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USING COGNITIVE TOOLS IN gSTUDY TO INVESTIGATE HOW STUDY ACTIVITIES COVARY WITH ACHIEVEMENT GOALS

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ABSTRACT

Links between students' achievement goal orientations and learning tactics were investigated using software (gStudy) that supports a variety of learning tactics and strategies. An achievement goal questionnaire was administered to 307 students enrolled in an introductory educational psychology course. Data tracing study tactics were logged for 80 of these students who prepared for a test by studying a textbook chapter presented as a multimedia document. Using correlations and canonical correlations, we found relationships between goal orientations and activity traces indicating different forms of cognitive engagement. Notably, mastery goal orientation (approach or avoidance) was negatively related to amount of highlighting, a study tactic that is theorized to be less effective than summarizing and other forms of elaborative annotation for assembling and integrating knowledge.

INTRODUCTION

Self-regulated learning (SRL) refers to the iterative cognitive, metacognitive, and motivational processes that learners engage to complete a learning task (Winne, 2001; Zimmerman, 2001). SRL has been posited as conducive to developing skills in critical thinking, analysis, evaluation, and communication. Winne and colleagues (Winne, 2001; Winne & Hadwin, 1998; Winne & Perry, 2000) have described a 4-stage model of SRL: 1) understanding the task; 2) setting goals and making plans to attain them; 3) enacting study tactics and strategies; and 4) revising SRL knowledge. The competence and effort with which these processes are performed are thought to depend on a host of factors specific to the situation, person, and task. According to Pintrich (1995, p. 7), "self-regulation of cognition involves the control of various cognitive strategies for learning, such as the use of deep processing strategies that result in better learning and performance." Zimmerman (2001, p. 5) describes students who effectively self-regulate as "metacognitively, motivationally, and behaviorally active participants in their own learning process."

Study Tactics

We define study tactics as procedural knowledge structures which generate relatively fine-grained learning actions such as underlining a segment of printed text or annotating it with a summary or comment. In contrast, study strategies are larger-grained procedural knowledge structures which coordinate and deploy tactics. Because the research in which study activities have been observed or logged is not extensive, there is generally insufficient evidence to inform prescription of specific tactics (Hadwin & Winne, 1996). Some research suggests that underlining or annotating text has little or no benefit unless the products of the activity (the underlined text or annotations) are reviewed (e.g., Kierwa et al., 1991; Marxen, 1996). Other research, which manipulated variation in the tactics' cognitive operations, found that the degree of direct information encoding by a study tactic depends on how the tactic is executed (e.g., Huffman & Spires, 1994; Igo, Bruning, & McCrudden, 2005).

When students underline or highlight a text with a single color, they make a series of binary decisions to assign text segments to a category (signifying importance or relevance) and exclude the remaining segments. When additional highlight colors are used to represent additional categories, the tactic becomes more elaborate. The copy and paste operation available on computers serves a similar function to highlighting, with the paste locations corresponding to different colored highlight pens and different cognitive categories. Igo, Bruning and McCrudden (2005) found that students restricted to copying and pasting segments no longer than seven words learned more than students who were not restricted. Observing that the restricted group showed more intensive decision-making and deeper processing, they suggested that "although restricting [copy and paste] seems to have more positive cognitive consequences than using an unrestricted version, typing notes in response to electronic texts might be superior to either" (p. 113).

When students annotate a text, they write summaries or comments relevant to nearby portions of the text, and in doing so cognitively engage with the text in various ways that have been found to enhance comprehension and learning. They may construct self-explanations (Chi, de Leeuw, & Chiu, 1994), recall suitable examples from long term memory (Gorrell, Tricou, & Graham, 1991), argue for or against claims made in the text (Nussbaum & Sinatra, 2003), or organize and integrate related information from other sections of the text (Foos, 1995; Mayer, 1996).

How do the cognitive effects of outlining and annotating relate to the research that has investigated study skills and preferences using self report data? Individual difference research has recognized deep and surface approaches to learning which are characterized by differing learning goals and levels of cognitive processing (Marton & Säljö, 1976). In this literature, a deep approach to learning is identified with intention to understand, intrinsic motivation, use of evidence, critical thinking, and relating ideas (Entwistle & McCune, 2004). A surface approach to learning is identified with intention to reproduce, extrinsic motivation, and literal memorization. We hypothesize that the choice to underline or highlight, especially when the selection of text is indiscriminant and unrestricted, often manifests a surface approach to learning because it requires minimal cognitive processing and is deployed to aid reproduction of information. In contrast, the choice to annotate text, especially when the annotation integrates related information and links the text with prior knowledge, often manifests a deep approach to learning because it requires greater cognitive processing and is deployed to aid understanding.

Achievement Goal Theory and Approaches to Learning

Achievement goal orientation (Elliot, 1999) has received much attention from researchers interested in explaining SRL. Theorists often posit learning goals as playing a key role in models of self-regulated learning (Pintrich, 2000). Goal orientation is thought to influence metacognitive monitoring and regulation, which, in turn, affect learner achievement. In particular, there is evidence from self-report data that students adopting mastery goals are more likely to engage deep learning strategies such as comparing and contrasting concepts or generating examples (Ravindran, Greene, & DeBacker, 2005). But, as Winne and Jamieson-Noel (2002, 2003; Jamieson-Noel & Winne, 2003) showed, students may not be accurately calibrated in reporting how they study, thereby reducing the degree to which studies such as Ravindran et al.'s indicate how or whether goal orientation affects the cognitive events that are proximal causes of learner achievement.

Until the 1990s, learners' achievement goals were thought to consist of a combination of two factors: mastery goals and performance goals (e.g., Dweck & Leggett, 1988). Under this basal model, learners are judged to have a mastery goal when they report an intrinsic interest in gaining knowledge. They are judged to have a performance goal when they report a motivational focus on grades and demonstrating their abilities to others. Theorists revised achievement goal theory by introducing an approach-avoidance valence (Elliot, 1999; Elliot & Church, 1997; Elliot & Harackiewicz, 1996; Pintrich, 2000). A trichotomous model was developed by disassembling the performance goal into a performance approach goal, in which the learner strives to demonstrate high ability, and a performance avoidance goal, in which the learner intends to avoid demonstrating low ability. Eventually, the model was further expanded to four factors (the 2 × 2 model) by applying the approach-avoidance distinction to disassemble the mastery goal (Elliot & McGregor, 2001).

Studies in which students report their learning strategies in questionnaires have typically found positive correlations between mastery goal orientation and self-reports of deep learning or elaboration strategies (Elliot, McGregor, & Gable, 1999; Harackiewicz, Baron, Tauer, Carter, & Elliot, 2000; Ravindran et al., 2005; Schraw, Horn, Thorndike-Christ, & Bruning, 1995). Having a mastery goal predicted agreement to statements such as, "I treat the course material as a starting point and try to develop my own ideas about it" (Elliot et al., 1999, p. 563), and "when I study, I try to explain the key concepts in my own words" (Harackiewicz et al., 2000, p. 320). Self-report studies have found positive correlations between performance approach goals and surface learning or rehearsal strategies (e.g., Ravindran et al., 2005). For example, reporting a performance approach goal predicted agreement to statements such as, "When I study, I try to memorize as many facts as I can" (Harackiewicz et al., 2000, p. 320).

Self Reports are Insufficient

When trace data are combined with other forms of data, such as the self-reports of achievement goals obtained in the present research, researchers can construct a more complete model of learners' self-regulatory processes. Researchers can significantly reduce under- or misspecification in their models with respect to constructs like metacognitive monitoring, elaborating, searching for information, and recall of prior knowledge in the midst of learning. This is because, while learners' self reports about study tactics describe their probable choices among tactics, traces reflect how learners actually cognitively engage with information. The products of those cognitive engagements are primary grounds upon which learners regulate subsequent choices among study tactics. As well, when learners' self reports about study tactics are poorly calibrated to study tactics they actually use, self-regulation would be predicted to be less effective than if calibration were high.

Methodological Goals for SRL Research

Advancing understanding of links between achievement goals and SRL requires a research model with two essential elements. First, to preserve authentic motivational conditions, research should be conducted with students in natural learning situations. Second, the research must observe behavioral indicators (traces) that document features of monitoring and regulation. These two requirements are rarely attained in a single data set because detailed trace records can be difficult to obtain without retreating to the laboratory.

The Learning Kit Project is a research program that is developing interactive software (gStudy) for scaffolding and researching SRL (see www.learningkit.sfu.ca). A premise of the project is that software-based cognitive tools can aid learning in a wide range of authentic educational situations. The log data generated by gStudy include traces of learners' engagements with content. These are useful to researchers in documenting learning strategies and tactics students use as they write essays, read assignments, prepare for exams, and collaborate on projects. In this article we present a research case showing how gStudy can be used to investigate relations between individual difference variables, such as goal orientation, and SRL.

gStudy: Cognitive Tools for Learning

gStudy (Winne, Hadwin, Nesbit, Kumar, & Beaudoin, 2005) realizes suggestions by Winne (1992) about designing software for research on learning. Learners use gStudy to engage with information in software-based learning kits. Information in a kit can be presented in all the multimedia formats found in libraries and on the Web, including text, audio and video clips, diagrams, photos, charts, tables, and animations. As learners study in a learning kit, they use gStudy tools to create *information objects* and to forge links among information objects. The cognitive tools are designed as much as possible to apply findings that research demonstrates can positively influence solo and collaborative learning and problem solving. The kinds of information objects a learner can create include highlighted selections of content, notes, glossary entries, hierarchical (tree structured) indexes, hierarchical labeling systems applied to other information objects, entries in a table of contents, nodes and arcs and sets of nodes in concept maps, search queries, HTML documents, spreadsheet documents, documents that record chats learners generate in conversation with peers and with gStudy's software coach, and archives of web sites.

The note-making feature of gStudy is central to the research presented here. To make a note about content in a learning kit, a learner first selects information presented in gStudy's web browser by clicking then dragging the cursor across the target information. The selection can be a string of text, a rectangular region in a diagram or chart, or a frame in a video or audio clip. The learner then opens a menu to create a new note and, thereby, create a link between the selection and that note.

The user can choose a *note template* before entering the content of the note. Note templates are schemas that instructional designers, teachers, researchers, or learners can design to structure the note content. Note templates are often designed to scaffold cognitive or metacognitive processing. For example, a debate template we designed includes seven fields that students can fill in to annotate contentious information: issue, position A, evidence for position A, position B, evidence for position B, my position, and justification. A note template could also present metacognitive scaffolds, such as a slider that learners can move to rate how well they understand selected text.

Creating a note as guided by a template in gStudy is an instance of using a tool for learning. As a learner uses this tool, gStudy traces in detail all the events involved in creating a note: which content was selected, when the selection was made, which type of object (in this case, note) was created, which note template the learner chose, which fields of the note template the learner filled in, what information was entered in those fields, and when the learner closed the note window or deactivated it by activating another window. All these data are traces of the learner's engagements with multimedia information presented in the web browser.

Based on patterns in trace data, inferences can be generated about cognitive and motivational activities during learning. To make a note, the learner first metacognitively monitors content in the learning kit to determine that some of it merits annotation. This is traced when the learner selects a portion of the information and chooses the option, "link to new note." Second, the learner metacognitively monitors how to classify the selected information as traced by the learner's choice of template to use in recording this note. Third, if the learner fills in the slots of the schema that refer to position B in the debate note's template, this traces that the learner was able to identify a counterargument in the learning kit's content or construct a counterargument based on prior knowledge.

Trace data that gStudy logs are time-stamped records of events that support grounded interpretations about how a learner constructs knowledge. Trace data reflect what learners do. This helps to step beyond *whether* a tool helps learners construct knowledge because trace data reveal more accurately, although not perfectly, *whether*, *when*, and *how* learners access prior knowledge. Trace data track a learner's actual choices as well as methods they use to express agency through self-regulated learning.

Research Hypotheses and Variables

On the basis of prior research, we hypothesized that, for undergraduate students studying educational psychology, mastery goal orientation would drive the use of deep processing tactics and performance goal orientation would lead to surface processing tactics. Specifically, we expected that greater self-reported mastery goal orientation, either approach or avoidance, would predict creation of more notes or notes with more elaborative content, and less highlighting. We hypothesized that performance goal orientation would drive the use of surface learning tactics. Specifically, we expected that greater self-reported performance goals, either approach or avoidance, would predict more highlighting, and creation of fewer notes or notes with less elaborative content.

Because the research was designed to observe students learning in an actual academic setting with no experimental control, it was not possible to regulate the time on-task. Also, we were uncertain whether the predicted effects would manifest as frequencies of highlighting and annotation, or as rates. Therefore, the amount of gStudy time-on-task was obtained to serve as a separate dependent variable, and to allow creation of rate variables. Because a tendency toward annotation could be manifested as either more notes, or more elaborate notes, both the number of notes and the number of words entered into notes were obtained.

METHOD

Participants

In total the participants were 320 students, 78.8% female, enrolled in one of two semester-long courses in introductory educational psychology offered at a Canadian university. The courses were offered in fall 2004 and spring 2005. Because the course draws students mainly from the Faculty of Arts, 89.1% of the participants were undergraduate Arts students. The remaining participants were undergraduates in Science (3.1%), Education (3.1%), Business (1.9%), and other programs.

Procedure

Data were collected as students participated in activities and assessments throughout the 13-week course. The course consisted of lectures, tutorials, textbook readings, two written assignments, and two multiple choice exams. Lectures and tutorials followed the chapter structure of the course textbook (Woolfolk, Winne, & Perry, 2003). A midterm examination consisting of 48 multiple-choice items was administered in week 6. A final examination consisting of 60 multiple-choice items was administered approximately 1 week after the last lecture.

In weeks 2 to 4 of the course, students completed the Achievement Goal Questionnaire (AGQ; Elliot & McGregor, 2001) and several other measures of individual difference not examined here. The AGQ was repeated on a regular schedule (weekly in the fall offering and biweekly in the spring offering) until week 8. In the present article, only data from the week 8 AGQ are reported because these self reports are most proximal to the learning activity data collected through gStudy. Students were able to access their week 8 AGQ subscale scores immediately after completing the questionnaire. The theory and meaning of the AGQ subscale scores were explained in a lecture after they had completed the questionnaires.

In week 8 (fall term) or week 5 (spring term) learners participated in tutorials where they were shown how to use four fundamental cognitive tools available in gStudy to study: 1) making and editing notes; 2) linking information objects to one another; 3) highlighting browser content; and 4) making a special type of note called a *quick note* in which browser content was labeled with a predefined phrase such as "Important" or "I disagree." Students were offered participation in a lottery to win a $100 gift certificate in exchange for releasing their questionnaire responses, log data, and other information to the research project. Students then studied chapter 7 of the textbook using gStudy and were instructed to keep a record of when and how they studied. Based on this experience, students were required to submit an assignment in which they wrote a short essay reflecting on their learning strategy.

Achievement Goal Questionnaire

The Achievement Goal Questionnaire (AGQ) consisted of the 12 items reported by Elliot and McGregor (2001). Participants indicated the perceived appropriateness of each item using a scale from 1 (not at all true of me) to 7 (very true of me). Previous analyses of this instrument have reported a clear 4-factor structure, with each of the achievement goal factors represented by three items showing high internal consistency (e.g., Elliot & McGregor, 2001). Our confirmatory factor analysis replicated this structure.

gStudy Measures

When log files were collected from all participants it was discovered that many participants did not make substantial use of gStudy to complete the assignment. To increase the authenticity of the log data as records of learning activities, only those participants who used gStudy to study for at least two sessions, each one greater than 20 minutes duration, were included in the analysis. For each of these participants, only the last two sessions greater than 20 minutes were selected for analysis. It was possible to extract from the logs the duration of the last two sessions, the frequency of learning activities such as highlighting, note creation and linking in those sessions, and the content of notes.

RESULTS

Learning Activity Variables

Among students who completed the questionnaires, 90 participants had produced at least two gStudy sessions exceeding 20 minutes. The log files were analyzed to obtain counts of highlighting and note-creation events during the two sessions, and the number of words students entered (and did not delete) to create notes. Although traces of linking operations were collected, linking measures were not obtained because the student-generated links could not be reliably distinguished from system-generated links.

The durations of the two sessions were summed to create a *time invested* variable (*Mdn* = 90.0 minutes). Events in the two sessions were summed to create a *number of highlights* variable (*Mdn* = 26.5) and a *number of notes* variable (*Mdn* = 33.5). Because the number of words entered during only the focal two sessions could not be determined, the total number of words entered in the learning kit over all sessions by each student was used to create a *words entered* variable (*Mdn* = 235). The number of notes and words entered variables showed very high positive skewness and were transformed by the log10 function. The number of highlights was divided by the time invested to obtain a *highlight rate* variable (*Mdn* = .31 highlights per minute), which then was also transformed by log10 due to high skewness. A *note rate* variable was created by dividing number of notes (after transformation by log10) by time invested. Likewise, a *word productivity* variable was created by dividing words entered (after transformation by log10) by time invested. Word productivity was used as a proxy for rate of word entry in subsequent correlational analyses. Transformation of skewed variables can be a valuable method for decreasing type I error in inferential tests which assume normal distributions. But the results obtained from transformed variables can also be more difficult to interpret. Although the log10 transformation maintains the original order of data in the distribution, it alters the distance between measurements.

After the log10 transformations, outliers were treated to further improve normality. Over all activity variables, seven univariate outliers having z-scores exceeding 3.29 ($p < .001$) were removed. After outliers on the goal orientation variables were removed (as reported later), learning activity data were available for 80 participants. Table 1 shows the means, medians, standard deviations, skewness, and kurtosis of the learning activity variables.

Table 1. Properties of the Learning Activity Variables ($N = 80$)

	M	*Mdn*	*SD*	Skewness ($SE = .27$)	Kurtosis ($SE = .53$)
Time invested (minutes)	92.11	90.00	26.40	.64	.81
Number of highlights	29.60	26.50	26.35	.77	–.02
Highlight rate†	1.30	1.60	.718	–.90***	–.59
Number of notes†	1.55	1.54	.35	–.82	3.80***
Note rate†	.170	.136	.109	1.53***	4.09***
Words entered†	2.31	2.37	.49	–.68	.34
Word productivity†	.027	.025	.009	.81	.62

***$p < .001$.
†Variable was either transformed by the log10 function or constructed from a transformed variable.

Content of Notes

Inspection of the log data revealed that the notes students created with gStudy were almost entirely elaborative, that is, they were very rarely copied verbatim from the information provided in the learning kit. Although the notes tended to be elaborations in which students paraphrased short passages in the text, they included some student-generated examples, references to personal experience, and expressions of agreement or disagreement. The most common types of notes were summaries and definitions of terms.

Many of the notes were similar to the following example in which the text entered by a student is enclosed in quotation marks.

Note type:	Summary
Topic:	"Long Term Memory"
Main Ideas:	"hold info well-learned, high in memory strength or durability More time/effort to move from working to long term-search and retrieval prob: finding right info when needed 3 categories: semantic, episodic, procedural"

The student linked this note to the phrase "Long-term memory," which appeared in the chapter paragraph in which the long-term memory concept was defined. The student's summary in the main ideas field of the note recombined several terms located in that paragraph (well-learned, time and effort, retrieval, search), and terms located several paragraphs later in the chapter (semantic, episodic, produral). The student independently generated the terms memory strength and durability.

The following example is a question note that a different student linked to the term "serial-position effect" in the chapter sentence which defined that concept.

Note type:	Question
Question:	"How can you avoid experiencing the serial-position effect?"
Answer:	"Use part learning (breaking list into smaller chunks so that there are fewer words in the middle of the sentence to forget) ex. telephone numbers"

In this note, the student converted a sentence in the chapter from a statement to a question by substituting equivalent terms and re-ordering other terms. In the answer field, the student integrates an example of chunking ("telephone numbers") used in an earlier section of the chapter.

Goal Orientation Variables (*N* = 307)

Chi-square and Mahalanobis distance tests were applied to data from the 12 questionnaire items to detect univariate and multivariate outliers (Tabachnick &

Table 2. Properties of the Goal Orientation Variables (N = 307)

	α	*M*	*Mdn*	*SD*	Skewness (*SE* = .139)	Kurtosis (*SE* = .277)
Mastery approach	.91	15.39	16.0	3.72	–.459***	–.450
Mastery avoidance	.92	12.51	12.0	4.42	–.073	–.691
Performance approach	.96	12.92	14.0	4.65	–.503***	–.541
Performance avoidance	.90	13.17	14.0	4.74	–.420	–.766

***$p < .001$

Fidell, 2007). A total of 13 cases were deleted, leaving 307 participants in the data set. Each of the four goal orientation variables in the 2 × 2 model (mastery approach, mastery avoidance, performance approach, performance avoidance) was constructed as the sum of responses to the three semantically corresponding items. Because the research design sampled participants from two semesters, it was necessary to demonstrate equivalence before pooling the two samples. Analysis of variance and Levene's test of homogeneity of variance were separately applied at the $p = .05$ level to each of the goal orientation variables and failed to statistically detect differences between the means and variances of the two samples. Table 2 shows the internal consistency, mean, median, standard deviation, skewness, and kurtosis for each of the goal orientation variables after pooling the two samples. There was high internal consistency for all four variables. When skewness and kurtosis were examined by z-tests, negative skewness was statistically detected ($p < .001$) for the performance approach and mastery approach variables.

Goal Orientation of gStudy Users (n = 80)

As described previously, only a subsample ($n = 80$) of the participants made sufficient use of gStudy to provide substantive learning activity data. Table 3 shows the internal consistency, mean, median, standard deviation, skewness and kurtosis for each of the goal orientation variables in the gStudy subsample. Skewness and kurtosis were not statistically detected by z-tests at the $p = .001$ level.

To determine whether substantial use of gStudy to study chapter 7 of the textbook related to self-reports of goal orientation, participants in the gStudy subsample, who had produced at least two gStudy sessions greater than 20 minutes each ($n = 80$), were compared with those who had not ($n = 227$). Analysis of variance and the Levene test of homogeneity of variance were separately applied at the $p = .05$ level to each of the goal orientation variables and failed to statistically detect differences between the means of the two samples. Heterogeneity of variance was statistically detected only for mastery avoidance (Levene = 7.265, $p = .007$). On this variable, the gStudy sample had a variance of

Table 3. Properties of the Goal Orientation Variables for gStudy Users ($N = 80$)

	α	M	Mdn	SD	Skewness ($SE = .269$)	Kurtosis ($SE = .532$)
Mastery approach	.91	15.60	16.0	3.61	–.176	–.849
Mastery avoidance	.94	12.93	12.0	4.99	–.022	–1.073
Performance approach	.96	12.98	15.0	4.71	–.456	–.707
Performance avoidance	.92	13.25	14.0	5.02	–.337	–.919

17.64 and the non-gStudy sample had a variance of 24.9. A chi-square test failed to statistically detect an association between gender and membership in the gStudy group, $\chi^2(1) = 1.28$, $p = .311$.

Correlations among Goal Orientations and Learning Activities

The correlations among self-report and trace variables are presented in Table 4. The table reports statistically detected relationships at the $p < .05$, $p < .01$, and the Bonferroni adjusted level of $.05/k \Rightarrow .0009$ for the $k = 55$ correlations in the table. Mastery approach and mastery avoidance negatively correlated with number of highlights ($p < .05$). Mastery avoidance also negatively correlated with highlight rate. Performance avoidance negatively correlated with word productivity ($p < .05$).

Canonical Correlation between Goals and Learning Activities

Canonical correlations were calculated between the four goal orientation variables and the four primary activity variables (time invested, number of highlights, number of notes, words entered). Canonical correlation is a method for assessing relationships between two sets of variables (Tabachnick & Fidell, 2007). The method returns correlations between paired canonical variates, each composed of a linear combination of variables from one set. The canonical correlation program available to us was limited by an inability to rotate the canonical variates to improve interpretability.

The program returned correlations for four pairs of canonical variates. With all four canonical correlations included, a relationship was statistically detected at $p = .056$, $\chi^2(16) = 25.86$. The first and second canonical correlations were .42 (18% overlapping variance) and .33 (11% overlapping variance).

Table 5 shows the results for the first two variate pairs, including correlations between the variables and the canonical variates, standardized canonical variate coefficients, within-set variance accounted for by the canonical variates (proportion of variance), and redundancies. The total proportion of variance and

Table 4. Correlations among Goal Orientations and Study Activities for gStudy Users ($n = 80$)

	1	2	3	4	5	6	7	8	9	10
1. Mastery approach	—									
2. Mastery avoidance	.68***	—								
3. Performance approach	.08	.02	—							
4. Performance avoidance	.10	.40***	.36**	—						
5. Time invested	−.14	.13	.05	.17	—					
6. Number of highlights	−.26*	−.23*	.15	−.05	.26*	—				
7. Highlight rate†	−.19	−.25*	.13	−.09	.03	.80***	—			
8. Number of notes†	.01	.09	−.07	.01	.10	−.28**	−.44***	—		
9. Note rate†	.06	.08	−.05	−.05	−.23*	−.40***	−.51***	.84***	—	
10. Words entered†	.19	.12	.01	−.10	.29**	−.11	−.13	.00	−.15	—
11. Word productivity†	.20	−.08	−.05	−.29**	−.68***	−.25*	−.06	−.07	.13	.42***

*$p < .05$; **$p < .01$; ***$p < .0009$.
†Variable was either transformed by the log10 function or constructed from a transformed variable.

Table 5. Two Canonical Correlations between Goal Orientation and Learning Activity

	First canonical correlation = .42		Second canonical correlation = .33	
	Correlations	Coefficients	Correlations	Coefficients
Goal orientation set				
Mastery approach	–.56	–1.18	.71	.34
Mastery avoidance	.18	.85	.88	.57
Performance approach	.07	.03	–.38	–.49
Performance avoidance	.56	.33	.31	.22
Proportion of variance	.17		.38	Total = .55
Redundancy	.03		.04	Total = .07
Learning activity set				
Time invested	.78	.99	.13	.36
Number highlights	.23	–.08	–.92	–1.01
Number notes	.17	.05	.28	–.03
Words entered	–.36	–.66	.33	.12
Proportion of variance	.21		.26	Total = .47
Redundancy	.04		.03	Total = .07

total redundancy indicate that canonical variates were moderately related within both pairs.

Goal orientation variables correlating greater than .3 with the first goal orientation variate were mastery approach (–.56) and performance avoidance (.56). Using the same criterion, learning activity variables correlating with the first learning activity variate were time invested (.78) and words entered (–.36). These data show that students with lower mastery approach and higher performance avoidance tended to invest more time and enter fewer words.

In the second canonical variate pair, the correlations of the goal orientation variables were mastery approach (.71), mastery avoidance (.88), and performance approach (–.38), and performance avoidance (.31). Learning activity variables correlating greater than .3 with the learning activity variate were number of highlights (–.92) and words entered (.33). Thus, students with higher mastery orientation (approach or avoidance), lower performance approach, and higher performance avoidance, tended to make fewer highlights and enter more words.

Multiple Regression Analysis

A series of seven exploratory multiple regressions were performed, each using the four goal orientation variables as independent variables and one of the seven learning activity variables as the dependent variable. No relationships were statistically detected. The failure to reject the null in the cases where number of highlights, highlight rate, and word productivity served as the dependent variable, despite the reported findings of correlations and canonical correlations involving these variables, was attributed to redundancy of predictive variance across goal orientation variables combined with loss of degrees of freedom incurred by introducing multiple predictors.

DISCUSSION

We interpret these findings to suggest that students' self-reports of achievement goal orientations were related to traces of their tactics while studying a textbook chapter using gStudy. Our research hypotheses were partially confirmed: Students' mastery orientations (approach and avoidance) negatively covaried with number of highlights; mastery avoidance negatively covaried with a log transform of highlighting rate; and performance avoidance negatively covaried with word productivity, a variable related to rate of word entry. Some other predicted relationships, most notably that between mastery approach and words entered, were present in the sample but not statistically detected. Relevant to this, we interpret the multivariate results to suggest that students with higher mastery approach and lower performance avoidance had shorter study sessions but created longer notes.

These findings are consistent with the two-part claim that a) students who have stronger mastery goals are more likely to avoid surface processing tactics, and b) the frequency and rate of highlighting in gStudy represent such tactics. These results are also consistent with the claim that a) students who have a stronger mastery approach goal and are less concerned about poor performance tend to choose relatively deep processing tactics, and b) the number of words entered into gStudy notes is an index of processing depth. The positive but statistically undetected relationship between mastery approach and words entered may indicate that there was insufficient statistical power to detect it.

The lack of covariation between note creation and goal orientation was inconsistent with our research hypotheses. We suspect that the frequency of note creation events was a less reliable measure because there was some evidence that students often created and then deleted untitled, empty notes as if exploring or practicing use of the note tool. We were not able to adjust the number of notes variable to account for deleted notes. Another possibility is that mastery oriented students express their tendency toward deeper processing by adding more detail to their notes, not by making notes more extensively throughout the material.

The lack of significant covariation between performance goals and activity traces was also inconsistent with our research hypotheses. We speculate that, when they are aware they are observed, performance oriented students are more likely to socially distort their activity traces by engaging more tactics that they believe are valued by the observer, and engaging fewer that they believe are not valued. The conditions of the study may have precipitated such social distortion because the participants knew their activities were being recorded, had been taught both highlighting and note-taking during the training sessions, and may have inferred from the course lectures and readings that summarizing is regarded as a more effective tactic than highlighting. Similar social distortion may explain the positive, though not statistically detected, correlation between performance avoidance and session duration. Longer session duration may, in turn, have contributed to the negative relation between performance avoidance and word productivity. Certainly, session duration in this study cannot be used as an estimate of effort because there is evidence of widely varied activity rates within sessions, and it is likely that many students pursued learning goals by studying the same chapter in the paper version of their textbook.

The finding that notes were almost entirely elaborative is important. It suggests that the use of deeper learning tactics may be meaningfully measured by counting notes or words in notes. The correlation of words entered with mastery approach further indicates that counting words may be a more sensitive measure of deeper learning tactics than counting whole notes. We intend to modify our analysis software so that word counts from individual sessions can be more easily obtained.

A limitation of the study is that data were collected from only a single assigned task, and analyses include only the subset of students who used gStudy for at least two 20-minute sessions. Notwithstanding, our results indicate that traces recorded by gStudy indicate the motives, preferences and decisions that characterize learners' SRL. Although traces can be difficult to gather and under some conditions may be subject to social distortion, as indicators of learning tactics and strategies they have potential as an alternative to self-reports which are more prone to misjudgment and errors of recall (see Winne, Jamieson-Noel, & Muis, 2002; Winne & Perry, 2000).

Although the results are only partially consistent with the many studies which have used self-reports to link mastery goals to deep processing and performance goals to surface processing (e.g., Elliot et al., 1999), much of the inconsistency can be attributed to the different properties of self-reports and activity traces. When students fill out a learning strategy self-report instrument such as the motivated strategies for learning questionnaire (Duncan & McKeachie, 2005), they are not forced to choose between strategies. The student may express high preferences for both deep processing and surface processing strategies, thus attenuating the expression of negative correlations between the two types. While actually studying, however, the student must either choose between tactics or increase studying time. Research using self-report measures of learners' strategies and tactics may find that mastery orientation predicts deep processing, but is unrelated to surface processing (e.g., Elliot et al., 1999). But if the same learners used gStudy, a negative correlation between mastery orientation and surface processing would be observed, as in the present research.

Challenges of Analyzing Trace Data Collected Outside the Laboratory

In the research reported here, students chose whether, how, and how much to use software tools to study a chapter for a graded assignment. The wide variation in engagement afforded by these conditions introduced significant barriers to meaningfully analyzing log data. For example, a student might choose to highlight in gStudy but leave gStudy running while making notes on paper or raiding the refrigerator. An analyst may be unable to distinguish that strategy or the interruption of studying from the approach of a student who only highlights at a low rate. In the research reported here, students used gStudy in high demand university computer labs, a situation that somewhat mitigated the problem of going off-task while logged in. In other research, however, gStudy is being used by students at home where much greater variation in usage patterns can be expected.

These issues can be addressed in three ways: a) observe subsamples of learners in laboratory environments to identify common patterns of gStudy usage; b) have students self-report their gStudy usage; and c) gather more detailed log data such as mouse movements or navigation clicks and use them to estimate active gStudy time more accurately than login duration.

Events like taking notes and highlighting are theorized to be causes of variance in achievement. Moreover, rather than be forced to assume *a priori* that variance around a mean is random, trace data allow researchers to measure *in situ* many key sources of that variance. This provides a basis for blocking participants *a posteriori* (Winne, 2006). Importantly, it allows researchers to avoid risky and very likely invalid interpretations growing out of statistical methods by which the variance of some measures is partialed from others.

Analyzing Relationships between Achievement Goals and Content Studied

The present research investigated the frequency and rate of learning activities but did not examine whether the content of textbook information that students chose to highlight or annotate varied with achievement goals. In future research, we plan to investigate whether students with a mastery goal orientation may be more willing to read, highlight, and annotate peripheral information, such as titles of referenced articles and side bars titled "further reading" that are less likely to appear on an examination. This behavior would reflect the theoretical supposition that students having mastery goals strive for deeper and broader understanding. Students with performance approach goals may prefer to attend to information directly related to course assessments, such as an outline of the main ideas of the chapter, or information signaled in text by features such as bold font or phrasing like, "The important distinction . . . ." This behavior would reflect the theoretical supposition that performance orientation leads to processing that is relatively superficial and less guided by schemas in the domain of knowledge being studied.

Future research will be able to use gStudy's log analysis capability to track students' information preferences and analyse their relationships with individual differences and task characteristics.

REFERENCES

Chi, M. T. H., de Leeuw, N., & Chiu, M.-H. (1994). Eliciting self-explanations improves understanding. *Cognitive Science, 18,* 439-477.

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational Psychologist, 40,* 117-128.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review, 95,* 256-273.

Elliot, A. J. (1999). Approach and avoidance motivation and achievement goals. *Educational Psychologist, 34,* 169-189.

Elliot, A. J., & Church, M. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology, 72*, 218-232.

Elliot, A. J., & Harackiewicz, J. M. (1996). Approach and avoidance achievement goals and intrinsic motivation: A mediational analysis. *Journal of Personality and Social Psychology, 70,* 549-563.

Elliot, A. J., & McGregor, H. A., (2001). A 2 × 2 achievement goal framework. *Journal of Personality and Social Psychology, 80,* 501-519.

Elliot, A. J., McGregor, H. A. & Gable, S. L. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology, 91,* 549-563.

Entwistle, N., & McCune, V. (2004). The conceptual bases of study strategy inventories in higher education. *Educational Psychology Review, 16,* 325-346.

Foos, P. W. (1995). The effect of variations in text summarization opportunities on test performance. *Journal of Experimental Education, 63,* 89-95.

Gorrell, J., Tricou, C., & Graham, A. (1991). Children's short- and long-term retention of science concepts via self-generated examples. *Journal of Research in Childhood Education, 5*, 100-108.

Hadwin, A. F., & Winne, P. H. (1996). Study strategies have meager support: A review with recommendations for implementation. *Journal of Higher Education, 67,* 692-715.

Harackiewicz, J. M., Baron, K. E., Tauer, J. M., Carter, S. M., & Elliot, A. J. (2000). Short-term and long-term consequences of achievement goals: Predicting interest and performance over time. *Journal of Educational Psychology, 92,* 316-330.

Huffman, L. E., & Spires, H. A. (1994). Effects of explicit instruction in notetaking on sixth graders' lecture comprehension and attitudes toward notetaking. *Reading Improvement, 31,* 72-76

Igo, L. B., Bruning, R., & McCrudden, M. T. (2005). Exploring differences in students' copy-and-paste decision making and processing: A mixed-methods study. *Journal of Educational Psychology, 97,* 103-116.

Jamieson-Noel, D. L., & Winne, P. H. (2003). Comparing self-reports to traces of studying behavior as representations of students' studying and achievement. *German Journal of Educational Psychology* [*Zeitschrift für Pädagogische Psychologie*], *17*, 159-171.

Kierwa, K. A., DuBois, N. F., Christian, D., McShane, A., Meyerhoffer, M., & Roskelley, D. (1991). Notetaking functions and techniques. *Journal of Educational Psychology, 83,* 240-245.

Marton, F., & Säljö, R. (1976). On qualitative differences in learning: I. Outcome and process. *British Journal of Educational Psychology, 46,* 4-11.

Marxen, D. E. (1996). Why reading and underlining a passage is a less effective strategy than simply rereading the passage. *Reading Improvement, 33,* 88-96.

Mayer, R. E. (1996). Learning strategies for making sense out of expository text: The SOI model for guiding three cognitive processes in knowledge construction. *Educational Psychology Review, 8,* 357-371.

Nussbaum, E. M., & Sinatra, G. M. (2003). Argument and conceptual engagement. *Contemporary Educational Psychology, 28,* 384-395.

Pintrich, P. R. (1995). Understanding self-regulated learning. In P. R. Pintrich (Ed.), *Understanding self-regulated learning* (pp. 3-12). San Francisco: Jossey-Bass.

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 451-502). San Diego: Academic Press.

Ravindran, B., Greene, B. A., & DeBacker, T. K. (2005). Predicting preservice teachers' cognitive engagement with goals and epistemological beliefs. *Journal of Educational Research, 98,* 222-232.

Schraw, G., Horn, C., Thorndike-Christ, T., & Bruning, R. (1995). Academic goal orientations and student classroom achievement. *Contemporary Educational Psychology, 20,* 359-368.

Tabachnick, B. G. & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston, MA: Allyn & Bacon.

Winne, P. H. (1992). State-of-the-art instructional computing systems that afford instruction and bootstrap research. In M. Jones & P. H. Winne (Eds.), *Adaptive learning environments: Foundations and frontiers* (pp. 349-380). Berlin: Springer-Verlag.

Winne, P. H. (2001). Self-regulated learning viewed from models of information processing. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives* (2nd ed., pp. 153-189). Mahwah, NJ: Lawrence Erlbaum Associates.

Winne, P. H. (2006). How software technologies can improve research on learning and bolster school reform. *Educational Psychologist, 41,* 5-17.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277-304). Mahwah, NJ: Lawrence Erlbaum Associates.

Winne, P. H., & Jamieson-Noel, D. L. (2002). Exploring students' calibration of self-reports about study tactics and achievement. *Contemporary Educational Psychology*, *27,* 551-572.

Winne, P. H., & Jamieson-Noel, D. L. (2003). Self-regulating studying by objectives for learning: Students' reports compared to a model. *Contemporary Educational Psychology, 28,* 259-276.

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In M. Boekaerts, P. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531-566). Orlando, FL: Academic Press.

Winne, P. H., Hadwin, A. F., Nesbit, J. C., Kumar, V., & Beaudoin, L. (2005). gStudy: A toolkit for developing computer-supported tutorials and researching learning strategies and instruction (version 2.0) [computer program]. Simon Fraser University, Burnaby, BC.

Winne, P. H., Jamieson-Noel, D. L., & Muis, K. (2002). Methodological issues and advances in researching tactics, strategies, and self-regulated learning. In P. R. Pintrich & M. L. Maehr (Eds.), *Advances in motivation and achievement: New directions in measures and methods* (Vol. 12, pp. 121-155). Greenwich, CT: JAI Press.

Woolfolk, A. E., Winne, P. H., & Perry, N. E. (2003). *Educational psychology* (2nd Canadian ed.). Toronto, ON: Pearson.

Zimmerman, B. J. (2001). Theories of self-regulated learning and academic achievement: An overview and analysis. In B. J. Zimmerman & D. H. Schunk (Eds.), *Self-regulated learning and academic achievement: Theoretical perspectives* (2nd ed., pp. 1-37). Mahwah, NJ: Lawrence Erlbaum Associates.

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