8 Instructional Support, Feedback, and Coaching in Game-Based Learning

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Introduction

Advances in game-based learning environments are introducing a broad range of opportunities for supporting student learning. The past decade has witnessed significant theoretical developments (Adams & Clark, 2014; Clark, Sengupta, Brady, Martinez-Garza, & Killingsworth, 2015; Gee, 2007; Gibson, Aldrich, & Prensky, 2007; Habgood & Ainsworth, 2011), the creation of game-based learning environments for many subjects (Adams & Clark, 2014; Halpern, Millis, & Graesser, 2012; Kebritchi, Hirumi, & Bai, 2010; Warren, Dondlinger, & Barab, 2008), and an expanding body of literature on the design and educational effectiveness of digital games (Adams & Clark, 2014; Habgood & Ainsworth, 2011; Ketelhut, Nelson, Clarke, & Dede, 2010; Meluso, Zheng, Spires, & Lester, 2012; Wouters, van Nimwegen, van Oostendorp, & van der Spek, 2013).

Games have long held great promise for creating learning experiences that are both effective and engaging. Although in the past the potential of games to support learning was viewed as substantial, until recently there was little empirical evidence to support this view. Recent syntheses of the game-based learning literature have found that games can yield positive learning outcomes across a range of subjects and settings (Connolly, Boyle, MacArthur, Hainey, & Boyle 2012; Martinez-Garza, Clark, & Nelson, 2013; McClarty et al., 2012; Perrotta, Featherstone, Aston, & Houghton, 2013; Sitzmann, 2011). Furthermore, a pair of meta-analyses independently concluded that game-based learning is often more effective than traditional instructional methods with respect to learning and retention (Clark, Tanner-Smith, Killingsworth, & Bellamy, 2013; Wouters et al., 2013).

Although there is now significant evidence suggesting that games can serve as an effective medium for learning, a key problem posed by game-based learning is how to support learners most effectively. In particular, an open question in research on game-based learning environments is how to design instructional support, feedback, and coaching that are artfully integrated into core game mechanics in a manner that serves the dual functions of advancing gameplay while simultaneously promoting learning.

Instructional Support, Feedback, and Coaching in Game-Based Learning

Instructional support, feedback, and coaching serve an important role in game-based learning environments. The guidance provided by various forms of support holds the potential to promote deeper learning experiences and enable learners to focus on the most salient aspects of a learning scenario. In contrast, one can imagine game-based learning environments that operate in a pure discovery learning fashion in which learners are given no support (Kirschner, Sweller, & Clark, 2006). In these environments, learners would be expected to support their own learning experiences without any guidance, and these might yield the same types of unsatisfying outcomes as some discovery learning experiences (Mayer, 2004). Thus, embedding guidance in game-based learning holds much appeal.

A particularly compelling category of game-based learning environments that provide dynamic instructional support, feedback, and coaching is *intelligent game-based learning environments*, which integrate game technologies and intelligent tutoring systems (Lester et al., 2013). Research on intelligent game-based learning environments is investigating a broad range of functionalities for providing dynamic instructional support, feedback, and coaching that are tightly integrated into game-based learning environments (DeFalco et al., 2018; Lee, Rowe, Mott, & Lester, 2014; Lester et al., 2013; Pezzullo et al., 2017; Robison, McQuiggan, & Lester, 2009; Rowe & Lester, 2015).

Because it is hypothesized that game-based learning environments can promote learning through adaptive support, the design of intelligent game-based learning environments is guided by the premise that intelligent tutoring system functionalities can be introduced into games to provide key support mechanisms that have emerged from several decades of research on intelligent tutoring systems (Woolf, 2009). These mechanisms are often decomposed into what are termed “outer loop” mechanisms and “inner-loop” mechanisms (VanLehn, 2006).

Functionalities in the “outer loop” of an intelligent tutoring system are responsible for selecting the tasks that students will perform. For intelligent game-based learning environments, task selection could be used to determine which episode of a game a student will interact with, which level of a game a student will play, or which problem-solving scenario within a level a student might be given. As with “outer loops” in intelligent tutoring systems, a variety of pedagogies might be implemented, and an intelligent game-based learning environment can select from a predefined set of these or perhaps dynamically generate them using procedural content-generation techniques (Shaker, Togelius, & Nelson, 2016).

Intelligent game-based learning environments can also implement intelligent tutoring systems’ “inner loop.” Functionalities in the “inner loop” of intelligent tutoring systems typically focus on support that is centered on smaller granularities of subject matter and span shorter intervals of time (VanLehn, 2006). Intelligent tutoring system “inner-loop” supports include providing minimal feedback on a fine-grained problem-solving action, providing feedback that is specific to particular conceptual or problem-solving errors, providing hints on potential upcoming problem-solving actions, assessing students' knowledge, and conducting a review of a student's proposed solution. Intelligent game-based learning environments can provide analogous families of support for students. For example, they can use nonplayer characters or pedagogical agents (Johnson & Lester, 2016) to provide minimal or error-specific feedback on a student's actions in the game or hints related to a student's upcoming quest; they can conduct stealth assessment (Min et al., 2015; Min, Frankosky, et al., 2017; Shute, 2011) to provide a formative assessment of the student's competencies as evidenced through gameplay; and they can perform an after-action review (Brown, 2011) to review a student's recent gameplay experience.

This chapter explores instructional tactics that can be implemented in intelligent game-based learning environments to support learning with a focus on inner-loop functionalities. Connections between instructional strategies and theories of learning are used to highlight how support can be designed to help learners select relevant information in the learning environment, organize information into coherent mental representations, and provide learners with hints and support during task performance to guide learning.

What Do We Know about Instructional Support, Feedback, and Coaching in Game-Based Learning?

In this section, we review relevant research literature regarding the effectiveness of instructional support, feedback, and coaching in game-based learning environments. To foreshadow the discussion, we note that research in this area is still in its infancy. Although many claims have been made about the benefit of game-based learning environments, empirical evidence regarding their effectiveness is fragmented and riddled with methodological limitations. Mayer and Johnson (2010) described three general methods researchers have used to evaluate learning outcomes with games. The *cognitive consequences* method is used to investigate whether playing a game improves a specific cognitive skill (i.e., what do players learn from playing the game?). With the *media comparison* method, researchers compare whether people learn better with games or conventional media. A third method researchers use is to compare the learning outcomes of students who receive different versions of the same game (i.e., which type of feedback is most beneficial for learning; see Mayer & Johnson, 2010). This third approach, referred to as the *value-added approach*, is the most relevant for evaluating the impact on learning outcomes of instructional support and feedback in games (Mayer & Johnson, 2010). In the following sections, we review research that has used each of these approaches and discuss how the results can be used to improve student outcomes in game-based learning environments.

Supporting Learning in Game-Based Environments through Feedback

It is well established that feedback is important for learning in game-based learning environments (Azevedo & Bernard, 1995; Mayer, 2014). The purpose of feedback is to help learners evaluate their progress and performance, identify knowledge gaps, and repair faulty knowledge (Johnson & Priest, 2014). Ultimately, providing learners with feedback can be an effective method of guiding them to achieve a deeper understanding of the subject matter.

In a recent review of the feedback and gaming literature, Johnson, Bailey, and Van Buskirk (2017) identified four general ways in which feedback can be instantiated in game-based learning environments and provided a review of their effectiveness. Specifically, the authors found feedback can vary according to (1) the content of the feedback message, (2) the timing of the feedback message, (3) the modality in which feedback is presented, and (4) whether feedback is adapted based on learner aptitude or characteristics. They also proposed that content feedback be further classified according to whether the feedback message is outcome oriented or process oriented. *Outcome-oriented feedback* provides learners with information about their current level of performance or the correctness of their response (Johnson et al., 2017). Examples of outcome feedback include knowledge of results ("your answer is correct"), knowledge of correct results (the correct answer is D), error flagging ("the last part of your answer is incorrect"), and environmental feedback (a student's answer results in a character receiving an award). *Process-oriented feedback* provides learners with explanatory information about the processes or strategy used to reach the correct answer (Johnson et al., 2017). Its purpose is to provide the learner with information that can be used to close the gap between his or her current level of understanding or performance and the level of performance required to meet the objective in the game. Examples of process-oriented feedback include informational prompts and hints that guide students toward the correct answer, topic-specific feedback, and error-sensitive feedback that provides information related to why an answer is correct or incorrect. As noted by Johnson et al., outcome and process feedback are not mutually exclusive: feedback statements can include both forms of content (Johnson et al., 2017).

What do we know about the effectiveness of feedback content in game-based learning environments? In general, empirical evidence suggests that process-oriented feedback is superior to outcome-oriented feedback (e.g., minimal feedback) for helping learners develop a deeper understanding of instructional material. The benefits of process-oriented feedback are evident in near transfer tasks and tests of knowledge retention. For example, Mayer and Johnson (2010) explored the benefits of explanatory feedback in an arcade-style educational game designed to teach students how to solve problems about electrical circuits. In the game, students gained or lost points based on their ability to correctly solve circuitry problems. When students submitted a correct answer, they received a “correct” tone and several points. When they submitted an incorrect answer, they received an “incorrect” tone and lost points from their score. Students who played the standard version of the game received minimal feedback (through the tones and points). Students who played the explanatory version of the game received minimal feedback as well as process-oriented feedback that explained the correct answer. The last level of the game served as an embedded transfer test and required students to use their knowledge of electrical circuitry to solve a complex circuitry problem. Results showed that students in the explanatory feedback condition outperformed participants in the outcome-oriented feedback condition during gameplay ($d = 1.31$) and on the embedded transfer task ($d = .68$). The authors concluded that providing direct guidance in the form of explanatory feedback helped students develop a deeper understanding of the material than providing minimal guidance through corrective feedback alone.

Using a value-added approach, Moreno and Mayer (2005) also found benefits from providing learners with explanatory feedback in a multimedia-style game. In their study, college students learned about botany while playing an interactive game called *Design-a-Plant* (Lester, Stone, & Stelling, 1999). During gameplay, students traveled to five alien planets, learned about plant parts and weather conditions, and learned how to design a plant that could flourish in different environmental conditions (figure 8.1). Students were supported during the game by a pedagogical agent, Herman the Bug, who offered individualized advice and feedback on the relationship between plant features and weather conditions. Students were randomly assigned to receive either minimal feedback on the correctness of their answer during game play or explanatory feedback about why a certain plant design would survive or perish in the planet’s environment. After finishing the game, students completed a retention test to assess their understanding of basic factual information about botany and a problem-solving test, which required students to apply the principles they learned in the game. Results showed that students who received explanatory feedback scored higher on near ($d = .75$) and far ($d = 1.68$) transfer problem-solving tasks than students who received corrective feedback only, and they produced fewer incorrect answers during gameplay. These results suggest that providing learners with explanatory feedback in game-based multimedia environments can promote deep, meaningful learning.

More recently, researchers have investigated the generalizability of providing process-related feedback in more immersive game-based training environments. For example, Billings (2012) used a value-added approach to investigate the effect of providing learners with different levels of feedback specificity during a game-based training exercise designed to teach search-and-rescue procedures. The training exercise required participants to navigate in a virtual environment and search buildings for different items while following a set of procedures outlined in the learning objectives. The learning objectives included procedures for entering and exiting buildings, clearing buildings, and communicating with headquarters. Four feedback conditions were

Figure 8.1
Screenshot of *Design-~~a~~-Plant* learning environment.

compared: nonadaptive detailed feedback, nonadaptive general feedback, adaptive top-down feedback, and adaptive bottom-up feedback. Each condition corresponded to different levels of feedback specificity. In the nonadaptive detailed condition, participants received feedback about which learning objectives they failed and how to correctly perform them after each mission (e.g., “Before entering or tagging a building, you should walk around the entire building to make sure it is not already tagged”). In the nonadaptive general condition, participants only received general feedback statements about the learning objectives they forgot to apply during the training mission (i.e., “Remember to apply the procedures for entering and exiting a building”). In the adaptive bottom-up feedback condition, students began the training missions by receiving detailed feedback about the errors they committed. After demonstrating increased mastery of the learning objectives, the feedback statements changed from detailed to general. Conversely, in the adaptive top-down condition, participants started with general feedback and then faded to statements that were more detailed if learning objectives were not being met. Billings (2012) postulated that providing students with adaptive bottom-up feedback would produce better learning outcomes than the nonadaptive strategies, because of the advantages associated with personalized instruction. Billings also posited that detailed feedback would be better at supporting knowledge integration because it facilitated learning at the subtask level rather than providing support at an overall conceptual level of the task. Results generally supported these hypotheses. Participants in the adaptive bottom-up and detailed conditions achieved higher levels of performance more quickly than participants in the top-down or general feedback conditions. That is, providing detailed feedback facilitated learning that was more efficient compared to providing general feedback. Further results showed that participants in the general condition performed significantly worse than those in the adaptive bottom-up condition. Billings concluded that detailed feedback seemed to be the best option for designing feedback in simulation-based training environments and that the results support theories such as cognitive load theory. Specifically, the benefits of providing learners with specific rather than general feedback appeared to stem from telling learners directly what procedure they needed to follow rather than their having to recall this information themselves. This reduced cognitive load and made learning more efficient.

Serge, Priest, Durlach, and Johnson (2013) conducted a follow-up experiment to further examine feedback specificity properties in game-based learning environments. Participants in this experiment performed the same search-and-rescue training and transfer task as in Billings's (2012) study described earlier and received the same types of feedback (general, specific, adaptive top-down, adaptive bottom-up). In addition, Serge et al. allowed trainees in the general feedback condition to review the training manual at the end of each mission. They included this option to determine whether individuals who took advantage of this opportunity (i.e., reviewing detailed procedures for performing the task) performed similarly to those who received detailed feedback. Overall results showed that participants who received detailed feedback learned how to perform the task more quickly than those under other conditions. In addition, participants in the general feedback condition who reviewed the training manual between missions performed just as well on the task as trainees who received detailed feedback. However, individuals who chose not to review the training manual performed as poorly as those in the control condition who did not receive any feedback. These results lend support for the powerful benefits of providing detailed feedback to learners through inner loop functionalities in game-based training environments.

In sum, the results of these experiments show that process-oriented feedback improves learning outcomes for novice learners when compared to outcome-oriented feedback in game-based learning environments (Johnson et al., 2017). One explanation for these observed benefits is that providing learners with error-specific information or explanative information reduces extraneous processing and helps learners more easily identify the source of their misunderstandings. In turn, learners have more cognitive resources to dedicate to essential processing, which helps facilitate deeper learning (Johnson & Priest, 2014; Mayer, 2009). These results suggest that intelligent game-based learning environments that offer detailed or error-specific feedback through inner-loop functions might more effectively support learning.

What do we know about the effectiveness of feedback timing in game-based learning environments? In addition to feedback content, feedback timing can also influence learning in game-based environments. A major question facing designers of game-based learning environments is whether to present feedback to learners immediately after they make a mistake or after a delay. As noted by Johnson et al. (2017), guidance for this question is rather mixed because of conflicting theories and empirical findings. Proponents of immediate feedback suggest that providing feedback immediately after errors prevents errors from being encoded during the acquisition phase of learning (Bangert-Drowns, Kulik, Kulik, & Morgan, 1991; Shute, 2008). The benefits of immediate feedback have been demonstrated in cognitive tutors and step-based intelligent tutoring systems for two decades (Anderson, Corbett, Koedinger, & Pelletier, 1995; Corbett & Anderson, 1995). In these environments, results show a strong learning effect associated with students who receive immediate feedback on step-based learning errors. Advocates for delayed feedback adhere to the interference-preservation hypothesis proposed by Kulhavy and Anderson (1972), which asserts that errors interfere with encoding corrective information when feedback is delivered immediately and that people make fewer preservation errors if feedback is delayed.

A review of the feedback literature suggests that the question of when to provide feedback partly depends on the intended goal of learning. Immediate feedback seems to be more beneficial during the acquisition phase of learning (Anderson, Magill, & Sekiya, 2001; Corbett & Anderson, 1995; Dihoff, Brosvic, Epstein, & Cook, 2004), but delayed feedback may be better for promoting transfer. This general assumption has received some empirical support. For instance, Schmidt, Young, Swinnen, and Shapiro (1989) found that providing feedback immediately after a trial produced higher performance during practice but led to worse performance during training transfer. Conversely, delayed feedback resulted in lower performance during the acquisition phase of training but better performance during a transfer phase.

Although one may imagine the benefits of both immediate and delayed feedback in game-based environments, relatively little research has systematically evaluated feedback-timing policies in game-based learning. One notable exception is a study by Johnson, Priest, Glerum, and Serge (2013) that examined three feedback-timing policies for training procedural skills in a game-based environment. Participants were trained to perform the same search-and-rescue task described in the study by Serge et al. (2013), but received feedback at one of three timing schedules: immediately after an error (immediate condition), at a logical stopping point in the scenario (chunked condition), or at the end of the scenario (delayed). Although the results did not reveal any statistically significant differences between the timing conditions, data trends showed that participants in the immediate feedback condition performed slightly better than those in the delayed or chunked condition. Importantly, the authors found that the delayed feedback groups reported higher levels of cognitive load, while the chunked and immediate groups reported lower levels of cognitive load. These findings led the authors to suggest that immediate feedback may help reduce extraneous cognitive load in game-based training environments but that more research is needed in this area (Johnson et al., 2013).

Van Buskirk (2011) found a similar benefit from providing immediate feedback in a simulation-based task designed to train military call-for-fire procedures. During the simulation, participants scanned simulated terrain for enemy targets, identified targets, determined which threats to neutralize based on a set of prioritization rules, and then called in artillery fire to the position of the threat. The author manipulated the type of feedback participants received (outcome vs. process feedback), when they received it (immediate vs. delayed feedback), and the modality in which the message was presented (visual vs. auditory feedback). An important contribution of this study was that the author hypothesized that the effectiveness of the feedback delivery parameters would depend on the processing demands imposed by the task. More specifically, Van Buskirk hypothesized that because learners were performing a visual-spatial task, the relative effectiveness of feedback content (process vs. outcome) would depend on when and how it was presented. She hypothesized that outcome feedback would be more effective if it was presented immediately after an error, whereas process feedback would be more effective if the message was delayed. She also hypothesized auditory feedback that was presented immediately would be most effective because the message delivery modality would not suffer from the same level of processing interference as a message presented in the visual modality. Results showed that participants who received immediate, auditory, process feedback outperformed those receiving all other types of feedback on the target prioritization portion of the task. Although the results of the study did not support the hypothesized interaction, the author noted that a confounding factor caused by exposure to environmental feedback in the simulation may have attenuated the differences between the immediate and delayed feedback. These results highlight the importance of considering the processing demands of the feedback message and task when designing feedback timing policies.

More recently, Landsberg, Bailey, Van Buskirk, Gonzalez-Holland, and Johnson (2016) found benefits from providing learners with delayed feedback in a similar type of simulation-based training system. This experiment investigated the relationship of feedback timing, feedback granularity, and environmental feedback in a simulation testbed designed to train individuals to estimate a ship's angle relative to their own line of sight. The task required participants to make accurate and timely decisions about the orientation of their ship relative to a simulated ship viewed through a periscope. Participants received feedback either immediately after each trial (immediate feedback condition) or after every 15 trials (delayed feedback condition). Results showed that participants in the delayed feedback condition made decisions more quickly than individuals in the immediate feedback condition. Furthermore, participants in the delayed feedback condition also viewed feedback messages for longer than participants in the immediate condition did. Landsberg et al. (2016) concluded that by delaying feedback, participants had a chance to more actively process the feedback message, which led to faster decision making and response times on subsequent trials.

Based on the results presented here, it may be that one of the primary benefits of delaying feedback is to provide students with a chance to reason about their own errors and self-correct before receiving feedback. Mathan and Koedinger (2005) found support for this type of reasoning in two studies that examined two feedback-timing policies in an intelligent tutoring system designed to teach novices how to write formulas in a spreadsheet. Although the study was not performed in a game-based environment, the results have implications for the design of game-based learning environments. Specifically, Mathan and Koedinger reasoned that the debate regarding when to give feedback should not be based on a simple policy of feedback timing alone but rather on the model of desired performance. If the model of desired performance includes promoting metacognitive skills for error detection and correction, then learners should be allowed to exercise these skills before receiving feedback. If the model of desired performance mimics that of an expert, then immediate feedback should be provided. These researchers found that participants who were allowed to make reasonable errors, self-evaluate, and correct their errors prior to receiving feedback performed better on tests of problem solving, conceptual understanding, transfer, and retention compared to learners who received immediate feedback.

As demonstrated in these studies, feedback during the learning process is clearly beneficial to individuals. Detailed process feedback seems to provide the most benefits to learners (Billings, 2012; Johnson et al., 2013; Serge et al., 2013). However, guidance on when to deliver feedback is mixed. Many decisions about whether to delay feedback or provide it immediately seem to depend on moderating factors, such as the type of task or the intended learning objectives (e.g., promoting retention vs. promoting transfer). Of the studies we reviewed, none focused on narrative-centered learning environments or story-driven game-based learning environments, which have become increasingly prominent. Narrative-centered learning environments can serve as an ideal "laboratory" for investigating how to deliver feedback compared to other types of game-based environments because of their story-driven design and tendency to utilize first- or third-person perspectives through gameplay. These environments offer an interesting opportunity for integrating feedback within a believable world. Storyline characters could provide detailed feedback to learners during gameplay, and changes to the story line could provide a form of realistic environmental feedback (Johnson et al., 2017; Johnson & Lester, 2016). Understanding when and how to give feedback in these types of games, as well as other forms of game-based learning environments, continues to be an important question that needs to be answered with empirical research.

Support and Coaching in Game-Based Learning

Like feedback, support and coaching in game-based learning environments can take many forms. Some game-based environments include cues for guiding learners' attention and selection, some include features that provide support for organizing and recognizing important information, and others provide support for reflection and integration of knowledge. Although it is generally accepted that including support is necessary to prevent learners from floundering (Mayer, 2004), empirical research on the effectiveness of different approaches and types of support in game-based environments is still somewhat sparse. Several notable examples, however, have addressed this question using a value-added, cognitive consequences, or media comparison approach. We describe several of these studies.

Supporting information selection in game-based learning environments One of the challenges of situating learning in game-based environments is that these environments offer a greater number of possible paths and objectives to explore compared to traditional forms of instruction (e.g., PowerPoint slides). The higher level of interactivity and the story-driven design of some environments may impact the ways that learners select, organize, and integrate information compared to static forms of multimedia instruction (Adams, Mayer, McNamara, Koenig, & Wainess, 2012; Mayer, 2009). To alleviate these demands, some researchers have incorporated attentional cues within games to draw users' attention toward characters or critical elements that need to be explored. For instance, in *Crystal Island* (Lester et al., 2014; Lester, Rowe, & Mott, 2013), a game-based learning environment for middle school microbiology education, visual cues such as highlighting are added to books and other articles that learners can interact with (figure 8.2). These cues are meant to direct learners' attention toward important task-relevant cues while at the same time reducing extraneous load.

Similar forms of attentional support have been implemented in other inquiry-based learning games. For instance, Nelson, Kim, Foshee, and Slack (2014) used a value-added approach to investigate the efficacy of including visual cues in a narrative-centered virtual environment designed to assess scientific inquiry. The virtual environment involved gathering evidence and testing hypotheses regarding why a new flock of sheep was not thriving at a new farm. Learners played the role of a local scientist who could interact with virtual characters, explore the local landscape, and use a set of virtual tools to collect data from sheep scattered around the farm. The study included two test conditions: (1) a visual signaling condition in which 3-D symbols (i.e., visual cues) hovered above characters and objects (e.g., sheep) with which learners could interact, and (2) a nonvisual signaling condition. To indicate that an object had been viewed, the status and color of each visual signal changed once a learner interacted with it. The authors hypothesized that by including visual cues, learners would be more likely to interact with relevant objects and experience decreased cognitive load. Study results

Figure 8.2
Screenshot of *Crystal Island* game-based learning environment.

supported these hypotheses. Specifically, participants in the visual signaling condition reported lower levels of cognitive load in a postgame survey. Furthermore, trace data from the game revealed that participants in the visual signaling condition interacted with key objects more often ($d = .34$), collected more measurements from sheep ($d = .51$), and took more notes in the electronic clipboard provided in the game ($d = .48$) than participants in the nonsignaling condition. These results show that the signaling principle, which states that people learn better when the design of interactive instruction includes visual or auditory cues that highlight the organization of essential material to be learned, is applicable to game-based learning environments (Mayer, 2009). Applied to intelligent game-based learning environments, these results suggest that one important function of the inner loop is to highlight important game elements or interactive objects. Providing this form of attentional support could reduce a learner's extraneous processing and free working-memory resources to create a more engaging and meaningful learning experience.

Supporting knowledge organization In addition to facilitating the appropriate selection of relevant objects in game-based learning, support can also be seamlessly embedded in game-based learning environments to help learners mentally organize selected information into coherent mental representations (Mayer, 2009). Examples include embedding into gaming environments concept graphs, graphic organizers, notebooks, and checklists that students can use to record key pieces of information or

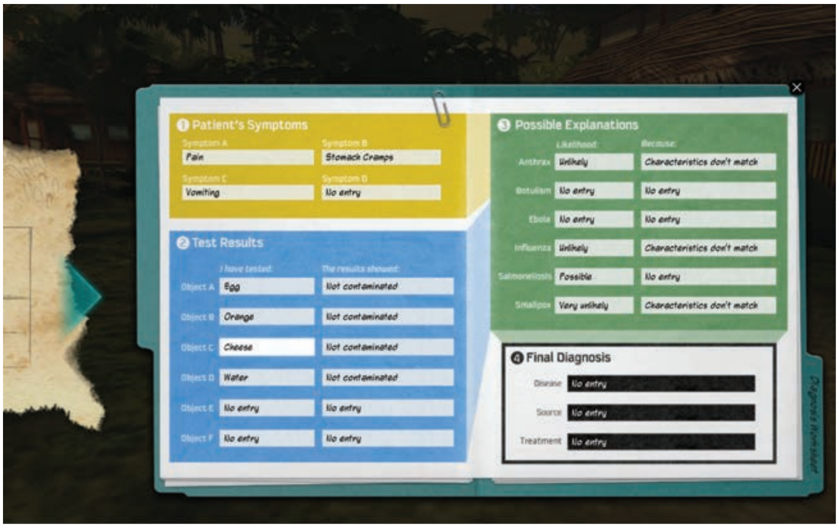

Figure 8.3
Diagnosis worksheet in *Crystal Island*.

self-reflect on what they currently know in regard to the problem they are trying to solve. Results of several studies exemplify how these types of cognitive tools can promote learning gains and interest in game-based learning environments (Shores, Rowe, & Lester, 2011).

For instance, Nietfeld, Shores, and Hoffman (2014) examined whether a structured note-taking tool embedded in a narrative-centered learning environment could effectively scaffold students' knowledge-organization processes and promote learning outcomes. Embedded in *Crystal Island* (Rowe, Shores, Mott, & Lester, 2011), the cognitive tool was a virtual diagnosis worksheet that learners could use to list patient symptoms, make notes, select likely causes, and provide a final diagnosis as they tried to solve a mystery about what caused an illness outbreak on a virtual island (figure 8.3). Using a sample of 130 middle school students, Nietfeld et al. (2014) found that students who used the virtual worksheet more frequently reported higher levels of interest, were more engaged, and showed higher learning gains than students who did not use this scaffolding. The authors summarized these results by stating how critical it is for students to use in-game cognitive tools to assist in off-loading and organizing information pertinent for successful performance in these environments.

Similar types of cognitive tools have been implemented in other interactive learning environments. For instance, *BioWorld*, an intelligent tutoring environment that trains medical practitioners on diagnostic reasoning across an array of simulated exercises, uses embedded cognitive tools to help students externalize and evaluate their reasoning processes as they diagnose patient cases and illnesses (Lajoie, 2009). These tools are designed to support monitoring processes and provide help-seeking resources commonly used during medical diagnostic events (Lajoie, 2009). One such tool embedded in the environment is termed the "evidence palette," as it provides a notebook interface to record information deemed important for supporting a diagnosis. McCurdy, Naismith, and Lajoie (2010) found that experts and novices used the tool differently, with experts collecting more evidence during the investigation phase of the game. Additional studies have found that tool usage is an important predictor of problem-solving performance in inquiry-based learning environments (Liu et al., 2009).

Graphical organizer and concept matrices are another set of cognitive tools frequently found in game-based learning environments. These instructional scaffolds can be used to help learners self-test and self-reflect on their current state of knowledge (Rowe, Lobene, Mott, & Lester, 2013). *Crystal Island* includes concept matrices that students can use to reinforce and regulate their understanding of microbiology principles. Preliminary findings of student usage activities have suggested that students' concept matrix performance is predictive of posttest knowledge scores, suggesting that this form of cognitive support plays an important role in helping students learn important scientific concepts (Min, Rowe, Mott, & Lester, 2013). In applications such as *Betty's Brain*, students use concept maps to represent their understanding of earth science topics such as food chains, photosynthesis, or waste cycles. Students receive feedback on the correctness of their concept linkages through their interactions with the virtual agent in the platform. This support was found to improve students' own reflective behaviors (Jeong & Biswas, 2008).

Empirical evidence also suggests that embedding subproblems (e.g., miniquests) within a game-based learning environment can support more efficient learning compared to asking learners to solve a more complex activity (Shores, Hoffman, Nietfeld, & Lester, 2012). As a form of cognitive support, these more proximal goals have the potential to scaffold the learning process by breaking down learning objectives into cognitively manageable units, providing useful, frequent feedback, and maintaining motivation and the novelty of the experience (Shores et al., 2012).

Taken together, these results show the promise of including cognitive tools in game-based environments to support learning outcomes. Cognitive tools can be used to offload and organize information that is pertinent to successful performance in the environment. Perhaps more importantly, cognitive tools can help prompt self-regulatory behaviors among learners. Self-regulation has been identified as an important component that supports learning in game-based environments. Learners with high self-regulatory skills are more likely to set goals, check their progress against these goals, and adjust their strategy when their current level of performance is not aligned with their goals (Azevedo, Behnagh, Duffy, Harley, & Trevors, 2012). Cognitive tools can also serve as an indirect method for reminding learners to engage in specific tasks and facilitate metacognitive and self-regulatory learning processes (Lester, Mott, Robison, Rowe, & Shores, 2013; Roll, Wiese, Long, Aleven, & Koedinger, 2014).

Supporting knowledge integration and task performance In addition to directing a learner's attention and supporting knowledge organization, support can be used in game-based learning environments to provide explicit guidance to learners as they perform a task. Such support can be instantiated in the form of hints, prompts, pumps, and elicitation statements designed to provide learners with reminders about the goals of the task, hints about how to solve a problem, or prompts to elaborate an answer, self-explain a concept, or self-reflect on their current level of understanding (Aleven & Koedinger, 2002; Lester, Mott, et al., 2013; Roll et al., 2014). In traditional step-based intelligent tutoring systems, such as those designed to teach mathematics or physics, students can request hints as they work toward solving a problem. The first hint may offer a "nudge" to remind students about a concept they should apply. The second hint may be more directive. The final hint—called the bottom-out hint—may provide the answer. The tutor may also provide hints proactively. Intelligent game-based learning environments that incorporate intelligent tutoring capabilities offer similar forms of support, and there is growing evidence that these interventions can have a positive impact on learning.

For instance, *BiLAT*, a game-based instructional system designed to teach cultural awareness and bilateral negotiation skills, has been shown to improve the negotiation skills of novice negotiators during meetings (Kim et al., 2009). *BiLAT* requires that learners interact with virtual characters (e.g., a local doctor) in a situated story line to achieve a particular outcome (e.g., move the local clinic). Prior to engaging in negotiations, learners complete an initial research and preparation phase, in which they gather information about the characters they will interact with and learn culturally appropriate negotiation tactics. After this initial phase, learners are placed in narrative-driven scenarios where they must successfully negotiate with virtual characters to achieve their mission goals. Learners select speech acts or actions from a menu, and the virtual characters react to these selections. The menu serves as a scaffold for novice users who may not be able to generate these actions on their own. During negotiation meetings, the system provides students with hints regarding appropriate actions. Hints are triggered according to the phase of the meeting (e.g., greeting and rapport phase, business phase), the list of available actions, and the learning objective. Hints start by offering general information in regard to the learning objective (e.g., begin with a sign of respect) and then progress to more detailed and corrective hints and suggestions if the trainee does not demonstrate competence during the negotiation (e.g., "take off your sunglasses"). The coach also offers feedback based on a student's most recent action. In an evaluation of *BiLAT*, Kim et al. (2009) found that novice negotiators who trained with *BiLAT* over a relatively short period increased their negotiation skills as measured through pretest and posttest learning gains ~~in~~ a situational judgment test.

Nelson (2007) investigated the impact of an individualized guidance system that was embedded in an educational multiuser virtual environment called River City. The guidance system was designed to help students solve scientific inquiry problems. River City depicted a late nineteenth-century town that included shops, a library, an elementary school, and other institutions. Upon entering the town, students could interact with virtual characters, digital objects, and avatars of other students. Students were required to explore different sections of town and develop hypotheses about why residents were ill. Students could view objects in the virtual world, such as historical photos, books, and charts, and could use interactive tools. They could also interact with virtual characters to learn more about the town and potential causes of illness. The guidance system compiled a cumulative model of student interactions with these objects and used this information to provide students with personalized support and guidance. For instance, when a student initially interacted with an object, the system would provide a default set of questions or prompts that would provide guidance for the student. If the student returned to the same object after interacting with other objects, it would provide more tailored guidance and reflection-oriented prompts based on the student's previous actions. In a sample of approximately 290 middle school students, Nelson (2007) tested the impacts of three levels of support within the game—no guidance, extensive guidance, and moderate guidance—on learning outcomes. Students in the extensive guidance condition could view three guidance messages per predefined object, while participants in the moderate guidance condition had access to only one guidance message per object. Initial results showed that students who had access to individualized guidance did not score better on measures of learning than students in the no guidance condition. The authors found that although students had access to guidance, they viewed on average 12 to 15 messages out of a total of more than 200 in the moderate condition and 600 in the extensive condition. However, post hoc analyses showed a significant linear relationship between frequency of guidance usage and test score gains, suggesting that individuals who were more frequent users of the guidance learned more from the game.

Additional examples of support and coaching in game-based learning environments can be found in several studies that have used *Crystal Island*. McQuiggan, Rowe, Lee, and Lester (2008) used a media comparison approach to investigate whether story-driven content included in *Crystal Island* supported student learning. The authors compared two versions of *Crystal Island* against a traditional form of multimedia-based instruction. The full version of *Crystal Island* included a rich story line about patient illness, complex character interrelationships, and interactions. The minimal version contained a trimmed-down version of the storyline that was minimal enough to support only the problem-solving scenario. Results showed that students in the full and minimal conditions achieved learning gains, but they did not learn as much as students who received traditional multimedia instruction covering the same curricular material. However, further analyses revealed that students who interacted with *Crystal Island* reported high levels of self-efficacy, presence, and interest in the topic compared to those in the traditional condition. These findings shed light on the motivational benefits of narrative-centered learning.

In a later study, Rowe et al. (2011) used a revised version of *Crystal Island* and found improved learning gains compared to the study by McQuiggan et al. (2008). Specifically, learners showed higher levels of in-game performance, presence, and situational interest in the game. The improved learning gains were believed to be associated with several key additions that resulted in a more immersive and supportive learning experience. These additions included an expanded diagnosis worksheet that learners could use to record, organize, and integrate information, a tighter coupling between the narrative and microbiology curriculum, and a new activity in which students actively labeled parts of cells. These items were meant to provide learners with more scaffolding during the game. While additional research is needed to determine the benefits of these features systematically, the results show a promising trend toward improving student learning and student affect in game-based learning.

Support Offered through Pedagogical Agents

Pedagogical agents are another form of scaffolding and support found in many game-based learning environments. A growing body of research has shown that pedagogical agents can benefit learning experiences (Schroeder, Adesope, & Gilbert, 2013). Pedagogical agents are interactive computer characters that "cohabitate learning environments with students to create rich, face-to-face, learning interactions" (Johnson & Lester, 2016, p. 26). They are often used in inner-loop functions of intelligent game-based learning environments to mimic many of the same activities performed by human tutors: they evaluate a learner's understanding through interactions, ask questions, offer encouragement, and give feedback. They can also present relevant information and hints, offer examples, and interpret student responses (Johnson, Rickel, Stiles, & Munro, 1998). Examples of pedagogical agents include Steve, a lifelike agent designed to help students learn equipment maintenance and device troubleshooting procedures, and Herman the Bug, a cartoon-like agent designed to help students learn botanical anatomy. Steve can demonstrate skills to students, answer student questions, and give advice if the students run into difficulties (Rickel & Johnson, 1999). Herman the Bug watches students as they build plants, offering them assistance and problem-solving advice (Elliott, Rickel, & Lester, 1999). Pedagogical agents are particularly effective when they offer support, coaching, and guidance that encourage students to engage in generative or active processing (Moreno & Mayer, 2005).

Virtual learning companions are a special class of pedagogical agents that take on the persona of a knowledgable peer and are designed to share the learning experience with the student (Kim & Baylor, 2006; Ryokai, Vaucelle, & Cassell, 2003). Unlike virtual tutors, these agents do not serve a teaching role in the learning environment. Instead, they are meant to experience learning tasks alongside the learner and serve as near peers. These companions can support learning through social modeling (Ryokai et al., 2003), and they have the ability to improve self-efficacy by reducing frustration (Buffum, Boyer, Wiebe, Mott, & Lester, 2015), boosting confidence and empathizing with the student (Woolf, Arroyo, Cooper, Burleson, & Muldner, 2010). Thus, these agents can offer social-emotional support, which can in turn improve student motivation in game-based learning environments.

Support Offered through Teachable Agents

Teachable agents are interactive computer characters that are designed to offer support in game-based learning environments. Students teach the teachable agent about a subject and assess the agent's knowledge by asking it to solve problems or answer questions (Biswas et al., 2005). The teachable agent uses artificial intelligence techniques to answer questions. The feedback the student receives by observing the teachable agent's performance helps them discover gaps in the agent's knowledge. Students can use this feedback to provide remedial tutoring to the agent, similar to what a real human tutor does with a struggling student. Teachable agents capitalize on the experience of learning-by-teaching and in doing so allow students to engage in three critical activities that promote learning: knowledge structuring (students acting as tutors organize their own knowledge), motivation (students acting as tutors take responsibility for learning the material), and reflection (students acting as tutors reflect on how well their ideas were understood and used by the tutee) (Biswas et al., 2005; Chin et al., 2010). Studies have shown that tutors and teachers often engage in these actions during and after the teaching process in order to better prepare for future learning sessions (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001).

Perhaps one of the most well-proven and extensively researched teachable agents is *Betty's Brain*, which was developed by researchers at Vanderbilt University and used in middle schools to help students learn about earth science (Leelawong & Biswas, 2008). In *Betty's Brain*, the agent has no initial knowledge and is taught about a subject through peer tutoring. Students teach Betty about a particular topic (such as a river ecosystem) using concept map representations. As students teach Betty, they can ask her questions to see how much she has understood. Once taught, Betty applies qualitative reasoning techniques to answer questions related to the subject. Students can also ask Betty to take a quiz. Mr. Davis, a mentor agent within the learning environment, grades the quiz and provides hints to help students debug and make corrections in Betty's concept map. This cycle of teaching and assessing continues until the virtual tutee performs up to standards.

The idea of learning-by-teaching is both intuitively appealing and one that has garnered support in the research literature. Research on the effectiveness of teachable agents indicates that students who tutor teachable agents exhibit higher levels of motivation and learning compared to students who passively receive training from an artificial agent (Leelawong & Biswas, 2008). For instance, Leelawong and Biswas (2008) conducted a study comparing two versions of a teachable agent system—one baseline version and a second version that included self-regulated learning principles and provided metacognitive hints to students—to a condition in which students were taught by a pedagogical agent. The findings indicated that students in the two learning-by-teaching conditions learned more than students in the pedagogical agent condition and that these benefits persisted in a transfer study. Specifically, students who learned via learning-by-teaching made greater effort and had better success in learning material on their own compared to students who received instruction. These results highlight the benefit of supporting generative processing through teachable agents.

What Are the Implications for the Design of Game-Based Learning?

The research discussed in this chapter has several implications for the design of game-based learning. Instructional support such as attentional cues, cognitive tools, hints, prompts, and feedback offer significant promise for helping learners select relevant objects and information in the learning environment, organize this information into coherent mental structures, and facilitate meaningful learning, while at the same time off-loading working memory and promoting engagement.

Empirical evidence suggests that attentional cueing and visual signaling are two ways to help learners recognize and select essential material in game-based learning environments (Mayer, 2010). These cues help to direct learners' attention toward relevant objects and locations in a learning environment and reduce extraneous cognitive load. This advice follows the signaling principle of multimedia instruction (Mayer, 2009). Cognitive tools are another critical form of support in game-based learning, particularly those that focus on inquiry and problem solving. Cognitive tools are used to replicate the externalization of knowledge by providing tools and processes that are inherently used by an expert when solving a problem (Lajoie, 2009). They assist learners in solving problems and organizing relevant information, with the intended benefits of reducing cognitive load and scaffolding the problem-solving process. Evidence shows that learners who use cognitive tools often produce better scores in learning games than those who do not take advantage of this support (Chin et al., 2010; Lajoie, 2009; Nietfeld et al., 2014). Furthermore, research shows that prompts and hints that encourage learners to self-reflect and engage in generative processing, and feedback messages that provide principle-based explanations for errors, are particularly effective for promoting learning in game-based learning environments. These messages can prompt students to engage in metacognitive processing that is important for learning, such as elaboration, self-explanation, and self-checking (Aleven, Stahl, Schworm, Fischer, &

Wallace, 2003; Azevedo & Hadwin, 2005; Roll et al., 2014). These forms of support may be especially important in narrative-centered learning environments where students participate in story-based educational experiences and must demonstrate reasoning and other higher-order analytical thinking and reasoning skills to achieve the goals of the game (Lester, Mott, et al., 2013).

When implementing feedback, coaching, and support, designers should be cautious not to overload a learner's already limited processing resources and capacity. Designers should also take into account a learner's evolving level of knowledge as they deliver and provide support. Ideally, the level of support offered by the inner loop of a game-based learning environment should be tailored to a learner's evolving competence. For instance, a novice student might begin an exercise with a high level of coaching and support, but over time the level of support should decrease as the student's level of mastery increases, until the student is performing the task on his or her own, which is the process of *fading* (Wood & Wood, 1999). One of the challenges for game designers is to determine what type of support to offer and when to make it available to learners. In addition, research also shows that using pedagogical agents and teachable agents as a mechanism for offering support and promoting reflection and self-explanation can promote learning while at the same time providing learners with educational and social-emotional support. These instructional features can be tightly intertwined in game mechanics to keep the learner on task, promote reflection, and reduce frustration and confusion.

What Are the Limitations of Current Research, and What Are some Implications for Future Research?

While there is growing evidence suggesting that game-based learning environments can serve as an effective medium for learning, a key problem posed by game-based learning is how to support learners most effectively. Feedback, support, and coaching can be implemented in a variety of ways. Identifying the optimal methods, modalities, and timing of delivery is critical for supporting learners in game-based learning environments. There is a significant need to investigate how learners use cognitive tools in game-based learning environments. Exploring game trace log data and using eye-tracking measures are promising directions for identifying effective learner behaviors (Taub et al., 2017). There is also a lack of research examining how cognitive tools could be dynamically tailored to meet individual needs (Rowe et al., 2013). Research on the expertise reversal effect and cognitive load theory suggests that scaffolding should be gradually removed as learners become more proficient in a topic (Kalyuga, 2007). If scaffolding remains at a fixed level, it could cause extraneous load for learners who are more experienced. Following this theory, one could reasonably predict that too much structure and support could result in diminished learning gains for knowledgeable students. Fading support can be implemented in a variety of ways. For example, in the case of a diagnosis worksheet, learners could be provided with minimal structure and be required to fill in sections with important information in the form of freeform text rather than selecting multiple-choice options. Alternatively, learners could be required to specify how the worksheet should be designed and then complete the form themselves (Rowe et al., 2013).

Another limitation in the literature is that most studies measure retention and transfer immediately after a student completes a learning task. In doing so, there is no way to determine the lasting impact of the intervention on learning. As noted in the feedback literature, approaches that promote immediate retention and transfer may not foster delayed transfer and vice versa. Future research should address this by examining performance on delayed retention or transfer tasks as well as immediate tasks. This would provide evidence on potential moderating factors associated with certain forms of support and feedback.

In line with these suggestions, another promising avenue for future research is to explore boundary conditions on the effectiveness of feedback, support, and coaching. A guiding question for this line of research is: does the effectiveness of certain forms of support depend on the type of game or other learner-based factors (e.g., gender, expertise, personal interests)? Empirical evidence suggests that males and females use cognitive tools and pedagogical agents differently (Nietfeld et al., 2014). Pezzullo et al. (2017) found that boys experienced higher mental demand compared to girls when they interacted with a virtual agent that was embedded within the story line of a game-based learning environment. These gender effects held even after controlling for prior knowledge and video game experience.

Furthermore, with advancements in artificial intelligence, multimodal sensors, and learning analytics, there are a multitude of emerging technologies that could be used to investigate the impact of feedback, support, and coaching on learning outcomes. For example, we are seeing the appearance of multimodal models of goal recognition that can accurately recognize the goals that students are pursuing when interacting with game-based learning environments (Baikadi, Rowe, Mott, & Lester, 2014; Ha, Rowe, Mott, & Lester, 2014; Min, Ha, Rowe, Mott, & Lester, 2014; Min, Mott, et al., 2017; Min, Mott, Rowe, Liu, & Lester, 2016), approaches for using multichannel data to assess in-game performance during gameplay (Taub et al., 2017), and student modeling techniques that utilize facial expression recognition (Sawyer, Smith, Rowe, Azevedo, & Lester, 2017). Perhaps even more enticing is the prospect of dynamically customizing gameplay experiences with advanced computational models utilizing deep reinforcement learning (Wang, Rowe, Min, Mott, & Lester, 2017) and techniques for balancing learning and engagement with multiobjective reinforcement learning (Sawyer, Rowe, & Lester, 2017). These customized experiences can be created with both outer-loop and inner-loop functionalities of intelligent game-based environments to provide learners with challenging scenarios while at the same time offering tailored support for individual learners. These are exciting times for game-based learning research, and the next few years are likely to see the appearance of the next generation of theoretically driven, empirically based approaches to support, feedback, and coaching.

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References

Adams, D. M., & Clark, D. B. (2014). Integrating self-explanation functionality into a complex game environment: Keeping gaming in motion. *Computers & Education, 73*, 149–159.

Adams, D. M., Mayer, R. E., MacNamara, A., Koenig, A., & Wainess, R. (2012). Narrative games for learning: Testing the discovery and narrative hypotheses. *Journal of Educational Psychology, 104*(1), 235–249.

Aleven, V., & Koedinger, K. R. (2002). An effective metacognitive strategy: Learning by doing and explaining with a computer-based cognitive tutor. *Cognitive Science, 26*, 147–179.

Aleven, V., Stahl, E., Schworm, S., Fischer, F., & Wallace, R. (2003). Help seeking and help design in interactive learning environments. *Review of Educational Research, 73*(3), 277–320.

Anderson, D. I., Magill, R. A., & Sekiya, H. (2001). Motor learning as a function of KR schedule and characteristics of task-intrinsic feedback. *Journal of Motor Behavior, 33*(1), 59–66.

Anderson, J. R., Corbett, A. T., Koedinger, K. R., & Pelletier, R. (1995). Cognitive tutors: Lessons learned. *Journal of the Learning Sciences, 4*(2), 167–207.

Azevedo, R., Behnagh, R. F., Duffy, M., Harley, J. M., & Trevors, G. (2012). Metacognition and self-regulated learning in student-centered learning environments. In D. H. Jonassen & S. M. Land (Eds.), *Theoretical foundations of student-centered learning environments* (2nd ed.) (pp. 171–197). New York, NY: Routledge.

Azevedo, R., & Bernard, R. M. (1995). A meta-analysis of the effects of feedback in computer-based instruction. *Journal of Educational Computing Research, 13*(2), 11–127.

Azevedo, R., & Hadwin, A. F. (2005). Scaffolding self-regulated learning and metacognition: Implications for the design of computer-based scaffolds. *Instructional Science, 33*(5–6), 367–379.

Baikadi, A., Rowe, J., Mott, B., & Lester, J. (2014). Generalizability of goal recognition models in narrative-centered learning environments. In V. Dimitrova, T. Kuflik, D. Chin, F. Ricci, P. Dolog,

& G. J. Houben (Eds.), *Lecture Notes in Computer Science: Vol. 8538. International Conference on User Modeling, Adaptation, and Personalization.* (pp. 278–289). Cham, Switzerland: Springer.

Bangert-Drowns, R. L., Kulik, C. L. C., Kulik, J. A., & Morgan, M. (1991). The instructional effect of feedback in test-like events. *Review of Educational Research, 61*(2), 213–238.

Billings, D. R. (2012). Efficacy of adaptive feedback strategies in simulation-based training. *Military Psychology, 24*, 114–133.

Biswas, G., Leelawong, K., Schwartz, D., Vye, N., & the Teachable Agents Group at Vanderbilt. (2005). Learning by teaching: A new agent paradigm for educational software. *Applied Artificial Intelligence, 19*(3–4), 363–392.

Brown, R. (2011). Assessment using after-action review. In L. Annetta & S. C. Bronack (Eds.), *Serious educational game assessment: Practical methods and models for educational games, simulations, and virtual worlds* (pp. 119–129). Rotterdam, Netherlands: Sense Publishers.

Buffum, P. S., Boyer, K. E., Wiebe, E. N., Mott, B. W., & Lester, J. C. (2015). Mind the gap: Improving gender equity in game-based learning environments with learning companions. In C. Conati, N. Heffernan, A. Mitrovic, & M. Verdejo (Eds.), *Lecture Notes in Computer Science: Vol. 9112. International Conference on Artificial Intelligence in Education* (pp. 64–73). Cham, Switzerland: Springer.

Chi, M. T. H., Siler, S. A., Jeong, H., Yamauchi, T., & Hausmann, R. G. (2001). Learning from human tutoring. *Cognitive Science, 25*(4), 471–533. doi:10.1207/s15516709cog2504

Chin, D. B., Dohmen, I. M., Cheng, B. H., Oppezzo, M. A., Chase, C. C., & Schwartz, D. L. (2010). Preparing students for future learning with teachable agents. *Educational Technology Research and Development, 58*(6), 649–669.

Clark, D., Tanner-Smith, E., Killingsworth, S., & Bellamy, S. (2013). *Digital games for learning: A systematic review and meta-analysis* (executive summary). Menlo Park, CA: SRI International.

Clark, D. B., Sengupta, P., Brady, C., Martinez-Garza, M., & Killingsworth, S. (2015). Disciplinary integration in digital games for science learning. *International STEM Education Journal, 2*(2), 1–21.

Connolly, T. M., Boyle, E. A., MacArthur, E., Hainey, T., & Boyle, J. M. (2012). A systematic literature review of empirical evidence on computer games and serious games. *Computers & Education, 59*(2), 661–686.

Corbett, A. T., & Anderson, J. R. (1995). Knowledge tracing: Modeling the acquisition of procedural knowledge. *User Modeling and User-Adapted Interaction, 4*(4), 253–278.

DeFalco, J., Rowe, J., Paquette, L., Georgoulas-Sherry, V., Brawner, K., Mott, B., … Lester, J. (2018). Detecting and addressing frustration in a serious game for military training. *International Journal of Artificial Intelligence in Education, 28*(2), 152–193.

Dihoff, R. E., Brosvic, G. M., Epstein, M. L., & Cook, M. J. (2004). Provision of feedback during preparation for academic testing: Learning is enhanced by immediate but not delayed feedback. *Psychological Record, 54*(2), 207–231.

Elliott, C., Rickel, J., & Lester, J. (1999). Lifelike pedagogical agents and affective computing: An exploratory synthesis. In M. J. Wooldridge & M. Veloso (Eds.), *Artificial intelligence today: Recent trends and developments* (pp. 195–212). Berlin, Germany: Springer.

Gee, J. P. (2007). *What video games have to teach us about learning and literacy* (2nd ed.). New York, NY: Palgrave Macmillan.

Gibson, D., Aldrich, C., & Prensky, M. (2007). *Games and simulations in online learning: Research and development frameworks*. Hershey, PA: Information Science Publishing.

Ha, E. Y., Rowe, J., Mott, B., & Lester, J. (2014). Recognizing player goals in open-ended digital games with Markov logic networks. In G. Sukthankar, R. Goldman, C. Geib, D. Pynadath, & H. H. Bui (Eds.), *Plan, activity and intent recognition: Theory and practice* (pp. 289–311). Waltham, MA:. Morgan Kaufman.

Habgood, M. J., & Ainsworth, S. E. (2011). Motivating children to learn effectively: Exploring the value of intrinsic integration in educational games. *Journal of the Learning Sciences, 20*(2), 169–206.

Halpern, D., Millis, K., & Graesser, A. (2012). Operation ARA: A computerized learning game that teaches critical thinking and scientific reasoning. *Thinking Skills and Creativity, 7*(2), 93–100.

Jeong, H., & Biswas, G. (2008). Mining student behavior models in learning-by-teaching environments. In R. Baker, T. Barnes, & J. Beck (Eds.), *The First International Conference on Educational Data Mining* (pp. 127–136). Montreal, Canada. International Educational Data Mining Society.

Johnson, C. I., Bailey, S. K., & Van Buskirk, W. L. (2017). Designing effective feedback messages in serious games and simulations: A research review. In P. Wouters & H. van Oostendorp (Eds.), *Instructional techniques to facilitate learning and motivation of serious games* (pp. 119–140). Cham, Switzerland: Springer.

Johnson, C. I., & Priest, H. A. (2014). The feedback principle in multimedia learning. In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (2nd ed., pp. 449–463). New York, NY: Cambridge University Press.

Johnson, C. I., Priest, H. A., Glerum, D. R., & Serge, S. R. (2013). Timing of feedback delivery in game-based training. In *Proceedings of the Interservice/Industry Training, Simulation & Education Conference,* (pp. 1–12). Arlington, VA: National Training Systems Association.

Johnson, W. L., & Lester, J. C. (2016). Face-to-face interaction with pedagogical agents, twenty years later. *International Journal of Artificial Intelligence in Education, 26*(1), 25–36.

Johnson, W. L., Rickel, J., Stiles, R., & Munro, A. (1998). Integrating pedagogical agents into virtual environments. *Presence: Teleoperators and Virtual Environments, 7*(6), 523–546.

Kalyuga, S. (2007). Expertise reversal effect and its implications for learner-tailored instruction. *Educational Psychology Review, 19*(4), 509–539.

Kebritchi, M., Hirumi, A., & Bai, H. (2010). The effects of modern mathematics computer games on mathematics achievement and class motivation. *Computers & Education, 55*(2), 427–443.

Ketelhut, D. J., Nelson, B. C., Clarke, J., & Dede, C. (2010). A multi-user virtual environment for building and assessing higher order inquiry skills in science. *British Journal of Educational Technology, 41*(1), 56–68.

Kim, J., Hill, R., Durlach, P., Lane, H., Forbell, E., Core, M., … Hart, J. (2009). BiLAT: A game-based environment for practicing negotiation in a cultural context [Special issue on ill-defined domains]. *International Journal of AI in Education, 19*, 289–308.

Kim, Y., & Baylor, A. L. (2006). A social-cognitive framework for pedagogical agents as learning companions. *Educational Technology Research and Development, 54*(6), 569–596.

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. *Educational Psychologist, 41*, 75–86. doi:10.1207/ s15326985ep4102_1

Kulhavy, R. W., & Anderson, R. C. (1972). Delay-retention effect with multiple-choice tests. *Journal of Educational Psychology, 63*(5), 505–512.

Lajoie, S. P. (2009). Developing professional expertise with a cognitive apprenticeship model: Examples from avionics and medicine. In K. A. Ericson (Ed.), *Development of professional expertise: Toward measurement of expert performance and design of optimal learning environments* (pp. 61–83). New York, NY: Cambridge University Press.

Landsberg, C. R., Bailey, S., Van Buskirk, W. L., Gonzalez-Holland, E., & Johnson, C. I. (2016). Designing effective feedback in adaptive training systems. In *Proceedings of the Interservice/Industry Training, Simulation & Education Conference*, (pp. 1–12). Arlington, VA: National Training Systems Association.

Lee, S. Y., Rowe, J. P., Mott, B. W., & Lester, J. C. (2014). A supervised learning framework for modeling director agent strategies in educational interactive narrative. *IEEE Transactions on Computational Intelligence and AI in Games, 6*(2), 203–215.

Leelawong, K., & Biswas, G. (2008). Designing learning by teaching agents: The Betty's Brain system. *International Journal of Artificial Intelligence in Education, 18*(3), 181–208.

Lester, J., Ha, E. Y., Lee, S., Mott, B., Rowe, J., & Sabourin, J. (2013). Serious games get smart: Intelligent game-based learning environments. *AI Magazine, 34*(4), 31–45.

Lester, J., Stone, B., & Stelling, G. (1999). Lifelike pedagogical agents for mixed-initiative problem solving in constructivist learning environments. *User Modeling and User-Adapted Interaction, 9*(1–2), 1–44.

Lester, J. C., Mott, B. W., Robison, J. L., Rowe, J. P., & Shores, L. R. (2013). Supporting self-regulated science learning in narrative-centered learning environments. In R. Azevedo & V. Aleven (Eds.), *International handbook of metacognition and learning technologies* (pp. 471–483). New York, NY: Springer.

Lester, J. C., Spires, H. A., Nietfeld, J. L., Minogue, J., Mott, B. W., & Lobene, E. V. (2014). Designing game-based learning environments for elementary science education: A narrative-centered learning perspective. *Information Sciences, 264*, 4–18.

Lester, R., Rowe, J., & Mott, B. (2013). Narrative-centered learning environments: A story-centric approach to educational games. In C. Mouza & N. Lavigne (Eds.), *Emerging technologies for the classroom: A learning sciences perspective* (pp. 223–238). New York, NY: Springer.

Liu, M., Horton, L. R., Corliss, S. B., Svinicki, M. D., Bogard, T., Kim, J., & Chang, M. (2009). Students' problem solving as mediated by their cognitive tool use: A study of tool use patterns. *Journal of Educational Computing Research, 40*(1), 111–139.

Martinez-Garza, M., Clark, D. B., & Nelson, B. C. (2013). Digital games and the US National Research Council's science proficiency goals. *Studies in Science Education, 49*(2), 170–208.

Mathan, S. A., & Koedinger, K. R. (2005). Fostering the intelligent novice: Learning from errors with metacognitive tutoring. *Educational Psychologist, 40*(4), 257–265.

Mayer, R. E. (2004). Should there be a three-strikes rule against discovery learning? The case for guided methods of instruction. *American Psychologist, 59*, 14–19.

Mayer, R. E. (2009). *Multimedia learning* (2nd ed.). New York, NY: Cambridge University Press.

Mayer, R. E. (2010). Unique contributions of eye-tracking research to the study of learning with graphics. *Learning and Instruction, 20*(2), 167–171.

Mayer, R. E. (2014). *Computer games for learning: An evidence-based approach*. Cambridge, MA: MIT Press.

Mayer, R. E., & Johnson, C. I. (2010). Adding instructional features that promote learning in a game-like environment. *Journal of Educational Computing Research, 42*, 241–265.

McClarty, K. L., Orr, A., Frey, P. M., Dolan, R. P., Vassileva, V., & McVay, A. (2012). A literature review of gaming in education. Retrieved from http://images.pearsonassessments.com/images/tmrs/tmrs/Lit_Review_of_Gaming_in_Education.pdf

McCurdy, N., Naismith, L., & Lajoie, S. (2010). Using metacognitive tools to scaffold medical students developing clinical reasoning skills. In *AAAI Fall Symposium: Cognitive and Metacognitive Educational Systems* (pp. 52–56) Menlo Park, CA: AAAI Press.

McQuiggan, S., Rowe, J., Lee, S., & Lester, J. (2008). Story-based learning: The impact of narrative on learning experiences and outcomes. In. B. P. Woolf, E. Aïmeur, R. Nkambou, & S. Lajoie (Eds.), *Lecture Notes in Computer Science: Vol. 5091. Intelligent tutoring systems* (pp. 530–539). Berlin, Germany: Springer.

Meluso, A., Zheng, M., Spires, H. A., & Lester, J. (2012). Enhancing 5th graders' science content knowledge and self-efficacy through game-based learning. *Computers & Education, 59*(2), 497–504.

Min, W., Frankosky, M., Mott, B., Rowe, J., Wiebe, E., Boyer, K. E., & Lester, J. (2015). DeepStealth: Leveraging deep learning models for stealth assessment in game-based learning environments. In C. Conati, N. Heffernan, A. Mitrovic, & M. Verdejo (Eds.), *Lecture Notes in Computer Science: Vol. 9112. Artificial intelligence in education* (pp. 277–286). Cham, Switzerland: Springer.

Min, W., Frankosky, M., Mott, B., Wiebe, E., Boyer, K. E., & Lester, J. (2017). Inducing stealth assessors from game interaction data. In E. André, R. Baker, X. Hu, M. Rodrigo, & B. du Boulay

(Eds.), *Lecture Notes in Computer Science: Vol. 10331. Artificial intelligence in education* (pp. 212–223). Cham, Switzerland: Springer.

Min, W., Ha, E., Rowe, J. P., Mott, B. W., & Lester, J. C. (2014). Deep learning-based goal recognition in open-ended digital games. In *Proceedings of the Tenth Annual Conference on Artificial Intelligence and Interactive Digital Entertainment* (pp. 37–43). Menlo Park, CA: AAAI Press.

Min, W., Mott, B. W., Rowe, J. P., Liu, B., & Lester, J. C. (2016). Player goal recognition in open-world digital games with long short-term memory networks. In G. Brewke (Ed.), *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence* (pp. 2590–2596). Menlo Park, CA: AAAI Press.

Min, W., Mott, B., Rowe, J., Taylor, R., Wiebe, E., Boyer, K. E., & Lester, J. (2017). Multimodal goal recognition in open-world digital games. In *Annual AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*. Retrieved from https://aaai.org/ocs/index.php/AIIDE/AIIDE17/paper/view/15910

Min, W., Rowe, J. P., Mott, B. W., & Lester, J. C. (2013). Personalizing embedded assessment sequences in narrative-centered learning environments: A collaborative filtering approach. In H. C. Lane, K. Yacef, J. Mostow, & P. Pavlik (Eds.), *Lecture Notes in Computer Science: Vol. 7926. Artificial intelligence in education* (pp. 369–378). Berlin and Heidelberg, Germany: Springer.

Moreno, R., & Mayer, R. E. (2005). Role of guidance, reflection, and interactivity in an agent-based multimedia game. *Journal of Educational Psychology, 97*(1), 117–128.

Nelson, B. C. (2007). Exploring the use of individualized, reflective guidance in an educational multi-user virtual environment. *Journal of Science Education and Technology, 16*(1), 83–97.

Nelson, B. C., Kim, Y., Foshee, C., & Slack, K. (2014). Visual signaling in virtual world-based assessments: The SAVE Science project. *Information Sciences, 264*, 32–40.

Nietfeld, J. L., Shores, L. R., & Hoffmann, K. F. (2014). Self-regulation and gender within a game-based learning environment. *Journal of Educational Psychology, 106*(4), 961–973.

Perrotta, C., Featherstone, G., Aston, H., & Houghton, E. (2013). Game-based learning: Latest evidence and future directions. NFER Research Programme: Innovation in Education. Slough, England: NFER. Retrieved from https://www.nfer.ac.uk/publications/GAME01

Pezzullo, L. G., Wiggins, J. B., Frankosky, M. H., Min, W., Boyer, K. E., Mott, B. W., … Lester, J. C. (2017). "Thanks Alisha, keep in touch": Gender effects and engagement with virtual learning companions. In E. Andre, R. Baker, X. Hu, M. Rodrigo, & B. du Boulay (Eds.), *Lecture Notes in Computer Science: Vol. 10331. Artificial intelligence in education* (pp. 299–310). Cham, Switzerland: Springer..

Rickel, J., & Johnson, W. L. (1999). Animated agents for procedural training in virtual reality: Perception, cognition, and motor control. *Applied Artificial Intelligence, 13*(4–5), 343–382.

Robison, J., McQuiggan, S., & Lester, J. (2009). Modeling task-based vs. affect-based feedback behavior in pedagogical agents: An inductive approach. In V. Dimitrova, R. Mizoguchi, B. Du

Boulay, & A. C. Graesser (Eds.), *Proceedings of the Fourteenth International Conference on Artificial Intelligence in Education* (pp. 25–32). Brighton, England. Amsterdam, Netherlands: IOS Press.

Roll, I., Wiese, E. S., Long, Y., Aleven, V., & Koedinger, K. R. (2014). Tutoring self- and co-regulation with intelligent tutoring systems to help students acquire better learning skills. In R. Sottilare, A. Graesser, X. Hu, & B. Goldberg (Eds.), *Design recommendations for adaptive intelligent tutoring systems* (Vol. 2, pp. 169–182). Orlando, FL: US Army Research Laboratory.

Rowe, J. P., & Lester, J. C. (2015). Improving student problem solving in narrative-centered learning environments: A modular reinforcement learning framework. In C. Conati, N. Heffernan, A. Mitrovic, & M. F. Verdejo (Eds.), *Lecture Notes in Artificial Intelligence: Vol. 9112. Artificial intelligence in education* (pp. 419–428). Cham, Switzerland: Springer.

Rowe, J. P., Lobene, E. V., Mott, B. W., & Lester, J. C. (2013). Embedded scaffolding for reading comprehension in open-ended narrative-centered learning environments. In G. Biswas, R. Azevedo, V. Shute, & S. Bull (Eds.), *AIED 2013 Workshops Proceedings: Vol. 2. Scaffolding in open-ended learning environments (OELEs)* (pp. 69–72). Retrieved from: http://ceur-ws.org/Vol-1009/aied2013ws_volume2.pdf

Rowe, J. P., Shores, L. R., Mott, B. W., & Lester, J. C. (2011). Integrating learning, problem solving, and engagement in narrative-centered learning environments. *International Journal of Artificial Intelligence in Education, 21*, 115–133.

Ryokai, K., Vaucelle, C., & Cassell, J. (2003). Virtual peers as partners in storytelling and literacy learning. *Journal of Computer Assisted Learning, 19*(2), 195–208.

Sawyer, R., Rowe, J., & Lester, J. (2017). Balancing learning and engagement in game-based learning environments with multi-objective reinforcement learning. In E. Andre, R. Baker, X. Hu, M. Rodrigo, & B. du Boulay (Eds.), *Lecture Notes in Computer Science: Vol. 10331. Artificial intelligence in education* (pp. 323–334). Cham, Switzerland: Springer.

Sawyer, R., Smith, A., Rowe, J., Azevedo, R., & Lester, J. (2017). Enhancing student models in game-based learning with facial expression recognition. In *Proceedings of the Twenty-Fifth Conference on User Modeling, Adaptation, and Personalization* (pp. 192–201). ACM, New York, NY.

Schmidt, R. A., Young, D. E., Swinnen, S., & Shapiro, D. C. (1989). Summary knowledge of results for skill acquisition: Support for the guidance hypothesis. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 15*(2), 352–359.

Schroeder, N. L., Adesope, O. O., & Gilbert, R. B. (2013). How effective are pedagogical agents for learning? A meta-analytic review. *Journal of Educational Computing Research, 49*(1), 1–39.

Serge, S. R., Priest, H. A., Durlach, P. J., & Johnson, C. I. (2013). The effects of static and adaptive performance feedback in game-based training. *Computers in Human Behavior, 29*(3), 1150–1158.

Shaker, N., Togelius, J., & Nelson, M. J. (2016). *Procedural content generation in games*. Cham, Switzerland: Springer.

Shores, L., Hoffmann, K., Nietfeld, J., & Lester, J. (2012). The role of sub-problems: Supporting problem solving in narrative-centered learning environments. In S. A. Cerri, W. J. Clancey, G.

Papadourakis, & K. Panourgia (Eds.), *Lecture Notes in Computer Science: Vol. 7315. Intelligent tutoring systems* (pp. 464–469). Berlin, Germany: Springer.

Shores, L., Rowe, J., & Lester, J. (2011). Early prediction of cognitive tool use in narrative-centered learning environments. In G. Biswas, S. Bull, J. Kay, & A. Mitrovic (Eds.), *Lecture Notes in Computer Science: Vol. 6738. Artificial intelligence in education* (pp. 320–327). Berlin, Germany: Springer.

Shute, V. J. (2008). Focus on formative feedback. *Review of Educational Research, 78*(1), 153–189.

Shute, V. J. (2011). Stealth assessment in computer-based games to support learning. In S. Tobias & J. D. Fletcher (Eds.), *Computer games and instruction* (pp. 503–524). Charlotte, NC: Information Age Publishers.

Sitzmann, T. (2011). A meta-analytic examination of the instructional effectiveness of computer-based simulation games. *Personnel Psychology, 64*(2), 489–528.

Taub, M., Mudrick, N. V., Azevedo, R., Millar, G. C., Rowe, J., & Lester, J. (2017). Using multichannel data with multi-level modeling to assess in-game performance during gameplay with Crystal Island. *Computers in Human Behavior, 76*, 641–655.

Van Buskirk, W. L. (2011). *Investigating the optimal presentation of feedback in simulation-based training: An application of the cognitive theory of multimedia learning* (Unpublished doctoral dissertation). University of Central Florida, Orlando.

VanLehn, K. (2006). The behavior of tutoring systems. *International Journal of Artificial Intelligence in Education, 16*, 227–265.

Wang, P., Rowe, J., Min, W., Mott, B., & Lester, J. (2017). Interactive narrative personalization with deep reinforcement learning. In C. Sierra (Ed.), *Proceedings of the 26th International Joint Conference on Artificial Intelligence* (pp. 3852–3858). Menlo Park, CA: AAAI Press.

Warren, S. J., Dondlinger, M. J., & Barab, S. A. (2008). A MUVE towards PBL writing: Effects of a digital learning environment designed to improve elementary student writing. *Journal of Research on Technology in Education, 41*(1), 113–140.

Wood, H., & Wood, D. (1999). Help seeking, learning and contingent tutoring. *Computers & Education, 33*, 153–169.

Woolf, B. P. (2009). *Building intelligent interactive tutors: Student-centered strategies for revolutionizing e-learning*. Burlington, VT: Morgan Kaufmann.

Woolf, B. P., Arroyo, I., Cooper, D., Burleson, W., & Muldner, K. (2010). Affective tutors: Automatic detection of and response to student emotion. In R. Nkambou, J. Bourdeau, & R. Mizoguchi (Eds.), *Studies in Computational Intelligence: Vol. 308. Advances in intelligent tutoring systems* (pp. 207–227). Berlin, Germany: Springer.

Wouters, P., van Nimwegen, C., van Oostendorp, H., & van der Spek, E. D. (2013). A meta-analysis of the cognitive and motivational effects of serious games. *Journal of Educational Psychology, 105*(2), 249–265.