

## Using multiple, contextualized data sources to measure learners' perceptions of their self-regulated learning

Lindsay McCardle · Allyson F. Hadwin

Received: 18 November 2013 / Accepted: 28 December 2014 /

Published online: 20 January 2015

© Springer Science+Business Media New York 2015

**Abstract** As theory and research in self-regulated learning (SRL) advance, debate continues about how to measure SRL as strategic, fine-grained, dynamic adaptations learners make during and between study sessions. Recognizing learners' perceptions are critical to the strategic adaptations they make during studying, this research examined the unique contributions of self-report data for understanding regulation as it develops over time. Data included (a) scores on the Regulation of Learning Questionnaire (RLQ) completed in the first and last few weeks of a 13-week course and (b) diary-like Weekly Reflections completed over 11 weeks. Participants were 263 undergraduate students in a course about SRL. First, exploratory factor analysis resulted in a five-factor model of the RLQ with factors labeled Task Understanding, Goal Setting, Monitoring, Evaluating, and Adapting. Second, latent class analysis of Time 1 and 2 RLQ scores revealed four classes: *emergent regulators*, *moderate regulators*, *high regulators with emergent adapting*, and *high regulators*. Finally, in-depth qualitative analysis of Weekly Reflections resulted in group SRL profiles based on a sub-sample of participants from each RLQ class. Qualitatively, these groups were labeled: *unengaged regulators*, *active regulators*, *struggling regulators*, and *emergent regulators*. Quantitative and qualitative SRL profiles were juxtaposed and similarities and differences discussed. This paper explicates and discusses the critical importance of sampling self-reports of SRL over time and tasks particularly in contexts where regulation is developing.

**Keywords** Self-regulated learning · Self-report data · Metacognition

The past two decades have witnessed a proliferation of research on self-regulated learning (SRL). Despite advancements in SRL theory and research, debate continues about how to measure SRL, especially when defined as fine-grained, dynamic adaptations learners make during and between study sessions (Winne and Hadwin 1998). For the most part, self-report instruments have treated SRL as a disposition (Boekaerts and Corno 2005; Winne and Perry 2000). In contrast, SRL can be viewed as a series of events, where each event is a snapshot in

---

This research was supported by the Social Sciences and Humanities Research Council of Canada, Standard Research Grant 410-2008-0700 (PI: Hadwin).

L. McCardle (✉) · A. F. Hadwin

Educational Psychology and Leadership Studies, University of Victoria, Victoria, BC V8W 3N4, Canada  
e-mail: [mcardle@uvic.ca](mailto:mcardle@uvic.ca)

time. Measuring SRL as an event means documenting SRL as it occurred in a particular task, context, and study episode.

Attempts to measure SRL as an event, or a series of events, have shifted focus away from self-report inventories and toward observation measures of SRL such as video records and computer-generated traces (or logfiles) of inferred SRL actions (Azevedo et al. 2013; Hadwin et al. 2004, 2007) and think aloud protocols (Azevedo 2005). This shift is due in part to the fact that self-report inventories have failed to capture fine-grained adaptation, in terms of specific learning events or actions that together comprise self-regulatory processes (Boekaerts and Corno 2005; Pintrich et al. 2000; Winne et al. 2002; Winne and Perry 2000). However, consistent with Nelson (1996), we posit self-perceptions are critical for understanding regulatory actions and decisions. Therefore, this study examines the use of two kinds of self-report measures for capturing changes or adaptation in SRL processes over time, highlighting the importance of SRL in context.

## SRL framework

Self-regulated learners take an active approach to learning by planning, monitoring, and adapting in order to reach self-set goals (Boekaerts and Corno 2005; Winne 1997, 2001; Winne and Hadwin 1998; Zeidner et al. 2000; Zimmerman 1986, 1989), and several theoretical models of SRL have been proposed (e.g., Boekaerts 1996, 2006; Boekaerts and Niemivirta 2000; Pintrich 2004; Winne and Hadwin 1998, 2008; Zimmerman 1989, 2000). Most SRL models emphasize the importance of strategic approaches to learning that are intentional or goal-driven, and adaptive (Puustinen and Pulkkinen 2001). While each model recognizes the importance of planning, monitoring, and strategically engaging or adapting, they tend to emphasize different facets of SRL. For example, Boekaerts' (1996, 2006) model of adaptable learning is noted for its attention to the interaction between metacognitive, motivational, and emotional control systems. Pintrich (2000) emphasizes motivation, self-efficacy, and goal orientation as critical features of SRL associated with four phases: forethought, monitoring, control, and reflection. Zimmerman (1989, 2001) models SRL over three phases including forethought, performance, and self-reflection with each phase comprising specific regulatory processes such as: task analysis and self-motivation beliefs during the forethought phase, self-control and self-observation as part of the performance phase, and self-judgment and self-reaction comprising the self-reflection phase.

A limitation of these models is that they emphasize broader aspects of self-regulated learning, rather than detailing specific mechanisms operating across phases and facets of regulation. In contrast, Winne and Hadwin's (1998, 2000) model of SRL details a common cognitive architecture that accounts for interaction of a person's conditions, operations, products, evaluations, and standards (COPES) within and across phases of SRL. "Winne and Hadwin's model complements other SRL models by introducing a more complex description of the processes underlying each phase" (Greene and Azevedo 2007, p. 335).

Winne and Hadwin (1998) model SRL as unfolding over four loosely sequenced phases of studying. From this perspective, SRL is a recursive cycle in which learners may revisit phases in any order. Metacognitive monitoring and control are central components. In phase 1, learners construct task perceptions that are internal representations of the task at hand. If learners misperceive tasks, their engagement, monitoring, and control are likely to be miscalibrated. Phase 2, goal setting and planning, involves translating task perceptions into specific standards and plans for successful task completion. When learners set specific, clear, proximal goals (McCardle et al. 2012; Zimmerman 2008), opportunities arise for more

accurately monitoring and regulating as the task unfolds. In phase 3, learners put their plans into action by engaging tactics and strategies for task enactment. For high quality learning, students must match cognitive processing strategies to the task and to their goals for the task. In phase 4, learners evaluate and adapt their studying. This is the reflective component of SRL wherein learners respond to challenges, shortcomings, and failures during a study episode and into future study episodes. This adaptive process in response to challenge is the essence of productive self-regulation. It requires learners to monitor and evaluate progress against their standards and to actively adapt or revise studying based on those evaluations. Successful learners recognize and address problems as they study. By being metacognitively aware of their studying, they experiment with methods of learning (Winne 1997, 2011).

Winne and Hadwin (1998) expand on the processes learners engage in each phase of SRL with the COPES cognitive architecture. *Conditions* are the contexts that surround a learners' work and can be both internal (e.g., cognitions, motivation, and affect) and external (e.g., environment, social aspects). *Operations* are the manipulations of information that create mental products in each phase (i.e., perceptions of the task, goals, plans, task enactment status, and adaptive responses). *Products* are created by operating on information or knowledge. Products from each phase become the conditions for the following phase. *Evaluation* takes place when learners compare products to the *standards* they have set. Learners evaluate and regulate at the level of both phases and tasks. The potential of Winne and Hadwin's model lies in its ability to guide a nuanced and contextualized examination of learning (Greene and Azevedo 2007). This creates a strong foundation for designing and examining the efficacy of a self-report measure of self-regulatory processes sensitive to the ways SRL unfolds and changes over time.

## Measurement of SRL

Considering SRL from Winne and Hadwin's (1998) model, three critical aspects influence assessment design. First, regulation unfolds over time; as Winne and Perry (2000) describe it, SRL can be viewed as an event. Popular self-report measures (e.g., LASSI, Weinstein et al. 1987; MSLQ, Pintrich et al. 1993; SBI, Bliss and Mueller 1993) have tended to measure SRL as a disposition, prompting responders to aggregate responses across time. This provides limited information to understand how learners make strategic decisions and small-grained adaptations over time. Assessing SRL as an event means measuring SRL as it occurred in a particular study episode, rather than learners' perceptions of what they generally do (Patrick and Middleton 2002).

Second, regulation is sensitive to context. Learners adjust what they do and how they study depending upon task, self, and context conditions (Winne and Hadwin 1998). Hadwin, Winne, Stockley, Nesbit, and Woszczyna (2001) found learners adjusted tactics, resources, and goals in each of three separate learning tasks. Measures of SRL need to be sensitive to conditions that influence learners' regulatory decisions, yet many self-report inventories aggregate responses across different types of tasks (Patrick and Middleton 2002). For instance, contextual frames for LASSI and MSLQ include varied task contexts, such as completing course readings, studying for exams, and writing term papers.

Third, learners use more than strategy knowledge and application to productively self-regulate. The specific tactics or strategies learners engage vary from task to task and goal to goal. However, successful learners engage in regulatory processes regardless of the task or goal. Existing self-report questionnaires have focused mainly on strategies learners use, such as highlighting, elaborating or time use (e.g., Yang and Bliss 2014). Rather, the focus for

measuring SRL needs to be on the regulatory processes learners engage, such as attempts to unpack task descriptions and monitor learning.

From our perspective, assessing SRL requires measures that are sensitive to time, task, and metacognitive processes. In addition, researching SRL needs to be done in authentic learning situations that have meaning for learners and present real challenges, whether cognitive, metacognitive, motivational, or behavioral. Knowing how students adjust studying when they have just failed an economics midterm or how they tackle an essay when they are struggling with procrastination reveals active regulation processes that arise in response to student-centered challenges and authentic problems in their own learning milieu. Therefore, we posit that understanding and providing timely SRL support requires more systematic assessment of students' challenges, experiences, and perceptions in authentic learning situations.

While several self-report measures exist and are used extensively in the literature, more recent research has shifted to use of observation measures using observation protocols or computer-generated traces of SRL that track learners' actions in online material (Boekaerts and Corno 2005; Hadwin et al. 2004). Trace data include logs of keystrokes and clicks, tracking when learners click back to re-read a section, add notes or highlights, or check grades on a quiz, for instance. This requires researchers to make inferences about learners' intentions and decision making processes that guide learners' actions. The shift to objective observation measures has been spawned in part by findings that reveal the inaccuracy, or poor calibration, of student self-reports of learning (Hadwin et al. 2007). Winne and Jamieson-Noel (2002) found that students overestimated their use of study tactics when compared to traces of their actual tactic use. Furthermore, Winne and others (Winne 2010; Winne and Perry 2000; Winne et al. 2011) argue self-reports are limited simply because they depend on human memory. Learners base responses on (a) inaccurate recall of SRL products and processes, (b) an incomplete and biased sample of experiences, (c) a variety of contexts, and (d) strategies they know or believe to be effective rather than ones they actually engage (Winne et al. 2011). From this perspective, relying on learners' self-reports provides a skewed view of SRL on which to base and modify theories and interventions, and a shift towards observation-based measures of SRL is warranted.

However, consistent with Butler (2002), we argue self-reports provide important information for examining and interpreting SRL even when the reports are inaccurate or skewed. Learners' perceptions are central when the object of inquiry is self-regulated learning. Self-regulation refers to an individual's capacity to respond adaptively during learning; learners use their own monitoring judgments as a basis for control and regulation whether those judgments are accurate (Nelson 1996; Winne and Hadwin 1998; Winne et al. 2011). Learners are not always accurate in their judgments of learning (Nelson and Dunlosky 1991). Often they base studying decisions on how readily they can recall information, failing to take into account critical information such as delays between studying and testing that influence this evaluation (Bjork et al. 2013). However, understanding self-regulated learning means understanding learners' perceptions of the ways they interpret and respond to tasks, set goals, monitor and adapt learning in the context of those inaccurate evaluations.

In addition, a recent focus of SRL research has been on understanding SRL as an event. As a result, many self-report measures have been criticized for emphasizing SRL as a disposition under the assumption that self-report data are always dispositional in nature, requiring respondents to aggregate data across time and context. However, several innovative self-report approaches have been successfully employed to research SRL beyond its dispositional characteristics. These include diaries (Schmitz et al. 2011), microanalysis (Cleary 2011), and think aloud protocols (Greene et al. 2011). Each of these methods focuses on one specific event and thus has the ability to capture evolutions in learners' perceptions both during and

across study sessions. These event-focused self-report approaches provide a much-needed qualitative lens for understanding how learners regulate (Butler 2002; Patrick and Middleton 2002; Perry 2002). However, research has rarely combined data from multiple self-report instruments to examine patterns in students' perceptions and actions as regulatory responses to unfolding learning situations.

The purpose of this study was to explore the use of two forms of self-report data to understand SRL as it unfolds over time and context. We introduce the Regulation of Learning Questionnaire as a questionnaire designed to be sensitive to time, context, and metacognitive processes. Combining this with Weekly Reflection diary data, we examine three interrelated research questions: (1) What components of SRL are captured by the Regulation of Learning Questionnaire? (2) What quantitative patterns of regulatory engagement emerge across one semester during which learners were enrolled in a course to improve SRL? and (3) What patterns emerge when quantitative and qualitative self-report data are combined?

## Method

### Participants

Participants were 263 students from a mid-sized, non-urban Canadian university. Students were recruited from a first year, graded undergraduate course across three semesters. Participants' mean age was 19.5 years (57 % female). Participants came from a range of faculties and disciplines. For 27 % of participants, this was their first semester enrolled in post-secondary education.

### Educational context

Data were collected in a 12-week academic course called *Learning Strategies for University Success* about SRL processes and strategies, taught by members of our research team. Students attended a weekly lecture and corresponding lab component for a total of 3 h of instruction a week. The lecture taught about the four-phase cycle of SRL (Winne and Hadwin 1998), the facets of SRL (cognition, behaviour, motivation/affect) and cognitive and behavioural strategies for becoming a productive self-regulated learner. The lab engaged learners in guided activities involving the application of regulatory strategies to regular academic work for courses outside *Learning Strategies*. As such, students were required to be concurrently registered in at least one other course. Of note, participants were strategically sampled from a course where students were expected to demonstrate changes in their SRL over time in order to maximize variance in responses across participants and within participants over time. In other words, this research intentionally strived to test instruments that would be sensitive to event-based changes over time as well as student-based variability in SRL.

### Measures

*Regulation of learning questionnaire* The Regulation of Learning Questionnaire (RLQ; Hadwin 2009) is based on Winne and Hadwin's (1998) model of SRL. It assessed participants' perceptions of actions and strategies specific to key processes and phases associated with SRL: task understanding, goal setting and planning, monitoring, evaluating, and adapting. Rather than reporting on what they do generally, learners were instructed to think about a recent,

particular study session for an exam and to respond based on that particular study session. In order to be used in other task contexts (e.g., writing a paper, reading for class, note-taking during a lecture), specific items may need to be modified.

Students' instructions were, "Think of a recent study session you did for an upcoming test or exam. When you answer the following questions think about that specific study session." Students focused on exam preparation and provided the name of the course for which they had been studying. Learners responded to items on a 7-point Likert response scale anchored at 1 *not at all true of me* and 7 *very true of me*. This scale is consistent with those used in other contemporary measures of studying (e.g., MSLQ).

The original RLQ comprised of 49 items targeting 5 a priori subscales: (a) Task Understanding (11 items; B1-B11; e.g., figured out why I am being asked to know this stuff), (b) Goal Setting and Planning (9 items; B12-B20; e.g., set goals that would be useful for checking on my own progress as I studied), (c) Monitoring (9 items; A1-A9; e.g., asked myself if I was remembering the material), (d) Evaluating (10 items; A10-A19; e.g., appraised or estimated my progress), and (e) Regulating (10 items; A20-A29; e.g., switched to a different strategy or studying process).

*Weekly reflections* Weekly Reflections were composed of two separate sections focused on (a) reflecting on last week and (b) planning for this week (see [Appendix A](#)). The cycle began with a *planning* section in the first lab where the focus was to set a goal for one study session in the following week. In week 2, students started with the *reflecting* section and considered their goal attainment and challenges in meeting their goal followed by completing another *planning* section for the following week. The cycle continued over 12 weeks with each student reflecting on the previous week's goal accomplishment and planning for the upcoming week. Though there were minor changes in the specific wording of items across the semesters, the items were consistent in their focus and intent with respect to target regulatory processes. Weekly Reflection diaries were anchored in participants' authentic learning tasks in their other course work that varied week to week.

## Procedure

The institution's Human Research Ethics Board approved all procedures. Students consented to participate in research. Participants completed the RLQ online as a lab activity once during the first 3 weeks of the semester (Time 1;  $n=244$ ) and again in the last 2 weeks of the semester (Time 2;  $n=221$ ). Completion of the RLQ was required for a participation mark, but responses were not graded. Students were given immediate feedback in the form of a profile of a priori subscale scores and were required to use those scores to reflect on their own studying strengths and weaknesses. Participants completed the Weekly Reflections at the beginning of each lab. Completion of the Weekly Reflections was required for a participation mark, but the responses were not evaluated.

## Analysis and findings

Research question 1: what is the factor structure of the RLQ?

*Analysis* Normally, confirmatory factor analysis (CFA) is used to confirm a priori subscale structure. However, CFA results in a previous study (McCardle et al. 2012) indicated poor model fit for each subscale, with the exception of Goals and Planning. Thus for this study, a

more exploratory approach was chosen to identify a set of latent constructs with exploratory factor analysis (EFA). EFA was conducted in MPlus 6.12 (Muthén and Muthén 2010) using maximum likelihood estimation. Promax rotation, an oblique rotation, was used as it allows factors to correlate. This approach is consistent with theory positing that SRL phases are related (Winne and Hadwin 1998) and expected to correlate. Time 1 and Time 2 data were analyzed in separate models. Considering participants were in a course to improve SRL, we expected there would be some differences in factor structure at these two data collection points. We were interested in a factor structure that would allow researchers to capture changes in SRL across time. Goodness of fit was assessed using the following indices and their suggested values for good model fit:  $p$ -value for  $\chi^2$  statistic ( $ns$ ; Kline 2011), standardized root mean square residual ( $.00 \leq SRMR \leq .05$ ; Byrne 2001), and root mean square error of approximation ( $.00 \leq RMSEA \leq .05$ ; Kline 2011).

As Step 1, separate EFAs with 49 items were run for data at Time 1 and Time 2 with 1-factor through 7-factor models. Following a priori subscales, it was expected 5 factors would best account for the data. At this point, items that loaded on two factors, had low factor loadings, or loaded on different factors at different times were removed from analysis; items that consistently loaded on a factor together were retained. For Step 2, separate EFAs with 4 and 5 factors for Time 1 and 2 were run with the remaining items. These data were examined for items that loaded on two factors, had low factor loadings, or loaded on different factors at different times. Final factors were created based on consistent grouping of items at Time 1 and Time 2 and similar grouping of items in the 4- and 5-factor solutions.

Finally, because students were learning about SRL and we expected changes in SRL across time, it is important to consider factorial invariance. Factorial invariance examines whether measures are equal across time or samples (Meredith 1993). Low factorial invariance implies differences between samples or across time may be due to changes in the factor weightings of the subscales rather than in the construct itself. Models of factorial invariance between Time 1 and Time 2 were run separately for each factor. Three levels of factorial invariance were examined: (a) the configural baseline provides a model for comparison where the same items are constrained to load on a factor at Time 1 and Time 2 but the regression-loadings are free to vary, (b) the model of weak factorial invariance constrains item factor loadings to be equal at Time 1 and Time 2, and (c) the model of strong factorial invariance constrains factor loadings and item intercepts to be equal. Model fit was assessed using the same indices as the EFA, with the addition of comparative fit index ( $CFI \geq .90$ ; Kline 2011), and the Tucker-Lewis index ( $TLI \geq .95$ ; Byrne 2001).

**Findings** In Step 1, models with 6 and 7 factors did not converge for Time 1 data. Models with 4 and 5 factors had the best, though very poor model fit (see Table 1). At Time 2, 6- and 7-factor models did converge and model fit was improved over 4- and 5-factor models. However, the additional factors in these models did not add anything substantive to the 4- and 5-factor models from Times 1 and 2 and included factors that were difficult to interpret. Thus, 4- and 5-factor solutions at Time 1 and 2 were examined more closely (see Appendix B). Twelve items were removed from the analysis at this step: B5, B7, B10, B11, B14, B18, B20, A14, A15, A19, A26, A27 (see Appendix C).

In Step 2, separate EFAs were run with the remaining 37 items with Time 1 and Time 2 data. Acceptable model fit was obtained at Time 1 for the 4-factor solution ( $\chi^2(524) = 1215.7$ ,  $p = <.001$ ,  $RMSEA = .074$ ,  $RMSR = .049$ ) and 5-factor solution ( $\chi^2(491) = 1059.7$ ,  $p = <.001$ ,  $RMSEA = .069$ ,  $RMSR = .046$ ). At Time 2, acceptable model fit was found for the 4-factor solution ( $\chi^2(524) = 1098.7$ ,  $p = <.001$ ,  $RMSEA = .070$ ,  $RMSR = .052$ ) and the 5-factor solution ( $\chi^2(491) = 926.2$ ,  $p = <.001$ ,  $RMSEA = .063$ ,  $RMSR = .045$ ). Due to acceptable fit of both 4-

**Table 1** Step 1 EFA model fit

Fit indices	1-factor	2-factor	3-factor	4-factor	5-factor	6-factor	7-factor
Time 1							
$\chi^2$	12,138.2*	11,398.3*	11,048.5*	10,625.4*	10,345.8*	<sup>a</sup>	<sup>a</sup>
<i>df</i>	1175	1126	1078	1031	985		
RMSEA	0.196	0.193	0.195	0.195	0.197		
RMSR	0.105	0.080	0.073	0.066	0.058		
Time 2							
$\chi^2$	3370.7*	2668.4*	2339.4*	2053.5*	1839.4*	1655.9*	1507.1*
<i>df</i>	1127	1079	1032	986	941	897	854
RMSEA	0.095	0.082	0.076	0.070	0.066	0.062	0.059
RMSR	0.107	0.077	0.066	0.058	0.053	0.047	0.043

\* indicates  $p < .05$ . <sup>a</sup> Models did not converge

and 5-factor solutions, we examined both solutions at both times to create the final factors (see [Appendix D](#)).

At this point, no items were removed due to loading on two factors, or having low factor loadings. There were some items loadings on different factors in different models, and these items were dealt with individually (see [Appendix C](#)): (a) B8 and B9 did not consistently load with the other Task Understanding items in the 5-factor solution but did in the 4-factor solution, and were retained with this factor as they were theoretically related; (b) B19 loaded with Goal Setting items in the 4-factor solutions but not in the 5-factor solutions and was removed as it is theoretically more consistent with planning while the remaining items in the Goal Setting factor were more focused on goals; (c) A1 loaded either with the Monitoring or Evaluating items but had stronger loadings with Evaluating and was retained with these items; (d) A20 cross-loaded with Evaluating items at Time 1 but not at Time 2 and was retained with the Adapting items as it was theoretically related; and (e) A29 had loaded with Task Understanding items in the first EFA but did not demonstrate loadings above .3 on any factor in the second EFA and was removed.

Five factors were created based on consistent grouping of items across Time 1 and Time 2 and similar grouping of items in the 4- and 5-factor solutions. Items in both the Task Understanding and Adapting factors were clearly and consistently grouped together across the solutions examined. The Goal Setting items and Evaluating items tended to group together at Time 1, but the Goal Setting items were a separate factor at Time 2 in both 4- and 5-factor solutions. As Goal Setting and Evaluating are theoretically distinct processes (Winne and Hadwin [1998](#)), Goal Setting was considered a separate factor. Similarly, Monitoring and Evaluating items were not clearly separated in the 4-factor solutions but were in the 5-factor solutions and are theoretically separate processes and were retained as two factors.

The final five factors were labeled (a) Task Understanding, (b) Goal Setting, (c) Monitoring, (d) Evaluating, and (e) Adapting. [Table 2](#) presents (a) items, (b) item and subscale means and standard deviations, and (c) Cronbach's alphas for the five factors. Cronbach's alpha, a measure of reliability, was above acceptable level of .7 (Nunnally [1978](#)) for all factors at Time 1 and Time 2.

Model fit indices for each of the factorial invariance models for the five factors are found in [Table 3](#), including differences in  $\chi^2$  and degrees of freedom. Change in  $\chi^2$  statistics for Task Understanding and Adapting factors indicated model fit did not become significantly worse in

**Table 2** RLQ items and descriptives by factor

No	Item	Scale <sup>a</sup>	Time 1			Time 2		
			M	sd	$\alpha$	M	sd	$\alpha$
<b>Task understanding</b>								
B1	Figured out what I was being asked to know	TU	5.37	1.44		5.96	1.13	
B2	Figured out why I am being asked to know this stuff	TU	4.42	1.72		5.12	1.49	
B3	Identified what I need to learn	TU	5.66	1.27		6.14	0.96	
B4	Made sure I understood terminology used in task instructions	TU	5.48	1.28		5.78	1.14	
B6	Figured out what course theories or big ideas I should know for this study session	TU	5.58	1.37		6.05	1.08	
B8	Figured out why studying this is important in this course or discipline	TU	4.86	1.66		5.09	1.52	
B9	Figured out what documents/resources I should use for my studying (files, notes and readings)	TU	5.85	1.23		6.05	1.19	
Scale (7 items)				5.32	0.97	.72	5.06	1.15
								.79
<b>Goal setting</b>								
B12	Set goals for my work	GP	4.63	1.67		5.44	1.33	
B13	Set goals that identify specific concepts, ideas, or terms I need to know	GP	4.68	1.67		5.42	1.39	
B15	Set goals that would be useful for checking on my own progress as I studied	GP	3.96	1.75		4.97	1.42	
B16	Set goals that can be completed within a 1–2 h time block	GP	4.23	1.82		5.14	1.64	
B17	Created a study timeline	GP	3.37	2.00		4.35	1.95	
Scale (5 items)				4.17	1.23	.80	5.74	.082
								.79
<b>Monitoring</b>								
A2	Asked myself if I knew what was important	MON	5.20	1.59		5.76	1.26	
A3	Asked myself if I was understanding what I needed to know	MON	5.35	1.55		5.80	1.24	
A4	Asked myself if I was remembering the material	MON	5.36	1.58		5.81	1.21	
A5	Asked myself if I was understanding the material	MON	4.31	1.81		5.07	1.47	
Scale (4 items)				5.23	1.41	.90	5.78	1.04
								.86
<b>Evaluating</b>								
A1	Reflected on the way I studied	MON	5.00	1.72		5.74	1.27	
A6	Checked to see if my strategy (approach) was working	MON	4.60	1.71		5.36	1.33	
A7	Checked to see if I was making progress toward my goals	MON	4.39	1.80		5.40	1.40	
A8	Checked to see how I was doing with respect to the time I had allotted	MON	4.48	1.85		5.36	1.46	
A9	Checked to see if the goals I set for my studying were appropriate for the kind of test/exam I would be having	MON	4.61	1.68		5.40	1.31	
A10	Appraised my current understanding of the material	EV	3.57	1.84		4.51	1.76	
A11	Looked at feedback about the way I was studying	EV	4.36	1.62		5.14	1.42	

**Table 2** (continued)

No	Item	Scale <sup>a</sup>	Time 1			Time 2		
			M	sd	$\alpha$	M	sd	$\alpha$
A12	Appraised or estimated my progress	EV	4.70	1.62		5.26	1.37	
A13	Appraised or estimated my memory for the information	EV	5.29	1.74		5.08	1.70	
A16	Made a judgment about the usefulness or value of something I was studying	EV	4.23	1.70		4.80	1.64	
A17	Appraised the effectiveness of the strategies I used	EV	4.09	1.71		4.85	1.59	
	Scale (11 items)		4.36	1.20	.89	5.12	0.97	.86
Adapting								
A20	Changed or revised my understanding of what I was trying to do (the task itself)	AD	3.89	1.77		4.29	1.78	
A21	Changed my studying goal (what I was aiming for)	AD	3.42	1.87		3.87	1.85	
A22	Changed my plans for how to study	AD	3.57	1.96		3.83	1.85	
A23	Switched to a different strategy or studying process	AD	3.34	1.96		3.68	1.93	
A24	Changed the way I was feeling about the studying	AD	3.91	1.88		4.31	1.73	
A25	Changed the level of effort I was engaging in the work	AD	4.38	1.75		4.46	1.77	
A28	Changed my beliefs about how well I would do on this test	AD	4.67	1.81		4.96	1.61	
	Scale (7 items)		5.32	1.23	.83	5.74	.082	.83

TU Task understanding, GP Goal setting and planning, MON Monitoring, EV Evaluating, AD Adapting

<sup>a</sup> A priori subscale

the strong model, suggesting acceptance of strong factorial invariance. For Goal Setting, Monitoring, and Evaluating, there were significant changes in  $\chi^2$  statistics, indicating poorer fit of the more stringent model, but inspection of RMSEA and other relative fit statistics did not show major changes, suggesting acceptance of strong factorial invariance. Overall, model fit indices were weak. This finding is of particular interest because theory predicts that students with more self-regulated learning experience (Time 2) should develop more stable and purposeful approaches to studying in contrast with inexperienced regulators (Time 1) who may adopt random patterns of studying, engaging (or reporting) particular actions out of habit rather than strategic intent. For this reason we continued with further analysis, recognizing that, in the absence of factorial invariance, some caution should be exercised in interpreting results.<sup>1</sup> This is considered at length in the discussion.

<sup>1</sup> Additional CFA and invariance models were run including only the items whose factor loadings did not change by more than .049 from Time 1 to Time 2 (based on original strong FI models). Thus, in these models items from TU (B4, B8, B9), Goal setting (B12, B15), Monitoring (A4, A5), and Evaluating (A10, A11, A12, A13, A17, A18) were not included. CFA of the RLQ as a whole had weak model fit and strong factorial invariance was considered acceptable for the modified subscales (FI models for Monitoring were unidentified with only two remaining items). Factorial invariance models had drastic improvement in fit relative to the models that included our final set of items. See discussion for further consideration of these items.

**Table 3** Model fit indices for factorial invariance models

Model	$\chi^2$	df	$\chi^2$ diff	df diff	RMSEA	CFI	TLI	RMSR
Task understanding								
Configural	159.8*	69			.079	.898	.866	.059
Weak	172.0*	75	12.3	6	.078	.891	.868	.071
Strong	178.6*	80	6.6	5	.076	.890	.874	.072
Goal setting								
Configural	45.5*	29			.052	.973	.958	.039
Weak	56.1*	33	10.7*	4	.057	.962	.948	.057
Strong	69.5*	37	13.3*	4	.064	.947	.935	.058
Monitoring								
Configural	66.0*	15			.127	.948	.902	.053
Weak	76.0*	18	10.0*	3	.123	.940	.907	.079
Strong	83.2*	21	7.1*	3	.118	.936	.915	.075
Evaluating								
Configural	564.2*	239			.080	.856	.833	.055
Weak	579.9*	250	15.7	11	.079	.854	.838	.063
Strong	611.2*	261	31.3*	11	.080	.836	.836	.069
Adapting								
Configural	161.5*	69			.080	.915	.888	.053
Weak	166.1*	75	4.6	6	.076	.916	.898	.056
Strong	169.9*	80	3.8	5	.073	.917	.906	.058

\* indicates  $p < .05$

Research question 2: what quantitative patterns of regulatory engagement emerge across one semester?

*Analysis* Latent class analysis (LCA) serves to identify discrete latent variables (class) based on participants' profile of responses to a group of items. Using LCA allowed us to explore patterns of change in RLQ across Time 1 and 2 data collection points. Participants who had complete data at both time points ( $n=212$ ) were included in analysis. Means for each subscale (as defined by the EFA) were created for Time 1 and Time 2 and a difference score (Time 1 subtracted from Time 2) was calculated, incorporating a time component to the analysis. This resulted in 10 variables: means on the five EFA-defined factors at Time 1 and a difference score for each factor to account for change to Time 2. Though the use of gain scores has been debated in the literature, they are appropriate for educational research because they address the intra-individual change indicating learning has taken place (e.g., Williams and D. Zimmerman 1996), which is the focus of the current study.

LCA models were fitted in Mplus 6.12 (Muthén and Muthén 2010) to these 10 variables. Six LCA models were run with 2, 3, 4, 5, 6, and 7 classes. Model choice was based on (a) goodness-of-fit indices and (b) interpretability of results. Goodness-of-fit indices considered were the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Lo-Mendell-Rubin Adjusted Loglikelihood Ratio Test (LMR), and the Bootstrap Likelihood Ratio Test (BLRT). As per Nylund, Asparouhov, and Muthén (2007), BIC was given most weight when deciding on best model fit.

**Table 4** Model fit indices for 2-, 3-, 4-, and 5-class models

	2-class model	3-class model	4-class model	5-class model	6-class model	7-class model
Estimated parameters	31	42	53	64	75	86
Loglikelihood	-3299.5	-3209.8	-3158.0	-3128.1	-3015.3	-3078.5
AIC	6660.9	6503.7	6421.9	6384.1	6360.5	6329.1
BIC	6666.7	6644.6	6599.8	6599.0	6612.3	6617.7
LMR <sup>a</sup>	512.1	176.2	102.0	58.8	44.9	52.2
<i>p</i>	0.014	0.061	0.13	0.33	0.77	0.38
Entropy	0.86	0.87	0.88	0.85	0.85	0.85
BLRT loglikelihood difference		179.232	103.841			
Δ parameters		11	11			
<i>p</i>		<.001	<.001			

<sup>a</sup> Lo-Mendell-Rubin Adjusted LRT Test

*Findings* A 4-class model was chosen amongst multiple options because it was statistically viable and theoretically interpretable. Table 4 contains fit indices and entropy values for 2-through 7-class models. The 5-class model had the lowest BIC, but this was only slightly improved over the 4-class model and the *p* value for the adjusted LMR was above .3. Both the 3- and 4-class models were significant at *p*<.05 after running the BLRT and both models were interpretable. The 4-class model was chosen because it had a lower BIC and higher entropy value.

Table 5 lists means and standard deviations of the five RLQ factors and the difference scores for each of the four classes. We labeled the four classes based on observed patterns. (1) **Emergent regulators** (*n*=21) were participants with relatively low RLQ scores at Time 1 with large increases at Time 2. (2) **Moderate regulators** (*n*=83) demonstrated relatively moderate scores at Time 1 with small to moderate increases. (3) **High regulators with emergent adapting** (*n*=40) had relatively high scores at Time 1 with little change at Time 2, with the exception of the Adapting subscale that started out low and improved at Time 2. (4) **High regulators** (*n*=68) were participants with relatively high scores at Time 1 and little change at Time 2.

Research question 3: what patterns emerge when we combine quantitative and qualitative self-report data?

*Analysis* Five participants from each of the four classes were selected for in-depth qualitative analysis. Participants were randomly selected from those in each class whose probability of being in another class was low (less than 1 %). There was at least one participant from each semester in each class, with the exception of class 3 *high regulators with emergent adapting* that had no participants from Spring 2010 semester. Data for participants were combined across the four classes for analysis so researchers were blind to the latent class of the participant. We created individual SRL profiles for each participant in three steps.

First, two researchers read the collection of Weekly Reflections to become familiar with the data and recorded overall impressions about each participant's SRL processes. Second, we

**Table 5** Subscale means (SD) and difference scores (SD) by four classes

Subscale	Emergent regulators ( <i>n</i> =21)		Moderate regulators ( <i>n</i> =83)		High regulators with emergent adapting ( <i>n</i> =40)		High regulators ( <i>n</i> =68)	
	Time 1	Diff	Time 1	Diff	Time 1	Diff	Time 1	Diff
Task understanding	4.12 (1.08)	1.88 (1.38)	4.92 (.76)	0.64 (.97)	6.13 (.66)	-0.29 (0.93)	5.75 (.65)	0.12 (1.31)
Goals	2.67 (.75)	2.78 (1.03)	3.54 (1.01)	1.51 (1.30)	4.90 (.90)	0.00 (1.29)	5.04 (.75)	0.10 (1.13)
Monitoring	3.16 (1.18)	2.87 (1.21)	4.84 (.92)	0.846 (1.16)	6.46 (.67)	-0.41 (1.08)	5.84 (1.02)	-0.15 (1.25)
Evaluating	2.61 (.83)	2.78 (.86)	3.82 (.81)	1.23 (.93)	5.11 (.81)	.275 (1.06)	5.26 (.74)	-0.30 (1.06)
Adapting	2.50 (.63)	1.82 (1.16)	3.83 (.85)	0.41 (1.31)	2.75 (.76)	1.29 (1.30)	5.22 (.92)	-1.03 (1.35)

*Diff* Difference score, calculated by subtracting Time 1 scores from Time 2 scores. Positive differences reflect higher scores at Time 2

coded quality of four SRL categories: task understanding, goal setting, monitoring/evaluating, and adapting. Monitoring and evaluating were combined because they were difficult to distinguish in the qualitative data. Quality codes were based on all Weekly Reflections items, though some codes focused more on data in particular items (e.g., goals codes were based mainly on the goals participants set). Quality was rated as low, moderate, high, improving, decreasing, or not enough information. Each of the two researchers closely examined Weekly Reflection diary entries for each participant over 11 weeks and independently rated each participant on each of the SRL categories. We identified a fifth category after our first time through the data that was labeled “metacognitive awareness” and this was coded in our second round of data coding. Ratings for all categories were discussed and discrepancies were resolved through discussion.

Third, we augmented quality ratings with case notes that briefly described each participant in terms of regulatory awareness or behavior. The resulting individual SRL profiles for each participant included quality ratings on five SRL categories (task understanding, goal setting, monitoring/evaluating, adapting, and metacognitive awareness) and a brief description of their SRL across the semester.

Finally, individual qualitative SRL profiles were grouped based on membership in RLQ latent classes, while being blinded to original four latent class labels or descriptors (see [Appendix E](#)). Each group of individual SRL qualitative profiles was examined to identify common themes and discrepancies in terms of SRL. This resulted in four qualitative group profiles or descriptions of cases. Individual and group profiles were presented to a panel of SRL research experts for discussion. The panel identified motivational aspects as a common theme in the individual and group profiles, so motivation was added as a sixth SRL category. The two original researchers then completed a third round of coding for quality of motivation for each participant and added motivation to the descriptions of the four groups.

**Findings** For each of the four groups, qualitative, Weekly Reflection-based group SRL profiles are described and then a comparison is made with the quantitative, RLQ-based profiles (see [Table 6](#) for a summary).

We labeled the first group as ***unengaged regulators*** because they evidenced low engagement of regulatory processes across the semester. Ratings for the SRL categories were generally low with a few exceptions of improving in terms of metacognitive awareness,

**Table 6** Summary of RLQ and weekly reflection profiles

Latent class	Quantitative label (RLQ)	Qualitative label (weekly reflection)
1	<i>Emergent regulators</i> Low scores at Time 1 with large improvements at Time 2	<i>Unengaged regulators</i> Demonstrated low engagement of SRL processes across the semester
2	<i>Moderate regulators</i> Moderate scores at Time 1 with small to moderate increases at Time 2	<i>Active regulators</i> Demonstrated intentional self-improvement attempts
3	<i>High regulators with emergent adapting</i> High scores at Time 1 and 2 except for Adapting that started out low and improved	<i>Struggling regulators</i> Demonstrated unsuccessful attempts to adapt learning
4	<i>High regulators</i> High scores at Time 1 and 2	<i>Emergent regulators</i> Demonstrated improvement in at least one facet of SRL

monitoring and evaluating, or goals. Improvements for these participants were still small. For example, one participant was rated as improving in goals due to some weeks having more specific standards and actions but this was not consistent from week to week. These students had fairly low metacognitive awareness in that although they described some difficulties, they did not evidence intent to address these challenges. One participant was an exception to these patterns. She had generally moderate levels of regulatory engagement but seemed to have unsuccessful attempts at regulating as she described continually high stress levels throughout the semester with these being potentially debilitating at the end. Her low GPA from that semester (1.8/9) suggests she was not successful in managing her stress.

Compared with the qualitative Weekly Reflection label of *unengaged regulators*, this group of participants was labeled as *emergent regulators* based on their quantitative RLQ profiles. This group had low RLQ scores at the beginning of the semester with relatively large increases at the end of the semester. In contrast to their RLQ scores, the Weekly Reflections suggested that these students were not actively taking charge of their own learning. This group was interesting because quantitative and qualitative profiles of these learners demonstrated little overlap and pointed to drastically different pictures of what occurred over the semester. There may be several explanations for this. First, it might seem as though this group of students learned in *Learning Strategies* how they should answer the RLQ but struggled to apply that knowledge to their own learning. It is possible these participants were responding to the quantitative measure in ways they perceived to be socially desirable (Fisher 1993). Second, it is also a possibility that these participants had cognitively adopted the course ideas and answered the RLQ based on how they thought they were engaging, but struggled to implement the strategies. Finally, it may be they were able to implement these regulatory actions in studying for their exams, but not in response to other challenges they saw in their academic learning.

We labeled the second group as *active regulators* because participants were characterized by intentional self-improvement. They had good metacognitive awareness evidenced by their description of their struggles. They demonstrated monitoring and evaluating as well as clear, deliberate attempts to make changes to their learning throughout the semester. Two participants had low task understanding, but evidenced awareness of this problem. Overall, these seemed to be students who were active and deliberate in experimenting with and improving their learning. Again, one participant was an exception to these patterns: an engineering student who was taking a drastically reduced course load (*Learning Strategies* plus one other course) and found he did not experience many challenges throughout the semester and likely had few opportunities to regulate.

Compared with the qualitative Weekly Reflection label of *active regulators*, this group of participants was labeled as *moderate regulators* based on their quantitative RLQ profiles. They had relatively moderate RLQ scores with moderate improvements to Time 2. This quantitative profile was supported by the qualitative profile of active regulators that were deliberate in their learning. This group of learners evidenced engagement of regulatory processes and attempts to adapt and improve their learning across the semester in their Weekly Reflections that was mirrored in their RLQ scores; this was a group with well-calibrated self-reports.

We labeled the third group as *struggling regulators* because participants in this group struggled to adapt to challenges. This group had a range of ratings in all phases of SRL and in metacognitive awareness. However, a common theme was that each of these students was aware of particular academic issues or problems encountered during studying, and reflected on difficulties in successfully addressing those problems. For instance, one student was rated as high on adapting because he attempted to deal with the same challenge in a different way each week despite never really succeeding. Thus, he was making adaptations but these were not

necessarily successful. Participants in this group tended to report similar challenges week to week and all participants in this group had goals that lacked specific standards upon which they could monitor and evaluate progress. Generally, the focus of regulation was around surface characteristics such as time, grades, and environment, rather than a focus on learning and active engagement with course content. There was one exception in this group: a student who often reported having no challenge in meeting his goal and thus perceived he had little reason to adapt.

Compared with the qualitative Weekly Reflection label of *struggling regulators*, this group was labeled as *high regulators with emergent adapting* based on their quantitative RLQ profiles. They had high RLQ scores at both Times 1 and 2 with the exception of the Adapting subscale that improved across time. Weekly Reflection data supports the increased engagement of adapting processes across the semester as this group evidenced consistent, yet unsuccessful or surface attempts at adaptation. However, high scores in the other RLQ processes were not always reflected qualitatively. The combination of this data revealed a group of active, but inefficient learners.

We labeled the final group as *emergent regulators* because students in this group demonstrated consistent improvement in some aspect of SRL. This group had a range of ratings in all phases of SRL and in metacognitive awareness but shared a common theme of improving and adapting. Four participants demonstrated improvement in setting task-focused academic goals while the fifth participant perceived that his goals were improving and helpful. Participants evidenced attempts to monitor/evaluate and adapt though these tended to focus on organization, time, and motivation rather than on learning and course content. Metacognitive awareness ranged from low to high with students seeming to have some awareness of struggles and strengths. The student with high metacognitive awareness was a qualitative anomaly in this group – she demonstrated high levels of SRL across all phases, except for goals that improved over time. She was a very proactive student who was continually taking steps to ensure she understood tasks. However, she had a fairly low GPA that semester (3/9).

Compared with the qualitative Weekly Reflection label of *emergent regulators*, this group of participants was labeled as *high regulators* based on their quantitative RLQ profiles. They had relatively high RLQ scores at both the beginning and end of the semester. Weekly Reflection data produced a slightly different picture of learners with emerging regulation. These learners demonstrated improvement in their engagement of regulatory processes that was not reflected quantitatively. It is possible these learners shifted in how they interpreted RLQ questions or were simply more aware of the extent to which they were engaging regulatory processes, that is, they became better at discerning evidence of their own regulation. Thus, it appeared that as their SRL engagement emerged, so did the calibration of their self-reports.

*Summary of quantitative/qualitative profiles* Table 7 summarizes the degree to which information from the two self-report data sources corresponded. The lowest overlap was seen between quantitative and qualitative self-reports for those with *inconsistent SRL*. By juxtaposing these data sources, we may have revealed a group of students who “feigned” SRL by using improved knowledge to answer RLQ questions to appear more self-regulating, but who were not evidencing regulation in their planning for and reflecting on weekly studying activities. Moderate levels of overlap were seen for the *actively inefficient SRL* and *emerging SRL* groups (see Table 7). Students in both these groups evidenced a high level of overlap in some but not all aspects of regulation. For example, the *emerging SRL* group had high RLQ scores at both times while demonstrating qualitative improvements over the semester suggesting the RLQ scores were more accurate at Time 2. It may be that this group answered the RLQ differently at Times 1 and 2, as they learned more about SRL and became more aware of their own regulatory processes. Only one group, *calibrated SRL*, demonstrated high overlap between

**Table 7** Overview of overlap between quantitative and qualitative findings

Overlap	Quantitative label (RLQ)	Qualitative label (weekly reflection)	What was revealed?
Low	Emergent regulators	Unengaged regulators	Inconsistent SRL <i>learners who gained knowledge about SRL to answer RLQ but did not evidence it weekly</i>
Moderate	High regulators with emergent adapting	Struggling regulators	Actively inefficient SRL <i>investing in adapting but finding little success</i>
Moderate	High regulators	Emergent regulators	Emerging SRL <i>change in SRL across semester not reflected in RLQ scores, potentially due to different interpretation of items or awareness of own learning</i>
High	Moderate regulators	Active regulators	Calibrated SRL <i>being honest with themselves about how they regulate</i>

the RLQ and Weekly Reflection profiles. RLQ scores for the *calibrated SRL* group were moderate with small to moderate increases across the semester and Weekly Reflections indicated active engagement in regulating. These students were engaged regulators from the beginning of the semester and continued to make attempts to apply what they were learning such as improvement in specificity of goals and metacognitive awareness of task perceptions. These changes were reflected in the moderate increases in RLQ scores, suggesting a high level of overlap between the qualitative and quantitative data sources.

## Discussion

We introduced a time- and context-specific questionnaire of SRL that focused on metacognitive processes (rather than cognitive tactics) with factor analysis resulting in five subscales: task understanding, goal setting, monitoring, evaluating, and adapting. Using means for these factors at two times, latent class analysis resulted in four patterns labeled emergent regulators, high regulators with emergent adapting, high regulators, and moderate regulators. Qualitative analysis was conducted on scripted, written diaries for a subsample of participants from each latent class. Based on qualitative analysis, latent class profiles were re-labeled, respectively, as unengaged regulators, struggling regulators, emergent regulators, and active regulators. The juxtaposition of quantitative and qualitative profiles revealed varied levels of overlap, despite both data sources being self-report. We highlight four facets of SRL measurement that we attempted to address in this study, discussing both strengths and weaknesses. We suggest further lines of inquiry to continue development of assessments that can capture learners' perceptions of their SRL as it unfolds over time.

### Information about context

Consistent with Winne et al. (2011), we concur that context cannot be ignored. Thus, in this study, all data focused on one study episode: either exam preparation (RLQ) or a participant-

chosen weekly task required for an academic course (Weekly Reflections). In some cases those tasks changed week to week; in others, they were repeated across multiple weeks. For example, while RLQ items were focused on the task of studying for an exam, one student most often completed Weekly Reflections around chemistry lab reports. This can be considered a strength of this study in that this data captured learners' perceptions of regulation situated in specific, authentic academic learning contexts. Profiles based on these particular instances created opportunities to capture the diversity and sometimes inconsistency in regulation across tasks and contexts.

On the other hand, the fact that we were unable to systematically control the specific exam and tasks contexts students reported in each of the self-report measures introduced some complexities and potential limitations. The diversity of task contexts differed within students over time, across reporting instruments (RLQ or weekly diaries), and amongst students. While transfer of SRL across different types of tasks is often assumed in theory, very few empirical studies have examined transfer or even changes in SRL across contexts and tasks (cf., Alexander et al. 2011). Some research has suggested learners engage similar metacognitive processes across tasks in different domains (e.g., Veenman and Spaans 2005), while other research suggests even within a domain, learners adjust their approach based on task contexts (Hadwin et al. 2001). In this study, we combined instances of SRL across tasks to create profiles. Further research needs to systematically examine similarities and differences in learners' perceptions of their regulatory engagement across varied, specific task and context conditions in multiple domains.

### Multiple time points

Regulation in Winne and Hadwin's (1998) model implies strategic adaptation over time and tasks based on conditions of the particular situation. Thus, in order to understand how regulation unfolds, SRL cannot be measured as aggregated across time and tasks, nor can it be measured as a single learning event (Winne and Perry 2000). Rather, because SRL is sensitive to changes in context, measurement of SRL should span multiple, in-context learning sessions. A strength of the current study was that quantitative and qualitative profiles in this study drew on multiple time samples focused on a variety of tasks and academic challenges. Each data point was considered one "snapshot" in time that contributed to a general characterization of SRL engagement. For instance, a typical member of the *emerging SRL* group, evidenced attempts to better understand the task in one session by reading "further into questions asked of me to complete my chemistry lab report" and adaptations such as using additional resources and consulting "with a friend to compare and edit my report". Together, these self-reported actions contributed to the characterization that she was metacognitively aware of her own learning. Rather than asking learners to aggregate across time, instruments used in this study created opportunities to gather data in multiple, in-context learning sessions to create a characterization of learners' SRL across multiple tasks. Profiles of regulation constructed in this manner have potential to reveal differing patterns between novice and experienced regulators.

A possible limitation of this study was that the RLQ was administered at only two points in times in this study in contrast to Weekly Reflection self-reports that were administered across 12 weeks. Therefore, quantitatively-derived profiles of regulation were based on much less frequent sampling of RLQ self-reports than qualitatively-derived profiles. Future research should create and contrast quantitative and qualitative profiles based on multiple samples of the same study sessions. While some researchers have been combining data sources in one laboratory session (e.g., Azevedo et al. 2010), this work needs to be extended to understand

how learners build upon experiences to adaptively regulate from one session to another. Winne and Hadwin (2008) propose that this kind of large-scale adaptation is what makes SRL so powerful.

### Changes in SRL

A major contribution of the current study has been in the attempt to analyze and examine SRL profiles in ways that are sensitive to context. As a result, instruments used in this study required students to self-report on aspects of their own regulation at multiple time points and across varied tasks. Yet, in our research, we are also interested in capturing how these patterns across multiple tasks change over time. That is, do our measurements capture systematic changes in SRL competencies, such as learning and applying new strategies or beginning to systematically analyze tasks in ways they did not previously engage? By researching regulation in a *Learning Strategies* course, we strategically examined and contrasted self-reports of SRL as learners developed knowledge and awareness of strategic learning and self-regulation. The strength of situating this research in a course about SRL constructs and practices is that it created an opportunity to examine the emergence of SRL over time in a context where intra-individual change was both expected and prompted. We acknowledge that while we aimed to capture this change from novice to experienced regulator, this change may also have affected measurement in terms of how learners answer items, particularly on the RLQ. In order to account for these potential changes, the RLQ factor structure was constructed with the goal of finding the best model fit that could be utilized for both time samplings (beginning *and* end of the semester in the *Learning Strategies* course). Several items had a change in factor loading from Time 1 to Time 2 over .05. These items may be particularly sensitive to development of sophistication in SRL processes. For example, items B8 “Figured out why studying this is important in this course or discipline”, B15 “Set goals that would be useful for checking on my own progress as I studied”, A4 “Asked myself if I was understanding the material”, and A17 “Appraised the effectiveness of the strategies I used” all showed relatively large changes in factor loading. Theoretically, these are important actions for regulating learning and may particularly be items that distinguish between more and less sophisticated regulators or metacognitive actions that develop through interventions such as *Learning Strategies*. Though we retained these items in our analysis, further research is warranted examining these items, perhaps employing an item response theory approach. Items such as these may particularly point to salient aspects of regulation that develop over time or in response to intervention. Because we aimed to capture these types of changes, we retained these items, trying to find the best model fit at both times and we acknowledge this approach comes with strengths and weaknesses.

Whereas participants were considered naïve to SRL theory and concepts at Time 1, they may have been primed to answer questions at Time 2 in ways that reflected the theory and concepts taught in the course. If learners interpreted or responded to questions differently based on their new knowledge, this may have contributed to poor overall fit of factorial invariance models, which has important implications for reliably and validly capturing intra-individual changes in students’ regulation. However, it is possible that changes in the factor structure from Time 1 to Time 2 reflect important changes in learners’ patterns of SRL. Perhaps a characteristic of developing expertise in SRL is that learners settle into more consistent and intentional patterns of studying that fit a factor structure most similar to the theoretical model proposed by Winne and Hadwin (1998). In contrast, novice regulators may engage in fairly random studying actions that lead to weaker model fit relative to the a priori

theory. Put simply, students who have not been exposed to SRL concepts and practices may not respond in similar ways to the RLQ due to weak regulatory knowledge and practice characterized by random efforts to invest in specific studying behaviors, rather than less frequent actions within factors themselves. Research exploring this possibility is warranted.

In addition, patterns in the qualitative data suggest there are different trajectories of growth and development of SRL; it is possible that different trajectories result in different patterns of factorial invariance. Our research did not examine patterns of factorial invariance across the groups of students with different qualitative profiles. Further research is needed to ascertain what changes in measurement (e.g., items, factors) take place as students develop SRL competencies at different rates and in different manners and how measurement can best capture these systematic changes in patterns of SRL.

Finally, it is also a possibility that a factor model is not the best approach for measuring regulation as a time- and context-specific event. As Winne (2010) alluded to, the field is still experimenting with measurement of SRL. Our findings suggest that further research is needed on the application of traditional statistical techniques to event-based measures of SRL that aim to capture changes in patterns over time.

#### Multiple types of data

In this study, we sought to explore the combination of quantitative and qualitative self-report. There was dramatic variation across latent classes in the degree to which quantitative and qualitative self-report profiles corresponded; in other words, the two types of self-report data did not always align. These findings suggest multiple self-report measures may reveal differences in the ways students perceive and report their own studying actions. The type of item or response modality might have influenced how learners responded (Dunn et al. 2010; Koning et al. 2010) or how they make sense of their own regulation (Winne and Perry 2000). Self-report questionnaires with ratings may promote self-evaluative reporting, encouraging learners to present themselves positively rather than reporting on what they did. In our study, receiving a personalized report of subscale scores immediately after completed the RLQ might have exacerbated this. A strength of this study was the use of latent classes to examine differences in students' patterns of regulation according to quantitative and qualitative self-reports. Another interesting approach to examining this combination of data would be to group individual qualitative SRL profiles based on similarities and examine differences in membership based on quantitative and qualitative data. Research using this approach may reveal further insights into influence of type of measure on how learners report and understand their SRL.

The focus on self-report might be considered a limitation in this study considering previous research demonstrated learners' self-reports are not always aligned with what they actually do (Hadwin et al. 2007; Winne and Jamieson-Noel 2002). The general explanation has been that students' beliefs about their studying differ from what they actually do. Findings from this study revealed that even multiple forms of self-report data provided rich and varied data about regulation in action. Since learners' inferences and understanding about their own actions theoretically become conditions that inform choices in future study sessions (Winne and Hadwin 1998), self-reports such as those used in this study cannot be ignored. Otherwise, there is a great risk of misinterpreting changes in student intent and actions as well as the conditions that drive them. Consistent with others (e.g., Azevedo et al. 2010; Winne 2010), we propose that combining these rich types of self-report measures with objective or trace-based measures of regulation is essential if future research is to examine (a) the ways learner intent

and reflection contribute to regulatory adaptation in studying and (b) the intra-individual differences that are characteristic of emerging regulation.

Despite the challenges, the combination of multiple data sources has important practical implications: if we base interventions solely on one data source, interventions and responses may be poorly calibrated with target areas for SRL support (see Table 7). For example, based solely on the latent class analyses of quantitative self-reports, the group with *inconsistent SRL* demonstrated growth and might not be a priority for intervention at all. More detailed analysis of Weekly Reflections indicated this same group of students appeared to lack awareness of their own learning and did not engage in attempts to improve and adapt their learning, suggesting immediate need of regulatory support. Putting the two self-report profiles together provided a richer picture of regulatory knowledge and proficiency, and a better basis for designing appropriate interventions than either data source alone. Scaffolding regulation requires support to be individualized, to target specific aspects and phases of SRL, and to shift as learners' regulatory competencies develop (Azevedo and Hadwin 2005). Future research needs to examine how to draw on multiple data sources to create profiles that can be used to develop and implement appropriate scaffolding of SRL processes.

### Concluding thoughts

This paper presents a novel way of capturing and analyzing SRL self-report that situates regulation in specific studying episodes (Winne and Perry 2000). SRL profiles based on multiple context-specific snapshots of regulation acknowledge the adaptation of SRL processes to specific conditions that vary across study episodes. Contrasting responses to a quantitative measure with qualitative diary entries revealed interesting differences across groups in terms of consistency between the two self-report measures. This raises some critical questions for the field about measurement of SRL and the importance of gathering data on learners' perspectives of their SRL. A challenge for the field is to continue to collect and examine self-report measures as a method for revealing how learners make sense of their own learning and regulation. Additionally, the emergence of motivation as an important factor in Weekly Reflections, serves as an important reminder that motivation is under-represented in the RLQ measure used for this study. As noted by several researchers (e.g., Boekaerts 1995, 1996; Schunk 2003), motivation is critical to understanding learners' engagement of SRL processes.

This paper also makes some strides toward examining the emergence in SRL expertise as a set of events that build on one another over time. This study reflects an important shift in SRL theory that views regulation as strategic adaptation over time rather than static competency. Future research needs to examine the relationship between emerging expertise in SRL and academic performance as much of the research relating SRL to academic performance has been based on aggregate measures of SRL (e.g., Cleary and Chen 2009; Pintrich and De Groot 1990; Rotgans and Schmidt 2010). Understanding ways learners systematically adapt patterns of regulation is critical for further development of support and scaffolds for SRL.

**Acknowledgments** This research was supported by the Social Sciences and Humanities Research Council of Canada, Standard Research Grant 410-2008-0700 (PI: Hadwin) and Joseph-Armand Bombardier Canada Graduate Scholarship. We would like to acknowledge (a) invaluable consultation and assistance from Drs. Scott Hofer and Philip Winne, (b) qualitative coding assistance by Adrianna Haffey, and (c) thorough feedback from the special issue editors and anonymous reviewers on drafts of this manuscript.

## Appendix A

**Table 8** Weekly reflection items by semester

Aim of item	Spring 2010	Fall 2010, Spring 2011
<i>Reflecting section</i>		
Rating of learners' perception of goal attainment	How successful were you in achieving your goal from last week? On a scale from 1 to 10, I was... (1 = not very successful to 10 = very successful) <i>[open]</i>	How well did I attain my goal last week? <i>[forced choice: 1 did not attain at all, 2, 3 moderate attainment, 4, 5 fully attained it]</i>
Difficulty encountered in enacting the task	Describe one thing you struggled with while trying to accomplish your goal. <i>[open]</i>	The main challenge I encountered while trying to achieve my goal this week was: <i>[forced choice]</i>
Adaptations made in response to challenge	Describe what you did to address that struggle. <i>[open]</i>	To address this challenge I did the following: <i>[forced choice]</i> Explain or elaborate about how you addressed your challenge... what did you do specifically? <i>[open]</i>
Evaluation of adaptations made	How successful was that approach? On a scale from 1 to 10, my approach was... (1 = not very successful to 10 = very successful) <i>[open]</i> Explain what worked well and what didn't work well. <i>[open]</i> How could you change or improve what you did? <i>[open]</i>	
<i>Planning section</i>		
List of tasks for the week in order to focus goal setting on one task		Something I would personally like to strive for this week is to: <i>[open]</i> The course I would like to focus on in my goal setting activity this week: <i>[open]</i>
Specify the task of focus	Name one specific task (e.g., a reading, an assignment, studying, etc.) to focus on this week. <i>[open]</i>	Tasks I want to accomplish in this course this: <i>[open]</i>
Set a goal	Set one SMART goal for the task you have chosen. <i>[open]</i> What is your goal about? <i>[forced choice: learning, behaviour; motivation, feelings, time management/organization]</i>	Choose a task and set one SRL goal for this week.
Rating of learners' perception of the goal difficulty	How challenging or difficult do you think your goal is this week? On a scale from 1 to 10, my goal is... (1 = not very challenging to 10 = very challenging). <i>[open]</i>	How challenging is this goal for me? <i>[forced choice: 1 easy, 2, 3 moderately challenging, 4, 5 extremely challenging]</i>

**Table 8** (continued)

<i>Aim of item</i>	Spring 2010	Fall 2010, Spring 2011
Rating of learners' confidence to achieve the goal	How confident are you that you will accomplish your goal this week? On a scale from 1 to 10, I am... (1 = not very confident to 10 = very confident). [open]	How certain am I that I can achieve the goal I have set this week? [forced choice: <i>I cannot do it at all</i> , 2, 3 <i>moderately certain I can do it</i> , 4, 5 <i>highly certain I can do it</i> ]
Open area to allow learners to comment on anything important for them		Comment on anything that is going on for you academically at the moment, or that has happened in the past week. This may be any struggles you have faced, worries you have had, or achievement you have made. This is your open space to tell us about your semester.

## Appendix B

**Table 9** RLQ item loadings for step 1 EFA with 4- and 5-factor solutions

Item	Four-factor EFA								Five-factor EFA								
	Time 1				Time 2				Time 1					Time 2			
	1	2	3	4	1	2	3	4	1	2	3	4	5	1	2	3	4
B1	.70				.78				.71					.78			
B2	.48				.51				.48					.66			
B3	.70				.60				.71					.53		.31	
B4	.69				.55				.64					.60			
B5	.32								.30								
B6	.74				.63				.71					.61			
B7	.33				.32									.60		.43	
B8	.31				.31									.38			
B9	.62				.32			.30		.61							
B10														.96			
B11									.32					.66			.30
B12																	.85
B13																	.84
B14	.42	.37			.31	.33			.40	.38							.39
B15																	.59

**Table 9** (continued)

Item	Four-factor EFA								Five-factor EFA									
	Time 1				Time 2				Time 1					Time 2				
	1	2	3	4	1	2	3	4	1	2	3	4	5	1	2	3	4	5
B16	.43					.45				.44								.52
B17	.42						.47				.42							.33
B18	.58					.41					.58							.46
B19	.42						.40				.42							.30
B20	.38					.35					.39							
A1	.40							.51			.39							.40
A2			.51				.65						.51		.31	.54		
A3			.65	.33			.57						.65			.56		
A4			.83	.32			.57						.82			.67		
A5			.78	.33			.57						.79			.53		
A6	.63						.45				.64							.59
A7	.75						.31	.54			.76							.48
A8	.59							.37			.58							.32
A9	.51							.51			.51							.54
A10	.43						.42			.45				.35	.46			
A11	.48						.31			.48					.55			
A12	.78						.66			.80					.67			
A13	.58						.67			.60				.41	.44			
A14							.33		.35				.34			.37		
A15								.32							.30	.31		
A16	.40							.48			.42					.37		
A17	.84							.59			.84					.83		
A18	.84							.73			.85					.72		
A19			.31						.35									.33
A20	.41	.37							.58		.42	.39						.56
A21			.67						.65			.69						.63
A22			.88						.81			.92						.80
A23			.84						.84			.89						.83
A24			.69						.68			.69						.69
A25			.44						.56			.36						.58
A26														.35		.32		
A27						.46												.40
A28				.37					.38						.30			
A29			.34							.35								

Only factor loadings >.3 are shown

## Appendix C

**Table 10** Items dropped from RLQ

No	Item	Scale	Reason
<b>Step 1</b>			
B5	Figured out how I will be graded	TU	low factor loadings
B7	Discussed what I am supposed to study (peers, TA, professor)	TU	low factors loadings at Time 1, loading on different factors at Time 2
B10	Asked someone what we were supposed to know or study	TU	low factor loadings
B11	Asked someone how we were supposed to study	TU	low factor loadings
B14	Set goals that focused on learning, understanding, or remembering	GP	loading on two factors (TU and GP)
B18	Estimated how much time my work would take	GP	loading on different factors at different times
B20	Prioritized what I needed to do	GP	low factor loadings, loading on different factors at different times
A14	Realized that I didn't know something or hadn't read something	EV	low factor loadings, loading on different factors at different times
A15	Realized that I wasn't understanding something	EV	low factor loadings, loading on different factors at different times
A19	Found I couldn't complete my goals at the end of a 1–2 h time block	EV	low factor loadings, loading on different factors at different times
A26	Talked myself into working a little longer	AD	low factor loadings, loading on two factors
A27	Told myself it would be ok	AD	low factor loadings, loading on different factors at different times
<b>Step 2</b>			
B19	Created a study plan or to-do list	GP	loaded on Goal Setting only in 4-factor solutions; not consistent with other Goal Setting items
A29	Reduced my anxiety about the upcoming test	AD	low factor loadings

## Appendix D

**Table 11** RLQ item loadings for step 2 EFA with 4- and 5-factor solutions

Item	Time 1				Time 2				Time 1					Time 2				
	1	2	3	4	1	2	3	4	1	2	3	4	5	1	2	3	4	5
B1	.70				.79				.71					.81				
B2	.48				.55				.52					.62				
B3	.73				.61				.75					.55				
B4	.67				.54				.66					.57				
B6	.74				.65				.74					.63				
B8					.32									.35				
B9	.64				.31				.65						.36			
B12		.62							.82					.69				.87
B13		.48							.73					.41				.83
B15		.61							.63					.58				.61
B16		.40							.52									.53
B17		.39							.49									.38
B19		.36							.45						.32			.34
A1	.41								.50					.42				.37
A2		.49	.31						.62						.48			.70
A3		.65	.32						.56						.65			.71
A4		.86	.30						.54						.88			.74
A5		.81	.30						.58						.85			.65
A6	.64								.51					.46				.62
A7	.78								.56					.48				.42
A8	.57								.40					.37				
A9	.54								.52					.49				.56
A10	.45								.49					.50				.45
A11	.48								.38									.60
A12	.79								.73					.77				.61
A13	.59								.71					.74				.57
A16	.44								.49					.32				.37
A17	.85								.61					.92				.93
A18	.86								.79					.97				.68
A20	.42	.37							.59					.31				.54
A21		.69							.65						.67			.63
A22		.93							.86						.95			.84
A23		.87							.86						.88			.86
A24		.67							.67						.68			.69
A25		.37							.53						.37			.57
A28		.31							.34						.32			.35
A29		.32												.34				

## Appendix E

**Table 12** Individual qualitative profiles for unengaged regulators

	P242	P253	P280	P320	P444
Age	20	18	22	18	19
M/F	Female	Female	Male	Male	Female
101	5	4	6	5	3
GPA	4.5	5.25	4	5	1.8
TU	N/A	Low	Low	Low	N/A
GO	Low	Low	Low	Improving	Improving
M/E	Low	N/A	Improving	Low	Moderate
AD	Low	N/A	Low	Low	Moderate
MET	Improving	N/A	Low	Low	Moderate
MOT	Low	Low	Low	Low	Moderate
Desc	No TU evidence	No completion of the <i>reflecting</i> portion, thus unable to rate	Consistently poor quality goals	Monitoring, evaluating, and adapting only related to environment.	Only completed 7 weeks of Weekly Reflections
	Goals were to do lists, some with specific actions	Seems to have missed purpose of Weekly Reflections, indicating poor TU	Improved descriptions of challenges and addressing challenges, but monitoring rarely took place against standard set in goal	Struggle to understand tasks or that university required active learning	Inconsistent improvement in goals
	Becomes more specific and realistic around time, which was important as she continually struggled with procrastination	Weak goals across semester	Lack of responsibility for his work	Goals improved in terms of standards and actions but inconsistent	Monitored against standards in goals and monitored usefulness of adaptations
	Some attempts to apply 101 concepts	Continual struggle with procrastination, no evidence of addressing	Continual struggle with work	High levels of stress that continue to increase	Attempts to apply 101 concepts in goals and motivation
	Monitoring, evaluating, and adapting related only to time				

101 Grade in ED-D 101, on a 9-point scale. GPA – Grade Point Average, on a 9-point scale, TU Task understanding, GO Goals, M/E Monitoring and evaluating, AD Adapting, MET Metacognitive awareness, MOT Motivation, Desc Description of main points, N/A Not enough information to rate

**Table 13** Individual qualitative profiles for active regulators

	P246	P290	P338	P369	P461
Age	19	19	31	17	20
M/F	Male	Female	Male	Female	Female
101	8	4	8	6	8
GPA	5.6	3.75	4.5	2.75	6
TU	Low	High	N/A	Low	High
GO	Low	Improving	Improving	Moderate	Improving
M/E	Moderate	Moderate	N/A	Moderate	High
AD	Improving	Moderate	N/A	Moderate	High
MET	Moderate	Moderate	Low	High	High
MOT	Moderate	Moderate	High	Moderate	High
Desc	Struggled with TU Large, vague goals with little specificity Some specificity in describing challenges Adaptations mostly came from help seeking with some other strategy changes Metacognitive awareness mostly around TU	Evidence of adapting Continual struggle with time and motivation suggests unsuccessful adaptations Broad, open goals became more specific Clear attempts to improve her learning	Slight increase in goal specificity but focused on task completion No challenges Seems metacognitively unaware, but only taking one other course, compared to normal Engineering course load	Struggling with TU Goals had strong standards but poor specificity in concepts Monitored and evaluated success of strategies, though little monitoring of learning standards Metacognitive awareness around TU, importance of strategy choice, and time management	Clear emphasis on TU right from start of semester Created her own goal scaffold Consistent evidence of monitoring learning and adapting to challenges High self-awareness in many aspects Attempts to apply 101 concepts

101 Grade in ED-D 101, on a 9-point scale. GPA – Grade Point Average, on a 9-point scale, TU Task understanding, GO Goals, M/E Monitoring and evaluating, AD Adapting, MET Metacognitive awareness, MOT Motivation, Desc Description of main points, N/A Not enough information to rate

Table 14 Individual qualitative profiles for struggling regulators

	P319	P341	P368	P386	P439
Age	19	22	18	23	18
M/F	Male	Male	Male	Male	Male
101	8	6	6	5	5
GPA	7.25	4.6	4.5	6.2	6
TU	Moderate	Improving	Low	High	N/A
GO	Improving	Moderate	Low	Moderate	Improving
ME	Low	High	Low	Moderate	High
AD	N/A	Moderate	Low	Low	High
MET	Low	High	Moderate	Moderate	High
MOT	Moderate	Moderate	Moderate	Low	High
Desc	Monitoring mostly around grades, not related to learning. Little evidence of adapting; often perceived there was no challenge. Procrastination was mentioned several times but never described as problem to deal with. Some attempts to understand task. Little evidence of metacognitive awareness	Some improvement in goals with scaffold. Monitoring and evaluating specific throughout. Demonstrated awareness of own learning processes. Some attempts to adapt; mostly surface but a couple around learning	Evidence of struggling with TU; metacognitively aware of this with some attempts to address this. Some evidence of monitoring performance after the fact and not being happy with results. Attempted to address environmental challenges but reported same challenge many weeks. More proactive in trying to understand tasks throughout semester	Proactive in understanding tasks. Goals had specific concepts and actions but lacked standards. Monitored and evaluated strategies but no evidence of adapting strategies. Assessment of challenges seemed at odds with descriptions. Some evidence of adapting the environment and motivation but continued to struggle with this throughout semester	Evidence throughout semester of adaptations and monitoring effectiveness of changes. Same challenge week-to-week but persistent in making changes and evaluating. Goals improved though sometimes still vague. Good awareness of issues. Attempts to apply 101 concepts
	Seemed pretty content with his learning		Metacognitive awareness of some issues but poor specificity in monitoring		

101 Grade in ED-D 101, on a 9-point scale. GPA – Grade Point Average, on a 9-point scale, TU Task understanding, GO Goals, MET Monitoring and evaluating, AD Adapting, MET Metacognitive awareness, MOT Motivation, Desc Description of main points, N/A Not enough information to rate

**Table 15** Individual qualitative profiles for emergent regulators

	P229	P308	P388	P393	P437
Age	18	18	20	19	21
M/F	Male	Female	Female	Female	Female
101	8	5	7	3	5
GPA	7	3	5.8	3.33	4.8
TU	Low	High	N/A	N/A	Improving
GO	Low	Improving	Improving	Improving	Improving
M/E	Low	High	N/A	N/A	Moderate
AD	Moderate	High	Moderate	Moderate	Moderate
MET	Moderate	High	Low	Low	Moderate
MOT	Moderate	High	Low	Low	Moderate
Desc	Evidence of adapting, around time/organization	Improvement in goals, especially standards but not consistent	Goals improved from very poor learning and environment to attain goals	No evidence of monitoring or TU except on small incident of poor TU	Goals improved from vague multi-session TU evidenced in use of Weekly Reflections and specificity in concepts
	Struggle with understanding tasks but able to address this	Evidence attempts to better understand tasks	Goals were continually multi-session but improved in concepts and actions	Monitored and evaluated time but not learning	Evidence of adapting to challenge
	Improved in awareness of TU	Specific in monitoring	Some evidence of adapting time and environment but no learning processes	A lot of planning challenges	Some awareness time and motivation issues
	Found 2-hour goals effective though his goals were large, multi-session	Proactive in making changes and taking feedback into account	Little evidence of being self-aware of similarity in challenges week-to-week		
	Monitored test scores and by “feel” but no learning standards				

101 Grade in ED-D 101, on a 9-point scale. GPA – Grade Point Average, on a 9-point scale, TU Task understanding, GO Goals, M/E Motivation and evaluating, AD Adapting, MET Metacognitive awareness, MOT Motivation, Desc Description of main points, N/A Not enough information to rate

## References

Alexander, P. A., Dinsmore, D. A., Parkinson, M. M., & Winters, F. I. (2011). Self-regulated learning in academic domains. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 393–407). New York: Routledge.

Azevedo, R. (2005). Using hypermedia as a metacognitive tool for enhancing student learning? The role of self-regulated learning. *Educational Psychologist*, 40(4), 199–209. doi:10.1207/s15326985ep4004\_2.

Azevedo, R., & Hadwin, A. F. (2005). Introduction to special issue: scaffolding self-regulated learning and metacognition: implications for the design of computer-based scaffolds. *Instructional Science*, 33(1), 367–379.

Azevedo, R., Harley, J., Trevors, G., Duffy, M., Feyzi-Behnagh, R., Bouchet, F., & Landis, R. (2013). Using trace data to examine the complex roles of cognitive, metacognitive, and emotional self-regulatory processes during learning with multi-agent systems. In R. Azevedo & V. Aleva (Eds.), *International handbook of metacognition and learning technologies* (pp. 427–449). Springer: New York.

Azevedo, R., Moos, D., Johnson, A. M., & Chaceey, A. D. (2010). Measuring cognitive and metacognitive regulatory processes during hypermedia learning: Issues and challenges. *Educational Psychologist*, 45, 210–223. doi:10.1080/00461520.2010.515934.

Bjork, R. A., Dunlosky, J., & Kornell, N. (2013). Self-regulated learning: beliefs, techniques, and illusions. *Annual Review of Psychology*, 64, 417–444.

Bliss, L. B., & Mueller, R. J. (1993). An instrument for the assessment of study behaviors of college students. *Reading Research and Instruction*, 32, 46–52.

Boekaerts, M. (1995). Self-regulated learning: Bridging the gap between metacognitive and metamotivation theories. *Education*, 30(4), 195–200.

Boekaerts, M. (1996). Self-regulated learning at the junction of cognition and motivation. *European Psychologist*, 1(2), 100–112.

Boekaerts, M. (2006). Self-regulation and effort investment. In E. Sigel & K. A. Renninger (Eds.), *Handbook of child psychology (Child psychology in practice, Vol. 4)*, pp. 345–377. Hoboken: Wiley.

Boekaerts, M., & Corno, L. (2005). Self-regulation in the classroom: a perspective on assessment and intervention. *Applied Psychology: An International Review*, 54(2), 199–231.

Boekaerts, M., & Niemivirta, M. (2000). Self-regulated learning: finding a balance between learning goals and ego-protective goals. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 417–451). San Diego: Academic.

Butler, D. L. (2002). Qualitative approaches to investigating self-regulated learning: contributions and challenges. *Educational Psychologist*, 37(1), 59–63. doi:10.1207/00461520252828564.

Byrne, B. M. (2001). *Structural equation modeling with Amos: Basic concepts, applications, and programming*. Mahwah, NJ: Erlbaum.

Cleary, T. (2011). Emergence of self-regulated learning microanalysis. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 329–345). New York: Routledge.

Cleary, T. J., & Chen, P. P. (2009). Self-regulation, motivation, and math achievement in middle school: variations across grade level and math context. *Journal of School Psychology*, 47(5), 291–314. doi:10.1016/j.jsp.2009.04.002

Dunn, K. M., Jordan, K. P., & Croft, P. R. (2010). Recall of medication use, self-care activities and pain intensity: a comparison of daily diaries and self-report questionnaires among low back pain patients. *Primary Health Care Research and Development*, 11, 93–102.

Fisher, R. J. (1993). Social desirability bias and the validity of indirect questioning. *Journal of Consumer Research*, 20, 303–315.

Greene, J. A., & Azevedo, R. (2007). A theoretical review of Winne and Hadwin's model of self-regulated learning: new perspectives and directions. *Review of Educational Research*, 77(3), 334–372. doi:10.3102/003465430303953.

Greene, J. A., Robertson, J., & Costa, L.-J. C. (2011). Assessing self-regulated learning using think-aloud methods. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 313–328). New York: Routledge.

Hadwin, A. F. (2009). *Strategic Learning Questionnaire*. Unpublished instrument.

Hadwin, A. F., Winne, P. H., Stockley, D. B., Nesbit, J. C., & Woszczyna, C. (2001). Context moderates students' self-reports about how they study. *Journal of Educational Psychology*, 93(3), 477–487.

Hadwin, A. F., Boutara, L., Knoetzke, T., & Thompson, S. (2004). Cross-case study of self-regulated learning as a series of events. *Educational Research and Evaluation*, 10, 365–418.

Hadwin, A. F., Nesbit, J. C., Jamieson-Noel, D., Code, J., & Winne, P. H. (2007). Examining trace data to explore self-regulated learning. *Metacognition and Learning*, 2(2–3), 107–124. doi:10.1007/s11409-007-9016-7.

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed.). New York: Guilford.

Koning, I. M., Harakeh, Z., Engels, R. C. M. E., & Vollebergh, W. A. M. (2010). A comparison of self-reported alcohol use measures by early adolescents: Questionnaires versus diary. *Journal of Substance Use*, 15, 166–173.

McCardle, L., Webster, E. A., Hadwin, A. F. (2012). *Supporting students in setting effective goals for self-regulated learning: Does a tool for weekly self-monitoring help?* Paper presented at the International Conference on Motivation, Frankfurt, Germany.

Meredith, W. (1993). Measurement invariance, factor analysis, and factorial invariance. *Psychometrika*, 58, 525–543.

Muthén, L. K., & Muthén, B. O. (2010). *Mplus (version 6) [computer software]*. Los Angeles: Muthén & Muthén.

Nelson, T. O. (1996). Consciousness and metacognition. *American Psychologist*, 51, 102–116.

Nelson, T. O., & Dunlosky, J. (1991). When people's judgments of learning (JOLs) are extremely accurate at predicting subsequent recall: the "delayed-JOL effect". *Psychological Science*, 4, 267–270.

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). New York: McGraw-Hill.

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: a Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, 14(4), 535–569. doi:10.1080/10705510701575396.

Patrick, H., & Middleton, M. J. (2002). Turning the kaleidoscope: what we see when self-regulated learning is viewed with a qualitative lens. *Educational Psychologist*, 37(1), 27–39.

Perry, N. E. (2002). Introduction: using qualitative methods to enrich understandings of self-regulated learning. *Educational Psychologist*, 37(1), 1–3. doi:10.1207/00461520252828500.

Pintrich, P. (2000). An achievement goal theory perspective on issues in motivation: Terminology, theory, and research. *Contemporary Educational Psychology*, 25, 92–104. doi:10.1006/ceps.1999.1017.

Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review*, 16, 385–407. doi:10.1007/s10648-004-0006-x.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, 82, 33–40.

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the motivated strategies for learning questionnaire (MSLQ). *Educational and Psychological Measurement*, 53, 801–813.

Pintrich, P. R., Wolters, C. A., & Baxter, G. P. (2000). Assessing metacognition and self-regulated learning. In G. Schraw & J. C. Impara (Eds.), *Issues in the measurement of metacognition* (pp. 43–97). Lincoln: The University of Nebraska Press.

Puustinen, M., & Pulkkinen, L. (2001). Models of self-regulated learning: a review. *Scandinavian Journal of Educational Research*, 45, 270–286.

Rotgans, J. I., & Schmidt, H. G. (2010). The Motivated Strategies for Learning Questionnaire: A measure for students' general motivational beliefs and learning strategies? *The Asia-Pacific Education Researcher*, 19, 357–369.

Schmitz, B., Klug, J., & Schmidt, M. (2011). Assessing self-regulated learning using diary measures with university students. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 251–266). New York: Routledge.

Schunk, D. H. (2003). Self-efficacy for reading and writing: Influence of modeling, goal setting, and self-evaluation. *Reading & Writing Quarterly*, 19, 159–172.

Veenman, M. V. J., & Spaans, M. A. (2005). Relation between intellectual and metacognitive skills: Age and task differences. *Learning and Individual Differences*, 15, 159–176.

Weinstein, C. E., Schulte, A., & Palmer, D. R. (1987). *The learning and study strategies inventory*. Clearwater: H & H Publishing.

Williams, R. H., & Zimmerman, D. W. (1996). Are simple gain scores obsolete? *Applied Psychological Measurement*, 20, 59–69. doi:10.1177/014662169602000106

Winne, P. H. (1997). Experimenting to bootstrap self-regulated learning. *Journal of Educational Psychology*, 89, 397–410.

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: Lawrence Erlbaum.

Winne, P. H. (2010). Improving measurements of self-regulated learning. *Educational Psychologist*, 45, 267–276. doi:10.1080/00461520.2010.517150.

Winne, P. H. (2011). A cognitive and metacognitive analysis of self-regulated learning. In B. J. Zimmerman & D. H. Schunk (Eds.), *Handbook of self-Regulation of learning and performance* (pp. 15–32). New York: Routledge.

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: Lawrence Erlbaum.

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 297–314). Mahwah: Lawrence Erlbaum.

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

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

Winne, P. H., Jamieson-Noel, D., & Muis, K. R. (2002). In P. R. Pintrich & M. L. Maehr (Eds.), *Advances in motivation and achievement: New directions in measures and methods* (Vol. 12, pp. 121–155). Amsterdam: Elsevier Science.

Winne, P. H., Zhou, M., & Egan, R. (2011). Designing assessments of self-regulated learning. In G. Shraw & D. R. Robinson (Eds.), *Assessment of higher order thinking skills* (pp. 89–118). Charlotte: Information Age.

Yang, Y., & Bliss, L. B. (2014). A Q factor analysis of college undergraduate students' study behaviours. *Educational Research and Evaluation: An International Journal on Theory and Practice*, 20, 433–453.

Zeidner, M., Boekaerts, M., & Pintrich, P. R. (2000). Self-regulation: Directions and challenges for future research. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 749–768). San Diego: Academic.

Zimmerman, B. J. (1986). Becoming a self-regulated learner: which are the key subprocesses? *Contemporary Educational Psychology*, 11, 307–313.

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning. *Journal of Educational Psychology*, 81(3), 329–339. doi:10.1037/0022-0663.81.3.329.

Zimmerman, B. J. (2000). Attaining self-regulation: a social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). San Diego: Academic.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: historical background, methodological developments, and future prospects. *American Educational Research Journal*, 45, 166–183.