpful and the remaining 36% felt it was not helpful. Students who found the software helpful explained that the system helped them become aware of habits and activities that they were previously unaware of and became aware of how their emotions affected their learning. For some students, using the software helped them become more focused and aware of their learning goals. Students who did not find the software helpful attributed this feeling towards the effort required for annotation. Students' comments regarding the annotation process and evaluation process in the software also reflects toward the retrospection phase because the software was an implementation of it.

Chapter 6

Conclusion

6.1 Summary

In this research we proposed a methodology that added the retrospection phase into Zimmerman's self-regulation model. The proposed methodology was tested by developing a software that encouraged students to engage in retrospection and conducting an experiment wherein students were asked to use the software while they learned in self-initiated learning scenarios.

We collected data of students' learning behaviors in self-initiated learning scenarios using a software we developed which recorded students' interactions with a computer, recorded desktop and webcam screenshots and asked students to provide annotations of their own behavior. The approach we designed also allowed students to provide information regarding their behavior outside of the computer.

Based on our results, the proposed methodology was able to promote retrospection by helping students recall their activities and evaluate their activity's short term and long term effects through the annotation process with the help of webcam and desktop screenshots taken during the learning session and contrast the utility of different activities by asking them policy-based questions to evaluate such activities. The retrospection process also allowed students to more easily adapt their learning behavior according to their realizations.

A profit sharing algorithm was used to create a learning policy which modeled effective and ineffective student behavior based on students' annotations. The resulting learning policy was promising wherein it was able to identify logical action transitions that would promote student motivation. However, due to the nature of extrinsically motivated students whose learning behavior involved more varied actions, it would probably take a longer time and would need more examples for the profit sharing algorithm to find effective actions compared to modeling intrinsically motivated students.

The results also showed that intrinsically motivated students seemed to benefit more from retrospection most likely because they were more interested in the learning task and improving themselves. However, even though extrinsically motivated students changed their behavior much slowly compared to intrinsically motivated learners, they were still able to change it. This indicates that there is a potential for the approach to work but it has to be adapted to address the specific concerns of extrinsically motivated learners.

The data from our experiments also revealed the differences in learning behavior in self-initiated learning scenarios wherein students have full control over which activities they can perform including non-learning related activities. Students seemed to experience more difficulty in selecting appropriate activities because of having little knowledge of the task manifested by their activity transitions (e.g., searching for information and help seeking) and affective states (i.e., experiencing boredom) while learning. We observed a big difference in the behavior of intrinsically motivated learners and extrinsically motivated learners wherein intrinsically motivated learners had a more consistent pattern of activity transitions and systematic method of behavior adaptation. Extrinsically motivated learners had more tendency to engage in many different activities which possibly caused them to adapt their behavior more slowly.

6.2 Contributions

The major contribution of this work is the design and implementation of a methodology that adds a retrospection phase after learning sessions in self-initiated learning scenarios wherein there is no control over students actions and there is minimal knowledge about students' activities. Current motivation and self-regulation support systems are bound by a system and do not handle activities outside of the learning context. Despite the challenges in self-initiated learning scenarios, results from our experiments showed that we were able to provide useful support for students.

The software we developed was domain agnostic such that students can use the tool in any other domain and get support. There is no need to create new content for specific domains. In special cases, the 11 predefined categories can easily be expanded to handle specific needs of other domains. Students' activities outside of the computer was also considered in providing support to students using the annotation process.

The retrospective annotation approach we implemented was an effective way of getting fine grained information regarding students' behavior without adding cognitive load and disrupting learning. The use of desktop and webcam screenshots helped students recall their behavior more easily compared to the usual pen and paper self-report questionnaires. It also helped ensure the quality of students' annotations with the help of additional contextual information.

The reinforcement learning approach we implemented is flexible such that other reward measures can easily be used instead of motivation. For example, learning gains may be used to drive the feedback wherein more importance will be given to learning than students' motivation levels.

6.3 Recommendations for future work

More work needs to be done in helping students change their behavior especially for those who are extrinsically motivated. Feedback has to be designed to address their limitations such as adding very minimal time and effort on top of the learning task, providing incentives to further encourage them to retrospect and providing more explicit feedback to reminded them of their identified behavior adjustments while learning. Aside from the annotated data, the system has also collected low level data which can be used to model different aspects of student behavior such as activities, affect and perceived contributions. These models can be used together with the students' learning policy and provide real-time feedback to the student.

Many students felt the annotation process was easy but, there was still a minority who found it difficult. It is important to find more ways to minimize the effort and time required for annotation. Automating the annotation process will probably be a good idea to alleviate such difficulties in annotation however we believe that annotation should not be completely removed. Annotation helps students retrospect so it might be best to find ways to semi-automate and minimize the process but ensure that important aspects of the learning session are still observed by the students.

Although the learning policy was able to model students' behavior with a limited amount of data, it will be interesting to see how much more accurate it will be with data exceeding 10 sessions. Furthermore it might also be a good idea to create a general learning policy which can be used to jumpstart or even update the students' learning policy over time.

Finally, the flexibility of the tool allows it to be used in many domains thus many different learning behavior based experiments may be conducted. Some interesting researches would be the comparison between novice and expert learners' behavior, a longitudal study of students' learning behavior, a cross cultural comparison of learning behavior and adapting the tool to a younger audience.

Bibliography

[1] V. Aleven. Rule-Based cognitive modeling for intelligent tutoring systems advances in intelligent tutoring systems. volume 308 of *Studies in Computational Intelligence*, chapter 3, pages 33–62. Springer Berlin / Heidelberg, Berlin, Heidelberg, 2010.

[2] S. Arai and K. Sycara. Effective learning approach for planning and scheduling in Multi-Agent domain. In *6th International Conference on Simulation of Adaptive Behavior (From animals to animats 6)*, pages 507–516, 2000.

[3] R. Azevedo, J. G. Cromley, D. C. Moos, J. A. Greene, and F. I. Winters. Adaptive content and process scaffolding: A key to facilitating students' self-regulated learning with hypermedia. *Psychological Testing and Assessment Modeling*, 53:106–140, 2011.

[4] R. Azevedo, J. T. Guthrie, and D. Seibert. The role of self-regulated learning in fostering students'conceptual understanding of complex systems with hypermedia. *Journal of Educational Computing Research*, 30(1):87–111, 2004.

[5] R. Azevedo, R. S. Landis, R. Feyzi-Behnagh, M. Duffy, G. Trevors, J. M. Harley, F. Bouchet, J. Burlison, M. Taub, N. Pacampara, and Others. The effectiveness of pedagogical agents' prompting and feedback in facilitating co-adapted learning with MetaTutor. In *Intelligent Tutoring Systems*, pages 212–221. Springer, 2012.

[6] R. S. Baker, M. M. Rodrigo, and U. E. Xolocotzin. The dynamics of affective transitions in simulation Problem-Solving environments. In *Proceedings of the 2nd international conference on Affective Computing and Intelligent Interaction*, ACII '07, pages 666–677, Berlin, Heidelberg, 2007. Springer-Verlag.

[7] L. Barnard-Brak, V. O. Paton, and W. Y. Lan. Profiles in self-regulated learning in the online learning environment. *The International Review of Research in Open and Distance Learning*, 11(1):61–80, 2010.

[8] A. E. Black and E. L. Deci. The effects of instructors' autonomy support and students' autonomous motivation on learning organic chemistry: A self-determination theory perspective. *Sci. Ed.*, 84(6):740–756, Nov. 2000.

[9] L. Bol, R. Riggs, D. J. Hacker, and J. Nunnery. The calibration accuracy of middle school students in math classes. *J. Res. Educ*, 21:81–96, 2010.

[10] S. D. Craig, A. C. Graesser, J. Sullins, and B. Gholson. Affect and learning: An exploratory look into the role of affect in learning with AutoTutor. *Journal of Educational Media*, 29(3):241–250, Oct. 2004.

[11] R. De Charms. *Personal causation: The internal affective determinants of behavior.* Academic Press New York, 1968.

[12] E. L. Deci and R. M. Ryan. A motivational approach to self: Integration in personality. In *Nebraska symposium on motivation*, volume 38, pages 237–288, 1991.

[13] M. K. DiBenedetto and B. J. Zimmerman. Construct and predictive validity of microanalytic measures of students' self-regulation of science learning. *Learning and Individual Differences*, 26:30–41, Aug. 2013.

[14] S. D'Mello and A. Graesser. Dynamics of affective states during complex learning. *Learning and Instruction*, 22(2):145–157, Apr. 2012.

[15] S. D'Mello, R. S. Taylor, and A. Graesser. Monitoring affective trajectories during complex learning. In *Proceedings of the 29th annual meeting of the cognitive science society*, pages 203–208, Austin, TX, USA, 2007. Cognitive Science Society.

[16] J. K. Garner and L. Bol. The challenges of e-Learning initiatives in supporting students with self-regulated learning and executive function difficulties. In *Annual*

Meeting of the International Congress for School Effectiveness and Improvement, January, pages 4–8, 2011.

[17] A. C. Graesser, K. Wiemer-Hastings, P. Wiemer-Hastings, and R. Kreuz. AutoTutor: A simulation of a human tutor. *Cognitive Systems Research*, 1(1):35–51, Dec. 1999.

[18] A. F. Hadwin, J. C. Nesbit, D. Jamieson-Noel, J. Code, and P. H. Winne. Examining trace data to explore self-regulated learning. *Metacognition and Learning*, 2(2-3):107–124, 2007.

[19] P. S. Inventado, R. Legaspi, R. Cabredo, and M. Numao. Student learning behavior in an unsupervised learning environment. In *Proceedings of the 20th International Conference on Computers in Education*, pages 730–737, Dec. 2012.

[20] J. M. Keller. Using the ARCS motivational process in Computer-Based instruction and distance education. *New directions for teaching and learning*, 1999(78):37–47, 1999.

[21] J. S. Kinnebrew, K. M. Loretz, and G. Biswas. A contextualized, differential sequence mining method to derive students' learning behavior patterns. *Journal of Educational Data Mining*, 5(1), 2013.

[22] M. S. Knowles. *Self-directed learning.* Association Press New York, 1975.

[23] D. Laurillard. *Rethinking University Teaching: A Framework for the Effective Use of Educational Technology.* Routledge, 1993.

[24] S. Manlove, A. W. Lazonder, and T. Jong. Software scaffolds to promote regulation during scientific inquiry learning. *Metacognition and Learning*, 2(2):141–155, Dec. 2007.

[25] J. L. Meece, P. C. Blumenfeld, and R. H. Hoyle. Students' goal orientations and cognitive engagement in classroom activities. *Journal of educational psychology*, 80(4):514, 1988.

[26] A. Mitrovic. Fifteen years of constraint-based tutors: what we have achieved and where we are going. *User Modeling and User-Adapted Interaction*, 22:39–72, 2012.

[27] S. B. Nolen. Reasons for studying: Motivational orientations and study strategies. *Cognition and instruction*, 5(4):269–287, 1988.

[28] P. R. Pintrich and E. V. De Groot. Motivational and self-regulated learning components of classroom academic performance. *Journal of educational psychology*, 82(1):33, 1990.

[29] P. R. Pintrich, D. A. F. Smith, T. Garcia, and W. J. Mckeachie. Reliability and predictive validity of the motivated strategies for learning questionnaire (mslq). *Educational and Psychological Measurement*, 53(3):801–813, Sept. 1993.

[30] M. Pressley, E. S. Ghatala, V. Woloshyn, and J. Pirie. Sometimes adults miss the main ideas and do not realize it: Confidence in responses to short-answer and multiple-choice comprehension questions. *Reading Research Quarterly*, pages 232–249, 1990.

[31] M. Pressley, J. R. Levin, and E. S. Ghatala. Memory strategy monitoring in adults and children. *Journal of Verbal Learning and Verbal Behavior*, 23(2):270–288, Apr. 1984.

[32] M. M. Rodrigo, R. S. J. D. Baker, M. C. V. Lagud, S. A. L. Lim, A. F. Macapanpan, S. A. M. S. Pascua, J. Q. Santillano, L. R. S. Sevilla, J. O. Sugay, S. Tep, and N. J. B. Viehland. Affect and usage choices in simulation Problem-Solving environments. In *Proceedings of the 2007 conference on Artificial Intelligence in Education: Building Technology Rich Learning Contexts That Work*, pages 145–152, Amsterdam, The Netherlands, The Netherlands, 2007. IOS Press.

[33] R. M. Ryan. Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of personality and social psychology*, 43(3):450, 1982.

[34] R. M. Ryan and E. L. Deci. Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary educational psychology*, 25(1):54–67, 2000.

[35] J. Sabourin, J. Rowe, B. Mott, and J. Lester. When Off-Task is On-Task: The affective role of Off-Task behavior in Narrative-Centered learning environments. In G. Biswas, S. Bull, J. Kay, and A. Mitrovic, editors, *Artificial Intelligence in Education*, volume 6738 of *Lecture Notes in Computer Science*, pages 534–536. Springer Berlin Heidelberg, June 2011.

[36] J. Simons, S. Dewitte, and W. Lens. Wanting to have vs. wanting to be: The effect of perceived instrumentality on goal orientation. *British Journal of Psychology*, 91(3):335–351, 2000.

[37] R. S. Sutton and A. G. Barto. *Reinforcement Learning: An Introduction (Adaptive Computation and Machine Learning).* A Bradford Book, Mar. 1998.

[38] P. H. Winne and A. F. Hadwin. nStudy: Tracing and supporting Self-Regulated learning in the internet. In R. Azevedo and V. Aleven, editors, *International Handbook of Metacognition and Learning Technologies*, volume 26 of *Springer International Handbooks of Education*, pages 293–308. Springer New York, 2013.

[39] P. H. Winne and D. Jamieson-Noel. Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology*, 27(4):551–572, Oct. 2002.

[40] B. J. Zimmerman. Self-regulated learning and academic achievement: An overview. *Educational psychologist*, 25(1), 1990.

[41] B. J. Zimmerman. Academic studying and the development of personal skill: A self-regulatory perspective. *Educational psychologist*, 33(2-3):73–86, 1998.

[42] B. J. Zimmerman. Becoming a Self-Regulated learner: An overview. *Theory Into Practice*, 41(2):64–70, May 2002.

[43] B. J. Zimmerman and M. Campillo. Motivating self-regulated problem solvers. *The psychology of problem solving*, pages 233–262, 2003.

[44] B. J. Zimmerman and M. M. Pons. Development of a structured interview for assessing student use of Self-Regulated learning strategies. *American Educational Research Journal*, 23(4):614–628, Jan. 1986.

Appendix A

Category Acronyms

Table A.1: Acronyms for the different activity categories

Acronym	Activity
MLP	Make a learning plan
RMLP	Review or modify learning plan
PS	Practice known skill
PK	Use previous knowledge
SI	Search for information
RI	Read information
AI	Apply acquired knowledge/information
TN	Take notes
RN	Review notes
SH	Seek help
OT	Off-task

Appendix B

Sidekick Questionnaires

B.1 Learning Self-regulated Questionnaire (SRQL)

The following SRQL was given to students before their first learning session. It is a slightly modified version of [8] to fit the students' domain. Students' answered the questionnaires using a 7-point scale.

1. I will participate actively in the courses I am enrolled in because I feel like its a good way to improve my understanding of the materials presented.

2. I will participate actively in the courses I am enrolled in because others would think badly of me if I didn't.

3. I will participate actively in the courses I am enrolled in because I would feel proud of myself if I did well.

4. I will participate actively in the courses I am enrolled in because a solid understanding of concepts taught in class are important to my intellectual growth.

5. I am likely to follow my teacher's suggestion for studying because I would get a bad grade if I didn't do what he/she suggests.

6. I am likely to follow my teacher's suggestion for studying because I am worried that I am not going to perform well.

7. I am likely to follow my teacher's suggestion for studying because its easier to follow his/her suggestions than come up with my own study strategies.

8. I am likely to follow my teacher's suggestion for studying because he/she seems to have insight about how best to learn.
9. The reason that I will work to expand my knowledge in these courses is because it is interesting to learn more about them.
10. The reason that I will work to expand my knowledge in these courses is because it is a challenge to really understand how to solve the problems I encounter in these courses.
11. The reason that I will work to expand my knowledge in these courses is because a good grade in these courses will look positive on my record.
12. The reason that I will work to expand my knowledge in these courses is because I want others to see that I am intelligent.

B.2 Pre-session Questionnaire

The following questions were asked from the students at the beginning of every learning session which they answered using a 4-point scale.

1. My current learning task is important to me.
2. My current learning task needs to be finished right away.
3. My current learning task requires a lot of time to complete.
4. My current learning task will require much effort to complete.
5. I will surely succeed in my current learning task.

B.3 Activity evaluation question template

Three templates were used for generating evaluative questions after the annotation process. Depending on the situation described below, the corresponding templates were used.

1. Students did not follow the optimal activity according to the learning policy.

   When you perform a <students' current activity> task, that has <low/medium/high> contribution to your goal and makes you feel <affect> for a <long/medium/short> time, do you think its a better idea to shift to a <optimal activity> task instead of other kinds of tasks?

2. Students tried performing a new activity but had worse effects than the optimal activity in the learning policy.

   Shifting to a <student's activity> task didn't seem to be very effective when you performed a <students' current activity> task which had a <low/medium/high> contribution to your goal and made you feel <affect> for a <long/medium/short> time. Do you think performing a <suggested activity> task is a better alternative?

3. Students tried performing a new activity which had better effects than the optimal activity in the learning policy.

   When you performed a <student's current activity> task which had a <low/medium/high> contribution to your goal and made you feel <affect> for a <long/medium/short> time, did you perform better when you shifted to a <student's activity> task?

B.4 Post-session Questionnaire

The following questions were asked from the students after the annotation process. These are based on the ARCS model of motivation [20].

1. The activities that I performed captured my interest.

2. The activities I did were relevant to what I wanted to achieve.

3. I was able to achieve my learning goals.

4. I can apply what I learned today in the activities that I do or will do in real life.

B.5 Post-session Survey

The following questions were asked from the students at the end of every learning session. These questions were mainly used to evaluate students' reactions to the annotation process and evaluative questions they answered.

1. Did you use the information you gained about your learning behavior from the previous learning sessions in the current one? If yes, kindly write "yes". If no kindly describe why. Kindly write "not applicable" if this is your first learning session with Sidekick.

2. Did you discover anything interesting while annotating your learning behavior? If yes, kindly write down what you discovered, if no, kindly write "no".

3. Did you feel the need to change how you learned after annotating your behavior? If yes, why and how do you think it should be changed? If no, kindly write "no".

4. Did you discover anything interesting when you were asked asked questions about your learning behavior? If yes, kindly write down what you discovered, if no, kindly write "no" or if you were not asked a question write "not appplicable".

5. Did you feel the need to change how you learned after you were asked questions about your learning behavior? If yes, why and how do you think it should be changed? Iif no, kindly write "no" or if you were not asked a question write "not appplicable".

6. Kindly write down any other realizations you had while using the software. If there are none, please write "none".