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Identifying Transitions Between Self-Regulated Learning Operations During Game-Based Learning

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Abstract: Self-regulated learning (SRL) is essential while learning with a game-based learning environment (GBLE) to effectively interact with instructional materials, monitor and regulate SRL strategy use, and increase domain knowledge. The field of SRL has had little progress in understanding how learners temporally deploy SRL operations, including Searching, Monitoring, Assembling, Rehearsing, and Translating (SMART; Winne, 2018) , during game-based learning. This study recruited 56 undergraduate students to play Crystal Island, a GBLE focused on increasing microbiology domain knowledge. Using both log-file and eye-tracking data, learners' SMART operations were captured as they completed the game. Results found that learners engaged in Searching and Assembling/Rehearsing significantly more than any other operations. Transition matrices revealed that while some transition sequences were detrimental to learning, directly monitoring after assembling/rehearsing information were positively related to learning gains. These results have implications for designing GBLEs whose features simultaneously promote and discourage the sequential deployment of SMART operations.

Introduction

Given continued developments in advanced learning technologies (ALTs) accompanied by dramatic changes in learning environments over the last decade, researchers and practitioners have increasingly turned to game-based learning environments (GBLEs) as an approach for increasing learner engagement and improving learning outcomes, with generally positive results (Taub et al., 2019). Despite the growing acceptance of GBLEs in the classroom, few studies have examined how learners' interactions with GBLEs are related to their self-regulated learning (SRL) and deployment of SRL strategies within GBLEs (Dever et al., 2021; 2022). Self-regulated learning (SRL) may be viewed as an ability (Dever et al., 2022), a complex system of recursive events (Taub et al., 2017), and a phenomenon (Winne, 2018; Winne & Azevedo, 2022) in which learners implicitly and/or explicitly monitor and regulate by enacting strategies to control their own cognitive, affective, metacognitive, and motivational (CAMM) processes during a goal-directed learning activity (Azevedo et al., 2019; Molenaar et al., 2023; Winne, 2018). Specifically in this study, we operationalize SRL as learners' behaviors within the GBLE (e.g., opening/closing instructional materials) aligned with Winne's (2018) **c**onditions, **o**perations, **p**roducts, **e**valuations, and **s**tandards (COPES) model. The focus of the current work is on the function of SRL SMART operations – searching, monitoring, assembling, rehearsing, and translating – learners' cognitive processes (i.e., searching, monitoring, assembling, rehearsing, translating) that facilitate SRL strategy use and on how learners deploy these SMART operations during learning with a GBLE and their relationship to learning gains.

Prior research with GBLEs in the context of SRL has focused on the use of multimodal data, including both log-file and eye-tracking data, to develop models predictive of learning outcomes (Cloude et al., in press; Dever et al., 2020; Geden et al., 2021). However, there have been calls for a broader application of interdisciplinary methodological approaches and analytical techniques toward understanding learners' deployment of SRL strategies during gameplay (Taub et al., 2017), and specifically, a need to use multichannel data to identify when and how learners enact specific SRL processes within GBLEs. Therefore, in this work, we collected eye-tracking and log-file data to examine the frequency of and transitions between learners' SRL processes while using a GBLE (i.e., Crystal Island) to provide actionable insights for the design of adaptive interventions to induce better learning outcomes through supporting learners' SRL.

Current study

Current SRL literature does not examine how learners deploy the specific SRL operations during learning with GBLEs. Specifically, it is not studied how learners transition between Searching, Monitoring, Assembling, Rehearsing, and Translating operations as they learn with a GBLE. Within the current study, we aim to use multimodal data to examine the frequency with which learners use SRL SMART operations and the transitional relationships between these operations during learning with a GBLE. To begin addressing this gap, we ask three research questions: (1) Are there differences between the frequencies in which participants deploy SMART operations with a GBLE?; (2) How do learners generally transition from one SMART operation to another?; and (3) To what extent do the probabilities of learners' SRL operation transitions relate to learning gains?

Method

Participants and experimental procedure

Undergraduate students (N = 56) aged 18 to 26 (M = 20.1, SD = 1.54) were recruited to play Crystal Island, a GBLE focused on increasing microbiology knowledge. Prior to the start of the experimental session, participants provided informed consent and were calibrated to an eye tracker. Participants then completed a series of questionnaires including a microbiology content knowledge pre-test. Afterwards, participants started Crystal Island in which eye-tracking and log-filed data were collected as learners interacted with non-player characters (NPCs), read instructional materials, moved around the environment, scanned food items for diseases, completed concept matrices, and filled out a diagnostic worksheet. Upon completion of the game, participants were asked to fill out post-test questionnaires including several self-reports and a microbiology content knowledge post-test similar to the pretest. Participants were thanked and compensated for their time $10 an hour up to $30.

Coding and scoring

SMART operations consisted of one or more activities that were directly related to and captured by the Crystal Island environment (see Table 1). These operations were recorded using both log-file and eye-tracking methods where the order in which participants engaged in activities were captured. All participants engaged in each activity and SMART operation.

Table 1
Activities Captured in Crystal Island and their SMART Operation Classification

Activity	Capture Method	SMART Operation Classification
Movement across Pre-Defined Areas	Log File	Searching
Completing Concept Matrices	Eye Tracking	Monitoring
Viewing Posters	Log File	
Filling out Worksheet	Log File	
Reading Books and Research Articles	Eye Tracking	Assembling/Rehearsing
Conversing with NPCs	Log File	
Scanning Food Items & Hypothesizing	Log File	
Submitting Final Diagnosis	Log File	Translating

Learning Gains were calculated using normalized change scores developed by Marx and Cummings (2007). The set of equations calculated the differences in participants' pre- and post-test scores on microbiology content knowledge while controlling for their prior knowledge.

Results

Research question 1: Are there differences between the frequencies in which participants deploy SMART operations?

A within-subjects ANOVA was conducted to examine the differences in the frequency of participants' use of SMART operations. There was an overall significant difference between the four groups, i.e., Searching, Monitoring, Assembling/Rehearsing, and Translating, where participants engaged in Searching and Assembling/Rehearsing operations the most followed by Monitoring and Translating ($F(1.86, 102.22) = 169.9$, $p < .001$). A pairwise t-test with a Bonferroni correction found that all groups were significantly different except for Searching and Assembling/Rehearsing. Participants engaged in Searching and Assembling/Rehearsing more often than any other SMART operation. This is followed by Monitoring and then Translating. For descriptive statistics, refer to Table 2.

Table 2
Means, Standard Deviations, and Pairwise T-Test Scores

Variable	*M*	*SD*	Searching	Monitoring	Assembling/ Rehearsing

Searching	132.5	56.42			
Monitoring	95.8	43.5	-4.54**		
Assembling/Rehearsing	137.91	48.1	0.70	23.2**	
Translating	8.8	4.4	17.3**	15.2**	20.8**

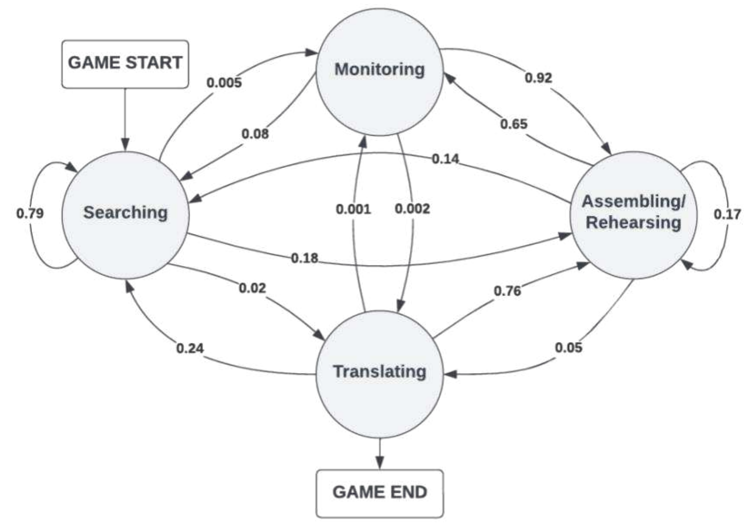
Note. * indicates $p < .05$; ** indicates $p < .01$.

Research question 2: How do learners generally transition from one SMART operation to another?

A transition matrix was calculated to identify the probability each participant would transition from one SMART operation to another. Each participant received a probability across 16 possible transition states. Each transition probability was averaged across participants to create Figure 2, a diagram depicting the average probability that specific state transitions could occur. From the transition probabilities, participants are most likely to transition from Searching to Searching, Monitoring to Assembling/Rehearsing, Assembling/Rehearsing to Monitoring, and Translating to Assembling/Rehearsing. However, it is essential to contextualize the meaning of these transition probabilities in relation to their effectiveness for learning outcomes to fully understand how to better promote learning through participants' deployment of SMART operations.

Figure 2

Diagram showing the average probability a participant would transition from one SMART operation to the next



Research question 3: To what extent do the probabilities of learners' SRL operation transitions relate to learning gains?

Multiple linear regressions were conducted to examine each transitions' relationship to learning gains. Results found that the greater the likelihood a participant had of transitioning from Assembling/Rehearsing to Assembling/Rehearsing (t = -2.16, p < .05; β = -1.44) as well as Translating (t = -2.35, p < .05; β = -3.58), the lower the learning gains. Conversely, the greater the likelihood a participant had of transition from Assembling/Rehearsing to Monitoring the greater their learning gains (t = 2.15, p<.05; β = 0.54). In sum, sequential and recurrent engagement in an Assembling/Rehearsing operation during game-based learning had a detrimental effect on learning gains along with transitioning directly from Assembling/Rehearsing into a Translating operation. However, when participants engage in a Monitoring operation directly after Assembling/Rehearsing more often, learning gains increase.

Discussion and future directions

The purpose of the current study was to examine how learners deploy SMART operations during game-based learning using multimodal data. Findings from this study support the assumptions of SRL models while enhancing Winne's (2018) SMART operations model. Specifically, this study examined how learners temporally engage in SMART operations and how transitions from one type of operation to the next support learning. This study serves as the baseline for future studies to examine the relationships between SMART operations across different GBLEs and domains. From the results, we identify a need to expand this study regarding learners' more detailed use of the SMART operations as well as GBLE design implications. For example, does the duration of each SMART operation influence which operation is next initiated, its quality, and is this related to learning outcomes? Can we identify accurate versus inaccurate SMART operations and does the transition between these (in)accurate SMART operations use relate to learning outcomes or reveal learners' lack of SRL skills? Does the spatial layout of the GBLE influence how SRL SMART operations are deployed through an embedded cognition perspective? Could an analysis of transitions between observed SRL strategies provide more insight than an analysis of observed SRL operations? These questions and future directions elicited by the current study have the potential to better support our understanding of SRL and how GBLEs can be used as a tool to detect, measure, and support SRL processes.

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