A Questionnaire for Capturing Perceptions of Self-Regulated Learning Processes during Information Seeking

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Abstract

We present the SRL Perceptions Questionnaire (SPQ), developed to measure perceptions of self-regulated learning (SRL) after information seeking and learning sessions. In a crowd-sourced study ($N = 127$), participants completed the SPQ after searching to learn about a complex topic. The SPQ asked participants to report their perceptions of particular SRL constructs (e.g., planning, monitoring, strategy use, adapting). A principal component analysis supported a five-factor structure with high reliability ($\alpha >= .87$). Perceived SRL did not correlate with normalized learning gains, yet pre-task and post-task perceptions showed correlations with several SPQ dimensions. We offer both the SPQ as an instrument for measuring SRL (processes critical to supporting human learning) after information seeking and insights into how perceptions of SRL constructs align with objective learning outcomes, pre-task perceptions, and post-task perceptions while learning during search.

CCS Concepts

• **Information systems → Users and interactive retrieval**.

Keywords

Search as learning, learning outcomes, self-regulated learning

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1 Introduction

Our research in this paper lies at the intersection of self-regulated learning (SRL) and search-as-learning (SAL). SRL is the process through which people monitor and control their own learning [29, 39, 45]. SRL involves both cognitive and metacognitive processes, such as goal setting, strategizing, self-evaluation, progress monitoring, and adapting. Research in education has studied SRL from different perspectives. Studies have investigated the extent to which students engage in specific SRL processes [10, 17], the effects of SRL processes on learning [27, 28, 43, 44], and the effects of tools to encourage and support effective SRL engagement [1, 2].

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People often use search systems to learn about new topics. SAL research aims to understand and improve this process. Prior SAL studies have investigated factors that impact learning during search, including characteristics of the searcher [3, 6, 22] as well as access to novel tools [9, 13, 18, 24, 25, 34–36]. Other SAL studies have aimed to predict learning from search behaviors [7, 14, 19, 33, 42].

In recent years, SAL researchers have argued that information-seeking environments should encourage and support engagement with SRL processes as a means to improve learning during search [37]. However, few SAL studies have explicitly investigated SRL engagement. In one such study, Urgo and Arguello [36] experimented with a simple tool for searchers to set goals during a learning-oriented search session. The tool enabled study participants to set goals, take notes with respect to goals, and mark goals as completed. The tool also provided reminders for participants to set *high-quality* goals (e.g., with measurable success criteria). Based on think-aloud comments, access to the tool resulted in greater engagement in SRL processes such as goal-setting, prior knowledge activation, and progress monitoring. Access to the tool also resulted in better learning outcomes, highlighting the importance of SRL engagement.

SRL engagement can be captured objectively through recorded think-aloud comments and activities. However, it can also be captured *subjectively* through a questionnaire. In this paper, we introduce the SRL Perceptions Questionnaire (SPQ). We designed the SPQ to capture post-task *perceptions* of engagement with five SRL processes that are central to the Winne & Hadwin (W&H) model of SRL [40]: (1) planning, (2) strategy use, (3) monitoring, (4) evaluating progress, and (5) adapting. To validate the SPQ, we conducted a crowdsourced study ($N = 127$) in which participants were asked to learn about a complex topic. We validate the structure and reliability of the SPQ using principal component analysis (PCA) followed by a Cronbach's α analysis, and by examining the correlation between perceptions of SRL engagement and other pre- and post-task perceptions. Additionally, we investigate the correlations between perceptions of SRL engagement and learning outcomes. We examine four research questions:

- RQ1: To what extent does the SPQ capture SRL constructs?
- RQ2: How do post-task perceptions of SRL relate to learning outcomes?
- RQ3: How do post-task perceptions of SRL relate to pre-task perceptions?
- RQ4: How do post-task perceptions of SRL relate to other post-task perceptions?

Information seeking has evolved beyond traditional document retrieval. It now encompasses interactions with GenAI systems, where learners pose questions and receive generated responses.

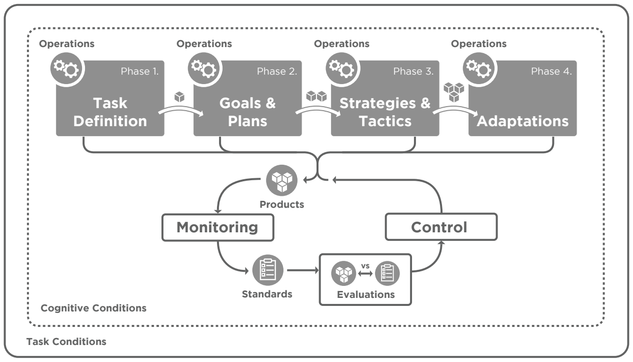

Figure 1: Conceptualization of the Winne & Hadwin Model

This shift introduces new challenges for human learning. While search engines require learners to actively formulate queries, evaluate sources, and synthesize information across documents, GenAI systems can provide fluent, integrated responses that may create an illusion of understanding without meaningful human learning. The SPQ can help researchers measure perceptions of SRL engagement as information-seeking environments become more sophisticated.

2 Background

Winne & Hadwin (W&H) Model of SRL: The Winne & Hadwin (W&H) model of SRL (Figure 1) consists of four weakly iterative phases. Learners progress sequentially through the phases but often return to earlier phases when needed.

Phase 1. Task Definition: Learners develop an understanding of the learning task using external resources (e.g., instructions) and internal resources (e.g., prior knowledge).

Phase 2. Goals & Plans: Learners set goals and select cognitive strategies to achieve them. Goals serve as standards for monitoring progress and are updated as understanding deepens.

Phase 3. Strategies & Tactics: Learners implement strategies and integrate information into existing knowledge. External and internal feedback during this phase may prompt goal modifications.

Phase 4. Adaptations: Learners disengage from the learning task to reflect on what has worked and what has not, making large-scale adjustments to their approach.

Throughout all phases, learners engage in metacognitive monitoring (i.e., comparing products to standards) and control (i.e., adjusting strategies when mismatches are found).

SRL Questionnaires: Several questionnaires have been developed to capture the extent to which learners engage in SRL processes. However, most of these questionnaires ask about students' attitudes and habits. In contrast, the SPQ asks about SRL engagement during a specific learning-oriented search session. The Metacognitive Awareness Inventory (MAI) [26] consists of two dimensions: knowledge of cognition and regulation of cognition. The first dimension focuses on strategy awareness, execution, and adoption. The second dimension focuses on planning, information management, comprehension monitoring, debugging strategies, and evaluation. The Motivated Strategies for Learning Questionnaire (MSLQ) [23] consists of two dimensions: motivational beliefs and SRL strategies. The SRL strategies dimension includes questions about planning, strategy use, and monitoring. The Learning and Study Strategies Inventory (LASSI) [38] consists of 10 dimensions: anxiety, attitude, concentration, information processing, motivation, selecting main ideas, self-testing, test strategies, time management, and using academic resources. The dimensions of concentration, time management, self-testing, and using academic resources relate to self-regulation, particularly strategy use and monitoring. The Regulation of Learning Questionnaire (RLQ) [20] was developed based on the W&K model. It contains items about: task understanding, goal-setting, monitoring, evaluating, and adapting. However, unlike the SPQ, the RLQ was *not* developed specifically for information-seeking sessions.

SRL in Search as Learning (SAL): Although SRL has been shown to increase learning outcomes [5, 30, 32, 40, 45], little work has explored SRL in SAL. Urgo and Arguello [36] investigated the role of goal-setting on learning during search. SRL processes were analyzed from think-aloud data and search behaviors. Results found that goal-setting improved learning retention and increased the frequency and diversity of SRL processes engaged during the search session. Crescenzi et al. [8] investigated the impact of a tool called the OrgBox on metacognition. The OrgBox tool allowed participants to group and rearrange information as they searched to explore a topic. Participants reported greater support for monitoring, evaluation, and planning with the OrgBox. Singh et al. [31] explored the role of SRL while learning with a GenAI system that provided metacognitive prompts to encourage processes such as judgments of learning and prior knowledge activation. Participants who used the GenAI system with metacognitive prompting searched more topics and issued more follow-up inquiries.

3 SRL Perceptions Questionnaire (SPQ)

We designed the SPQ to reflect the phases of the W&H model of SRL. The first set of items (*Planning*) capture Goals & Plans. The second and third sets of items (*Connecting* and *Organizing*) capture Strategies & Tactics. The fourth and fifth sets of items (*Monitoring* and *Evaluating Progress*) capture metacognitive monitoring processes. The final set of items capture *Adaptations*.

Planning: During the search task, I was able to:

- Decide where to begin my search. (plan_search)
- Develop a plan for exploring the topic. (plan_explore)
- Decide how to approach the task. (plan_approach)
- Set goals for what information I needed to find. (plan_find)

Connecting: During the search task, I was able to:

- Make connections between the information I found and my own prior knowledge. (conn_to_pk)
- Consider how parts of the topic relate to each other. (conn_topics)
- Consider connections between ideas. (conn_ideas)

Organizing: During the search task, I was able to:

- Understand the structure of the topic related to the task. (org_structure)
- Organize the information that I found. (org_found)
- Structure my thoughts. (org_thoughts)
- Figure out how the information I found fit together. (org_fit)

Monitoring: During the search task, I was able to:

- Question whether I understood the information I needed to know to complete the task. (mon_needed)

- Question whether I would be able to recall the information I encountered. (mon_recall)
- Question whether I knew what was important to complete the task. (mon_important)
- Question whether I understood the information I encountered. (mon_understood)

Evaluating Progress: During the search task, I was able to:

- Decide when to transition from one goal to the next. (eval_next)
- Keep track of my progress toward goals. (eval_prog)
- Decide when a goal was successfully accomplished. (eval_complete)

Adapting: During the search task, I was able to:

- Change or revise how much effort I devoted to a specific goal. (adapt_effort)
- Change or revise my approach to the task. (adapt_approach)
- Change or revise my level of confidence during the task. (adapt_conf)
- Change or revise my understanding of the task itself. (adapt_task)
- Change or revise my feelings about my approach to the task. (adapt_feelings)

4 Methods

To address RQ1-RQ4, we conducted a crowdsourced study ($N = 127$) on Amazon Mechanical Turk (MTurk). The study was reviewed by our organization's institutional review board (IRB). Participants were 26-71 years old ($M = 40$). Sixty-two participants identified as male and 65 as female. We limited our study to MTurk workers within the U.S. who had completed at least 100 MTurk HITs with ≥ 95% approval rate. Participants were given US$20 for participating.

Study Protocol: During the study, participants used a "Study Workflow Page" to complete the following steps. First, participants watched a video describing the study protocol. Second, they completed a consent form and demographics questionnaire. Then, to measure their prior knowledge, they completed the Osmosis and Diffusion Conceptual Assessment (ODCA) [12]. Then they were asked to review the main search task and completed a pre-task questionnaire. Following this, participants watched a video describing the system they would use to gather information and take notes. Then they proceeded to the main search task. Participants were instructed to use our customized search system to gather information and learn about diffusion and osmosis. The system included a customized tool for participants to take notes. Participants were instructed to spend at least 30 minutes on the main search task. Then participants completed a post-task questionnaire. Finally, to measure learning, participants completed the ODCA a second time.

Search Task: Participants completed the following task:

Scenario: One of your family members is a high school senior who is about to take an important biology exam. Your family member has told you that she is struggling to understand the concepts of diffusion and osmosis and has asked for your help.

Task Objective: Your goal is to use our search system to learn everything you can about the concepts of diffusion and osmosis. After searching and gathering for information, you will be asked to answer some questions about both diffusion and osmosis.

System: During the main search task, participants used a custom-built search system to gather information and take notes. The corpus was generated by segmenting modules from the Biology 2e textbook, a free online textbook from OpenStax. The search system was implemented using Lucene. The interface included buttons for participants to: (1) open the note-taking tool in a new browser window; (2) revisit the task description if needed; and (3) indicate they were done with the main search task.

Pre- and Post-task Questionnaires: Participants completed a pre- and post-task questionnaire before and after the main search task. In both, participants responded to agreement statements on a 7-point scale ranging from strongly disagree (1) to strongly agree (7). The pre-task questionnaire asked about: (1) interest in the task (1 item); (2) prior knowledge (5 items); and (3) expected difficulty (4 items). The items for prior knowledge and expected difficulty had high internal consistency (Cronbach's $\alpha \geq .89$). Therefore, responses were averaged to form two composite measures.

The post-task questionnaire had two parts. The first part asked about: (1) interest increase (1 item); (2) knowledge gains (5 items); (3) satisfaction (4 items); and (4) difficulty (4 items). The items for knowledge gains, satisfaction, and difficulty had high internal consistency (Chronbach's $\alpha \geq .82$). Therefore, responses were averaged to form three composite measures. The second part of the post-task questionnaire was the SPQ (§ 3). All questionnaires are available in our online appendix.

Learning Assessment: To measure learning, participants completed the multiple-choice Osmosis and Diffusion Conceptual Assessment (ODCA) [12] before and after the search task. The ODCA targets common misconceptions that students have about diffusion and osmosis [12]. To measuring learning, we used participants' pre- and post-task scores on the ODCA to compute *normalized gain* (i.e., (PostScore - PreScore)/(1 - PreScore)). PreScore and PostScore are the percentage of correct answers in the pre- and post-task ODCA.

5 Results

RQ1 - SPQ & SRL Constructs: To validate the structure and reliability of the SRL Perceptions Questionnaire (SPQ), we used principal component analysis (PCA) followed by a Cronbach's α analysis. PCA served as an exploratory method to uncover the underlying dimensional structure of the questionnaire items and verify that items clustered according to the five theorized SRL constructs. Following established prior work on psychometric analysis [4, 11, 15], we then calculated Cronbach's α for each identified dimension to assess the internal consistency of items within each component. This two-step approach ensures that we assess consistency only within empirically supported dimensions.

PCA resulted in five distinct factors corresponding to the intended SRL constructs (Table 1). Items loaded strongly on their respective factors: Planning ($\alpha = 0.87$), Strategy Use ($\alpha = 0.91$), Monitoring ($\alpha = 0.90$), Evaluating Progress ($\alpha = 0.90$), and Adapting ($\alpha = 0.93$). All primary component loadings exceeded 0.56 with minimal cross-loadings.

RQ2 - Learning Outcomes & Post-Task Perceptions of SRL: Normalized learning gains showed no significant correlations with any SPQ dimension.

RQ3 - Pre-Task Perceptions & Post-Task Perceptions of SRL: Table 2 shows the correlations between pre-task perceptions and post-task perceptions of SRL engagement. Pre-task interest *positively* correlated with Planning, Strategy Use, Evaluating Progress, and Adapting ($r > .240$). Perceptions of prior knowledge positively

Table 1: PCA Component Loadings & Cronbach's α Values

	PC1 Plan	PC2 StratUse	PC3 Monitor	PC4 EvalProg	PC5 Adapt
plan_explore	0.75	0.33	0.03	0.34	0.15
plan_approach	0.73	0.37	0.04	0.19	0.26
plan_search	0.69	0.24	-0.02	0.17	0.25
plan_find	0.62	0.19	-0.01	0.49	0.09
org_fit	0.19	0.82	0.03	0.26	0.24
org_structure	0.14	0.74	0.09	0.39	0.19
org_found	0.14	0.74	-0.06	0.25	0.20
conn_topics	0.41	0.72	0.11	0.16	0.14
conn_ideas	0.47	0.72	0.10	0.03	0.13
org_thoughts	0.13	0.65	0.00	0.55	0.15
conn_to_pk	0.37	0.56	0.19	0.08	0.30
mon_needed	0.07	0.01	0.90	-0.01	0.19
mon_understood	0.08	0.03	0.88	-0.03	0.20
mon_recall	0.02	0.09	0.82	0.11	0.11
mon_important	-0.10	0.05	0.81	0.12	0.25
eval_next	0.32	0.26	0.08	0.78	0.17
eval_prog	0.16	0.38	0.10	0.76	0.21
eval_complete	0.34	0.26	0.07	0.74	0.25
adapt_approach	0.15	0.12	0.10	0.17	0.90
adapt_feelings	0.17	0.23	0.23	0.11	0.83
adapt_conf	0.12	0.26	0.18	0.27	0.77
adapt_effort	0.19	0.24	0.34	0.01	0.77
adapt_task	0.19	0.16	0.27	0.20	0.75
Cronbach's α	**0.87**	**0.91**	**0.90**	**0.90**	**0.93**

Table 2: Correlations between pre-task perceptions and post-task perceptions of SRL engagement. Gray cells indiciate significant correlations ($p < .05$)

	Plan	StratUse	Monitor	EvalProg	Adapt
interest	0.389	0.355	0.008	0.424	0.246
prior know.	0.208	0.320	-0.005	0.225	0.092
expected diff.	-0.411	-0.423	0.072	-0.384	-0.110

Table 3: Correlations between post-task perceptions of SRL engagement and other post-tasks perceptions. Gray cells indiciate significant correlations ($p < .05$)

	Plan	StratUse	Monitor	EvalProg	Adapt
interest inc.	0.411	0.440	0.022	0.423	0.344
satisfaction	0.604	0.605	0.026	0.564	0.352
learning	0.548	0.685	0.059	0.563	0.290
difficulty	-0.512	-0.503	0.032	-0.519	-0.325

correlated with Planning, Strategy Use, and Evaluating Progress ($r > .220$). Finally, expected difficulty *negatively* correlated with Planning, Strategy Use, and Evaluating Progress ($r < -.380$).

RQ4 - Post-Task Perceptions & Post-Task Perceptions of SRL: Table 3 shows the correlations between post-task perceptions of SRL engagement and *other* post-task perceptions. Perceptions of SRL Planning, Strategy Use, Evaluating Progress, and Adapting *positively* correlated with interest increase ($r > .340$), satisfaction ($r > .350$), and perceived learning ($r > .280$). The same four perceptions of SRL engagement *negatively* correlated with post-task difficulty ($r < -.320$). Monitoring showed no significant correlations with other post-task perceptions.

6 Discussion & Conclusion

PCA confirmed that SPQ items clustered into five distinct factors matching the intended SRL constructs, with strong internal consistency ($\alpha \geq .87$). The high loadings and minimal cross-loadings demonstrate that learners can distinguish between planning, strategy use, monitoring, evaluating progress, and adapting when reflecting on their learning processes. Future research should apply the SPQ to both interactions with traditional search and GenAI systems to determine its generalization across environments.

SRL perceptions showed no correlation with objective knowledge gains. Prior work has found that *perceptions* of SRL engagement do not always align with *actual* SRL engagement [41]. Therefore, it may be that participants who reported high SRL engagement overestimated their actual engagement. Nevertheless, researchers have argued that perceptions of SRL engagement are as important as actual engagement [16]. Learners who perceive to have engaged in SRL processes are more likely to repeat these behaviors when they lead to better outcomes. Therefore, SAL research should aim to improve both perceived and actual SRL engagement. The SPQ can help researchers capture the former.

In terms of pre-task perceptions, task interest had a positive correlation with all but one SRL dimension. Interest in the learning task may be a *prerequisite* for effective SRL engagement. Prior knowledge and expected difficulty were (positively and negatively) correlated with three SRL dimensions. While not discussed on § 5, prior knowledge and expected difficulty were significantly correlated ($r = -.425$). It may be that participants with lower prior knowledge (who perceived the task as more difficult) were less able to engage in effective SRL. Prior work has also found an alignment between prior knowledge and perceptions of SRL engagement [21].

In terms of post-task measures, perceptions of SRL engagement aligned with other post-task perceptions as one might expect. Except for Monitoring, SRL dimensions had a positive association with positive perceptions (interest increase, satisfaction, learning) and a negative association with negative perceptions (difficulty).

In RQ3 & RQ4, we did not find any strong correlations with SRL Monitoring. Our Monitoring items asked participants to reflect on judgements of relevance, understanding, and learning. Items for the other SRL dimensions were more action-oriented, involving verbs like planning, organizing, deciding, and changing. Monitoring is more subtle. It may be that participants were less able to determine the extent to which they monitored.

Conclusion: The SPQ is an instrument that measures perceptions of SRL engagement during a learning-oriented information-seeking task. Our study results show that items in the SPQ capture engagement with five SRL processes: Planning, Strategy Use, Monitoring, Evaluating, and Adapting. To further validate the SPQ, we examined the correlations between participants' perceptions of SRL engagement and other pre- and post-task perceptions. Perceptions of SRL engagement did not correlate with learning outcomes, possibly because they do not necessarily align with *actual* SRL engagement. However, we argue that capturing perceptions of SRL engagement is critically important. Learners who *perceive* to have engaged in SRL processes may be more likely to attribute their successes to these processes and engage with them in the future.

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