Examining Gaze Behaviors and Metacognitive Judgments of Informational Text Within Game-Based Learning Environments

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Abstract. Game-based learning environments (GBLEs) are often criticized for not offering adequate support for students when learning and problem solving within these environments. A key aspect of GBLEs is the verbal representation of information such as text. This study examined learners' metacognitive judgments of informational text (e.g., books and articles) through eye gaze behaviors within Crystal Island (CI). Ninety-one undergraduate students interacted with game elements during problem-solving in CI, a GBLE focused on facilitating the development of self-regulated learning (SRL) skills and domain-specific knowledge in microbiology. The results suggest engaging with informational text along with other goal-directed actions (actions needed to achieve the end goal) are large components of time spent within CI. Our findings revealed goal-directed actions, specifically reading informational texts, were significant predictors of participants' proportional learning gains (PLGs) after problem solving with CI. Additionally, we found significant differences in PLGs where participants who spent a greater time fixating and reengaging with goal-relevant text within the environment demonstrated greater proportional learning after problem solving in CI.

Keywords: Metacognitive judgments · Content evaluation · Game-Based Learning Environments

1 Introduction

1.1 Self-regulated Learning and Metacognitive Monitoring

Self-regulation, the modulation of behavior and internal cognitive processes due to experience and stimuli in the environment, involves the integration of prior knowledge and learning strategies to reach a goal [1]. Learners with self-regulated learning (SRL) skills discern and apply effective strategies needed to accomplish a set goal, commonly the attainment of knowledge [2, 3]. SRL models highlight the importance of planning, strategizing, and monitoring [4] to demonstrate an improved academic performance through the utilization of these SRL strategies when engaging, responding, and adapting to Game-Based Learning Environments (GBLEs) [5].

A significant component of SRL is monitoring and controlling progress of learning by modifying strategies and goals [2, 6]. In comprehending information, learners

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interpret and integrate the meaning of information as it is presented [5]. To do so, learners may reread and reevaluate textual information they may not initially understand and judge their own learning through metacognition to evaluate their progress toward reaching the overall goal [5, 7]. Through metacognitive monitoring, learners identify discrepancies between their current state of learning and their desired state by modifying plans and goals to mitigate the discrepancy until the desired goal is reached [6, 8]. Learning outcomes are dependent upon the metacognitive monitoring strategies applied by learners [9, 10]. The implementation of these strategies has suggested an increase in the acquisition of deeper declarative knowledge through the integration of verbal and visual information provided by advanced learning technologies (ALTs; [11]). Further, a learner's ability to apply SRL strategies during learning significantly influences their performance and future learning [12]. Students using SRL strategies accurately apply monitoring judgments, such as identifying relevant information when encountering previously known information or when specified instructions and goals are provided [5, 13].

1.2 Metacognitive Judgments in Game-Based Learning Environments

Azevedo and colleagues [2] quantified student actions of metacognitive processes containing 35 micro-level metacognitive judgments under macro-processes (e.g., planning, monitoring, strategy use) to identify when students were using effective SRL processes and strategies. One of the micro-level metacognitive processes includes evaluating instructional content (e.g., textual information, diagram) known as content evaluations (CEs), which is described as the ability to monitor relevant information to attain goals [4]. For example, if a learner, while using a GBLE such as Crystal Island (CI), has a goal of learning about the Ebola virus, the learner should be able to discern relevant information related to the virus and disregard irrelevant information that is extraneous to the current goal (e.g., learning about smallpox). The actions taken towards achieving an overall goal within a GBLE are referred to as *goal-directed actions* within this paper (e.g., reading informational text, talking with non-player characters, scanning items, solving concept matrices, and consulting the scientific worksheet). Learners, with accurate CEs, should evaluate the relevancy of information and, once determined to be goal-relevant, expend more time and effort to studying and understanding that information which should then increase knowledge acquisition and improve learning outcomes [9].

ALTs, such as intelligent tutoring systems and GBLEs, are used to engage learners in educational tasks, such as problem solving, scientific inquiry, and reasoning to foster SRL processes such as selecting, organizing, and integrating novel or relevant information [14, 15]. GBLEs are designed to encourage learners to set and achieve goals [16] by providing tools that scaffold SRL processes. In GBLEs with narrative-focused goals, such as Crystal Island, a learner must be able to engage in SRL skills to properly interact and learn from the environment [12]. GBLEs provide an environment for learning through multiple modalities such as virtual text and interactive scenarios, where learning is supported through exposure to information accompanied by visual and verbal interactions, both enhancing the learning environment in conjunction [17, 18].

The Cognitive Theory of Multimedia Learning (CTML; [18]) assumes that processing visual and verbal information (text and diagrams) occurs separately, there is a limited amount of information that can be processed at once for visual and verbal information, and that learners actively process these types of multimedia information [7, 14]. These processes require the learner to successfully identify relevant information both from text and diagrams; as these processes occur separately, the identification of the level of relevancy may differ [7]. This model occurs differently within GBLEs where most information is presented with dynamic models such as videos, simulations, or as in Crystal Island, as interactions with the environment. This study focuses on the absence of dynamic models of information in CI when reading from a traditionally presented text.

Criticisms of GBLEs arise when several modalities with irrelevant content are presented to the learner, negating the support of the learner's self-regulatory development [19–21]. Learners within the environment may become distracted from the original plan or goal with content within the environment that does not directly support the overall goal. In GBLEs, learners' CEs result from self-monitoring actions throughout the game that helps distinguish relevant content from irrelevant content [9, 22]. In order to continue to develop and encourage the use of learners' metacognitive abilities, there needs to be monitoring of real-time cognitive processes and progress within an intelligent system which can lead to effective feedback [14].

1.3 Eye Tracking in Game-Based Learning Environments

Physiologically-based measures are becoming an increasingly utilized method to help infer the cognitive processes in conjunction with explicit behavior. Brain activity, trace data, log files, and eye movements have been used in order to supplement the traditional self-report measures of cognition [14, 22]. Recording eye behaviors can help track the cognitive processes of learners throughout the duration of a task, which may be reading, problem solving, or other actions available within a GBLE [23–25]. In order to record eye movements, there are two core measurements - eye fixations and saccades [24–26]. Eye fixations are relatively still positioning of the eye where researchers can measure how many times a learner fixates on an object, the average fixation duration, and the total time fixating on an object. Saccades are the rapid movements of the eye between fixations [23–25]. Information learners fixate on can be categorized by importance, by subject, or by the object within the environment. This type of information grouping is called the area of interest (AOI) [26].

These specific measures in eye-tracking technology allow for researchers to infer internal cognitive processes between domains of knowledge, expertise, and performance [23, 25–27]. Within text comprehension, eye movements differ with text difficulty where with more difficult texts, the fixation duration increases, saccades become shorter, and there is an increase in regressions [24]. Experts fixated on content less, had increased fixations on relevant areas, and was able to find the task-relevant information quicker than non-experts [27]. Eye tracking in GBLEs allow for researchers to understand learner engagement and SRL strategies in interactive environments by providing a better support system for the learner such as reorienting learner attention and highlighting task-relevant areas [25, 28].

1.4 Crystal Island: A Game-Based Learning Environment

Crystal Island [29], a GBLE which promotes the use of problem solving, scientific inquiry, reasoning focused on the development of knowledge in microbiology, begins on an island where its inhabitants have been infected with a mysterious illness. Participants are tasked with completing the game to identify the disease by engaging in goal-directed actions such as interacting with NPCs, consulting informational texts (e.g., books and research articles; Fig. 1), filling out concept matrices, collecting items (e.g., food) to later scan for diseases, gathering information via a worksheet, and creating and testing hypotheses to find what disease has infected the inhabitants. There is no difference between the two types of informational text where the books and articles do not provide varying quality of information to the participant in comparison to each other. The concept matrices measure the retainment of content knowledge To complete the game, the participant produces a final diagnosis that includes the type of illness (i.e., viral or bacterial), name of the illness (i.e., influenza or salmonellosis), and the transmission source (i.e., eggs, bread, or milk). With this, the learning gains can be used to investigate learners' metacognitive judgments as they evaluate the relevancy of content with GBLEs.

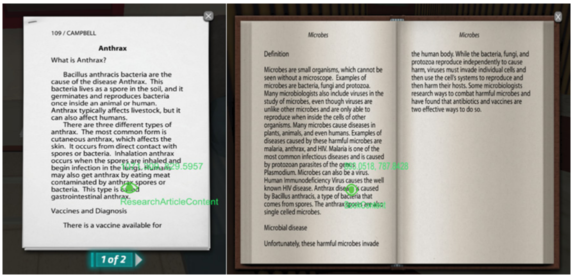

Fig. 1. Informational text (left: research article, right: book) with gaze behaviors indicated by the green markers. (Color figure online)

1.5 Related Works

Past studies investigating literacy and reading behaviors in Crystal Island have mostly examined participant performance throughout the game, measured by concept matrix attempts [15, 30]. These studies utilized eye gaze behaviors on books as well as the combination of books and articles to understand the metacognitive processes of participants. One study used Crystal Island to enhance student modeling through gaze behaviors in order to better predict the performance of a participant throughout the duration of the game [31]. An additional study incorporated relevancy of food item scanning and worksheet submission attempts to assess efficiency [32]. This current study aims to directly identify the importance of informational text within GBLEs as well as investigate the amount of time spent reading and the ability to make accurate CEs to predict proportional learning gains (PLGs).

2 Current Study, Research Questions, and Hypotheses

The objective of this study was to understand learners' metacognitive judgments of informational text by examining gaze behaviors and the PLGs within CI. The current study aimed to answer four research questions: (1) Are there differences in the proportions of fixation duration during goal-directed actions (e.g., reading informational text, talking with NPCs, scanning items, solving concept matrices, and consulting the scientific worksheet) over the duration of the game while problem solving in CI?; (2) Do the fixation duration proportions of goal-directed actions available to participants predict PLGs while problem-solving in CI?; (3) Do fixation durations of relevant informational text significantly predict PLGs?; and (4) Do the PLGs differ between groups of participants who revisit relevant texts more often and those who revisit relevant texts less often? To address the research questions, we hypothesize the following:

Hypothesis 1: There are differences in the proportions of goal-directed action (e.g., reading informational text, talking with NPCs, scanning items, solving concept matrices, and consulting the scientific worksheet) fixation durations while problem-solving in CI.
Hypothesis 2: The fixation duration proportions of goal-directed action available to participants throughout the game, specifically fixations on informational text, significantly predict PLGs while problem solving in CI.
Hypothesis 3: The fixation durations of relevant informational texts significantly predict PLGs.
Hypothesis 4: PLGs differ between groups of participants who revisit relevant texts more often and those who revisit relevant texts less often.

3 Method

3.1 Participants

107 undergraduate students from a public North American university participated in the current study. Fifteen participants were removed due to missing eye tracking data and one participant was removed as they did not complete the post-test. A total of 91 (66% females) participants' data were considered for these analyses. Participants were randomly assigned to either the full (n = 54) or partial (n = 37) agency conditions. Data loss resulted in the unequal number of participants assigned to each condition. A third condition (i.e., no agency condition) was not included in the current study. Participants' mean age was 20.01 (SD = 1.66). Participants were compensated $10/hour for a maximum of $30.

3.2 Crystal Island Conditions

Participants were randomly assigned to three groups: full agency, partial agency, and no agency. The conditions differed based on how students could freely navigate the environment. More specifically, *Full agency* allowed the most control, where participants can move freely throughout gameplay, while *Partial agency* provided a "golden path" to participants where they were directed to complete specific sequences of actions such as the order of building visitations. Participants in this condition were required to read all informational text (e.g., research articles and books) and complete all concept matrices from each book and research article. However, once the golden path was completed, participants were able to freely interact with the environment before they submitted their final diagnosis. The *no agency* condition did not allow any control as participants watched in third person as an expert solved the mystery illness. For the purposes of this study, only the full and partial agency conditions were used because the no agency condition did not allow for autonomy.

3.3 Materials

Participants were given a demographics questionnaire and a 21 item four-choice multiple choice microbiology content knowledge pre and posttest constructed by an expert in microbiology. The content knowledge pre and posttests contained questions that were randomized for both tests to diminish practice effects. The demographics questionnaire was distributed at pretest, asking about age, gender, and race along with video gaming habits of participants (e.g., frequency of play, self-perceived skill in video games, time spent playing games on a weekly basis, and the names of video games that participants play). Other self-report questionnaires investigating emotions and motivations were administered to participants, we do not provide more details on these measure as they were not used in our analyses. For purposes of this study, we only used demographics questionnaire and the content knowledge measured by the pre and posttests. A SMI EYERED 250 eye tracker was calibrated using a 9-point calibration to capture fixation duration and gaze movements during gameplay. Log-file data were also collected to track activity during game. However, for the purposes of this study, we only used eye-tracking and log-file data in our analyses.

3.4 Experimental Procedure

Participants were first asked to review and complete informed consent. Next, they completed pre-task measures including the demographics questionnaire and the content knowledge quiz. After completion, participants were given information about the study and were instrumented and calibrated to the SMI EYERED 250 eye-tracker by a researcher. All features in Crystal Island (e.g., informational text, NPCs, food item scanning, and the worksheet) were explained to the participant prior to gameplay. Multimodal multichannel data were collected on each participant throughout the duration of the experiment. After participants finished playing the game, they were instructed to immediately complete the content knowledge posttest. Participants then completed post-task self-report measures. After the completion of the post-task measures, participants were monetarily compensated for their participation, debriefed, and thanked for their time.

3.5 Coding and Scoring

Each participant's fixation duration for goal-directed actions were calculated by summing the fixation durations of all instances that action had occurred which was identified through AOIs which specified which action was occurring and for how long. We calculated the proportion of time fixating to control for differences in overall game time between participants by calculating the total time fixating on each goal-directed action (e.g., reading informational text, talking with NPCs, scanning items, solving concept matrices, and consulting the scientific worksheet) and dividing that time by total time in the game. PLG was calculated using pre- and post-test content knowledge scores using the following formula to control for differences in prior knowledge of microbiology [33]:

PLG = ((# correct post-test/total) − (# correct pre-test/total)) / (1 − (# correct pre-test/total)).

The fixation duration for informational text is the summation of the fixation durations of all instances for books, research articles, and posters. Relevant informational text was determined based on the correct diagnosis of the pathogen source for each participant. For example, if a participant's correct diagnosis was influenza, then the book on E. coli would be considered irrelevant, whereas the book on viruses would be relevant as it contains information crucial to concluding the correct diagnosis. The fixation duration on relevant informational text were then added for each participant. For the purposes of research question four in this study, participant data were split between two groups to identify the participants who engaged in more task-relevant informational texts (High; $n = 48$) and participants who did not (Low; $n = 43$). This was determined by the identification of relevant text revisits, where if a participant came back to a relevant text after an initial visit, it would be counted as one revisit. If a participant revisited a book that was relevant, it was also counted as one relevant revisit. The groups were determined by splitting the percentage, or value, so that the participants who revisited relevant texts over 50% of total revisits were placed in the high group and the others, who spent 50% of their time or greater revisiting irrelevant texts, were placed in the low group.

4 Results

4.1. *Research Question 1:* Are there differences in the proportions of fixation duration during goal-directed actions (e.g., reading informational text) over the duration of the game while problem solving in CI?;

A repeated measures ANCOVA was calculated to examine the differences of the proportion of time spent fixating on different goal-directed actions over the duration of gameplay with condition as a covariate. There was a significant difference between the fixation durations of the components over the duration of the game ($F(5,450) = 289.955$ s, $p < .0005$) where there are significant differences between the means for the proportion of informational text fixation duration over game time ($M = 0.323$ s, $SD = 0.145$ s) and the other components of the game with the exception of the proportion of concept matrix fixation durations over game time (see Table 1).

In sum, the time spent engaging with informational text within the game was significantly more than the time spent with other goal-directed actions except for concept matrices.

Table 1. Pairwise comparison of time spent on informational text to other goal-directed actions

Goal-directed action	N	Mean (s)	SD (s)	P-value
Talking to NPC	91	0.041	0.029	p < .0005
NPC dialog	91	0.084	0.036	p < .0005
Scanning food items	91	0.022	0.014	p < .0005
Concept matrices	91	0.325	0.145	p > .05
Worksheet	91	0.093	0.040	p < .0005

4.2. *Research Question 2:* Do the fixation duration proportions of goal-directed actions available to participants predict PLGs while problem-solving in CI?

A linear regression was run to examine whether goal-directed actions while problem solving in CI predict PLG. We found a significant correlation between fixation duration on concept matrices (M = 1707.41 s, SD = 859.01 s) and PLG (M = 0.269, S = 0.246; r = .269, p < .01) as well as the fixation duration on informational text (M = 1694.13 SD = 8859.08) and PLG (r = .285, p < .01). There was no relationship between PLG and fixation duration on other goal-directed actions (e.g., talking to NPCs, NPC dialog, scanning items, and worksheet instances). However, all components of the game used to achieve the goal of the game positively predicted PLG, (F(6,84) = 2.653, p < .05) with an R^2 of .159. An additional linear regression was run supporting the reading of informational text independently as a significant predictor of PLG, (F(1,89) = 7.884, p < .01) with an R^2 of .081, where as the fixation durations of informational text increased, so did participants' PLGs ($ß$ = .285, p < .01). Overall, time spent engaging with informational text positively predicted participant PLGs.

4.3. *Research Question 3:* Do fixation durations of relevant informational text significantly predict PLGs?

A linear regression was run to see if the amount of time spent fixating on relevant informational texts can predict PLGs. A significant positive correlation was found between the total fixation duration of relevant informational texts (M = 1110.61 s, SD = 526.00 s) and PLGs (r = .299, p < .01). The total fixation duration of relevant informational texts significantly predicts PLGs (F(1,89) = 8.733, p < .01) with an R^2 of .089 where as the fixation duration of information text increased, so did PLGs ($ß$ = .285, p < .01). Specifically within all engagement of informational text, the fixation on goal-relevant informational texts positively predicts participant PLGs. These results indicate that participants who engaged with relevant informational text for a greater period of time, demonstrated increased PLGs, supporting the presence of metacognitive monitoring.

4.4. *Research Question 4:* Do the PLGs differ between groups of participants who revisit relevant texts more often and those who revisit relevant texts less often?

Participants were split into two separate groups: those who revisit goal-relevant texts for more than 50% of the total revisits (Low) and those who revisit goal-irrelevant texts for 50% or more of the total revisits (High). An ANCOVA was run to examine differences in the number of relevant revisits between groups and PLGs using the full and partial agency conditions as a covariates. The results revealed a significant difference between groups, ($F(2,88) = 3.226$, $p < .05$), where participants who focused on relevant texts while revisiting text more than 50% of the time had significantly higher PLGs than those who revisited relevant texts 50% or less of the time. In sum, the fixation durations of participants in the High group have significantly higher PLGs than participants in the Low group. This supports the evidence for metacognitive judgments where participants discerned the relevancy of the text, how this may be relevant to their goal, understood their lack of knowledge in a subject, and adjusted their reading of informational text to optimize learning.

5 Discussion

The objective of this study was to examine learners' metacognitive judgments within CI, a GBLE. In support of the first hypothesis, results indicate that the proportion of time fixating on goal-directed actions differ from each other where the fixation duration of concept matrices and informational text are significant contributors to the overall game time. Further results support all goal-directed actions, including informational text independently, as predictors of PLGs. GBLEs contain activities that are crucial for the progress towards the goal of the game, but often lack in their ability to scaffold [19–21], especially informational text. In knowing the time distribution between actions as well as the ability for informational text within GBLEs to predict PLGs, more support can be directed toward these components of the game to increase overall content knowledge. Hypotheses were also supported where results indicated that participants who were able to make accurate metacognitive judgements as to the relevancy of informational text had higher PLGs. Further examination into evidence of metacognitive judgments yielded results in support of the hypothesis where participants who displayed a greater number of instances of content evaluation had higher PLGs. These results show that with informational text in GBLEs, without the aid of diagrams, are able to encourage the use of SRL skills while still having and positive impact on PLGs. This contradicts the CTML model and supporting studies in that within a game-based learning environment, text-only information presentations increase participants' proportional learning.

5.1 Implications for Adaptive Game-Based Learning Environments

This study investigates the importance of text within GBLEs as well as the need for increased scaffolding within these environments directed towards selecting relevant text-only information. As supported by the study, some students are not as adept at accurately monitoring and selecting relevant chunks of information from a large body of text and understand its relevancy towards the overall goal or their current learning goal. Time spent in informational text within these environments help to direct learners' improvements upon their SRL skills as well as having immediate impacts on their learning gains within the domain being studied. This encourages the need for intelligent feedback within Crystal Island and future adaptive GBLEs to provide needed real-time intelligent scaffolding to students in order to efficiently complete the game. These results propose that one way to identify the need for increased scaffolding on an individual level is to identify the patterns in reading informational text within GBLEs. In a narrative-based, text-centered GBLE like Crystal Island, participants are constantly engaging in informational text that may be relevant, irrelevant, or redundant to their overall goal that necessitates accurate metacognitive monitoring and regulation. A way to provide real-time scaffolding and improve metacognitive monitoring and regulation will be the use of real-time analysis of gaze behaviors supplemented with other trace data of self-regulatory processes (e.g., concurrent verbalizations, log-files, etc.).

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References

1. Schunk, D., Greene, J.: Handbook of Self-regulation of Learning and Performance, 2nd edn. Routledge, New York (2018)
2. Azevedo, R., Greene, J., Moos, D.: The effect of a human agent's external regulation upon college students' hypermedia learning. Metacogn. Learn. **2**, 67–87 (2007)
3. Greene, J., Azevedo, R.: A theoretical review of Winne and Hadwin's model of self-regulated learning: new perspectives and directions. Rev. Educ. Res. **77**(3), 334–372 (2007)
4. Greene, J., Azevedo, R.: A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. Contemp. Educ. Psychol. **34**, 18–29 (2009)
5. de Bruin, A., van Got, T.: Improving self-monitoring and self-regulation: from cognitive psychology to the classroom. Learn. Instruct. **22**, 245–252 (2012)
6. Winne, P.: Theorizing and researching levels of processing in self-regulated learning. Br. J. Educ. Psychol. **88**, 9–20 (2018)
7. Burkett, C., Azevedo, R.: The effect of multimedia discrepancies on metacognitive judgments. Comput. Hum. Behav. **28**, 1276–1285 (2012)
8. Winne, P., Azevedo, R.: Metacognition. In: The Cambridge Handbook of the Learning Sciences, pp. 63–87. Cambridge University Press, New York (2014)
9. Mudrick, N., Taub, M., Azevedo, R.: Do accurate metacognitive judgments predict successful multimedia learning? In: Proceedings of the 39th Annual Conference of the Cognitive Science Society, Austin, Texas, pp. 2766–2771 (2017)
10. Azevedo, R.: Multimedia learning of metacognitive strategies. In: The Cambridge Handbook of Multimedia Learning, pp. 647–672. Cambridge University Press, New York (2014)

11. Aleven, V., Koedinger, K.: An effective metacognitive strategy: learning by doing and explaining with a computer-based cognitive tutor. Cogn. Sci. **26**, 147–179 (2002)
12. Lester, J., Rowe, J., Mott, B.: Narrative-centered learning environments: a story-centric approach to educational games. In: Mouza, C., Lavigne, N. (eds.) Emerging Technologies for the Classroom, pp. 223–237. Springer, New York (2013). https://doi.org/10.1007/978-1-4614-4696-5_15
13. de Bruin, A., Thiede, K., Camp, G., Redford, J.: Generating keywords improves metacomprehension and self-regulation in elementary and middle school children. J. Exp. Child Psychol. **109**, 294–310 (2011)
14. Mayer, R.: Educational psychology's past and future contributions to the science of learning, science of instruction, and science of assessment. J. Educ. Psychol. **110**(2), 174–179 (2018)
15. Taub, M., Mudrick, N.V., Azevedo, R., Millar, G.C., Rowe, J., Lester, J.: Using multi-level modeling with eye-tracking data to predict metacognitive monitoring and self-regulated learning with Crystal Island. In: Micarelli, A., Stamper, J., Panourgia, K. (eds.) ITS 2016. LNCS, vol. 9684, pp. 240–246. Springer, Cham (2016). https://doi.org/10.1007/978-3-319-39583-8_24
16. Conati, C., Vanlehn, K.: Toward computer-based support of meta-cognitive skills: a computational framework to coach self-explanation. Int. J. Artif. Intell. Educ. **11**, 398–415 (2000)
17. Butcher, K.: The multimedia principle. In: The Cambridge Handbook of Multimedia Learning, pp. 174–205. Cambridge University Press, New York (2014)
18. Mayer, R.: Cognitive theory of multimedia learning. In: The Cambridge Handbook of Multimedia Learning, pp. 43–71. Cambridge University Press, New York (2014)
19. Sabourin, J., Shores, L., Mott, B., Lester, J.: Understanding and predicting student self-regulated learning strategies in game-based learning environments. Int. J. Artif. Intell. Educ. **23**, 94–114 (2013)
20. Kirschner, P., Sweller, J., Clark, R.: Why minimal guidance during instruction does not work: an analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. Educ. Psychol. **41**(2), 75–86 (2006)
21. Mayer, R., Johnson, C.: Adding instructional features that promote learning in a game-like environment. J. Educ. Comput. Res. **42**(3), 241–265 (2010)
22. Azevedo, R., Taub, M., Mudrick, N.: Understanding and reasoning about real-time cognitive, affective, and metacognitive processes to foster self-regulation with advanced learning technologies. In: The Handbook of Self-Regulation of Learning and Performance, pp. 254–270. Routledge, New York (2018)
23. Dogusoy-Taylan, B., Cagiltay, K.: Cognitive analysis of experts' and novices' concept mapping processes: an eye tracking study. Comput. Hum. Behav. **36**, 82–93 (2014)
24. Rayner, K.: The 35th Sir Frederick Bartlett Lecture Eye movements and attention in reading, scene perception, and visual search. Q. J. Exp. Psychol. **62**(8), 1457–1506 (2009)
25. Tsai, M., Hou, H., Lai, M., Liu, W., Yang, F.: Visual attention for solving multiple-choice science problem: an eye-tracking analysis. Comput. Educ. **58**, 375–385 (2016)
26. Hu, Y., Wu, B., Gu, X.: An eye tracking study of high- and low-performing students in solving interactive and analytical problems. Educ. Technol. Soc. **20**(4), 300–311 (2017)
27. Gagenfurtner, A., Lehtinen, E., Säljö, R.: Expertise differences in the comprehension of visualizations: a meta-analysis of eye-tracking research in professional domains. Educ. Psychol. Rev. **23**, 523–552 (2011)
28. D'Mello, S., Olney, A., Williams, C., Hays, P.: Gaze tutor: a gaze-reactive intelligent tutoring system. Int. J. Hum. Comput. Stud. **70**, 377–398 (2012)

29. Rowe, J.P., Shores, L.R., Mott, B.W., Lester, J.C.: Integrating learning, problem solving, and engagement in narrative-centered learning environments. Int. J. Artif. Intell. Educ. **21**, 115–133 (2011)
30. Taub, M., Mudrick, N.V., Azevedo, R., Millar, G.C., Rowe, J., Lester, J.: Using multi-channel data with multi-level modeling to assess in-game performance during gameplay with Crystal Island. Comput. Hum. Behav. **76**, 641–655 (2017)
31. Emerson, A., Sawyer, R., Azevedo, R., Lester, J.: Gaze-enhanced student modeling for game-based learning. In: Proceedings of the Twenty-Sixth ACM Conference on User Modeling, Adaptation and Personalization, Singapore, pp. 63–72 (2018)
32. Taub, M., Azevedo, R., Bradbury, A., Millar, G., Lester, J.: Using sequence mining to reveal the efficiency in scientific reasoning during STEM learning with a game-based learning environment. Learn. Instr. **54**, 93–103 (2018)
33. Witherspoon, A., Azevedo, R., D'Mello, S.: The dynamics of self-regulatory processes within self- and externally regulated learning episodes during complex science learning with hypermedia. In: Wolf, B.P., Nkambou, R., Lajoie, S. (eds.) Intelligent Tutoring Systems, pp. 260–269. Springer, Heidelberg (2008). https://doi.org/10.1007/978-3-540-69132-7_30