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Capturing and Scaffolding the Complexities of Self-Regulation During Game-Based Learning

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CAPTURING AND SCAFFOLDING THE COMPLEXITIES OF SELF-REGULATION DURING GAME-BASED LEARNING

by

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ABSTRACT

Game-based learning environments (GBLEs) can offer students with engaging interactive instructional materials while also providing a research platform to investigate the dynamics and intricacies of effective self-regulated learning (SRL). Past research has indicated learners are often unable to monitor and regulate their cognitive and metacognitive processes within GBLEs accurately and effectively on their own due mostly to the open-ended nature of these environments. The future design and development of GBLEs and embedded scaffolds, therefore, require a better understanding of the discrepancies between the affordances of GBLEs and the required use of SRL. Specifically, how to incorporate interdisciplinary theories and concepts outside of traditional educational, learning, and psychological sciences literature, how to utilize process data to measure SRL processes during interactions with instructional materials accounting for the dynamics of leaners' SRL, and how to improve SRL-driven scaffolds to be individualized and adaptive based on the level of agency GBLEs provide. Across four studies, this dissertation investigates learners' SRL while they learn about microbiology using CRYSTAL ISLAND, a GBLE, building upon each other by enhancing the type of data collected, analytical methodologies used, and applied theoretical models and theories. Specifically, this dissertation utilizes a combination of traditional statistical approaches (i.e., linear regression models), non-linear statistical approaches (i.e., growth modeling), and non-linear dynamical theory (NDST) approaches (aRQA) with process trace data to contribute to the field's current understanding of the dynamics and complexities of SRL. Furthermore, this dissertation examines how limited agency can act as an implicit scaffold during game-based learning to promote the use of SRL processes and increase learning outcomes.

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CHAPTER ONE: INTRODUCTION

Game-based learning refers to how games containing rules and challenges, can be used within an educational context to achieve pre-defined learning outcomes such as increased domain knowledge (Krath et al., 2021). Game-based learning environments (GBLEs) provide students with high-quality, engaging, and interactive instructional materials which foster domain knowledge and skill development (Gentry et al., 2019; Yu et al., 2022). Frequently used across science, technology, engineering, and mathematics (STEM) domains, GBLEs have been shown to enhance engagement by effectively capturing and holding learner attention (Schwartz & Plass, 2020), stimulating emotions (e.g., joy, surprise, frustration; Loderer et al., 2020), promoting active learning in which learners interact intentionally with instructional materials (Mayer, 2020), capturing and assessing content understanding (Shute & Sun, 2020), and facilitating human-computer and human-human-computer collaboration (Wang, 2020).

Although literature has shown that GBLEs have been used within traditional classroom environments to support learning and 70% of schools report teachers utilized technology in their lessons, only 33% of schools strongly agreed that the way technology is utilized help students become more self-regulated (Gray & Lewis, 2021). This is consistent with current literature which states that within open-ended learning environments, such as GBLEs, learners are typically unable to engage in self-regulated learning (SRL) effectively and accurately through their entire time learning (Carpenter et al., 2020; Poitras et al., 2021; Taub et al., 2020a; Wong et al., 2019; Yang & Lu, 2021). Ultimately, this discrepancy between the affordances of GBLEs and the benefits of SRL underscores multiple challenges and open questions regarding the theories and methodological approaches in which SRL during game-based learning is grounded (Mayer, 2020). This dissertation addresses the broad need to understand (1) how to incorporate interdisciplinary theories and concepts outside of traditional education literature, (2) how process data captured during game play can be used to measure how learners deploy SRL processes while interacting with instructional materials by considering the dynamics of learners' accuracy and SRL, and (3) how to improve GBLEs' ability to provide effective, individualized, and adaptive SRL-driven scaffolding via restricted agency. In this chapter, I will define SRL, review current theories and models of SRL, discuss three aims of the dissertation (i.e., expanding theories for SRL, capturing SRL use and dynamics with process data, and using agency-based scaffolding for SRL during game-based learning), and provide an overview of the four publications throughout the dissertation.

Self-regulated Learning

SRL involves how learners monitor and change their cognitive, affective, metacognitive, and motivational processes throughout a task to achieve learning outcomes (Schunk & Greene, 2018; Winne, 2018; Winne & Azevedo, 2022). SRL requires learners to engage in goal-setting and planning, use learning strategies, and reflect on their progress towards goals to then modify plans and learning strategies. This is a cyclical, recursive process that is needed throughout a learning task to successfully achieve learning outcomes. SRL typically incorporates learners' use of cognitive and metacognitive processes and strategies including reading instructional materials (e.g., books, research articles, posters, dialog with NPCs), evaluating instructional materials as either relevant or irrelevant towards the learner's goals, merging several sources of information together to form a mental representation of a phenomena, and retaining the information to achieve goals and tasks such as completing domain knowledge quizzes (Azevedo et al., 2022; Nelson & Kim, 2020).

Theories and Models of SRL

Several models and theories of SRL exist which describe SRL as occurring before (i.e., forethought), during (i.e., performance), and after (i.e., reflection) a learning task (Panadero, 2017; Schunk & Greene, 2018) including Winne and Hadwin's (2008) information-processing theory (IPT) of SRL, Winne's (2018) conditions, operations, products, evaluations, and standards (COPES) model, Zimmerman and Moylan's (2009) SRL model, and Pintrich's (2000) model. Critically, this dissertation focuses on Winne's (2018) COPES model as the theoretical grounding, however it highlights how additional theories and approaches outside of traditional SRL education and learning sciences research (i.e., cognitive theory of multimedia learning [see Mayer, 2022], complex systems theory [see Mitchell, 2009]) can be further incorporated to understand learners' SRL during game-based learning.

According to Winne (2018) COPES details the: (1) **cognitive and task conditions** learners encounter prior to and during learning including goal achievement orientation, prior knowledge, restrictions in the environment, etc.; (2) **operations** learners deploy during learning including SRL strategies and learning tactics, e.g., content evaluations; (3) **products** learners obtain during learning that are mostly measured as learning outcomes; and (4) **evaluations** of learners' products against (5) **internal and external standards** set by the student or external entity (e.g., GBLE) respectively. However, gaps exist in this theoretical model such that it is not detailed how learners' SRL ability and domain knowledge dynamically changes over the learning task. Researchers argue multimodal process data can be captured and measured during game-based learning to understand the dynamics of the relationships between learners' COPES components (Azevedo et al., 2013, 2018a; Azevedo & Gašević, 2019; Järvelä & Bannert, 2021; Molenaar et al., 2023). However, as Azevedo & Gašević (2019) highlight, this approach demands an interdisciplinary integration of theoretical models and frameworks. That is, by first considering multiple theories both inside and outside the educational research field, we can measure learners' SRL processes during game-based learning using multimodal process data (e.g., log files, eye tracking) for capturing *which* SRL processes are being enacted and *when* these SRL processes are implemented.

Traditional SRL models throughout literature have not been typically combined with theories from other domains to aid in explaining how learners deploy SRL during game-based learning (see Schunk & Greene, 2018). Specifically, GBLEs incorporate several elements including converging, integrating, and combining multiple sources of instructional materials, assessments, problem-solving tasks, etc. that require the use of additional theories and models to explain how learners are effectively using the environment to learn. For example, GBLEs include instructional materials in the form of interactive multimedia (e.g., non-player characters, text, diagrams, videos) which supports learning outcomes by providing the learner the domain content needed to increase their knowledge. Many of these affordances are not explicitly or exhaustively covered in traditional SRL frameworks and models (e.g., Efklides, 2011). In the next section of this chapter, I will address our first aim – expanding theories for SRL. This section will review current theories of SRL and their limitations and introduce two other theories, the cognitive theory of multimedia learning and complex systems theory, outside of the field of SRL to better contextualize and ground learners' use of SRL during game-based learning.

Aim 1: Expanding Theories for SRL

This dissertation highlights the advantage for researchers in using multiple theories in conjunction with each other to expand understanding of how SRL occurs in GBLEs. We can account for the unique affordances of GBLEs that consider nuances of specific learning constructs by using multiple theories from supporting research methodologies and analyses. For example, GBLEs often incorporate instructional material using various modes of media including large chunks of text such as that used in books, posters that incorporate visually appealing but informative information, dialog with NPCs that progress the narrative of the GBLE while providing important information about the learners' goals and tasks within the GBLE as well as instructional information, etc. (Plass et al., 2020). However, extraneous information not relevant towards learners' goals may be present within these materials as well (Mayer, 2020), requiring the use of SRL processes to evaluate the content as either relevant or irrelevant. As such, it is imperative when studying how learners interact with instructional content within GBLEs we consider relevancy and media type as they may result in conditional task differences and ultimately differences in SRL. However, the COPES model alone does not account for the interaction with multiple types of instructional content because it lacks the details of how learners should interact with instructional materials and the processes that need to occur to facilitate learner understanding. This demands the incorporation of other theories and approaches to both describe how learners use instructional materials and how these processes occur throughout SRL.

Specifically, Mayer's (2022) cognitive theory of multimedia learning (CTML) can be used to identify how learners actively interact with instructional materials containing multiple modes of media CTML details five cognitive processes combined into three phases: (1) *selecting* relevant visual and verbal information from instructional materials; (2) *organizing* the selected visual and verbal information into a mental representation; and (3) *integrating* the mental representation with prior knowledge to develop an updated mental model of the domain. By combining both CTML and traditional SRL models, we are able to fully explain how learners may deploy SRL processes while interacting with instructional materials within the GBLE.

As well as using additional educational theory to explain how learners use SRL processes to interact with GBLE features and instructional materials, we can look outside the field of educational research and learning sciences to identify theories that enhance the way researchers consider the complexities and dynamics of SRL. Specifically, within this dissertation, we expand the conceptualization of SRL to include the characteristics of a complex system according to Complex Systems Theory (Amon et al., 2022; Favela, 2020; Li et al., 2022). Complex Systems Theory describes how system behaviors can be explained and predicted from the pattern in which the behaviors change over time. Systems are considered complex if they display: (1) self-organization in which order arises out of disorder without the influence of a central controller; (2) interaction dominance in which system components interact with each other to display multiplicative, rather than additive, behaviors; and (3) emergence which refers to how the overall system behavior cannot be attributed to a single component (Haken, 2006). In applying complex systems theory to SRL, this dissertation argues that learning emerges from the multiple components within SRL models (e.g., COPES) that interact with each other and that no singular facet of SRL can explain learning. For example, prior knowledge, a cognitive condition, does not explain why learners deployed an SRL strategy at a certain point in time or how learners' deployment of metacognitive operations (e.g., content evaluations) was inaccurate. Rather, we research SRL components for their *contributions* in explaining the overall picture of learning behaviors.

Complex Systems Theory allows us to describe SRL and apply concepts and methodologies within this field to analyze (e.g., Non-linear Dynamical Systems Theory) and interpret (e.g., far-from-equilibrium) SRL behaviors (i.e., processes demonstrated during learning). Non-linear Dynamical Systems Theory (NDST) methods can then be leveraged to quantify the effects of interacting components on system behaviors in which small changes in the SRL behaviors at the beginning of a learner's time in game can lead to non-linear shifts in their future behaviors (Amon et al., 2019; Riley & Holden, 2012). NDST analytical methodologies can be used to identify the extent to which learners' repetitive or novel deployment of SRL behaviors indicate SRL function or malfunction. Additionally, the interpretation of the quantified behavior using NDST can also be explained by concepts within Complex Systems Theory such as far-from-equilibrium. This concept states that a functional system is indicated by the balanced proportion of stable (i.e., repetitive) and unstable (i.e., novel) states. This balance in SRL systems can indicate functional SRL behavior that needs to occur within GBLEs for increased learning outcomes.

Aim 2: Capturing SRL Use and Dynamics using Process Data

Although we can use theoretical models and frameworks from other disciplines to explain how learners engage in SRL during game-based learning, many of these require multimodal process data, such as log files and eye tracking, to capture the nuances of SRL behaviors (Azevedo, 2020; Fan et al., 2022; Giannakos et al., 2019, 2022; Noroozi et al., 2019; Malmberg et al., 2017). That is, this dissertation will also highlight how process data is needed to identify which SRL processes are being enacted by a learner and the dynamics of SRL processes deployment that indicate functional SRL behaviors.

Process data are data streams that can be captured during learning whereas multimodal process data specifically is the use of several different types of online data to infer the occurrence of learning processes through the triangulation of process data evidence (Azevedo & Hadwin, 2005; Azevedo & Gašević, 2019; Azevedo & Taub, 2020; Azevedo et al., 2018a; Bernacki, 2018; Gupta et al., 2022; Järvelä et al., 2021; Molenaar et al., 2023). Several types of process data have been used to capture SRL processes during learning including concurrent verbalizations (Lim et al., 2021), log files (Saint et al., 2021), eye tracking (Tsai et al., 2016b,c), and facial expressions (Buono et al., 2020; Taub et al., 2020a,b) along with the multimodal use of the aforementioned process data (Fan et al., 2022). In using multimodal process data, researchers are able to capture the multifaceted nature of SRL, including cognition, affect, metacognition, motivation, and social processes, as the learner completes a task. However, capturing multimodal process data leads to several challenges surrounding how process data can be analyzed to implicate learners' use of SRL processes over time (Azevedo, 2020). Specifically, researchers analyzing process data should (1) incorporate theoretical models and frameworks to reflect the nuances of how SRL is deployed over time and how the components of SRL interact to elicit SRL behaviors, (2) better contextualize SRL to the activities learners complete in the learning environment by merging theoretical models from other research fields with traditional SRL models, and (3) ensure the dynamics of SRL processes are reflected in the type of analytical methodologies used. Further, while capturing process data can indicate learners' use of SRL processes and measuring process data can aid researchers' understanding of how learners deploy SRL processes, more research is required to improve the practice of using process data to adequately scaffold SRL during game-based learning.

Aim 3: Agency-based Scaffolding of SRL during Game-based Learning

The goal of GBLEs is to increase learning by promoting learners' interest and engagement in instructional materials, oftentimes through introducing a narrative that necessitates the use of instructional materials to achieve a goal (Bainbridge et al., 2022; Plass et al., 2020; Rowe et al., 2012). These materials are typically placed throughout the digital environment in a non-linear fashion to facilitate learners' searching of information and exploration of the environment (Sawyer et al., 2017). Because of this, GBLEs uniquely position learners to be agents of their own learning, seeking information to both complete the narrative as well as support domain learning. However, while the agency, or the amount of freedom allotted to learners to make their own choices, afforded within GBLEs may increase engagement, agency may also hinder learning if SRL is not properly supported by the GBLE wherein learners are not given proper direction and are overwhelmed by choice. Where the provision of full agency within a GBLE may highlight learners' ability to goal-set, plan, and enact SRL strategies such as metacognitive judgments, learners typically lack the skillset and knowledge to deploy SRL without scaffolding (Josephsen, 2017; Poitras et al., 2021; Wong et al., 2019; Yang & Lu, 2021).

To counteract learners' inability to engage in self-regulation, GBLEs typically include scaffolds, or tools that provide guidance to learners. Researchers have used several different kinds of scaffolds, including static, dynamic, metacognitive, reflective, etc. A review by Zhao and Peng (2022) found that the majority of research on scaffolds SRL during game-based learning used external scaffolding and prompts (Brazilai & Blau, 2014; Johnson, 2019), including the use of an intelligent tutoring system within a GBLE to promote domain knowledge (Snow et al., 2014). A study by Munshi et al. (2022) used conversations with virtual agents including a teacher to impart knowledge and hints and an agent for the learner to "teach". One GBLE, CRYSTAL ISLAND (Cloude et al., 2020; Dever et al., 2022; Rowe et al., 2011; Taub et al., 2020b), uses restricted agency as a scaffold in which learners must complete an ordered playthrough. Several research articles using this GBLE have supported the effectiveness of restricted agency as a scaffold for SRL (Chapters 2-5 in this Dissertation; Sawyer et al., 2017; Taub et al., 2020c) but have yet to expand this as a method for adaptive scaffolding.

Although several studies and meta-analyses have supported the effectiveness of scaffolds as they are currently used in GBLEs (e.g., Cai et al., 2022), there is a large call for more adaptive scaffolds that individualize learners' experiences with GBLEs to more intelligently scaffold SRL. Additionally, these scaffold designs may need to be specific to the affordances of GBLEs, such as agency derived from the level of allotted interactivity and independence within a game. As this dissertation will show (multimodal) process data should be captured and analyzed to understand how learners' SRL changes over time depending on context.

Overview of Contributions

The goal of this dissertation is to capture the complexities and dynamics of SRL during game-based learning via (multimodal) process data and interpret learners' accurate use of SRL by combining traditional SRL theories with interdisciplinary theories and concepts to inform the future of adaptive agency-driven scaffolding, or scaffolds that restrict agency to varying degrees as learners demonstrate SRL competencies throughout their time on task. The studies included in this dissertation examine how learners engage in SRL while learning with CRYSTAL ISLAND, a GBLE teaching students scientific reasoning skills as they learn about microbiology. Each study builds on the previous, enhancing the type of data collected, analytical methodologies used, and applied theoretical models and theories to examine how limited agency can act as an implicit scaffold during game-based learning, promoting the use of SRL processes and increase learning outcomes. Each chapter of this dissertation build upon itself where: (1) Chapter 2 uses eye-tracking process data to identify how learners interact with instructional materials during CRYSTAL ISLAND while using CTML as a grounding theory; (2) Chapter 3 adds log-file process data in conjunction with eye tracking to capture how learners deploy SRL processes while learning with CRYSTAL ISLAND; (3) Chapter 4 incorporates time to examine how learners' accuracy of SRL changes over time during game-based learning; and (4) Chapter 5 introduces SRL as a complex system using complex systems theory to identify how learners' SRL deployment over time indicates SRL function or malfunction.

The first study (Chapter 2; Dever & Azevedo, 2019a) utilizes data from ninety participants to understand how learners use instructional materials (e.g., books and research articles, dialog with non-player characters [NPCs], posters) when they are allowed to interact with the GBLE freely (i.e., full agency) versus when the GBLE restricts their gameplay by requiring actions to prerequisite future actions (i.e., partial agency). This study used eye-tracking data to examine how restricted agency related to learners' fixation durations on different types of instructional materials and their resulting learning gains. Specifically, the study aimed to understand how GBLEs can scaffold learners' use of instructional materials by incorporating levels of agency as a scaffold. Results from this study supported restricted agency as an effective scaffold where learners who were restricted in their actions had greater learning gains and demonstrated longer fixations on instructional materials that had long chunks of text without supporting diagrams, figures, or interactions with NPCs. This study highlights limitations within the field of SRL and game-based learning including: (1) the lack of process data (e.g., eye-tracking) used to identify learners' use of SRL processes (i.e., information gathering); and (2) limited understanding of how GBLEs can incorporate implicit scaffolding techniques to increase learning outcomes.

The second study (Chapter 3; Dever et al., 2020) extends from the previous study, incorporating multimodal process data to detect how learners interacted with instructional materials based on their relevance to the learning outcome goals while learning with CRYSTAL ISLAND. In other words, this study answered the question: How can multimodal process data (i.e., log files, eye tracking) be used to identify how learners evaluate the relevance of the instructional material when provided scaffolding via restricted agency during game-based learning? This study attempted to close theoretical and methodological gaps in current SRL and scaffolding literature by using the cognitive theory of multimedia learning (Mayer, 2022) and a combination of eye-tracking and log-file process data for capturing and assessing learners' use of content evaluations, or judgements of instructional material as either relevant or irrelevant towards a goal. Data from

120 undergraduate students were used as they learned about microbiology with CRYSTAL ISLAND. Results from this study showed that restricting agency increases learning outcomes but did not support learners' use of content evaluations where, regardless of agency, participants interacted more with relevant instructional materials than irrelevant. Findings from this study suggest that GBLEs should demonstrate greater adaptivity based on process data to better scaffold learners by restricting agency in addition to better supporting the use of SRL strategies, i.e., content evaluations, during learning.

The third paper (Chapter 4; Dever et al., 2021) uses hierarchical growth models to understand how learners deploy content evaluations of instructional materials over time as they learn with CRYSTAL ISLAND and experience varying levels of agency. Specifically, eye-tracking data from 82 undergraduate students were collected and input into a two-level hierarchical growth models. Level 1 predictors consisted of the type of instructional material (i.e., book or research article, poster, dialog with NPCs), relevance of the instructional material to the microbiology pre-test, and relative game time. Level 2 predictors consisted of prior knowledge and agency conditions, or the amount of agency afforded to the participant (i.e., full or partial). Results from this study found that scaffolding via restricted agency, greater fixation durations on NPCs, and lower fixation durations on books and research articles were related to increased learning gains. Further, learners who had full control over their actions and lower learning gains fixated on books and research articles for a longer duration as time in game increased. Results from the model showed that learners, regardless of GBLE scaffolding, were unable to consistently deploy content evaluations as they engage in game-based learning. Findings from this study did not report a significant interaction for fixation durations on relevant versus irrelevant instructional materials over time and between agency conditions. This study showed that while agency is effective as a scaffold in supporting increased learning gains, GBLEs should start incorporating adaptive scaffolds that fully support both the duration of learners' gaze on instructional materials over time as well as the use of content evaluations where learners should be scaffolded in consistently and accurately deploying content evaluations as time progresses during game-based learning.

The last study (Chapter 5; Dever et al., 2022) incorporates complex systems theory, a theory typically used in team dynamics and thermodynamics to examine how learners deploy SRL processes over time. Within this study, eye-tracking and log-file data from 82 undergraduate students were collected as they learned with CRYSTAL ISLAND. Learners were split between two agency conditions (full or partial), based on the level of control afforded the player. Auto-Recurrence Quantification Analysis (aRQA) from non-linear dynamical systems theory was run on learners' sequences of instructional material interactions. When examining the relationship between how learners deployed SRL processes over time, its relevance to microbiology pre-test items, and learning gains, results from this study found: (1) dwell times on pre-test relevant instructional materials decrease over time; (2) learners scaffolded in their interactions had greater learning gains when they also demonstrated lower recurrence on books and research articles as well as posters.; and (3) greater predictability of SRL behaviors are related to greater dwell times on instructional materials. This study has significant contributions to the field of scaffolding SRL during game-based learning where in combining both SRL theory and complex systems theory and analytical methodologies, learner profiles can be extracted that demonstrate how recurrent sequences of learners' interactions with instructional materials and how this is related to learning gains as well as the scaffolding provided by the GBLE. Specifically, implications from this study conclude that GBLEs should simultaneously restrict learners' control over their actions while promoting the use of novel SRL processes in which actions within a GBLE are not repeated sequentially.

CHAPTER TWO: AUTONOMY AND TYPES OF INFORMATIONAL TEXT PRESENTATIONS IN GAME-BASED LEARNING ENVIRONMENTS

This chapter titled, “autonomy and types of informational text presentations in game-based learning environments” was originally published in the proceedings of the 20th International Conference on Artificial Intelligence in Education (AIED) and led by first author Daryn A. Dever with contributing co-author Roger Azevedo.

Abstract

Game-based learning environments (GBLEs) are being increasingly utilized in education and training to enhance and encourage engagement and learning. This study investigated how students, who were afforded varying levels of autonomy, interacted with two types of informational text presentations (e.g., non-player character (NPC) instances, traditional informational text) while problem solving with CRYSTAL ISLAND (CI), a GBLE, and their effect on overall learning by examining eye-tracking and performance data. Ninety undergraduate students were randomly assigned to two conditions, full and partial agency, which varied in the amount of autonomy students were granted to explore CI and interactive game elements (i.e., reading informational text, scanning food items). Within CI, informational text is presented in a traditional format, where there are large chunks of text presented at a single time represented as books and research articles, as well as in the form of participant conversation with NPCs throughout the environment. Results indicated significantly greater proportional learning gain (PLG) for participants in the partial agency condition than in the full agency condition. Additionally, longer participant fixations on traditionally presented informational text positively predicted participant PLG. Fixation durations were significantly longer in the partial agency

condition than the full agency condition. However, the combination of visual and verbal text represented by NPCs were not significant predictors of PLGs and do not differ across conditions.

Introduction

Autonomy in Game-based Learning Environments

Autonomy assumes people, or agents, actively interact with elements in their environment instead of being passive bystanders (Bandura, 2001). There is a need for autonomy within learning environments to promote understanding of content knowledge and skills critical for learning (Bradbury et al., 2017). It is assumed learners who are active within a learning environment can reflect on their progress, whether it be while learning or regulating motivation and emotions, leading to effective planning and the execution of plans to achieve sub-goals (Bandura, 2001). In the context of game-based learning environments (GBLEs) such as CRYSTAL ISLAND (CI; Rowe et al., 2011), learners are given autonomy to explore and interact with several game elements (e.g., choosing which text and science posters to read, generating hypotheses about potential pathogens, etc.), while also monitoring and regulating their cognitive, affective, metacognitive, and motivational (CAMM) self-regulatory processes, critical for effective learning with GBLEs (Azevedo et al., 2018b).

As such, self-regulated learning (SRL) involves actively monitoring all thoughts, behaviors, and feelings to then activate and integrate prior knowledge with new information for future planning, monitoring, and achievement of learning goals (Schunk & Greene, 2018). Plan development occurs when a goal is made explicit and challenges the learner which increases their motivation to achieve the goal with efficiency (Bandura, 2001). If a goal is not specific, learners with effective SRL skills will identify and modify the plan and strategies used towards achieving the goal (Greene et al., 2010). This may include redefining the goals to understand the task demands and steps needed to accomplish the task. In sum, SRL is extremely challenging for most learners, and it is even more challenging in GBLEs where the full agency afforded by these environments can further hinder effective SRL.

The amount of agency afforded to a learner can influence their ability and opportunity to use SRL effectively (Azevedo et al., 2019; Bradbury et al., 2017). GBLEs allow learners to choose how they interact with the environment, specifically while engaging in learning activities, such as reading about microbiology, collecting evidence, engaging in hypothesis testing, learning from biology experts, interviewing patients about their symptoms, etc. (Sabourin et al., 2013). GBLEs are engaging environments for learners to practice SRL skills, accumulate content knowledge, and develop problem solving and reasoning through learning activities (Taub et al., 2016). Learners exposed to these environments must monitor their CAMM SRL processes and adapt to the changing demands of the tasks within the environment to ensure successful goal achievement (e.g., identifying the disease causing the illness outbreak in CI). GBLEs are often criticized for their lack of scaffolding provided to the learner, where extraneous details within the game often distract learners from their role and the overall goal of the game (Mayer & Johnson, 2010). Thus, the level of autonomy afforded to a learner within a GBLE should balance with the scaffolding provided to a learner within the environment (Burkett & Azevedo, 2012; Sabourin et al., 2013). Scaffolding within GBLEs influences developing SRL competencies, where the components of the environment that introduce novel information, such as texts and diagrams, must be selected, organized, and evaluated for relevancy. If relevant, then the novel information is integrated with learners' prior knowledge to achieve their goal.

Application of the Cognitive Theory of Multimedia Learning to GBLEs

Multimedia learning occurs when the learner constructs a mental representation from the content provided through the combination of words and images presented within an advanced learning technology (Hu et al., 2017). Multimedia is typically used to describe learning environments which are enhanced through the use of combining pictures (e.g., photographs, illustrations, and animations) and words (e.g., audio and text; Kalyuga et al., 2000). GBLEs facilitate learners' construction of concepts and knowledge through navigating the environment (e.g., CI) and incorporating information that is received by the learner either through traditionally presented text via large blocks of information or through interactive elements in the environment such as non-player characters (NPCs).

The Cognitive Theory of Multimedia Learning (CTML; Butcher, 2014) can be presented within multimedia environments and their effect on learning processes. This theory is based on three assumptions: (1) visual and verbal/auditory processes have different channels; (2) these channels have a limit on the amount of information that can be processed at once; and, (3) learners actively process information in the environment (Azevedo, 2014). In addition to the three assumptions, there is a set of five specified cognitive processes present during multimedia learning: (1) selecting relevant words from text, (2) selecting relevant visuals, (3) developing a mental model for selected relevant words, (4) developing a mental model for selected relevant visuals, and (5) integrating relevant text and visuals into conjoined representations (Butcher, 2014). These cognitive processes are important to note in this model as they require learner utilization of SRL skills (e.g., retention and transfer of learned information) and learner agency for cognitive development (Hu et al., 2017). It is important to note that in deeper processing of multimedia presentations, information represented by words can be processed through either the visual (e.g., text) channel along with diagrams and graphs or auditory channel (e.g., spoken language) where they may then cross channels to be organized into either a verbal or pictorial model (Mayer & Johnson, 2010).

The multimedia principle specifically focuses on CTML's first basic assumption, visual and verbal information is processed through separate channels, and third basic assumption which asserts that learning with both channels simultaneously is more effective for deeper understanding than learning with information from a singular channel (Kalyuga et al., 2000). The interaction between the learner, more specifically the learner's ability to apply SRL strategies, and the presentation of information should be understood in order to optimally use multiple modes of presentations. This understanding will lead to the examination of the impact that these different modes can have on learning (Kalyuga et al., 2000). With both verbal and visual information being presented in conjunction with each other, the learner has a greater chance of recall with the information processed with two separate channels (Kalyuga et al., 2000).

These channels of information can be presented in multiple ways, including computers and face-to-face interactions with artificial intelligent agents (Butcher, 2014). However, in GBLEs, which offer a unique learning opportunity through direct interaction and exploration of the environment, these presentations can occur through slightly different means. Instructional materials are integrated with the environment so that the learner can interact with the information, which should be regulated to control for the influence the environment can have on the learner and their ability to select and organize critical information for the goal (Kalyuga et al., 2000). Traditionally presented informational texts in GBLEs mimic books with blocks of written text appearing on the screen, whereas NPCs, serving as intelligent agents, offer a variation of face-to-face conversations through real-world interactions and character design. Dynamic content (e.g., animation) has found to be beneficial to overall learning outcomes compared to static content (e.g., graphs) when the dynamic content is realistic to the learner (Kalyuga et al., 2000). This has been supported through studies (Tsai et al., 2016b) to increase support to low-knowledge learners (Kalyuga et al., 2000). It has also been applied to GBLEs as the NPCs are typical within the design of GBLEs (refer to Crystal Island Environment section) and can appear to be realistic and provide information crucial to achieving goals. Within CI, participants were also presented with audio as the NPCs interact and answer the prompted questions.

Eye Tracking in GBLEs

Using eye tracking technology allows researchers to infer cognitive processes, specifically attention and implicit strategies, of a learner through observable behavior (Dogusoy-Taylan & Cagiltay, 2014; Grant & Spivey, 2003; Rayner, 2009). Understanding the relationship between cognitive processes and eye movements has become increasingly popular over the past decade, especially in education and science domains (Rayner, 2009). Using eye movements to measure cognitive processes, researchers use two types of measures: saccades and fixation durations (Dogusoy-Taylan & Cagiltay, 2014; Rayner, 2009). Saccades are rapid eye movements between fixations which can be represented by regressions (Dogusoy-Taylan & Cagiltay, 2014; Rayner, 2009). Fixation durations result from a relatively still eye motion lasting approximately 250 ms and may produce several variables such as the number of fixations, average duration of fixations, and total time fixating on an area of interest (AOI; Rayner, 2009). For example, in a GBLE a learner could fixate on specific content within the environment and eye-tracking data captures how many times they fixate on an object, the proportion of time fixating on said object relative to other objects, as well as total amount of time the learner fixates on that object, providing inferences on what the learner may be thinking, the strategies they are using, and whether they are experiencing difficulties (Grant & Spivey, 2003).

Eye tracking allows researchers to understand relationships between SRL strategy use and learner performance to increase understanding of learner problem-solving processes that occur in GBLEs (Dogusoy-Taylan & Cagiltay, 2014) which introduces a large gap in current literature due to the limited study on these relationships. Problem-solving processes are described by transforming what occurs at the original state provided to the learner to the goal state when there is no evidence of the solution (Dogusoy-Taylan & Cagiltay, 2014). Past studies have indicated longer fixation durations within cognitive tasks perceived as difficult (Rayner, 2009). This includes problem solving within STEM education. Past research has also concluded improved problem-solving abilities in environments that highlight and emphasize critical components to the goal state (Kalyuga et al., 2000; Rayner, 2009). Eye tracking can support inferences about cognitive processes that are used while reading (Rayner, 2009). This can be combined with text structure and content within multimedia theories, such as CTML, to further understand the relationship between SRL strategy use, learning, and the acquisition of content knowledge within these environments (Rayner, 2009). Generally, understanding and integrating content is influenced by perceived difficulty of text and learners' reading ability, which affects eye movements where fixations increase as difficulty of text increases and saccades become shorter (Rayner, 2009). As such, learners' eye movements should allow for inferences in understanding learners' cognitive processes, progress throughout a GBLE, engagement, and SRL strategy use (Grant & Spivey, 2003).

CRYSTAL ISLAND Environment

CRYSTAL ISLAND (Rowe et al., 2011), a game-based learning environment, provides an opportunity for students to develop scientific reasoning skills through a microbiology-centered environment where students investigate an illness infecting an island of researchers. Participants are to identify the mysterious illness by interacting with NPCs and reading informational text (see Figure 1), collecting and scanning food items that may be transmitting the disease, and organizing evidence by completing a diagnosis worksheet.

Once evidence has been gathered, participants make hypotheses about the illness and the source of the pathogen and then test their hypotheses. Once a hypothesis has been tested correctly, the game will end.

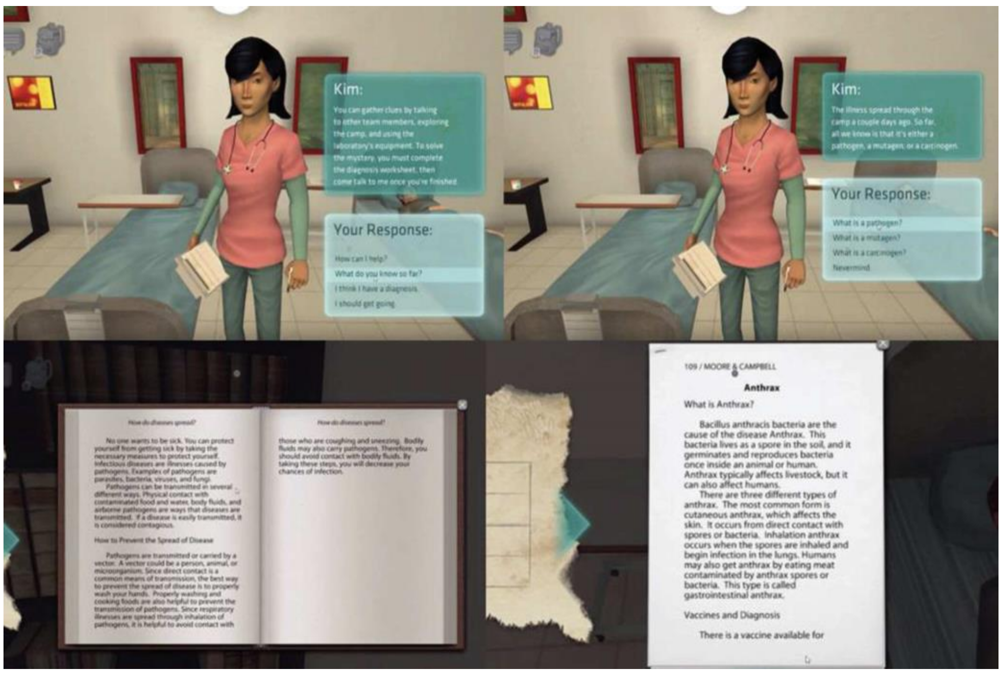

Figure 1: Top: Informational text presented with an NPC; Below: Traditional informational text presentation.

Current Study

To assess the role of autonomy and the types of presentation of informational text on PLGs within GBLEs, this study addresses the following research questions: (1) Do PLGs differ between the full and partial agency conditions?; (2) Do fixation durations on different types of informational text presentations in the environment predict PLGs?; and (3) Do fixation durations on different types of informational text presentations differ between the full and partial agency conditions? To address these questions, the hypotheses are as follows:

Hypothesis 1: Participants in the partial agency condition will demonstrate higher PLGs.

Hypothesis 2: The fixation durations of the different types of presentation of informational text in the environment will predict PLGs.

Hypothesis 3: Participants in the partial agency condition will have significantly greater fixation durations of both types of presentation of informational text.

Method

Participants

A total of 106[1] participants recruited from a large public North American university participated in the current study. Fifteen participants were removed due to eye tracking data inconsistencies while one participant was removed for not completing the post-task questionnaires. However, 90 (66% female) undergraduate students recruited from a large public North American university participated in the current study. Ages ranged from 18 to 26 years (*M* = 20.01, *SD* = 1.66). Participants were randomly assigned to one of three conditions: (1) full agency (*n* = 53), (2) partial agency (*n* = 37), or (3) no agency condition; we did not analyze data from the no agency condition, so details are excluded from this study. These conditions reflected the level of autonomy given to participants to navigate and problem solve with Crystal Island. Participants were compensated $10/h and up to $30 for completing the study.

[1] Our dataset derives from a larger study which was modified based on the quality of the data.

Experimental Conditions

Participants were randomly assigned into one of three groups which allowed for varied control of gameplay: full agency, partial agency, and no agency. *Full agency* concedes full control to the participant where they can interact with the game at their own pace and discretion. Participants were free to move from building to building in whichever order they decided as well as choose whether or not to interact with certain game features such as opening a book or collecting a food item to later scan. *Partial agency* contains a “golden path” where participants are required to follow a set path through the game dictating which building to continue to next, requiring participants to interact with non-player characters, and having the participants look at each informational text to complete the concept matrices. For example, once past the tutorial portion of the game, participants in the partial agency condition were directed to the infirmary building first while the full agency participants could go to whichever building they desired. Once in the infirmary, participants in the partial agency condition were required to talk to both NPCs until the conversation options were exhausted, open all posters, books, and research articles, and then accurately complete the concept matrices for all books and research articles. Only after all of these actions were completed, were the participants able to leave the infirmary and directed to go to the next building. The *no agency* condition does not allow control to the participants as the participants will follow a video of an expert run-through of gameplay. This condition was not used in the study as the participants were not able to control for how long they fixated on informational text or NPC dialog.

Materials

Pre-task measures consisted of a demographic questionnaire and a microbiology pretest. The pretest quiz contained 21, four-option, multiple choice questions developed by an expert in the field. Post-task measures consisted of a microbiology posttest similar to the content knowledge pre-test. The SIM EYERED 250 eye tracker, using a 9-point calibration, recorded fixation duration and gaze movements of participants throughout the task. Log-file data was collected containing participant actions and timestamps.

Experimental Procedure

Participants read and completed the informed consent. Participants then completed the demographics questionnaire and the microbiology content knowledge quiz. After completion, the research assistant calibrated the eye-tracking device individualized to each participant. The research assistant then explained the scenario of Crystal Island, the role of the participant in the game, the goal of the game, and the actions available to the participant throughout the game, such as reading informational text, talking to NPCs, gathering possible sources of disease transmission, and completing the virtual worksheet. After the participants finished playing, they completed the post-task measures. This consisted of the microbiology content knowledge quiz which was similar to the pre-task version. Participants were then compensated, debriefed, and thanked for their time.

Coding and Scoring

A data pipeline that temporally aligned the multimodal, multichannel data was used to aggregate data during the experiment. Fixation durations were calculated by predefined areas of interest (AOIs) which included books, research articles, and NPCs. To calculate content knowledge of an individual after gameplay, differences in prior knowledge were accounted for in measuring the learning gains from the post-test score. PLGs are calculated using the pre- and post-test content knowledge scores using a formula accounting for prior knowledge (Witherspoon et al., 2008).

Results

Research Question 1: Do PLGs Differ Between the Full and Partial Agency Conditions?

An independent samples t-test was conducted to compare the means of the PLGs between the full (M = .218, SD = .231) and partial (M = .328, SD = .245) agency conditions. There were significant differences in PLG ($t(88) = -2.18$, $p < .05$; $d = 0.46$) where participants in the partial agency condition had significantly higher PLGs than participants with full agency, suggesting those in the partial agency learned more about microbiology compared to those in the full agency.

Research Question 2: Do Fixation Durations on Different Types Of Informational Text Presentations in the Environment Predict PLG?

A linear regression was conducted to examine whether proportion of time fixating on NPCs over total game time (M = .124, SD = .035) predict PLG. There was no significant regression equation between the proportion of time fixating on NPCs and PLG ($p > .05$). An additional linear regression was calculated to assess whether the proportion of time fixating on traditional informational text over time (e.g., books and articles; M = .319, SD = .130) predict PLG. There was a significant positive correlation between the fixation duration of books and articles and PLGs ($r = .233$, $p < .05$), meeting the assumptions for our regression equation, and our results revealed a significant regression equation where the time spent fixating on informational texts was a significant positive predictor of PLG, $F(1,88) = 5.03$, $p < .05$ with an R^2 of .233, indicating that the longer participants fixated on traditionally presented informational texts, the higher their PLG ($\beta = .233$, $p < .05$). In sum, these findings showed that the fixation duration on traditionally presented text is a positive predictor of participants' PLG than the fixation duration of NPC instances, challenging the CTML model where text alone, not the integration of text and diagram, predicts PLGs.

Research Question 3: Do Fixation Durations on Different Types of Informational Text Presentations Differ Between the Full and Partial Agency Conditions?

A MANCOVA was conducted to examine differences in time spent fixating on different types of informational text between the two conditions with total game duration as a covariate (see Figure 2). There were no significant differences in fixation duration of NPC instances between the full (M = 593.84, SD = 154.17) and partial (M = 682.20, SD = 170.52) agency conditions ($p > .05$). However, there were significant differences in time spent fixating on books and research articles, ($F(2,87) = 16.05$, $p < .0005$) between full (M = 1565.97, SD = 755.05) and partial (M = 1851.13, SD = 915.84) agency conditions, where the partial agency condition has significantly higher fixation durations than the full agency condition. Overall, these results indicate that the autonomy afforded to a participant influences the fixation duration of the different types of informational text presentation. There were no differences in the fixation duration between types of informational text presentations for the full agency whereas participants afforded partial control of interaction with CI have greater fixation durations of traditionally presented text.

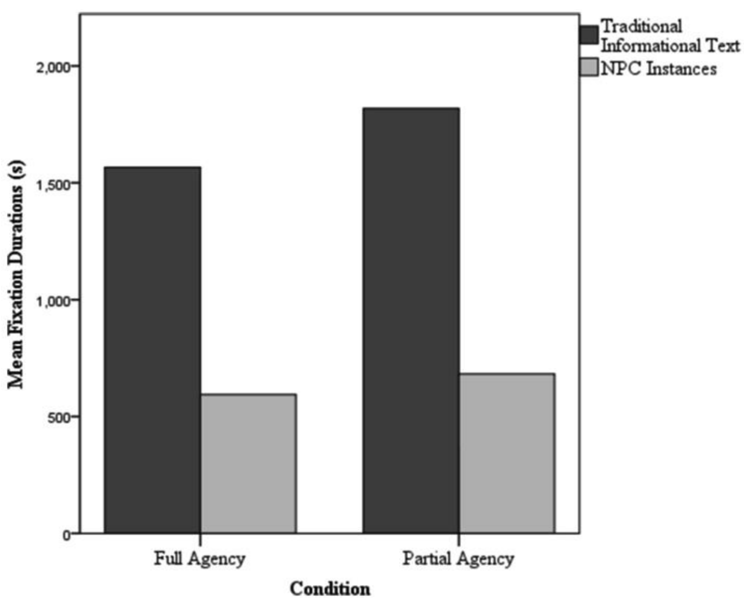

Figure 2: Mean fixation durations of types of informational text presentation between conditions.

Discussion

In support of the first hypothesis, results show that participants in the partial agency condition generally had significantly higher PLGs. This indicates that learners with less autonomy, based on a somewhat prescribed ideal path through game elements allowing for partial agency, is associated with higher overall content knowledge during learning and problem solving with GBLEs. Further, the hypothesis was partially supported when referring to time spent fixating on two types of informational text. NPC instances are not predictors of PLGs, but the fixation durations of traditional information text are significant predictors of PLGs. This indicates that the traditional presentation of information through large amounts of text are better indicators and significantly correlate with higher content knowledge than interacting with NPCs who provide microbiology content knowledge through a more conversationalist approach. This finding runs counter to CTML in which the NPC instances, demonstrating a visual (e.g., the character itself) in conjunction with verbal (e.g., audio and text) information does not predict higher content knowledge whereas just the presentation of text does without the aid of an NPC or audio. This could be explained as the NPC presents verbal information when prompted by the participant that is not as representationally rich as a relevant diagram, and then participants are given small bits of information, but through predetermined prompts the participants may or may not have asked otherwise without room for adjustment of questions. Results partially supported the hypothesis where the partial agency condition had a higher fixation duration when referring to books and articles than the full agency condition, but no difference between conditions when calculating the fixation durations in NPC instances. This indicates that participants who have a set path fixate more on traditionally presentation of informational text over NPC instances. The partial agency condition required the participant to ask every prompt for NPCs as well as open every book and article to complete the concept matrices. From this, participants in the partial agency condition may identify the traditional presentation of text to hold a greater value in the information that is provided.

Future Directions: More AI in GBLEs?

This study supports the need for integrating more AI in GBLEs to support reading activities that are critical to learning about complex topics such as science. In general, GBLEs should support the development of learners' SRL strategies where the learner is guided by the environment in the completion of the goal, especially critical in GBLEs that afford full agency that may not be beneficial for all learning lacking CAMM SRL skills. As supported by our results, GBLEs that intelligently and actively guide the learner through the environment are needed to optimize proportional learning of complex instructional content. For example, GBLEs are often preferred over traditional learning technologies (e.g., hypermedia) due to perceived affordance to agency, autonomy, and engagement based on constructivist learning models, but our results show that full autonomy is not ideal since most learners do not have the cognitive and metacognitive self-regulatory skills need to make accurate instructional decisions such as when, how, and why instructional text embedded in GBLEs is critical for learning. In addition, our study also demonstrates that the NPCs (acting as intelligent agents interacting with learners) did not provide the information-rich instructional material that was needed and were disregarded, or not engaged with by the learners. The contrast between the roles on informational text and NPS highlights the careful attention that is needed in providing adaptive scaffolding during learning with GBLEs that should be based on time spent on different representations and sequences within and between representations and other related GBLEs activities. For example, information presented through large chunks of text are large components of learner interaction and theses affordances are influenced by the amount of autonomy afforded to a learner when interacting with a GBLE. The study further supports the need for appropriate direction towards the overall goal of the GBLE in order to obtain optimum learning from the learner exposed to the environment. In future versions of CRYSTAL ISLAND, or any text-dependent GBLE, limited, but present support should be given to the learner through the environment to increase the expected content knowledge gain. We envision intelligent agents embedded in GBLEs can play a more active role (a) in assisting learners to select, organize, and integrate instructional content; (b) providing adaptive scaffolding and feedback based on multimodal multichannel trace data from log-files, eye tracking, screen recording, facial expression of emotions, and natural language understanding, and (c) modeling specific self-regulatory processes by prompting and scaffolding students' planning, cognitive strategy use, metacognitive monitoring processes, etc.

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CHAPTER THREE: THE IMPACT OF AUTONOMY AND TYPES OF INFORMATIONAL TEXT PRESENTATIONS IN GAME-BASED ENVIRONMENTS ON LEARNING: CONVERGING MULTI-CHANNEL PROCESSES DATA AND LEARNING OUTCOMES

This chapter titled, "the impact of autonomy and types of informational text presentations in game-based environments on learning: converging multi-channel processes data and learning outcomes" was originally published in the International Journal of Artificial Intelligence in Education and led by first author Daryn A. Dever with contributing co-authors Roger Azevedo, Elizabeth B. Cloude, and Megan Wiedbusch.

Abstract

Game-based learning environments (GBLEs) focus on enhancing learning by providing learners with various representations of information (e.g., text, diagrams, etc.) while allowing full autonomy, or control over their actions. Challenges arise as research shows that learners inaccurately use cognitive and metacognitive processes when given full autonomy. This study examined 105 undergraduates who were randomly assigned to autonomy conditions (i.e., full, partial, and no autonomy) as they interacted with scientific informational text presentations (i.e., non-player characters [NPCs], books and research articles, posters) during learning with CRYSTAL ISLAND, a GBLE. We assessed how learners' eye-tracking (e.g., fixation durations on objects) and log-file (e.g., durations of activities) data reflected how learners interacted with text presentations and selected pretest-relevant items (i.e., text providing answers to questions on the pretest). Results showed that participants in the partial autonomy condition (*n* = 38) demonstrated higher learning gains than those in the full autonomy condition (*n* = 45). Time spent interacting with all books and research articles within CRYSTAL ISLAND were positively correlated with learning gains. There

were significant differences in learners' duration and fixation duration on informational text presentation interactions between conditions and within types of presentations as well as significant interactions between pretest-relevant items and types of presentations. Overall, autonomy and pretest relevancy impact the time interacting with informational text presentations which influence learning. Implications are provided for applying autonomy during game-based learning, and how this may direct future implementations of AI within GBLEs to provide implicit scaffolding via adaptively limiting learners' autonomy as they interact with informational text.

Introduction

Game-based learning environments (GBLEs) afford autonomy while giving learners access to a myriad of game elements including books, posters, non-player characters (NPCs), scientific data, etc. with the implicit assumption that more autonomy, or learners' ability to control their own actions during learning (Bandura, 2001), leads to better learning and problem solving (Plass et al., 2015). In addition, narrative-centered GBLEs contain storylines that support informational content (e.g., scientific text) and provide real-world scenarios ranging across multiple domains for learners to practice problem-solving, critical thinking, cognitive, and metacognitive skills (Chen et al., 2018; Rowe et al., 2009; Shih et al., 2015). Thus, the role of narrative within GBLEs is critical in conveying informational content to enhance learning. Information within GBLEs include multiple representations of instructional materials (e.g., graphics, pictures, videos, text) designed using multimedia learning principles with aims of improving learning (Mayer, 2014; Plass et al., 2015). While the majority of research on GBLEs tend to focus on learning outcomes and using self-reports to measure motivation, engagement, and so forth (see Plass et al., 2020), we examined the role of autonomy and types of informational text presentations by converging college students' learning outcomes and process data (e.g., eye movements and log-files) during learning with a GBLE designed to foster learning about microbiology.

Affording autonomy in GBLEs increases opportunities to engage learners by allowing them to freely utilize authentic instructional materials and interact with contextualized problem-solving scenarios that require scientific reasoning and self-regulatory processes (e.g., solving a mystery related to a biological outbreak on an island). These interactive scenarios aid in transforming complex, rich information into easily interpretable concepts that are contextualized to engage and support learners in acquiring knowledge (Chen et al., 2018; Herrington et al., 2014). Although learners within GBLEs are able to engage in exploring various instructional materials through problem-solving activities (Lee et al., 2011) by affording autonomy, effective learning with GBLEs requires learners to accurately and dynamically monitor and regulate their cognitive, affective, metacognitive, and motivational processes, such as distinguishing between relevant and irrelevant instructional materials, evaluating competing hypotheses, comprehending informational texts, changing plans, and so forth (Azevedo et al., 2018b; Rowe et al., 2009). Typically, when provided with autonomy in a GBLE, learners tend to inaccurately monitor and regulate their self-regulatory processes by engaging in off-task behaviors as they are unable to deal with extraneous cognitive load, fail to comprehend relevant instructional materials, etc., thus leading to small or negligible learning gains and not completing the objectives of the GBLE (Rowe et al., 2009).

CRYSTAL ISLAND (Rowe et al., 2011) is a narrative-centered GBLE designed to support learning about microbiology while fostering scientific reasoning and self-regulated learning skills. It accomplishes this by providing learners with varying levels of autonomy and providing a range of game elements and tools to solve the mysterious illness on the island. By including informational content (i.e., scientific books and research articles, concept matrices measuring reading comprehension, NPCs including a camp nurse, patients, and scientists, scientific worksheet to record symptoms and hypotheses, scientific tools to analyze microbes), CRYSTAL ISLAND assists learners in obtaining content knowledge in microbiology and skills in scientific reasoning while self-regulating. Data generated from learners while interacting with these elements (e.g., durations on scientific text) could provide insight into their cognitive and metacognitive skills as they learn with a GBLE; however, most studies using GBLEs fail to capture and synchronize multiple channels of data (e.g., eye-tracking, log-file) to capture learning through these interactions.

Taub et al. (2016) investigated metacognition, specifically strategy use, while participants learned with CRYSTAL ISLAND by examining fixation durations on book and research article content as well as concept matrices to predict performance which was measured by the number of concept matrix attempts. This study found that, by using eye-tracking data, researchers can identify how learners strategize when collecting information from a book or research article to predict learners' in-game performance based on the number of books and research articles a learner uses and their proportion of fixations on the content (Taub et al., 2016). In another study, Emerson et al. (2018) used eye tracking to develop a framework to predict learners' performance and cognition with CRYSTAL ISLAND. This study emphasized that learners' eye-tracking data on in-game elements significantly improve models predicting problem-solving performance. Emerson et al. (2018) used multiple actions to measure performance, including which NPCs learners interacted with and the amount of time spent interacting with each NPC, testing a correct or incorrect object, the number of attempts on in-game measures (e.g., concept matrices), the efficiency of the learners' actions in relation to solving the problem, and the number of solution attempts.

Another study by Dever and Azevedo (2019a) examined whether varying levels of autonomy impacted how learners interacted with NPCs, books, and research articles. Their results showed that learners with partial autonomy had higher proportional learning gains and longer fixation durations on books, research articles, and NPC interactions than learners with full autonomy, highlighting that autonomy influences amount of time spent interacting with NPCs, books, and research articles and subsequent learning outcomes with GBLEs. Taub et al. (2018) examined how metacognition affected game efficiency and completion using log files. They found performance was measured by identifying how often learners' tested relevant, partially-relevant, and irrelevant objects. Learners who were defined as being more efficient in solving the game had significantly fewer instances of testing partially-relevant and irrelevant items than learners who were less efficient. Similarly, Dever and Azevedo (2019b) examined learners' selection of relevant from irrelevant information that would enable the learner to, not only solve the final diagnosis but, perform well on the domain pre- and posttests. These were examined using eye-gaze data, where fixation duration proportions between different goal-directed actions (e.g., scanning items, completing concept matrices) were compared and reading books and research articles and completing their concept matrices were identified as the greatest contributors to learners' overall time in game. As such, this study identified how learners' fixation duration and identification of the relevancy of the books and research articles affected their learning. Further, this study by Dever and Azevedo (2019b) identified that learners who spent a greater time revisiting relevant books and research articles had significantly greater learning gains than those who spent more time revisiting irrelevant books and research articles. This shows that learners identifying the relevancy of information within text presentations is critical for learning.

In contrast to the previous studies that used one type of process data (i.e., eye gaze), Taub et al. (2017) combined eye tracking and log files to investigate cognitive and metacognitive self-regulated learning during in-game performance measures. Their findings showed that learners with low proportions of fixations on information and the in-game performance measure demonstrated higher learning outcomes than those with high proportions of fixations on information and the in-game performance measure. These studies emphasize the using process data generated during learning with a GBLE has the potential to effectively accurately capture learners interacting with elements in the game, and how these variables are related to performance. However, the aforementioned studies do not directly investigate how learners interact with and learn using scientific information given external constraints (i.e., autonomy) imposed by a GBLE. Further, these studies demonstrate gaps where process data could indicate how learners use metacognitive strategies to select, organize, and integrate scientific information to enhance their learning using multiple data channels.

The current study differs from previous studies in multiple ways to address this gap in the literature. First, the current study addresses all sources of information within CRYSTAL ISLAND, where NPCs, books and research articles, as well as posters were defined as sources of information integral to accurately completing and performing well on the domain pre- and posttests. Secondly, this study extends previous work by Dever and Azevedo (2019a,b) and is in contrast to the other previous studies, where performance is measured by participants' learning gains to examine how learners' domain knowledge changes as a function of their interactions with different types of text within CRYSTAL ISLAND. Lastly, the current study identified the relevancy of information within several types of text presentations in reference to the items on the pre-test. By doing so, the current study adopted assumptions that all information contained in the pre- and posttests are addressed within the GBLE, not all information in the GBLE are relevant to the domain pre- and posttests, multiple sources of information may be identified as relevant to the domain pre- and posttests, and what is relevant to the final diagnosis, or the GBLE itself, may not be relevant to the domain pre-and posttests. This study 1) addressed how autonomy influences metacognition as captured through learners' process data while they interact with scientific information within and 2) identified gaps in current literature and explore the relationship between these two components (autonomy and interaction with scientific information) specifically within GBLEs.

Autonomy as Scaffolding in Game-Based Learning

GBLEs are designed to integrate autonomy as scaffolding techniques used to increase engagement and learning. More specifically, levels of autonomy have been implicitly designed in GBLEs to facilitate learning, increase motivation, and so forth, but have not been explicitly tested as a scaffold that supports learning, comprehension, problem solving and reasoning. Providing autonomy combined with learners' inability to use cognitive and metacognitive strategies within GBLEs (Azevedo & Hadwin, 2005; Sabourin et al., 2013; Taub & Azevedo, 2018) pose a challenge to learning. Previous research identified scaffolds as ways to guide learners within learning environments to support their understanding of complex information by providing adaptive scaffolding to foster learners' knowledge and skill acquisition, where the presence of these scaffolds fade as learners gain competence (e.g., Azevedo & Hadwin, 2005; Pea, 2004; Plass et al., 2015). Researchers have used different types of scaffolds including static, dynamic, conceptual, procedural, metacognitive, reflection, etc. with various technologies, especially intelligent tutoring systems (ITSs) such as AutoTutor, Affective AutoTutor, Betty's Brain, Gaze Tutor, MetaTutor, where they are delivered by pedagogical agents that prompt strategy and tool use, such as note-taking of concepts after reading to increase learning outcomes (Azevedo et al., 2018b; Winne & Hadwin, 2013; D'Mello et al., 2012; Graesser et al., 1999). However, while these prompts have been used extensively in ITSs and other learning technologies, they have not been widely used or empirically tested in GBLEs.

Implicit scaffolds (e.g., limited autonomy) unobtrusively support learners' knowledge and skill acquisition but rely on learners' competent, timely, and accurate use of cognitive and metacognitive processes without interrupting the learning experience with GBLEs. Studies have used autonomy, such as the amount of control learners have over how they interact during game-based learning, and assume learners, or agents, actively engage with elements when they select, organize, and integrate information presented in these environments such as informational content presented through video, text, pictures (Bandura, 2001). Autonomy allows learners to make their own choices and initiate planning behaviors, but for some learners it comes with negative consequences such as lack of skill acquisition, minute learning gains, and so forth because of both internal (e.g., low prior knowledge, lack of self-regulatory skills) and external conditions (e.g., full autonomy in a GBLEs without explicit scaffolding). Specific to GBLEs, learners must constantly choose which game elements or tools to use and their course of action to achieve the objectives for completing the game (Bandura, 2001). Varying levels of autonomy determine the control learners have over their choices and actions in the environment, where full autonomy gives learners complete control over planning, generating learning goals, decisions, use of tools, etc. In contrast, restricting autonomy reduces the amount of control learners have over their planning, generating learning goals, decisions, use of tools, etc. From a self-regulatory perspective, full autonomy in GBLEs is ideal if learners are capable of accurately and dynamically monitoring and regulating their cognitive, affective, metacognitive, and motivational processes, whereas more restrictive forms of autonomy are optimal for learners have challenges accurately and dynamically monitoring and regulating these process (Azevedo & Hadwin, 2005; Mayer, 2019; Sabourin et al., 2013; Taub & Azevedo, 2018). Limiting autonomy (i.e., learners ability to select, organize, and integrate information) in GBLEs enhances learning by using an implicitly fixed, procedural scaffold. Yet, the tradeoff of less autonomy is less engagement during learning (Plass et al., 2013, 2015; Sabourin et al., 2013) such that full autonomy encourages engagement but poses a threat to learning when learners cannot accurately apply cognitive and metacognitive strategies in selecting relevant informational content (Sabourin et al., 2013). The current study explores limited autonomy as a scaffold to support learners in selecting relevant information from scientific texts in a GBLE.

Theoretical Framework: Cognitive Theory of Multimedia Learning

GBLEs, such as CRYSTAL ISLAND, include multiple types and representations of information such as books and posters that learners must read and comprehend by selecting, organizing, and integrating relevant information in order to learn about microbiology and therefore solve the mystery. We used Mayer's (2014) Cognitive Theory of Multimedia Learning (CTML) which is based on three basic assumptions: 1) there are two separate processing channels that learners use to gather and interpret visual (e.g., picture) and verbal (e.g., audio) information; 2) learners are limited in the amount of information they can process simultaneously within each channel; and 3) learners are active in processing given information (e.g., Burkett & Azevedo, 2012; Butcher, 2014). In addition, CTML addresses five cognitive processes which are combined into three phases: (1) selecting, (2) organizing, and (3) integrating information. Selecting refers to identifying relevant information from multimedia such as text and images. Organizing involves developing cognitive models from information selected, thus prompting the integration of prior knowledge into learners' new cognitive models to create an updated model of knowledge.

While not explicitly related to autonomy, self-regulation, and GBLEs, we extended Mayer's (2014) CTML by arguing that the second and third assumptions closely align with previous assumptions about autonomy where learners actively process visual and verbal information presented as multimedia instructional materials, requiring learners to dynamically and accurately select, organize, and integrate multiple representations of information embedded in GBLEs (such as CRYSTAL ISLAND) by using their monitoring and self-regulatory skills as needed, depending on the amount of autonomy. In summary, we used and extended Mayer's CTML by testing the impact of varying levels of autonomy (in versions of the same GBLE), on learners' interactions with informational text and resulting learning gains.

Application of Metacognitive Processes, Autonomy, and CTML

CTML integrates cognitive processes and, when contextualized to learning, addresses learners' metacognitive processes and competencies. For instance, according to CTML, a learner must first select relevant information from informational content presented to learners within non-dynamic learning environments (e.g., tutoring systems, multimedia). Relevant information is identified as content critical to learners' goals. For example, the goal of CRYSTAL ISLAND is to learn microbiology concepts by interacting with the environment. As such, goals that pertain to learning domain content may be defined by the presence of an explicitly communicated goal (e.g., instructions on how to complete a GBLE), or through covert methods (e.g., pretest items detailing concepts learned within a GBLE). Within GBLEs, learners must constantly monitor their progress towards goals as they select, organize, and integrate information they identified as relevant to the overall objective (e.g., learning domain knowledge; Azevedo et al., 2018b). As such, CTML indirectly incorporates learners' metacognitive processing, where learners select information relevant to their goal (Greene & Azevedo, 2009). Selecting relevant informational content is difficult to achieve for learners who are given little direction in deciding which information to select that will aid in achieving goals to increase learning and complete the game (Greene et al., 2010).

Therefore, in this paper, we argue that the level of autonomy is an integral part of learners' ability to successfully demonstrate metacognitive processes.

Previous literature has primarily used CTML to study non-dynamic environments (e.g. Cierniak et al., 2009). However, some studies have used CTML with applications to military training (e.g., Serge, 2014) and foreign language acquisition (e.g., Alghamdi, 2016) within dynamic learning environments (e.g., GBLEs, augmented reality). Limited research has examined how CTML can be applied to GBLEs that contain informational content in STEM domains and how, in combination with external constraints (i.e., autonomy), these factors influence cognitive and metacognitive processes and their relation to learning. Further, the limited number of studies examining CTML with GBLEs (e.g., Serge, 2014) have not incorporated various process data necessary for examining cognitive and metacognitive processes. Therefore, there is a major gap in using CTML to study GBLEs, and how this model contributes to measuring learning, examining learners' interactions with game elements, and using process data to capture and understand cognitive and metacognitive processes critical for learning with GBLEs.

Process Data in Game-Based Learning

Multichannel process data facilitates researchers' ability to infer the cognitive and metacognitive processes that learners engage in by capturing and analyzing learners' interactions with learning environments (Azevedo & Gašević, 2019). This term, used throughout metacognition and self-regulated learning literature, refers to the variables which originate from multiple data streams (e.g., log files, eye tracking; Azevedo & Taub, 2020). This paper emphasizes the use of multi-channel process data, log files and eye tracking, to examine how learners interact with multiple text presentations within a GBLE.

Log Files during Game-Based Learning

A plethora of studies have harnessed and analyzed in-game behaviors using log files since these data capture the frequency and duration at which learners initiate actions during game-based learning. A study by Taub et al. (2018) investigated whether log files could distinguish between scientific-reasoning and problem-solving behaviors during game-based learning. By utilizing sequential pattern-mining analysis, log files revealed two distinct groups where participants were efficient and less efficient in their scientific-reasoning behaviors related to completing the game. Another study by Cheng et al. (2015) examined log files and their relation to conceptual learning and game performance. They found that the frequency and duration of viewing relevant information was associated with game performance, where the more frequent and longer time spent viewing relevant information were positively associated with game performance and conceptual learning (Cheng et al. 2015). Similarly, Spires et al. (2011) examined middle-school students learning outcomes based on their scientific-reasoning actions (i.e., hypothesis vs. experimental actions) using log files. Results indicated that generating effective hypotheses during problem solving was positively associated with higher learning outcomes and game performance. Recently, studies have introduced models to assess students' developing knowledge and skills based on their in-game actions using log files (Shute, 2011). A study by Akram et al. (2018) proposed a temporal-analytics framework that uses recurrent neural networks, a class of deep-learning methods that account for the temporal sequences in learners' log files, to analyze problem-solving strategies. Specifically, this analytical framework clustered students into groups based on the sequence of problem-solving strategies during game-based learning to develop predictive models that gauged competency and performance. From these studies, log files are primarily used to assess and predict learners' cognitive processes, learning, and performance as they interact with GBLEs.

Major challenges persist as researchers solely rely on log files to quantify learning and infer cognitive and metacognitive self-regulated learning processes (Azevedo et al., 2018b; Winne, 2018). Log files provide time-stamps for all learners' in-game actions, but do not provide fine-grained contextual information such as which elements learners were looking at when (e.g., content) they opened (i.e., they provide info that a specific book in a GBLE was open for a certain amount of time and preceded by another action and subsequently led to another action). We argue that log files need to be supplemented with finer-grained information supplied from eye-tracking data to examine attention allocation, gaze behaviors, and other relevant information that can be used to infer cognitive and metacognitive processes.

Eye-Tracking Methodology during Game-Based Learning

A large portion of studies have used eye tracking to investigate learning with GBLEs as it has been shown to reveal implicit indices of intent, reasoning, cognition, metacognitive monitoring, and decision-making processes (Chen & Tsai, 2015; Lai et al., 2013; Park et al., 2016; Taub et al., 2021). A study by Kiili et al. (2014) investigated pre- and post-test performance and its relation to total fixation and saccade duration on relevant and irrelevant informational content as learners interacted with GBLEs. They found that patterns in eye-gaze behaviors indicated when learners did not identify content relevant to the learning objective (Kiili et al., 2014). Tsai et al. (2016a) utilized eye tracking to assess differences in eye-gaze behaviors between high- and low-domain knowledge groups as they completed a problem-based learning task using a GBLE. They found that participants who had little to no domain knowledge before learning with the game demonstrated longer and more frequent fixations on most game features in the GBLE compared to the high prior knowledge group. This study suggests that differences in eye-tracking data to mental exertion when taking prior knowledge into account, further supporting when learners demonstrate cognitive processing required to select and organize new information and integrate the new information into a coherent model. Another study investigated eye-gaze patterns as participants solved various problems with differing levels of difficulty (Lin, 2014). This study concluded that longer time spent fixating on difficult problems relative to less difficult problems was indicative of higher cognitive load due to complex processing required for more difficult problems. These studies show that eye-tracking allow researchers to detect, measure, and understand cognitive processes related to selecting, organizing, and integrating information, and to examine how these processes relate to learning outcomes, performance, and comprehension during game-based learning (Mayer, 2019; Plass et al., 2020). However, major challenges continue to persist because, while eye-tracking captures where learners allocate their attention and fixate on elements during learning with GBLEs, it fails to directly capture learners' level of understanding. For instance, if learners fixate on text in a book within a GBLE, eye-gaze behavior can indicate which information learners selectively attend to, but not the extent to which information was understood. A study by O'Keefe et al. (2014) used fixation durations and transitions between areas of interest to examine how multiple representations within a science simulation corresponded to learning with high school students. While this study found that fixation durations on multiple representations were not related to learning, the eye-gaze transitions between multiple representations can indicate learners' comprehension and transfer of illustrated concepts (O'Keefe et al., 2014). This study emphasizes the limitation of using fixation durations in connection to learning as well as the strength of using gaze transitions between elements within a learning environment to examine learning processes. However, the aforementioned studies use either log files or eye tracking to provide evidence of learning and performance. By converging multichannel data, our paper mitigates limitations and provides evidence of overt and covert cognitive and metacognitive processes that learners' employ while completing a single action within GBLEs.

Combining Eye-Tracking and Log Files during Game-Based learning

In this current study, we harnessed the strengths of both eye tracking and log files as two critical data channels in examining underlying cognitive and metacognitive processes during learning about microbiology with CRYSTAL ISLAND. Empirical studies show that capturing multiple channels of process data to classify learning processes is superior than a single data channel (Alonso-Fernández et al., 2019; Di Mitri et al., 2019; Giannakos et al., 2019). Specifically, a study by Taub et al. (2017) assessed cognitive and metacognitive self-regulatory processes using eye-gaze and log-file data with a GBLE, and how these in-game behaviors related to learning and performance. Their findings highlighted that combining eye-gaze and log-file data during game-based learning taps into the quality of cognitive and metacognitive processes such that log files capture the quantity of in-game actions, but eye-gaze data reveal more information on the quality of cognitive and metacognitive processing. Similarly, a study by Dever and Azevedo (2019a) examined eye-gaze and log-file data to investigate metacognition and how its use related to textual comprehension and performance during game-based learning. Their results showed that eye-gaze and log-file data quantified, not only when a participant was opening textual information, but also fixating on it and suggested higher learning gains were predicted by both the frequency and duration learners spent examining informational texts. However, critical gaps exist as few studies have compared and combined eye-tracking and log-file data to quantify and understand learning processes involved in game-based learning, and how they contribute to comprehension and learning.

Current Study

To address the major gaps in literature related to evaluating scaffolding in GBLEs and using CTML to assess learners' metacognitive competency in selecting relevant information when accounting for autonomy, this study examined how learners interacted with various types of informational text presentations, selected relevant information, and whether these interactions differed between levels of autonomy. We further examined how these constructs impacted learning captured using multichannel process data (i.e., eye tracking, log files) during learning with a GBLE, CRYSTAL ISLAND. Within this paper we addressed four research questions:

Research Question 1) Do prior knowledge and learning gains significantly differ between learners with varying levels of autonomy?

Research Question 2) Do learners' process data for each type of informational text presentation predict learning gains?

Research Question 3) Do learners' varying levels of autonomy influence how learners interact with each type of informational text presentation?

Research Question 4) Do learners' varying levels of autonomy and the relevancy of informational text influence how learners interact with each type of presentation?

We directly address these research questions by examining multichannel process data generated during learning with CRYSTAL ISLAND to capture how learners interacted with different types of informational text presentations and whether these interactions vary based on level of autonomy, the relevancy of the informational text content, and whether these process data are related to learning. For the first research question, we hypothesized that participants' pretest scores measuring prior knowledge of microbiology will not differ between conditions due to the randomization of the assigned autonomy conditions. Further, we hypothesized that normalized change scores will be higher for those in the partial agency condition than the full agency condition, as learners who are unable to accurately demonstrate cognitive and metacognitive processes have greater learning gains when control over their actions is restricted (Sabourin et al., 2013). For the second research question, we hypothesized that types of informational text presentations containing text and diagrams (e.g., NPCs, posters) will positively predict normalized change scores, as CTML states that learning with text and diagrams will increase learning compared to one informational presentation. For the third research question, we first hypothesized that participant interactions captured using process data will differ across text presentations, where participants will spend more time on rich scientific text provided by books, or books that were text-dependent and provided more information on a single, complex topic. Secondly, we hypothesized that participants in the partial agency condition will have greater durations on informational text than those in the full agency condition. Lastly, for the fourth research question, we hypothesized that participants in the partial agency condition will demonstrate greater durations and fixation durations on informational text presentations across pretest-relevant presentations than those in the full agency condition. This is supported by previous literature (Mayer, 2014; Sabourin et al., 2013) as learners who are provided scaffolding will demonstrate a greater ability to identify and select relevant information compared to those with no support.

Methods

Participants and Materials

A sample of 120 undergraduate students were recruited from a large North American public university and participated in this study to learn about microbiology with a GBLE. However, only

105[2] undergraduate students (68.7% female), split between three conditions, full agency (*N* = 48), partial agency (*N* = 35), and no agency (*N* = 32) were included in our analyses due to missing data points, and measurement errors (e.g., eye-tracking calibration errors). The no agency condition is included only in specific research questions due to the nature of the condition itself, the data that is available for the condition, and the nature of the research questions. Ages ranged from 18 to 29 (*M* = 20.0, *SD* = 1.80).

Upon written consent, participants were administered a range of questionnaires before learning with the GBLE, which included demographics questions to gauge age, gender, ethnicity, and familiarity with video games (e.g., type of game, weekly length of play time) and self-report questionnaires to capture participants' emotions and motivation. We do not provide additional information about these scales to maintain concision in this paper as these data were not included in our statistical models. After participants answered the demographics and self-report items, they completed a 21-item, 4-option multiple-choice microbiology pre-test developed by a domain expert. These items addressed a range of topics such as the shape of a cell to identifying a genetic disease given a list of symptoms. All information measured on the pretest was provided in CRYSTAL ISLAND through various informational sources such as dialogue with NPCs (see Figure 3) and reading books (see Figure 4) and posters (see Figure 5). After participants finished the objectives of the game, they were immediately administered another set of questionnaires to gauge self-efficacy for learning science, emotions, and motivation. Additionally, we administered a similar 21-item, 4-option microbiology posttest to capture knowledge gained after learners interacted with the GBLE. We excluded one pre- and posttest item from our analyses since we operationalized actions based on their relevance to pre-test items and one of the corresponding

[2] In the original AIED 2019 paper (i.e., Dever & Azevedo, 2019a) we reported on 90 participants originating from the same study.

pretest items has conflicting information provided in the game. For example, participants could gather information about the reproduction of bacteria and viruses, but while one book provides the correct answer (i.e., bacteria can produce sexually or asexually), a poster and book both state a different answer (i.e., bacteria reproduce asexually). The question, when referring to the correct information regarding viral and bacterial reproduction, does not provide a correct answer. Therefore, this question was excluded from both pre- and posttests and a total score out of 20 was modified for these analyses.

CRYSTAL ISLAND Environment

CRYSTAL ISLAND (Rowe et al., 2011), a narrative-centered GBLE, encourages learners to develop scientific-reasoning and problem-solving skills along with learning microbiology. Learners within this environment are charged with diagnosing fellow researchers on a remote island who have contracted a mysterious illness by interacting with different elements (see Figure 4) provided by the environment. To solve the mystery, learners must provide the name (e.g., influenza, salmonellosis), source (e.g., bread, milk, eggs), and treatment (e.g., rest, vaccination) of a disease to complete the game. Once on the island, learners converse with non-player characters (NPCs) who provide information for either solving the mystery (e.g., symptoms) or information related to domain content knowledge, (e.g., the size of bacteria). Learners are also provided informational content in the form of books and research articles scattered around the island which contain blocks of text related to domain knowledge and may be used to complete the game. These books and research articles contain concept matrices which are used as performance measures, testing on the information from the corresponding text. Posters within CRYSTAL ISLAND provide short, sometimes uninformative, text and visuals that may coincide with the mystery of CRYSTAL ISLAND or the domain knowledge. For example, a poster may show an example of bacteria or virus structures with labels indicating the location of these structures. Often, the posters redundantly overlap information presented in books and research articles or conveyed by NPCs. Other tools and elements in CRYSTAL ISLAND include a scanner to hypothesize the disease and test food items to see if that disease is present. Learners are also given a diagnostic worksheet which allows for the documentation of symptoms, likeliness of the correct diagnosis to be a certain disease, and results from the scanning process. All items are necessary to complete the game.

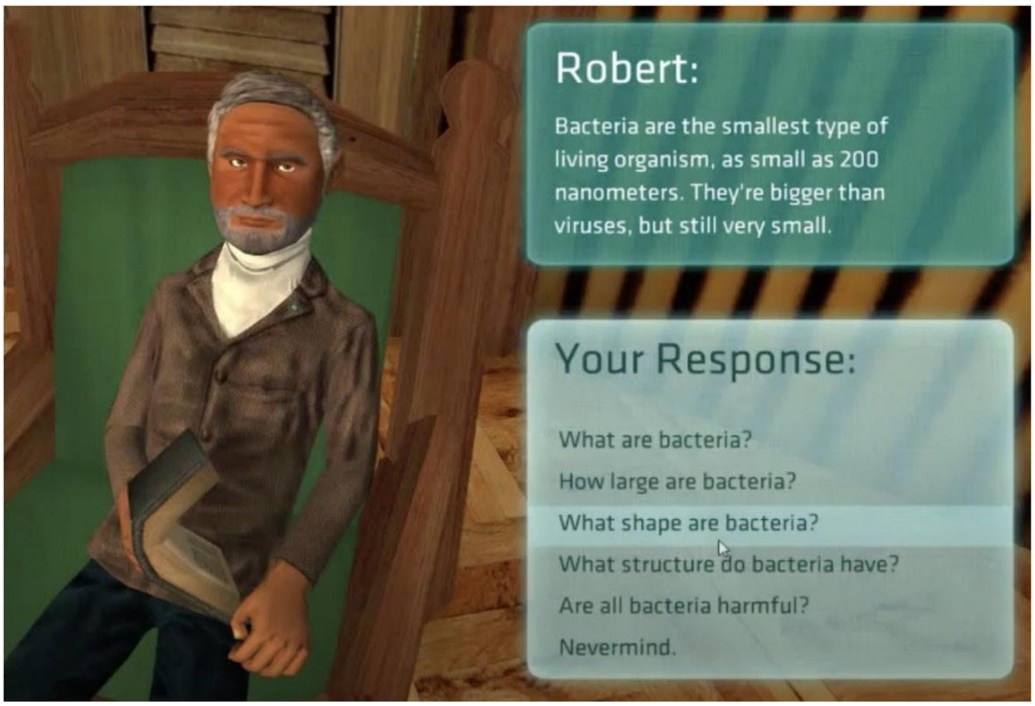
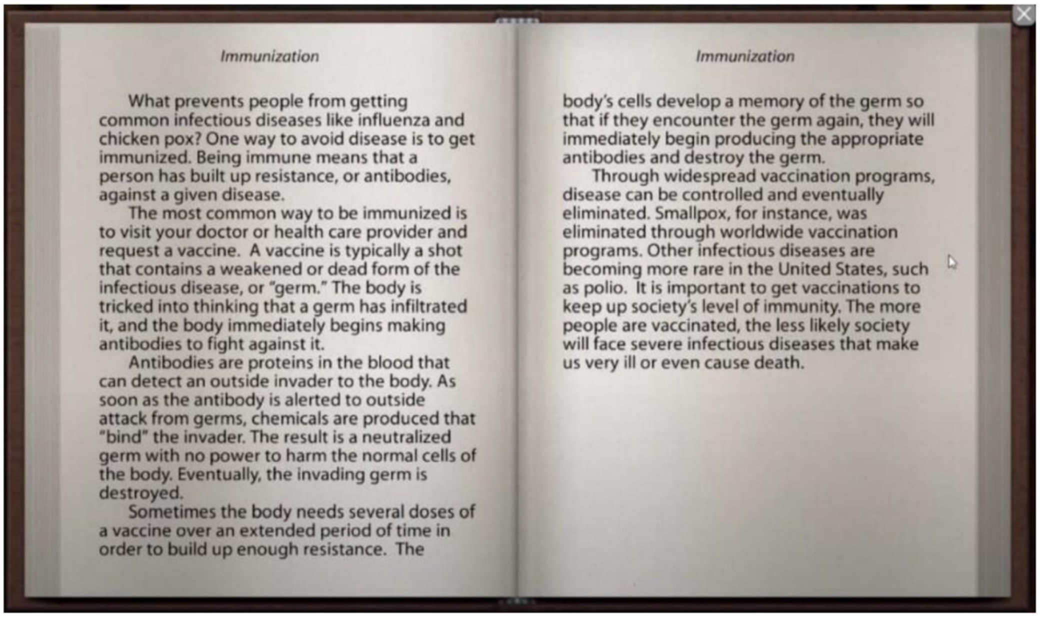


Figure 3: Example of an NPC in CRYSTAL ISLAND.


Immunization

What prevents people from getting common infectious diseases like influenza and chicken pox? One way to avoid disease is to get immunized. Being immune means that a person has built up resistance, or antibodies, against a given disease.

The most common way to be immunized is to visit your doctor or health care provider and request a vaccine. A vaccine is typically a shot that contains a weakened or dead form of the infectious disease, or "germ." The body is tricked into thinking that a germ has infiltrated it, and the body immediately begins making antibodies to fight against it.

Antibodies are proteins in the blood that can detect an outside invader to the body. As soon as the antibody is alerted to outside attack from germs, chemicals are produced that "bind" the invader. The result is a neutralized germ with no power to harm the normal cells of the body. Eventually, the invading germ is destroyed.

Sometimes the body needs several doses of a vaccine over an extended period of time in order to build up enough resistance. The body's cells develop a memory of the germ so that if they encounter the germ again, they will immediately begin producing the appropriate antibodies and destroy the germ.

Through widespread vaccination programs, disease can be controlled and eventually eliminated. Smallpox, for instance, was eliminated through worldwide vaccination programs. Other infectious diseases are becoming more rare in the United States, such as polio. It is important to get vaccinations to keep up society's level of immunity. The more people are vaccinated, the less likely society will face severe infectious diseases that make us very ill or even cause death.

Figure 4: Example of a book in C*RYSTAL* I*SLAND.*

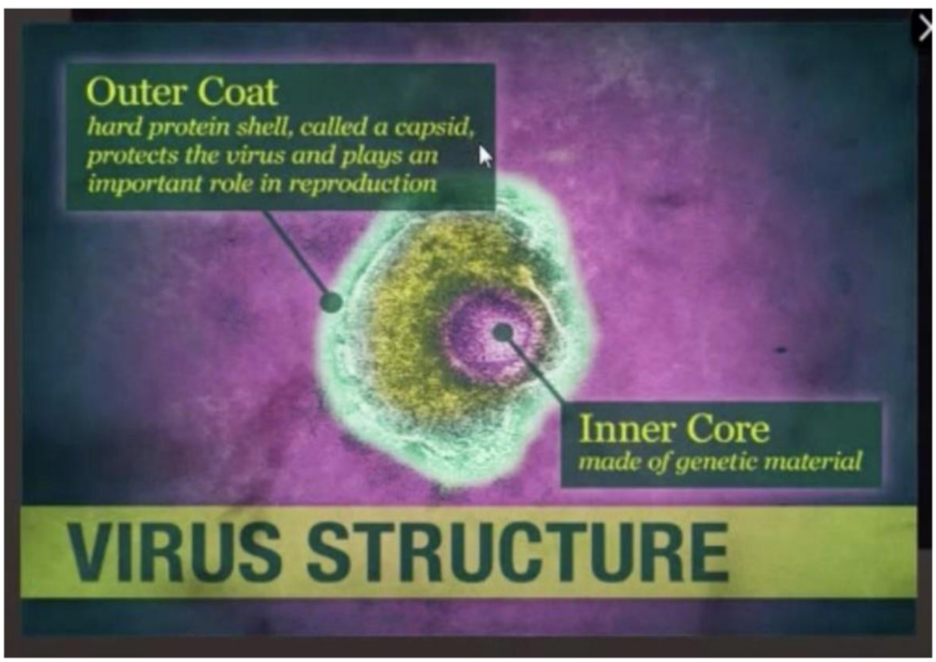


Figure 5: Example of a poster in C*RYSTAL* I*SLAND.*

Experimental Conditions

Participants were randomly assigned to one of three conditions after giving informed consent. Each of the conditions differed in level of autonomy participants were afforded during learning with CRYSTAL ISLAND. Specifically, the (1) *full agency* condition allocated complete autonomy to participants such that they could initiate any actions without constraints during learning. These actions included selecting elements to interact with such as books and research articles and testing food items when the participants wished, whereas the (2) *partial agency* condition set constraints on participants' actions by establishing a "ideal" path that participants were required to follow in order to complete the game. For example, participants were required to visit buildings in a specific sequence aimed at maximizing informational content acquisition (e.g., going to a building with information about influenza and then another building to talk with a non-player character about the symptoms of influenza). In the (3) *no agency* condition, participants watched a playthrough of the game using a third-person perspective without interacting with the game elements such as books and research articles or control the playthrough video (e.g., play, pause). This restricted any autonomy as participants learned with CRYSTAL ISLAND. These conditions were developed to represent the varying levels of autonomy that may be present throughout a GBLE to implicitly scaffold learners as they interact with the environment. As with most GBLEs, the full agency condition within CRYSTAL ISLAND represents the state of most GBLEs and how learners typically interact with these learning environments. Within this condition, participants are not provided any scaffolding while selecting and reading informational text presentations. Conversely, the partial agency condition implicitly scaffolds learners as they directly interact with the environment. The no agency condition did not allocate any level of autonomy to the participants as they learned with CRYSTAL ISLAND, and conversely did not serve as an implicit scaffold or directly support the participant. As such, we did not include participants in the no agency condition in parts of our analyses, but we include information about the conditions for replicability purposes.

Between the full and partial agency conditions, there were differences in their time on task. On average, participants in the full agency condition completed the game within 80.47 (*SD* = 19.97) minutes, while those assigned to the partial agency condition completed the game in 93.74 (*SD* = 15.71) minutes. While participants within different conditions differed in their time on task, they were not constrained in the time they could spend within their environment. In addition, total time in game accounts for multiple actions including editing the worksheet, completing concept matrices, and scanning food items. As such, total time on task was not considered as a covariate for the analyses, but rather the proportion of time spent on informational text presentations and the frequency of interactions learners had with NPCs, books and research articles, and posters (see Preliminary Analyses).

Apparatus

In this study, we captured eye-gaze behaviors and log files of each participant. An SMI RED250 eye tracker was used to collect participants' eye gaze behavior. Participants were calibrated using a 9-point calibration. This eye tracker was screen-based which sat at the bottom of the computer screen and had a sampling rate of 250 Hz which recorded 250 samples per second. Data from this eye tracker provided fixations, fixation durations, and regressions which where based off of predetermined areas of interest (AOIs). Log files were captured using information from the mouse and keyboard. This included the selection, or mouse clicks, of certain elements and objects in the CRYSTAL ISLAND environment, the time spent within one element (i.e., duration), and the movement of the participant throughout CRYSTAL ISLAND.

Participants' facial expressions of emotion and electrodermal activity (EDA) were identified using facial recognition of emotion software, implemented using iMotions FACET software run through Attention Tool 6.3 (iMotions Attention Tool, 2016), and a physiological bracelet respectively. Data from the facial recognition and EDA bracelet were collected using Attention Tool 6.3 and analyzed using the baseline from each participant. The emotion recognition software analyzed 10 different emotions (e.g., happiness, sadness, confusion, anger, etc.) as participants interacted with CRYSTAL ISLAND. The EDA bracelet collected participants' skin conductance and heart rate. These data were collected, but not used for the analyses in the current study as the interpretation of these data and their units of measures were out of the paper's scope.

Experimental Procedure

Upon entering the laboratory setting, a researcher greeted participants and instructed them to sit in front of a complete to complete a series of questionnaires such as demographics questions and multiple self-report scales as well as a microbiology pretest to capture prior knowledge of the domain. Self-report scales included the Achievement Emotions Questionnaire (Pekrun et al., 2011) and the Achievement Goals Questionnaire (Elliot & Murayama, 2008). Participants spent approximately 35 min to complete the pretest measures. Once the measures were completed, participants were calibrated to the SMI EYERED 250 eye tracker using a 9-point calibration to accurately measure individual eye-gaze behaviors. Next, participants were instructed to express a neutral facial expression and remain calm during calibration to the facial recognition of emotions software and electrodermal bracelet to determine a baseline that were captured using the Attention Tool 6.3 (see Figure 6 of participant set up). After successful calibration, participants started learning with CRYSTAL ISLAND. Upon starting the game, participants were told that to complete the game, they needed to accurately diagnose the mystery illness plaguing the research camp and provide an appropriate solution treat the disease (e.g., influenza). The importance of searching for clues using the various tools (e.g., books, research articles, conversing with non-player characters) provided to participants during game-based learning were emphasized during the tutorial phase of the game. As participants interacted with elements in CRYSTAL ISLAND, we captured their process data that ranged from eye movements (e.g., fixation and saccades), facial expressions of emotions (e.g., neutral, joy, frustration), and log files (e.g., time spent engaging in actions). After participants completed the game by providing the correct treatment solution to the mystery illness, they were administered a posttest to measure differences in microbiology knowledge. After participants finished the task, we administered several self-report questionnaires which addressed different concepts (i.e., motivation, interest) than those administered for the pretest. Posttests included the Intrinsic Motivation Inventory (Ryan, 1982), Perceived Interest Questionnaire (Schraw et al., 1995), and the Presence Questionnaire (Witmer & Singer, 1998). Collectively, participants completed posttest measures in approximately 35 min. The pre- and posttest self-report scales were not considered as this study did not examine emotions, motivation, or self-efficacy, but directly questioned how process data measured through eye tracking and log files are utilized in understanding participant interactions with game elements. Afterwards, the researcher debriefed, compensated $10/h (up to $30), and thanked the participants for their time.

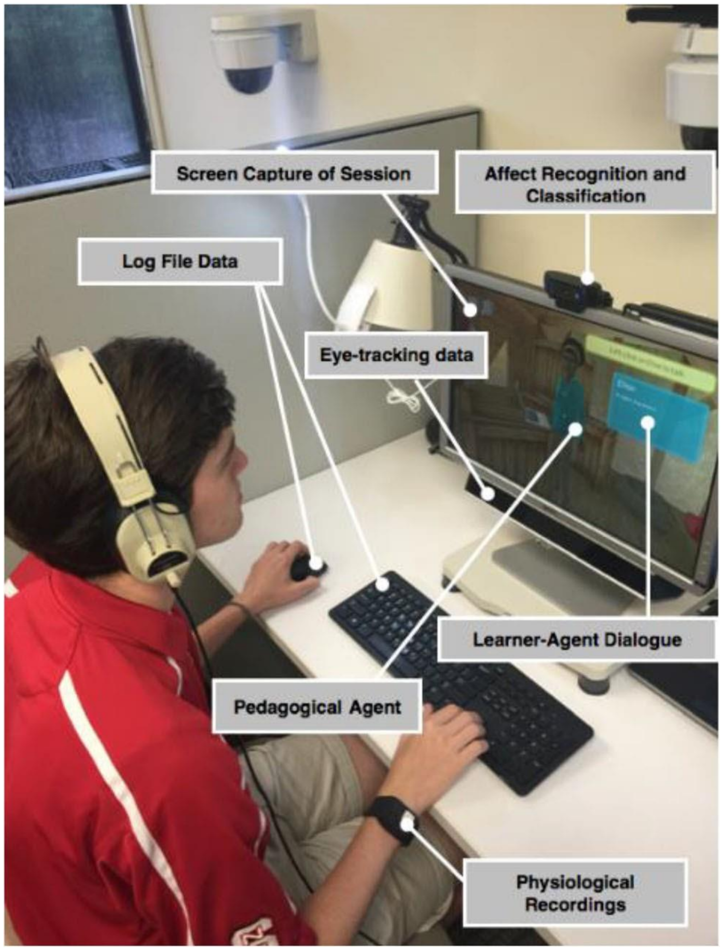


Figure 6: Experimental set-up illustrating instrumented participant.

Apparatuses

This study utilized an SMI RED 250 eye tracker to record participants' eye movements with a sampling rate of 60 Hz. The SMI RED 250 eye tracker is capable of a 250 Hz sampling rate, however, to be integrated with iMotions Attention Tool, the sampling rate was set lower. With a 9-point calibration, the gaze position accuracy had an expected error of 0.4 visual degrees from the target and a spatial resolution of 0.03°. The webcam was used to record participants' facial expressions (not used in this study) at 30Hz and 1080p to be automatically coded for facial affect presence by iMotions FACET. Finally, the Shimmer 3+ wireless bracelet was used to collect participants' skin conductance (not used in this study) with a 128Hz sampling rate. All data streams were collected and aligned with iMotions Attention Tool 6.2 software (iMotions Attention Tool, 2016; see Figure 2 for example experimental set up).

Coding and Scoring

Types of Informational Text Presentations

CRYSTAL ISLAND presents information in three different ways: (1) informative text with an uninformative visual (i.e., the visual does not add additional information that is not already provided in the text such as text on influenza with a picture of red blood cells), (2) informative text with no visuals (e.g., books and research articles), and (3) interchangeably informative and uninformative text and visuals (e.g., text and visuals that do not address items on pre- and posttest content knowledge measures vs. text and visuals that directly address items on pre- and posttest content knowledge measures). NPCs also convey information that discuss domain knowledge. We characterized NPCs as interactions that contain both visuals and text. However, the visuals are the depiction of the NPC themselves where there is no information that is conveyed by the visual alone. The text serves as a dialogue between the NPC and the participant where the participant selects a predefined prompt pertaining to domain-specific content (e.g., "What is the smallest type of living organism?") and the NPC will respond via text and audio information related to the prompt. We operationalized books and research articles as text with no supporting visuals. Posters varied by how informative the information was to the participant. For example, the visuals provided in one poster may have conveyed information useful for acquiring domain knowledge (e.g., visual and supporting text of a cell wall) while another contained a visual with no related information to the domain (e.g., picture of a rainbow). We classified three types of presentations used during learning with CRYSTAL ISLAND: (1) NPCs (i.e., informative text with uninformative visuals), (2) books and research articles (i.e., informative text with no visuals), and (3) posters (i.e., informative text with a combination of informative and uninformative visuals).

Pretest Relevancy of Items

The individual items (e.g., specific book or NPC) of the different types of informational text presentations were separated into categories based on their relevance to items on the pretest. For example, the pretest question "What is the smallest type of living organism" is addressed by an NPC named Robert who explains that, "Bacteria are the smallest type of living organism." This directly addresses the question, and therefore, interactions with Robert were labeled as relevant to the pretest. Between a total of 40 informational presentations, 47.5% of all types of presentations were relevant to pretest items (see Table 1Table 1. Pretest Relevancy Item Per Type of Presentation). This categorization stems from priming literature (e.g., McNamara, 2005) and assumes that participants should be more likely to identify information that relate to pretest answers as instructionally relevant as the learners have been pre-exposed to topics needed to successfully complete the posttest.

Table 1.
Pretest Relevancy Item Per Type of Presentation

Type of Presentation	Total Pretest-Relevant	% of Pretest-Relevant
NPCs	9	3
Books & Research Articles	21	12
Posters	10	4
All	40	19

Normalized Change Scores

Learning gains from pretest to posttest were calculated using normalized change scores based on each participant's pretest and posttest scores to mitigate learners' pretest score biases

(Marx & Cummings, 2007). The normalized change scores captured changes in domain knowledge during the learning session with CRYSTAL ISLAND while controlling for the level of prior domain knowledge to ensure the scores were not biased towards participants who had greater prior knowledge about microbiology. Normalized change scores were calculated using Equations 1 – 3 depending on the difference between the pre- and posttest scores:

$$Normalized\ Change = \frac{post - pre}{100 - pre} \tag{1}$$

$$Normalized\ Change = 0 \tag{2}$$

$$Normalized\ Change = \frac{post - pre}{pre} \tag{3}$$

Equation 1 was applied when posttest scores were greater than pretest scores (i.e., the participant had more correct answers after the learning session and this included 70 [84%] participants in our sample). Equation 2 was applied when participants received the same score on the pretest and posttest (6 or 7% of the sample). Equation 3 was applied when participants had lower posttest scores relative to their pretest scores (7 participants or 8% of the sample). One participant with a normalized change score of 1 was removed from analyses as they were the only participant to receive a 100% on the posttest and which may have been caused by the ceiling effect (see Marx & Cummings, 2007). The normalized change score was used in order to contextualize learning gains.

Eye-Tracking Data

Eye-tracking was used to identify fixation durations on AOIs (e.g., time spent fixating on text in books and research articles). In this study, we created predefined AOIs around the posters, books, research articles, and NPC visual/dialogue combined to identify the length of time participants fixated on the specific informational text presentations. A fixation in this study was operationally defined as a relatively still gaze on an AOI for a minimum of 250 ms (Salvucci & Goldberg, 2000; see **Error! Reference source not found.**). The fixation durations in this study u sed seconds as a unit of measurement. **Error! Reference source not found.** provides visualizations of AOIs and fixations. The AOIs are represented by the colored shading over the NPC, dialogue box, book, and poster. The numbered circles show the order in which the fixations on AOIs occurred as well as a relative fixation duration indicated by the size of the indicator where a greater fixation duration is depicted by a larger circle.

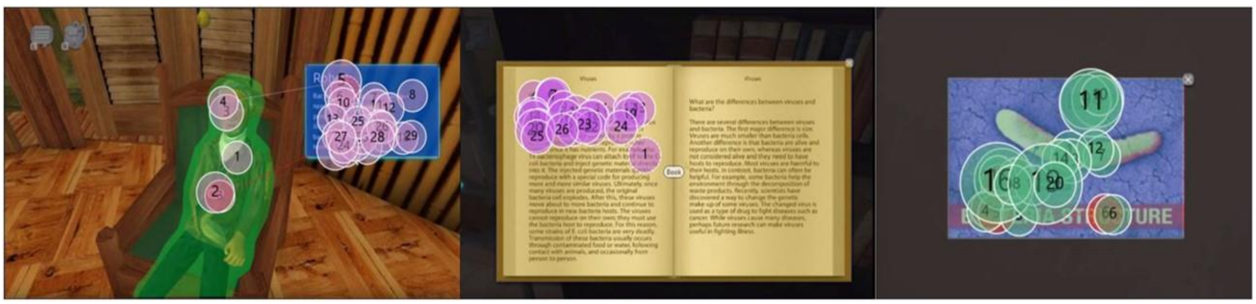


Figure 7: Example visualizations for NPCs, books, and posters.

Log-File Data

We used log-file data sequence and duration of participant interactions with game elements during learning with CRYSTAL ISLAND. Through these data, we identified different paths learners took and how they interacted with different game elements (i.e., books vs. NPCs). Specifically, when participants selected a poster, book, research article, or NPC, we captured and analyzed the frequency and time (in seconds) spent interacting with each of these game elements. Within this study, references made to log-file and eye-tracking data pertain to durations and fixation durations respectively. The differentiation between these two types of data are important in the connotation of cognitive processes that are represented by each. Log-file data indicate the opening and closing of an informational source (e.g., book). This denotes the selection process and the time spent within this source. Alternatively, eye-tracking data identifies fixations on the content of the source where this accounts for the participant looking off-screen or fixating on objects other than the content. As such, eye tracking denotes reading interactions whereas log files indicate overall time generally interacting with the object.

Outlier Removal

Outliers in the eye-tracking and log-file data were identified using boxplots and subsequently removed from the dataset. A total of 10 observations from the dataset containing 4779 observations from all 83 participants were removed, resulting in a total of 4769 observations between all participants.

Statistical Pre-Processing and Analysis

Data processing and analyses were completed using statistical programs Python (Python Core Team, 2015) and R (RStudio Team, 2018). Process data for analyses were collected and cleaned using Python. R was used to conduct statistical analyses. A three-level model used for this study was run using the ‘lmer’ and further analyzed with the ‘analyze’ functions using the ‘lme4’ (Bates et al., 2015) and ‘psycho’ (Makowski, 2018) packages in R respectively.

Model Selection

The fitted three-level model uses three levels to explain differences in the data (see Figure 8). This study utilized two models containing the same category of levels for each type of process data (e.g., eye-tracking, log-file). The third level for both models contains the participants who are separated based on their condition assignment. The second level contains the relevancy of level 1, types of informational text presentations, to answering the pretest items. The first level contains either the duration (captured from log files) or fixation duration (captured from eye-tracking) of the text, separating the two three-level models in terms of which process data each address. We identify the first level as being nested within pretest relevancy and the second level as being nested within participants. Maximum likelihood was used to fit both models to the data. From 83 participants, a total of 4769 observations were used to fit both models.

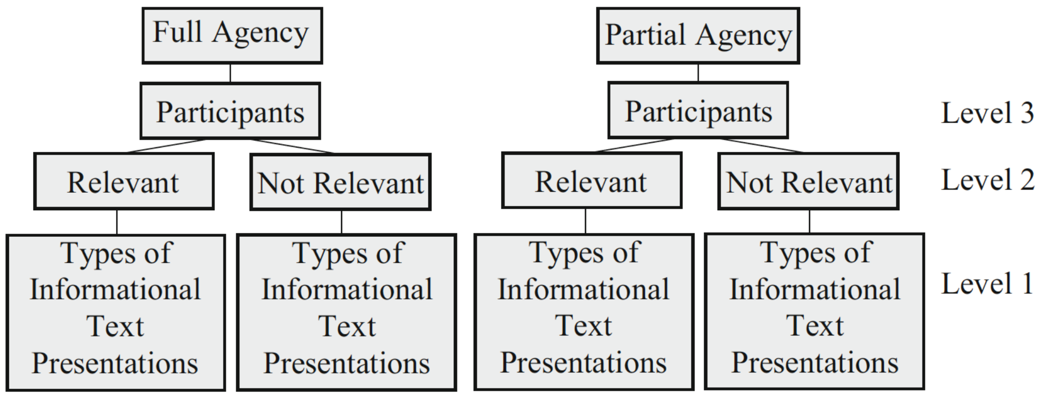


Figure 8: Selected three-level model.

Results

Preliminary Analyses

Preliminary analyses examined whether there were differences between informational text presentation process data to justify the analyses and interpretation of multiple types of data. Three paired t-tests were run to examine whether there were differences in the log-file and eye-tracking data between the types of presentations (see Table 2 for descriptive statistics). There was a significant difference, $t(1,82) = 6.73$, $p < .0001$, in the participant interactions with NPCs, where the durations of these instances were, on average, less than the fixation durations. Another paired t-test found a significant difference ($t(1,82) = 2.87$, $p < .01$) in participant interaction with books and research articles where participants had greater durations than fixation durations on these types of informational presentations. The third paired t-test identified differences in the types of data on posters ($t(1,82) = -12.0$, $p < .0001$) where, on average, durations were smaller than fixation durations.

Table 2.
Descriptive Statistics of Preliminary Analyses of Log-files and Eye-tracking Data

Type of Informational Text	Log-file		Eye-tracking	
Presentation	*M*(sec)	*SD*(sec)	*M*(sec)	*SD*(sec)
NPCs	529.4	103.0	625.0	155.6
Books & Research Articles	1829.5	554.3	1680.5	825.8
Posters	80.4	34.8	121.3	53.8

In sum, these preliminary findings suggest that there are significant differences in log-file and eye-tracking data regarding informational presentations in the CRYSTAL ISLAND environment. From these findings, we may not conclude that the cognitive and metacognitive processes measured from log-file and eye-tracking data can be interchangeably modeled. For example, because we see that fixation duration on books and research articles were shorter than the log file durations of when these were open on the screen, it might suggest participants were fixating elsewhere on the screen or distracted from reading. The fixation durations for NPCs and posters were longer than the log file durations. This suggests that participants fixated on the NPCs and posters before selecting the NPC to talk to or the poster to read. As such, this suggests that log files may be a more accurate measure of participant interaction with information whereas eye tracking may be a more accurate measure of intention. Therefore, we must keep the log-file and eye-tracking data distinct in the further analyses to correctly understand and interpret how each channel of data contributes to participants' internal processes, external constraints, and subsequent interactions with the GBLE.

To address the presence of covariates within this study's analyses, learners' proportion of time spent on collecting information from NPCs, books and research articles, and posters as well as the frequency of these interactions are compared between conditions. First, two t-tests for log-file and eye-tracking data were run to examine how conditions differed in their proportion of time spent collecting all information during their time within the environment. There were no differences between the full (*M* = 0.46, *SD* = 0.07) and partial (*M* = 0.50, *SD* = 0.07) agency conditions for duration proportion, $t(85.3) = 0.94$, $p > .05$. Similarly, full (*M* = 0.46, *SD* = 0.14) and partial (*M* = 0.49, *SD* = 0.16) agency conditions did not differ in their proportion of fixation durations, $t(96.8) = 0.90$, $p > .05$. Overall, the proportion of time collecting information does not vary between conditions.

Further analyses examined how conditions differed in their interactions with informational text presentations. Participants' interactions with informational text presentations were determined by the amount of control they were allowed within CRYSTAL ISLAND where participants in the partial agency were required to interact with all informational text presentations and those with full agency were not limited in their interactions. Three chi-squared tests were conducted to identify if participants differed in their informational text presentation frequency. Conditions did not vary in their frequency of NPC ($\chi^2 = 19.3$, $p > .05$), book and research article ($\chi^2 = 36.7$, $p > .05$), and poster ($\chi^2 = 17.5$, $p > .05$) interactions (see Table 3). Overall, condition did not influence the frequency with which learners interacted with informational text presentations.

Table 3
Frequency of Informational Text Presentations between Conditions

Type of Informational Text Presentation	Full Agency		Partial Agency	
	M	*SD*	*M*	*SD*
NPCs	18.7	5.98	19.9	5.23
Books & Research Articles	22.2	6.77	27.3	7.66
Posters	13.2	4.51	15.1	4.29

Research Question 1: Do Prior Knowledge and Learning Gains Significantly Differ between Learners with Varying Levels of Autonomy?

For this research question, we included the no agency condition ($N = 32$) in addition to the full and partial agency conditions to analyze how participants with no autonomy learn with CRYSTAL ISLAND in comparison to participants afforded autonomy. We ran two ANOVAs for differences in both prior knowledge and normalized change scores between the three conditions. Results indicate that participants between each condition did not differ in their prior knowledge, $F(2,112) = 2.37$, $p > .05$. Further results indicated that those in the partial agency condition ($M = 0.45$, $SD = 0.27$) had significantly higher normalized change scores than those in the full agency condition ($M = 0.32$, $SD = 0.26$; $t(1,71.1) = 2.20$, $p = 0.03$) and participants in the no agency condition ($M = 0.12$, $SD = .26$; $t(1,64.8) = 5.14$, $p < .0001$; see Figure 9). Participants with full agency had significantly greater normalized change scores than those in the no agency condition, $t(1,65.6) = 3.46$, $p < .001$. Overall, participants did not differ in prior knowledge between groups but did show a difference in their normalized change scores, with the partial agency condition learning more than learners with full and no autonomy. This suggests participants who were given restricted control (but therefore more scaffolding) over their choice of interacting with NPCs, read books and research articles, and consult posters in the environment had a significantly greater learning outcomes than those given complete control or no control over their actions in the environment.

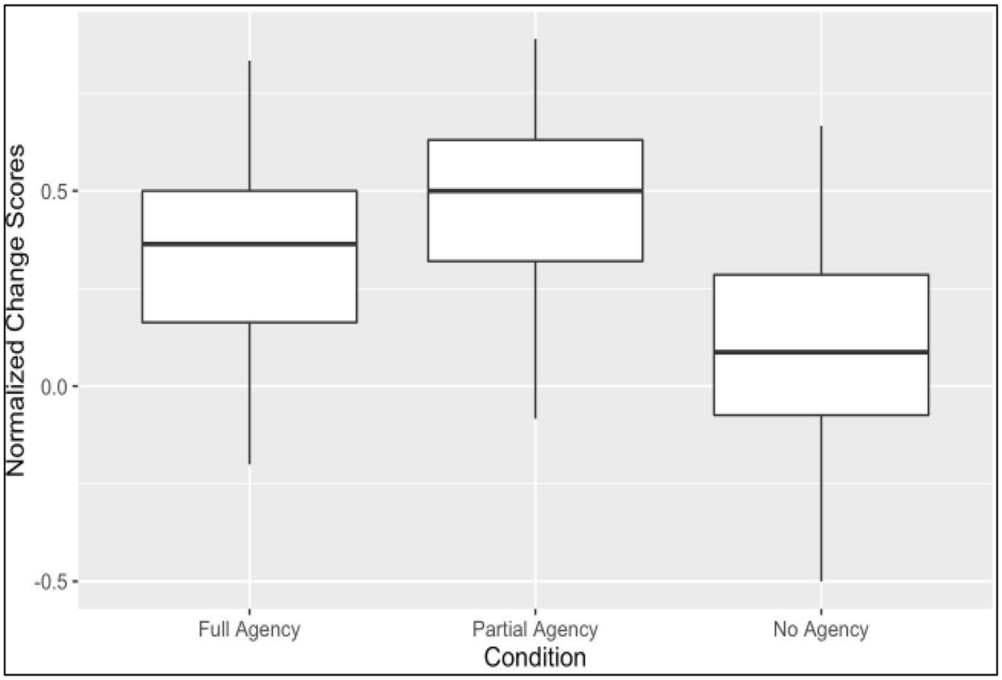


Figure 9: Visualization of normalized change score differences between conditions.

Research Question 2: Do Learners' Process Data for Each Type of Informational Text Presentation Predict Learning Gains?

Log-File Data

We first ran Pearson correlations for the participants' total content durations on each of the text presentations and normalized change scores (see Table 3). While total durations on NPCs and posters were not correlated with normalized change scores (p > .05), the total duration on books and research articles are significantly correlated with participants' normalized change scores, $r(83)$ =0.27, p = 0.02. In other words, the time a participant spent on books and research articles was significantly related to their learning.

A simple linear regression was calculated to identify if the total duration on books and research articles could predict participants' normalized change scores while controlling for participants' individual book and research article frequency and their proportion of time interacting with each type of informational text presentation. While durations on books and research articles are correlated with learning gains, when controlling for participants' frequency of book and research article interactions, these durations are unable to predict participants' normalized change scores.

Eye-Tracking Data

We calculated Pearson correlations for the participants' total content fixation durations on each of the text presentations and normalized change scores. Similar to the log-file data correlations, fixation durations on books and research articles was significantly correlated with participants' normalized change scores, $r(83) = 0.24$, $p = 0.03$, while fixation durations on NPCs and posters were not, $p > .05$. We calculated a simple linear regression to identify if total fixation duration on books and research articles could predict participants' normalized change scores while controlling for participants' book and research article frequency and their proportion of time interacting with each type of informational text presentation. While fixation durations on books and research articles are correlated with participants' normalized change scores, when controlling for participants' frequency of book and research article interactions, participants' fixation durations on these types of text presentations are unable to predict their learning gains ($p > 0.05$).

In sum, log-file (durations) and eye-tracking data (fixation durations) on books and research articles are significantly correlated with participants' normalized change scores in participants' while NPCs or posters are not. However, process data are not predictive of participants' normalized change scores. From these analyses, we question if participants' interactions with text presentations measured by process data is related to the quality of the information within the NPCs, books and research articles, and posters and the autonomy participants are afforded within the environment.

Research Question 3: Do Learners' Varying Levels of Autonomy Influence How Learners Interact with Each Type of Informational Text Presentation?

Two separate two-way repeated measures ANOVAs for log-file and eye-tracking data were run to analyze if there were significant differences between full and partial agency conditions and within the different types of informational text presentations. For these analyses, condition containing two levels (i.e., full agency, partial agency) represent the between-subjects effect while the type of informational text presentation is the between-subjects factor with each level (i.e., NPCs, books and research articles, posters) are repeatedly measured for each participant as they complete the game.

Log-File Data

A two-way repeated measures ANOVA was run to identify the differences between condition within the different types of informational text presentations using logfile durations as an outcome variable. Results indicated a significant main effect of condition, $F(1,81) = 21.2$, $p < .0001$, and type of informational text presentation on durations, $F(2,162) = 813.0$, $p < .0001$. Results for the content durations yielded a significant interaction value, $F(2,162) = 11.5$, $p < .0001$, between the condition and the type of information presentation. Post-hoc pairwise comparisons of the within-subjects factor supported significant differences between the content durations (i.e., types of text presentation; $p < .0001$). Specifically, participants interacted with books and research articles (M = 1829.5 s, SD = 554.3 s) for a longer duration than NPCs (M = 529.4, SD = 103.0) and posters (M = 80.4 s, SD = 34.8 s). All post- hoc pairwise comparisons of the interaction effect (condition and type of text presentation) indicated significant results using a Bonferroni correction ($p < .017$; see Table 4) where participants in the partial agency had greater durations than those in the full agency condition.

Table 4.
Descriptive Statistics and Post-hoc Comparisons of Each Process Data

Process Data	Type of Presentation	Full Agency		Partial Agency		t
		M(sec)	SD(sec)	M(sec)	SD(sec)	
Log-file	NPCs	491.6	101.1	581.1	81.7	−46.8*
	Books & Research Articles	1643.3	526.8	2084.0	491.4	−30.1*
	Posters	63.9	29.9	103.2	27.6	−20.9*
Eye-tracking	NPCs	584.3	155.0	680.8	140.2	−36.6*
	Books & Research Articles	1513.8	727.6	1909.1	905.4	−18.5*
	Posters	105.3	55.7	143.4	42.7	−20.5*

*$p < .0001$

Eye-Tracking Data

A two-way repeated measures ANOVA was run to identify the differences between condition within the different types of informational text presentations using eye-tracking fixation durations as an outcome variable. Findings indicated a significant relationship between fixation duration and condition, $F(1,81) = 6.92$, $p < .05$, as well as type of informational text presentation, $F(2,162) = 261.2$, $p < .0001$. Results for content fixation durations yielded a significant interaction value, $F(2,162) = 3.70$, $p < .05$, between the condition and the type of information presentation. Pairwise comparisons supported significant differences between the content durations of the within-subjects factor (i.e., types of text presentation; $p < .0001$) where fixations on books and research articles (M = 1680.5 s, SD = 825.8 s) are greater than those on NPCs (M = 625.0 s, SD = 155.6 s) and posters (M = 121.3 s, SD = 53.8 s). Post-hoc analyses with a Bonferroni correction ($p < .05$) identified significant pairwise comparisons between the levels of each factor (see Table 4) where those in the partial agency tended to have greater fixations on each type of presentation than those in the full agency.

In sum, log-file and eye-tracking data report similar findings where there are differences in the durations and fixation durations between conditions themselves, indicating that the total duration and fixation duration spent interacting with informational material in the environment differs between condition where participants in the partial agency had consistently greater durations and fixation durations than those in the full agency (see Table 4). When we introduce the type of presentation as a within-subjects factor, we can identify differences in the time spent and fixated on different types of presentations between the two conditions.

Research Question 4: Do Learners' Varying Levels of Autonomy and Relevancy of Informational Text Influence How Learners Interact with Each Type of Presentation?

Conditional three-level growth models were run for process data (Figure 10).

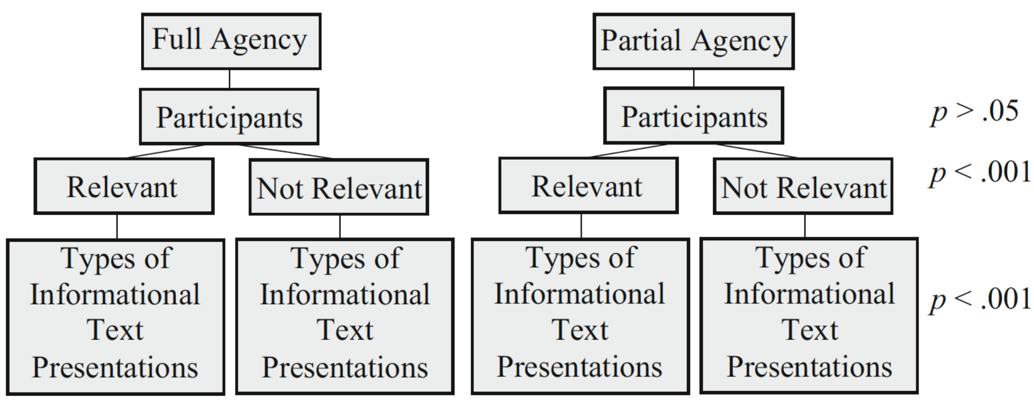


Figure 10: Three-level model used for process data.

Log-File Data

The first model examining differences in duration failed to converge, meaning that the model that was run does not fit the data well. Therefore, we disregarded this model for further analyses in order to accurately interpret the effects of condition, support of the pretest, and type of informational text presentations.

Eye-Tracking Data

The second model examining differences in fixation durations has a total explanatory of 40.16% where we may then examine the effects of the type of informational text presentations, relevance of the pretest questions, condition, and their interaction with each other. The relevancy of pretest questions significantly contributes to this model, $t(4686) = 11.3$, $p < .001$; std. $\beta = 0.62$. There is a significant difference between groups of pretest relevancy where participants fixated significantly more on pretest-relevant texts ($M = 50.5$ s, $SD = 58.3$ s) than pretest-irrelevant texts ($M = 35.1$ s, $SD = 48.2$ s), not accounting for the type of informational text presentation. In addition to this main effect and in support of previous analyses, books and research articles, $t(123) = 12.2$, $p < .001$; std. $\beta = 1.03$, and posters, $t(1377) = -4.36$, $p < .001$; std. $\beta = -0.23$, significantly contribute to the prediction of fixation durations (using NPCs as a reference variable), where fixation durations on books and research articles ($M = 69.0$ s, $SD = 65.3$ s), NPCs ($M = 32.6$ s, $SD = 37.1$ s), and posters ($M = 8.7$ s, $SD = 5.45$ s) significantly differ from each other. There is an interaction effect between types of informational text presentations and pretest relevancy (Table 5) where posters and pretest relevancy, $t(4687) = -7.36$, $p < .001$; std. $\beta = -0.62$, as well as books and research articles and pretest relevancy, $t(4615) = -10.5$, $p < .001$; std. $\beta = -0.77$, using NPC as a reference variable, significantly contribute to the model's overall explanatory power of fixation durations. Interestingly, condition does not significantly contribute to the overall model predicting fixation durations when separating informational text presentations based on their contribution and relevance to the pretest.

In sum, differences in durations are not able to be accurately identified through a complex model which takes into account repeated measures nested within multiple levels. Differences in fixation durations, however, are able to be identified within types of informational text presentations as well as whether or not the type of presentation item was relevant to information in the pretest that participants were exposed to prior to interacting with Crystal Island. Participants, regardless of autonomy afforded, interacted with more pretest-relevant text. However, looking at the descriptive statistics (see

Table 5), participants fixated longer on NPCs that were relevant to the pretest, but fixated for a greater period of time on books and research articles as well as posters which were not relevant to pretest answers. This could be used as a proxy addressing learners' competencies in metacognitive judgments where content evaluations were accurate relating to information provided by NPCs, but not information presented by the other types of presentations.

Table 5.
Descriptive Statistics of Pretest-Relevant Groups and Types of Informational Text Presentation Fixation Durations

Pretest Relevancy Group	Type of Presentation	*N*	*M*(sec)	*SD*(sec)
Relevant	NPCs	579	54.3	50.2
	Books & Research Articles	1150	66.3	65.3
	Posters	487	8.53	5.76
Not Relevant	NPCs	1101	20.2	17.4
	Books & Research Articles	871	72.6	65.2
	Posters	671	8.82	5.21

Discussion

In this study, we investigated types of informational text presentations and autonomy to assess the impact of learning and metacognitive process use within GBLEs captured through multiple types of data (i.e., eye-tracking, log-files). Preliminary results indicated that log-file and eye-tracking data significantly differed from each other when considering the overall time spent on different types of informational text presentations. Generally, eye-tracking data (i.e., fixation durations on AOIs) was found to have longer durations than those reported in log-files (i.e., durations of presentation instances) with the exception of book and research article interactions. Although seemingly contradictory, this is a result of the environment itself where learners could look at posters and NPCs before interacting with them as indicated by log files. This addresses the need for researchers to consider multiple types of data streams and analyses for different GBLE features. These preliminary analyses further suggest a need for future studies to examine which types of data accurately capture learner element interactions within GBLEs and learners' cognitive and metacognitive skills that are demonstrated through these interactions. However, based on the findings of the three-level model fit to durations and fixation durations, we suspect that fixation duration on posters, books, and research articles captured cognitive processes more accurately compared to log-file data, which captured cognitive processes during NPC interactions more accurately. Additional preliminary analyses confirmed that conditions did not differ in the proportion of time and the frequency of instances for each type of informational presentation. As a result, when conditions were compared, these factors were not included as covariates.

Overall Findings

Results from our first research question confirmed our hypothesis. There were no differences in the level of prior knowledge between all three agency conditions but suggested significant differences in learning gains between the conditions, where those with restricted control (i.e., in the partial agency condition) over their actions had higher learning gains compared to learners with full control. Learners with no agency had significantly lower learning gains than those in the full and partial agency conditions. This is partially consistent with previous research studies showing that limited autonomy within GBLEs increases learning outcomes (Bradbury et al., 2017; Sabourin et al., 2013). However, this emphasizes the need to moderate the autonomy afforded to learners where learners who are too restricted (e.g., no agency) and learners who have full control (e.g., full agency) exemplify that extreme levels of autonomy do not outperform learners with a moderate amount of control (e.g., partial agency). More specifically, this finding identifies autonomy, moreover restricted autonomy, as a scaffold which supports learning through directing learner interactions with informational content. As the availability of the text presentations within CRYSTAL ISLAND was consistent regardless of conditions, where learners were able to interact with the same amount of texts that share the same content, we must question why participants with total control over their actions did not engage with all information available to them through the environment.

Next, we investigated whether there were differences in the interactions of types of text presentations and how these presentations relate to overall learning between agency conditions. Results partially confirmed our hypotheses where time spent fixating and opening books and research articles were correlated with higher normalized change scores, while NPCs and posters do not. We initially expected that duration and fixation duration on types of text that contain both diagram and text would positively predict learning gains. The finding that fixation and fixation duration on NPCs and posters did not positively predict learning gains is misaligned with the CTML framework (Mayer, 2014). According to this framework, diagrams and text presented simultaneously, represented in this paper as NPCs and posters, were predicted to result in greater learning rather than books and research articles. Our results showed that even though durations and fixation durations on types of informational text presentations while controlling for proportion of time and frequency of interactions cannot predict learning gains, these process data for books and research articles are significantly correlated with learning gains. We posit that participants valued the context-rich information more than the presentation of a non-informative diagram alongside informative information. Future studies should examine if informative diagrams (e.g., physical symptoms of the illness) alongside relevant informative information (i.e., dialogue) are predictive of learning gains.

Our third research question investigated the differences in the duration and fixation duration between condition within types of informational text presentations. Findings confirmed our hypotheses and results suggested there were differences in total time spent on all text presentations and fixating on informational content between agency conditions, where learners with partial control over their actions (but consequently more scaffolding) consistently have greater durations and fixation durations on all types of presentations than those with full control. From the results, we see a difference in the overall time spent reading the types of informational text presentations where participants spent more time on books and research articles than any other presentation of information, followed by NPCs and then posters. From this we conclude that participants valued the context-rich information provided by books and research articles, closely following the conclusions from the previous research question. Examining the interaction between condition and types of informational text presentations utilizing process data, we see that there is a significant interaction where, accounting for each type of presentation, there were differences between the two conditions where partial agency had consistently greater durations and fixation durations than full agency. It is important to note that these findings are consistent with preliminary findings where, with the exception of NPCs, fixation durations on the presentation is less than durations.

Finally, we investigated the interaction of durations and fixation durations between condition, pretest-relevant items, and types of informational text presentations. This research question aimed to identify how learners used metacognitive processes within GBLEs which either limit or allow learners' control over their interactions with the environment. Overall results partially confirmed our hypotheses where we initially expected to see a difference between conditions as previous as previous studies have shown that autonomy is a detriment to learners' metacognitive judgements (e.g., content evaluations; Bradbury et al., 2017; Azevedo et al., 2019). However, the first model looking at durations would not converge, indicating that an accurate model could not be identified with log-file data. Our fitted model, using eye-tracking data, nested the items and presentations within participants. Results showed significant differences in the time spent fixating on books and research articles, NPCs, and posters, differences in fixation durations related to the relevancy of pretest items, with a significant interaction between these two factors, but there were no differences between agency conditions. Regardless of condition, there are differences in selecting and utilizing context in text presentations related to pretest items. Overall, participants fixated on content in text presentations related to pretest-relevant items more than irrelevant types of informational text presentations. This demonstrates participants employing metacognitive strategies as approximately half of the total number of informational text within the environment were relevant to the pretest and therefore, participants would not display a difference in their fixation durations if metacognitive strategies were not used by participant. However, when accounting for the type of presentation, NPCs are fixated on more for pretest-relevant than pretest-irrelevant information whereas greater fixations are spent on pretest-irrelevant books and research articles and posters. This finding indicates that learners, regardless of autonomy, make accurate metacognitive judgments when encountering NPCs than any other type of informational text presentation. This may be due to the content of NPCs which contain a diagram and information that is presented in a more conversational method. From these overall findings, we conclude that for all types of informational text presentations, there is a need for an increase in scaffolding to fully support learners in their metacognitive judgments.

Application to CTML

Our findings highlight the need for CTML to be integrated into GBLEs that provide multiple presentations of informational content critical for learning. Specifically, our results show that learning is impacted by how information is represented. In Mayer's (2014) CTML framework, information related to the overall goal of learning is provided to learners, where learners are then required to evaluate individual sources of information. Alternatively, within GBLEs, learners must first seek out sources of information throughout their interaction with the game elements before identifying how relevant information within individual sources are related and relevant within each other (i.e., visual and text) and between different sources in relation to game completion and learning.

The current study's results support modifying the CTML model to consider how various features, elements, and goals of narrative-centered GBLEs impact learners' metacognitive judgments in selecting relevant information and their impact on learning gains. Features generalizable to all GBLEs include the autonomy afforded to learning which may be manipulated within the environment, ultimately changing the control learners have over their learning with the intention of optimizing their learning. Elements, including the type of text presentations, directly address CTML in how learners must select, organize, and integrate multiple sources of information that are presented in several ways using text and diagrams.

Within this study, limited autonomy prompted the participant to interact with all types of informational text presentations, forcing the exposure of all content related to domain knowledge including the specific knowledge items represented on the pretest. Given the results of the current study referencing the autonomy feature of narrative-centered GBLEs, we conclude that autonomy captures context-relevant sources of information and this type of scaffold influences domain content knowledge where a greater amount of autonomy ultimately resulted in lower learning gains than restricted autonomy. Modifications to CTML are proposed to fully apply this cognitive theory to GBLEs that contain informational content. We propose modifying CTML using the three condensed phases of cognitive processes: 1) selecting; 2) organizing; and 3) integrating content from an informational source. We identify two levels within the selecting phase of CTML which may vary dependent upon the level of autonomy allowed to learners. There are two proposed levels within the selection phase: 1) GBLE Information Presentation; and 2) Content of Information Presentation. The first level refers to the unique need in GBLEs to identify and select information presentations (e.g., scientific books and research articles) which relate to domain-specific content, or content related to the pretest, but also to the overarching goal of the game itself where learners must identify information relevancy in reference to the domain content they must know or the information needed to complete the immediate goal of the GBLE. However, this level may include elements that do not contribute to the knowledge needed to complete the posttest or the GBLE itself. For example, the way in which learners synthesize information with the CRYSTAL ISLAND worksheet could influence how learners identify and select relevant information. The second level refers to the traditional use of CTML where, given a large chunk of information, learners must select relevant information which will increase learning. This emphasizes the need for the learner to identify relevant information across multiple documents and types of informational text presentations. This modification to Mayer's CTML would allow for learners' metacognitive judgments of informational text within GBLEs to be evaluated at multiple levels.

Limitations and Future Directions of the Study

We acknowledge limitations in our study related to the interpretation of analyses, classification of groups, and potentially influential factors. It is first important to note that in the simple linear regression models (Research Question 2), given our positive intercept beta, our model fails to correctly capture when a participant performs worse on posttest compared to the pretest performance. This is due to the fact that our predictor variable must be positive as a participant cannot look at informational text presentations for a negative amount of time. Although this is a limitation to the interpretation of analyses, it raises the question of how a learner would perform worse on the posttest. Specifically, did the participant guess on answers on the pretest and were incorrect for the congruent form of the question on the posttest? If so, this would be an example of a participant not learning compared to the "unlearning" if analyses were to be interpreted using negative values. Alternatively, did the environment prove to be too distracting and only serve to confuse certain students resulting in worse performance on the posttest?

Limitations of this study include the identification of item pretest relevancy. The relevancy of NPCs was determined by a singular piece of information shared by the NPC, where other information shared may not have been relevant. For example, learners have the choice of selecting 3 questions for the NPC to answer. If one of the three questions contained pretest-relevant information, regardless of the relevancy of the other questions, that NPC was determined to be relevant to the pretest items rather than the question itself.

Further limitations include the exclusion of additional influences of time spent in the environment itself. Although the time in the environment varied between conditions, the time exposed to the different types of informational text presentations in comparison to overall time in game did not differ between conditions. As such, these analyses ignore the duration of time participants spent on concept matrices, worksheet edits, and scanning food items. However, as the goal of this current study was to identify how autonomy and metacognitive judgements influenced learners' interactions with informational text in GBLEs measured by process data, the inclusion of these elements was outside the scope of the study. Further, the three game elements investigated within this study were the only sources of information that could contribute to learners' domain knowledge for items tested in the posttest and, therefore, are the instrumental elements in examining learning gains that should be investigated within this study.

Additionally, this study did not account for how much information is included in each presentation where books and research articles contained significantly more information than posters. However, these times are compared with each other as the same metacognitive processes are utilized to read, select, organize, and integrate information within each source. Although this may be considered a limitation of the study, this may be a limitation of the environment itself as these types of presentations which do not offer rich text and do not influence learning gains may be considered distractions from the presentations which promote learners' domain knowledge. Despite these potential limitations, this study incorporates all elements that are critical to identifying how learners interact with informational text presentations within GBLEs.

While limitations are identified, we acknowledge multiple directions in which this study can expand. This study emphasizes the need for metacognitive processes to be integrated within cognitive literature, and as such, it is important to mention conditions driving individual learners' interaction with GBLEs and implementation of these processes. For example, learners' executive functions, cognitive resources, motivation, emotions, prior knowledge, etc. can influence how learners interpret the task, or environment, and implement metacognitive and cognitive processes while learning with a GBLE (McCardle & Hadwin, 2015; Winne, 2018). Future directions of investigation may also include comparing an open-ended learning environment, such as a GBLE, to simulations which are a more restricted environment (e.g., O'Keefe et al., 2014). In examining these comparable environments, researchers can understand the effect of a more restricted environment with a limited number of resources from which the learners receive information.

Results from our first research question confirmed our hypothesis. There were no differences in the level of prior knowledge

Future Directions in AI and GBLEs

This study supports the need for artificial intelligence interfaces to include adaptable scaffolds using autonomy which functions off of eye-tracking and log-file data which changes depending upon the type of informational text that is being presented. Generally, this applies to GBLEs which focus on presenting complex instructional multimedia content related to topics and STEM domains. Given the results of this study, we identify the need for GBLEs to intelligently and adaptively support learners throughout the environment as they use metacognitive judgements to select information deemed relevant to learning outcomes. The aim of integrating AI with GBLEs stems from the need for scaffolding where learners are given support through restricted autonomy to address the challenge of accurately applying metacognitive processes. Indicated by results from this study, learners are not able to accurately identify and select relevant information. Therefore, AI within GBLEs should address the need for a constantly adaptable scaffold for autonomy to fade in and out throughout learner interactions with the environment dependent upon the individualized (and contextualized) process data of each learner. Additionally, this should account for the type of informational text presentation as, according to the preliminary analyses, different types of process data should be used for each type of learning resource and depending on how they are utilized by learners. Future iterations of CRYSTAL ISLAND, as well as other GBLEs, should include greater AI to (a) support metacognitive judgements by assisting learners in selecting, organizing, and integrating informational sources and content within these sources and (b) integrate adaptive scaffolding dependent upon the real-time feedback from individual process data.

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CHAPTER FOUR: CAPTURING LEARNERS' INTERACTIONS WITH MULTIMEDIA SCIENCE CONTENT OVER TIME DURING GAME-BASED LEARNING

This chapter titled, "capturing learners' interactions with multimedia science content over time during game-based learning" was originally published in the proceedings of the 1st Annual Conference of the International Society of the Learning Sciences (ISLS) and led by Daryn A. Dever with contributing co-authors Allison M. Banzon, Nikki Anne M. Ballelos, and Roger Azevedo.

Abstract

Learners demonstrate difficulties effectively deploying self-regulated learning (SRL) strategies while using game-based learning environments (GBLEs). Features designed to scaffold and support learners' SRL with GBLEs may limit autonomy and impact their performance. However, the effectiveness of limiting autonomy as individual learners engage in SRL over time (i.e., throughout a 90-minute learning session) has been largely unexplored. Therefore, this study examines how learners' prior knowledge and varying levels of autonomy (i.e., full versus partial) moderate the relationship between fixation durations over time on different information representations (i.e., books and research articles, conversations, posters) that are either considered relevant or irrelevant to the pre-test. Undergraduate students (N = 82) learned with CRYSTAL ISLAND, a microbiology GBLE. Results identified interaction effects between (1) fixation durations and representations on learning gains and (2) text relevance, type of representation, and relative game time as well as a moderating effect of autonomy.

Autonomy and SRL During Game-based Learning

Game-based learning environments (GBLEs) incorporate tasks and game elements while allowing learners full autonomy (i.e., complete control over actions; Bandura, 2001) to enhance learning, motivation, and cognitive engagement (Plass et al., 2020; Taub et al., 2020c). Because of the open-ended nature of GBLEs, learners must engage in self-regulated learning (SRL) to monitor and adapt their learning strategies to meet goals (Winne & Azevedo, 2022). However, as learners typically lack the SRL skills needed to successfully interact with GBLEs (Josephsen, 2017), GBLEs embed scaffolds (e.g., guidance through restricted autonomy) to support learners' use of SRL processes and strategies (Josephsen, 2017).

GBLEs must balance the level of autonomy afforded to learners to simultaneously increase motivation through full autonomy and scaffold learning by restricting autonomy (Dever & Azevedo, 2019a; Dever et al., 2020). For example, CRYSTAL ISLAND, a microbiology GBLE, limits autonomy by dictating the order in which learners interact with game elements (e.g., informational text) and forcing learners to engage with all information. However, regardless of the level of autonomy, learners must use SRL strategies to select relevant information from the text, organize the information into a mental model, and integrate their mental models with prior knowledge. As such, it is important to consider how limited autonomy moderates learners' interactions with GBLE elements by capturing process-oriented data as learners monitor and regulate learning processes. This study focuses on how learners' gaze fixations on different information representations (i.e., large paragraphs of text, conversations, posters) within CRYSTAL ISLAND contribute to learning gains, change over time, and are related to representation relevance, learners' autonomy, and prior knowledge.

Capturing SRL via Eye-tracking Methodology

Eye-tracking methodologies are utilized to capture learners' cognition and SRL strategy use (Azevedo et al., 2018b; Catrysse et al., 2018; Mayer, 2019). Fixation durations, which are defined as relatively still gaze for at least 250ms, and saccades are regularly used (see Cloude et al., 2020) to quantify learners' underlying cognitive processes (e.g., reading; Bolzer et al., 2015; Catrysse et al., 2018; Cutumisu et al., 2019). For example, time fixating on in-game texts indicates when learners are monitoring their understanding of text and capture the total time learners need to process information. These gaze behaviors further indicate learners' ability to accurately and efficiently apply SRL strategies. For example, learners fixating on irrelevant text for a long period of time may indicate the learner has not made an appropriate or efficient content evaluation (i.e., inaccurate metacognitive monitoring). Yet, accurately identifying relevant from irrelevant information is influenced by the multimedia material where accuracy increases when information is represented by multiple modalities (e.g., text and picture versus solely text; Azevedo & Dever, 2022a; Butcher, 2014; Mayer, 2019, 2022). Within this paper, we use eye-tracking data to explore this relationship between information representations and SRL.

Theoretical Frameworks

To examine the relationship between learners' SRL processes, specifically content evaluation, and the cognitive processes required to select and comprehend multimedia material, both Mayer's (2019, 2022) CTML and Winne's (2018) COPES models are used to ground this study. CTML is centered around three cognitive processes: (1) selecting relevant visual and auditory information; (2) organizing the selected visual and auditory information into mental models; and (3) integrating mental models together with prior knowledge to construct a cohesive representation of information (Mayer, 2019). These processes are assumed to be linearly structured, limited by learners' cognitive resources, and elicited by learners' active processing of multimedia.

COPES details learners' conditions, operations, evaluations, and standards as they engage in SRL throughout learning (Winne, 2018). Within this paper we examine the conditions, operations, and products that influence learners' interactions with different representations of information. Conditions refer to the types of resources and constraints that are available to a learner through internal (e.g., prior knowledge) or external/environmental (e.g., limited versus full autonomy) factors (Winne, 2018). Conditions can significantly influence learners' deployment of SRL strategies during learning. For example, Taub et al. (2014) found that learners with high prior knowledge had a greater number of and duration on SRL strategies than learners with low prior knowledge. Operations are the internal cognitive processes that a learner continuously deploys while learning with a GBLE which, when combined with conditions, results in products, or the new understanding of the content based on information presented in the GBLE (i.e., learning gains).

Current Study

Limited research has examined how learners' interactions with information representations change over time as a result of prior knowledge, autonomy, and learners' SRL abilities. The goal of this study is to add to this area by examining learners' fixation durations on relevant versus irrelevant types of representations over time and how learners' prior knowledge and autonomy throughout the environment are related to this interaction by examining three research questions. The first research question focuses on learners' products: To what extent does the proportion of time learners spend on different representations influence learning gains? Supported by CTML, we propose that the greater amount of time learners spent reading information from non-player character (NPC) dialog and posters relative to their total time in game and accounting for the type of representation will increase learning gains. The second research question focuses on learners' operations: How does relative game time, relevance of the text to the pre-test, type of representation, and their interactions account for the variation of fixation durations within and between learners? We propose that (1) the variation in fixation durations within and between learners will be increasingly accounted for as we add these variables within our model, and (2) as relative game time increases, fixation durations across all types of relevant representations will increase at a greater rate than fixation durations on all types of irrelevant representations. The third research question focuses on learners' conditions: How does autonomy and prior knowledge moderate the effects between relative game time, relevance of the text to the pre-test, type of representation, and learners' fixation duration? Supported by previous literature (Dever et al., 2020; Sawyer et al., 2018; Taub et al., 2014), we propose that learners with high prior knowledge and limited autonomy will have greater fixation durations on relevant representations over time than learners with lower prior knowledge and full autonomy.

Methods

Participants

Undergraduates (N = 139) from a large North American public university were randomly assigned to either the full, partial, or no agency conditions that varied in the autonomy afforded (see CRYSTAL ISLAND). Only 82 participants ($Range_{age}$: 18-26, M_{age} = 20.1, SD_{age} = 1.69; 68.3% female), split between full (n = 47) and partial (n = 35) agency conditions, were included in our analyses. Participants were removed if they had missing data and measurement errors in eye-tracking calibration (n = 25) or belonged to the no agency condition (n = 32).

Crystal Island: A GBLE for Microbiology

Crystal Island, a GBLE set on a remote island, aims to cultivate learners' SRL and scientific reasoning skills by introducing microbiology content through a problem-solving scenario. Learners must identify an unknown disease infecting island residents by reading informational content (e.g., books, research articles, dialogue with NPCs, posters), completing concept matrices corresponding to informational content, filling out a diagnosis worksheet, and scanning food items. Agency conditions were embedded within Crystal Island. Full agency did not restrict participants' interactions with the environment, generalizable to the majority of GBLEs. Partial agency consisted of a predetermined path (i.e., "Golden Path") that restricted the participants' choice of actions to provide learners support and optimize their learning outcomes. No agency required learners to watch a playthrough of Crystal Island. Learners in this condition could not directly interact with any video (e.g., pause, rewind) or game features.

Experimental Procedure

At the start of the experimental session, participants signed an informed consent and were calibrated to the eye tracker. Participants then completed a demographic questionnaire, a microbiology content knowledge pre-test, and several self-report measures. Following pre-task measures, participants started the learning session. As participants interacted with Crystal Island, eye-tracking data were collected. Once a correct diagnosis was identified and submitted, participants completed post-task measures including a microbiology post-test similar to the pre-test and self-reports. Participants were then thanked and compensated, receiving $10 an hour (up to $30).

Apparatus

Gaze behavior data were captured using an SMI RED250 eye tracker with 9-point calibration at a sampling rate of 250 samples per second (s). The SMI eye tracker captured fixation durations, saccades, and regressions on preidentified areas of interest (AOIs) which are boundaries that contain the object on which the participants fixate.

Coding and Scoring

Reading

Reading duration and instances were operationalized as learners' fixation duration (i.e., relatively stable eye movements for at least 250ms) on different types of representations using AOIs overlaid on top of each representation. Types of information representations refer to NPCs (informative text, uninformative visual), books and research articles (informative text, no visual), and posters (informative and uninformative text and visual). Books and research articles are combined as both representations contain large paragraphs of text.

Learning Gains

Normalized change scores (Marx & Cummings, 2007) are used to identify learning gains, or the differences between pre- and post-test scores, while controlling for the prior knowledge of each participant.

Relevance of Representations

Individual representations were evaluated for relevance to the pre-test where if a representation contained information addressed in the pre-test, the representation was classified as relevant (see Table 6). If the representation did not hold any information addressed in the pre-test, the representation was labeled as irrelevant. This classification is based on priming literature (see McNamara, 2005) assuming that participants will identify information as more instructionally relevant based off of the pre-test domain-related questions and is needed for the post-test.

Table 6.
Relevance of Representations

Representation	Total #	# Relevant Representations
Books & Research Articles	21	12
NPC Dialog	9	3
Posters	10	4

Relative Game Time

As each participant varied in their total game duration, relative game time was calculated by dividing the time in game participants fixated on content by the participants' total game duration, scaling instances from 0 to 1 so that all participants could be compared. This measure was found to first look at a continuous scaling of time to normalize all participants' time in game, which ranged from 39.7 to 135.8 minutes.

Model Building and Estimation

Our model examines how fixation duration, the outcome variable, was related to several observation- and individual-level variables (see Table 7). Several leveraging outliers (N = 72), i.e., data that falls approximately 1.5 interquartile ranges below or above the first and third quartile of data respectively, from the observations were removed from analyses. Fixation duration values were transformed through natural logs to normalize the data (skew and kurtosis < |2|) and reduce heteroscedasticity. As such, geometric means for fixation durations are interpreted within results. Two-level multilevel linear growth models analyzed our hierarchically structured data with observations (i.e., level one, N = 4274) nested within individual learners (i.e., level two, N = 82) where each learner had approximately 52 observations (Range: 25-75). Observation-level variables included relative game as a latent time variable with a random slope in all growth models. To interpret model intercepts, relative game time values were forced to zero to exemplify learners' first interactions with representations as learners cannot fixate on a representation when they first enter the game. Pre-test relevancy (irrelevant versus relevant) and type of representation (i.e., NPC, books and research articles, posters) were added as fixed effect observation-level variables. Individual-level variables included pre-test scores and conditions.

Table 7.
Definitions of Variables Included in the Models

Level	Variable	Definition	Effects
Observation-Level (Level 1)	Relative Game Time	Proportion of time learners initiate an action	Random
	Representation	Book or Research Article, NPC, Poster	Fixed
	Relevance	Representation contains information related to a question on the pre-test (1). Representation does not contain information related to a question on the pre-test (0)	Fixed
Individual-Level (Level 2)	Condition	Full Autonomy (1); Restricted Autonomy (0)	Fixed
	Prior Knowledge	Raw scores on the domain knowledge pre-test quiz	Fixed

Five models were calculated using maximum likelihood estimation within R (R Core Team, 2019) utilizing packages 'lme4' (Bates et al., 2015), 'jtools' (Long, 2020), and 'emmeans' (Lenth, 2020) for model building and analysis. The unconditional means model was estimated first. Based on this model, the intraclass correlation coefficient was 0.05, suggesting that about 5% of the variation in fixation duration on representations within CRYSTAL ISLAND is between learners and about 95% is within learners. There was a statistically significant variation between learners

(t(82.64) = 75.14, p < .01). Thus, it is reasonable to proceed with multilevel linear growth models. The next four models were built with: (1) an unconditional growth model; (2) level one predictors and their interactions; (3) predictors from (2) and level two predictors; and (4) predictors from (3) and cross-level interactions. Tests of model fit were calculated using maximum likelihood estimates.

Model 4: $Y_{ti} = \pi_{0i} + \pi_{1i}(RelativeGameTime)$

$$+ \pi_{2i}(TypeofRepresentation) + \pi_{2i}\,(PretestRelevance)$$

$$+ \pi_{3i}(RelativeGameTime * TypeofRepresentation)$$

$$+ \pi_{4i}(RelativeGameTime * PretestRelevance)$$

$$+ \pi_{5i}(RelativeGameTime * TypeofRepresentation * PretestRelevance)$$

$$\pi_0 = \beta_{00} + r_0$$

$$\pi_1 = \beta_{10}$$

$$\pi_2 = \beta_{20}$$

$$\pi_3 = \beta_{00} + \beta_{01}(Condition) + \beta_{02}(PriorKnowledge)$$

$$\pi_4 = \beta_{10}$$

$$\pi_5 = \beta_{20}$$

Results

Research Question 1: To What Extent Does the Proportion of Time Learners Spend on Different Representations Influence Learning Gains?

A multiple linear regression was run and, while the overall model was not significant (p > .05), there was a significant interaction effect for proportion of time fixating on NPCs (t(485) = 8.99, p < .05) where as proportion of time on NPCs increased by one unit, normalized change scores increased by 0.48 points. As the proportion of time fixating on books and research articles increased by one unit, normalized change scores increased by approximately 1.28 points compared to the proportion of time fixating on NPCs ($t(485) = 2.81$, $p < .01$). Proportion of time on posters did not significantly relate to learning gains. In sum, the proportion of time spent on NPCs as well as books and research articles were positively related to normalized change scores.

Research Question 2: How does relative game time, relevance of the text to the pretest, type of representation, and their interactions account for the variation of fixation durations within and between learners?

To answer this question, we utilize Models 1 and 2. Model 1, the unconditional growth model, includes time as a level-1 predictor of learners' fixation duration. The average fixation duration at participants' initial interaction with text is approximately 31.19s (SE = 0.06) and decreases by approximately 67% (i.e., 20.81s; SE = 0.11) for every unit increase in relative game time. This model (BIC = 14379, D = 14329) is significantly better in terms of fit than the unconditional means model (BIC = 14582, D = 14557) wherein adding time, the model explains approximately 11% of individual-level variance in fixation duration ($\chi^2(3) = 227.41$, $p < .01$). Model 2 (BIC = 12623, D = 12506) examined the extent to which level 1 variables contribute to variation in learners' fixation durations. This model is a significantly better fit than the unconditional growth model ($\chi^2(8) = 1822.8$, $p < .01$). Holding all other variables constant, the average fixation duration is 104.58s (SE = 1.08, $t(301.39) = 60.69$, $p < .01$). There was a main effect for relative game time where, holding all variables constant, fixation durations decreased 89% (i.e., 93.08s) for every unit increase in relative game time (SE = 16.15; $t(653.86) = -13.36$, $p < .01$). There was a main effect where, when text was relevant, fixation durations were greater than those on irrelevant text by approximately 25.9% (i.e., 27.04s; SE = 1.96; $t(4186.66) = 3.37$, $p < .01$). There were significant differences between the type of representation and their effect on fixation durations. In comparison to book and research article observations and holding all other variables constant, fixation durations are lower on both NPCs and posters by approximately 85.6% (i.e., 89.55s; SE = 6.49; $t(4200.02) = -26.8$, $p < .01$) and 91.5% (i.e., 95.65s; SE = 9.01; $t(4210.62) = -28.31$, $p < .01$) respectively.

Holding all variables constant, there were significant two-way interactions between relative game time, NPCs ($t(4211.68) = 11.85$, $p < .01$), and posters ($t(4209.54) = 8.86$, $p < .01$) compared to book and research articles. Books and research articles (by 92.6% or 96.89s; SE = 14.45; see Figure 11) decreased at a greater rate over time than posters (by 44.4% or 46.43s; SE = 7.68). NPCs did not have a significant decrease in fixation durations over time. There was a significant interaction effect for pre-test relevancy and relative game time where fixation durations on relevant text were lower over time than fixation durations on irrelevant text by approximately 56.4% (i.e., 58.98s; SE = 11.63; $t(4182.43) = -4.65$, $p < .01$). When examining a three-way interaction and controlling for all observation-level variables, fixation durations on relevant posters (SE = 9.75; $t(4180.03) = 2.65$, $p < .05$) and NPCs (SE = 40.01; $t(4176.82) = 6.70$, $p < .01$) increased over time by 53.7% (i.e., 56.19s) and 206% (i.e., 215.94s) respectively compared to fixations on books and research articles. As relative game time increased, fixations decreased on relevant books and research articles by 95.1% (i.e., 99.50s; SE = 17.85) and posters by 54.3% (i.e., 56.83s; SE = 10.73). Over time, fixation durations decreased on irrelevant books and research articles by 88.9% (i.e., 92.95s; SE = 16.67) and posters by 32.3% (i.e., 33.78s; SE = 6.46).

In sum, fixation durations generally decreased at a greater rate over time for representations that were relevant to the pre-test than irrelevant. However, there were only significant interaction effects on fixation durations between books and research articles (regardless of relevancy to the pre-test) and posters relevant to the pre-test where fixation durations decreased over time.

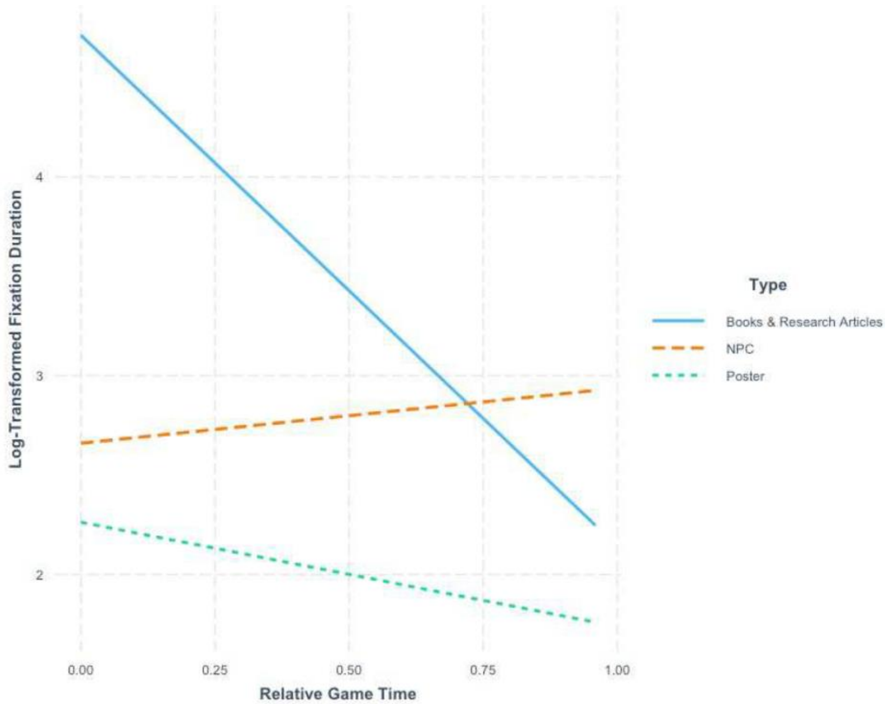

Figure 11: Interaction between relative game time, fixation durations, and type of representation.

Research Question 3: How does autonomy and prior knowledge moderate the effects between relative game time, relevance of the text to the pre-test, type of representation, and learners' fixation duration?

Preliminary analysis on condition and learning gains using a t-test confirmed participants with partial agency (M = 0.45, SD = 0.27) had significantly greater learning gains than participants within the full agency condition (M = 0.32, SD = 0.26; $t(71.6) = 2.18$; $p < .05$). Because of this significant preliminary finding, Model 3 (BIC = 12640, D = 12506) added prior knowledge and condition as variables but these variables were not significant (ps > .01). Model 4 (BIC = 12608, D = 12466) examined the moderating effects of condition on the relationship between the type of representation and fixation duration. This model was a significantly better fit than Model 2 ($\chi^2(3) = 40.43$, $p < .01$), explaining approximately 44% of individual-level variance in fixation duration. Prior knowledge was initially included but removed due to non-significance. While there was no moderating effect (ps > .01) of condition on the relationship between NPCs and fixation durations over time, there was a three-way cross-level interaction effect where learners who were in the full agency condition had greater fixation durations on books and research articles over time compared to learners in the partial agency condition ($t(169.3) = 3.89$, $p < .01$). For every unit increase in relative game time, fixation durations on books and research articles increased by 97.4% (i.e., 101.84s; SE = 18.87) for learners with full autonomy than those with partial autonomy. For every unit increase in relative game time, fixation durations on posters decreased by 30.2% (i.e., 31.62s; SE = 5.86) for learners with full autonomy compared to those with partial autonomy. In sum, learners with more control during gameplay had increasingly greater fixation durations on books and research articles over time and lower fixation durations on posters compared to learners with restricted control, regardless of prior knowledge.

Discussion and Future Directions

The goal of this paper was to examine how learners' fixation durations on relevant and irrelevant types of representations changed over time and how prior knowledge and autonomy moderated this relationship. The first research question examined how learners' products were related to the proportion of time fixating on different types of representations. Results partially support our hypothesis where the proportion of time fixating on NPCs and books and research articles were positively related to learning gains, but there was no relationship between posters and learning gains. This is not in complete alignment with CTML (Mayer, 2019, 2022) where NPCs have text, pictures, and audio, and posters have both text and pictures, but books and research articles only contain large blocks of text. Findings may be attributed to the breadth of knowledge contained within books and research articles where posters do not explain relationships between terms or constructs related to microbiology.

Results for the second research question did not confirm our hypothesis where, as relative game time increased, fixation durations tended to decrease. Interestingly, results showed an interaction between text and relevancy where fixation durations tended to decrease at a greater rate over time for posters and books and research articles that were relevant than texts that were irrelevant. This may be due to the presence of other instructional activities within CRYSTAL ISLAND such as completing concept matrices, filling out the worksheet, and scanning items (Azevedo et al., 2018b). However, this result emphasizes learners' inability to consistently and accurately use SRL strategies, such as content evaluations, throughout the game (Taub et al., 2020c).

The third research question examined how findings in research question two are affected by autonomy. Results did not support our hypothesis and contradicted prior works where learners with full autonomy had increasingly greater fixation durations on books and research articles over time and lower fixation durations on posters compared to learners with limited autonomy, regardless of prior knowledge (McCardle & Hadwin, 2015; Winne, 2018). Previous work has emphasized the relationship between autonomy and learning gains (Dever et al., 2020). Traditionally, limited autonomy is associated with greater learning gains (Dever & Azevedo, 2019a; Dever et al., 2020; Sawyer et al., 2018). Between the first and third research question results, learners with full autonomy had greater fixation durations on books and research articles over time which is further associated with greater learning gains. When accounting for preliminary findings on autonomy and learning gains in the third research question, results from this study suggest that learners with full autonomy were not able to employ efficient or accurate SRL strategies while reading books and research articles whereas learners supported in their actions throughout gameplay had significantly less time interacting with information, but efficiently employed SRL strategies to achieve greater learning gains.

Findings from this current study partially validate the relationship between COPES and CTML where we find that learners' conditions and operations are directly related to their products, especially as we explore the role of different types of representations of information within GBLEs. This study serves as a baseline for future studies to further examine the relationship between COPES, autonomy, and information representations over time within GBLEs. Future studies should incorporate searching, monitoring, assembling, rehearsing, and translating processes into the COPES and CTML model over time within GBLEs to better understand how SRL strategies are used by learners over time (Azevedo & Dever, 2022). From the results, we identify the need for adaptive GBLEs depending on learners' eye-tracking behaviors as they read information over time and between different types of representations, especially as we see mixed results compared to previous studies about the role of autonomy as a scaffold for acquiring information. Using adaptive GBLEs from learners' gaze behaviors has the potential to better support learners in navigating the environment, selecting relevant instructional text, and integrating this information to increase learning outcomes while supporting self-regulated learning.

Acknowledgments

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CHAPTER FIVE: CAPTURING SEQUENCES OF LEARNERS' SELF-REGULATORY INTERACTIONS WITH INSTRUCTIONAL MATERIAL DURING GAME-BASED LEARNING USING AUTO-RECURRENCE QUANTIFICATION ANALYSIS

This chapter titled, "capturing sequences of learners' self-regulatory interactions with instructional material during game-based learning using auto-recurrence quantification analysis" was originally published in Frontiers in Psychology and led by first author Daryn A. Dever with contributing co-authors Mary Jean Amon, Hana Vrzákova, Megan D. Wiedbusch, Elizabeth B. Cloude, and Roger Azevedo.

Abstract

Undergraduate students (N = 82) learned about microbiology with CRYSTAL ISLAND, a game-based learning environment (GBLE), which required participants to interact with instructional materials (i.e., books and research articles, non-player character [NPC] dialogue, posters) spread throughout the game. Participants were randomly assigned to one of two conditions: *full agency*, where they had complete control over their actions, and *partial agency*, where they were required to complete an ordered play-through of CRYSTAL ISLAND. As participants learned with CRYSTAL ISLAND, log-file and eye-tracking time series data were collected to pinpoint instances when participants interacted with instructional materials. Hierarchical linear growth models indicated relationships between eye gaze dwell time and (1) the type of representation a learner gathered information from (i.e., large sections of text, poster, or dialogue); (2) the ability of the learner to distinguish relevant from irrelevant information; (3) learning gains; and (4) agency. Auto-recurrence quantification analysis (aRQA) revealed the degree to which repetitive sequences of interactions with instructional material were random or predictable. Through

hierarchical modeling, analyses suggested that greater dwell times and learning gains were associated with more predictable sequences of interaction with instructional materials. Results from hierarchical clustering found that participants with restricted agency and more recurrent action sequences had greater learning gains. Implications are provided for how learning unfolds over learners' time in game using a non-linear dynamical systems analysis and the extent to which it can be supported within GBLEs to design advanced learning technologies to scaffold self-regulation during game play.

Introduction

Self-regulated learning (SRL) refers to learners' ability to dynamically monitor and modify their cognition, affect, metacognition, and motivation to control their learning (Winne, 2018). SRL, within this study, is captured from learners' observable events of self-regulatory processes and strategies during game-based learning. Several studies have examined how learners engage in SRL processes and employ SRL strategies to increase their learning outcomes across math (Gabriel et al., 2020; Musso et al., 2019; Roick & Ringeisen, 2018; Sun et al., 2018), reading (Harding et al., 2019; Snow et al., 2016; Thiede & de Bruin, 2018), writing (Nuckles et al., 2020; Sophie & Zhang, 2018; Sun & Wang, 2020), and science (Gandomkar et al., 2020; Garcia et al., 2018; Li et al., 2020; Taub et al., 2020c) domains and technologies including hypermedia, intelligent tutoring systems, and games (Azevedo et al., 2019). In this article, we examine and analyze how learners engage in SRL behaviors as they learn within a science game-based learning environment (GBLE) to discuss how to best support learners' deployment of SRL strategies and examine the relationship between SRL behaviors and learning.

To accomplish this goal, this article: (1) defines and describes the several interacting components of SRL according to Winne's (2018) COPES model, a traditional conceptualization of SRL; (2) defines what a complex system is and defends SRL as a complex system using Winne's COPES as system components; (3) explains how SRL can be supported by GBLEs; and (4) discusses how non-linear dynamical systems theory (NDST) can measure SRL within GBLEs. From these discussions, this article introduces research questions that are grounded in and supported by the multiple theories considered in the introduction. Our ultimate goal and novel contribution to the study of SRL is the examination of dynamical SRL strategy deployment its relationship to learners' prior knowledge, agency within a GBLE, and learning outcomes, all through the lens of complex systems theory using NDST analytical tools.

Self-regulated Learning

As previously mentioned, SRL is the ability for learners to enact processes and strategies that both monitor and modulate cognitive, affective, metacognitive, and motivational processes (Winne, 2018). SRL primarily encompasses cognitive and metacognitive strategies that are deployed by the learner, such as reading instructional materials (i.e., books, research articles, posters, dialogue with non-player characters [NPCs]), gathering information important for achieving the overall goal, and retaining information required to increase domain-specific knowledge. Learners typically deploy SRL strategies throughout the phases of learning including: (1) prior to a task (i.e., forethought); (2) during a task (i.e., performance); and (3) after a task (i.e., reflection). These phases are mentioned recursively throughout SRL models and literature including Zimmerman and Moylan's (2009) SRL model, Winne and Hadwin's (2008) information-processing theory of SRL, Pintrich's (2000) model of SRL, and Nelson and Narens' (1990) metamemory framework.

To support the current article and ground the research questions, we specifically focus on Winne's (2018) conditions, operations, products, evaluations, and standards (COPES) model of SRL. This model details COPES components as occurring throughout the four phases of learning from Winne's (2018) information-processing model of SRL. This model states leaning occurs in 4 phases: (1) defining the learning task; (2) identifying and setting goals as well as plans to achieve those goals prior to interacting with their environment or starting the task; (3) deploying cognitive and metacognitive strategies that aid learners in achieving their goals; (4) adapting their learning strategies, goals, and plans to better achieve their goals. Through this COPES model, we review SRL literature that examines the relationships between learners' cognitive and task conditions, operations deployed during learning, and their products. However, this study does not incorporate evaluations nor standards when examining SRL behaviors as these were not directly measured by the learning environment. Therefore, this study specifically reviews learners' SRL behaviors in terms of how learners' conditions were related to the operations that were deployed during learning and how the interaction between these two components elicited learners' products.

Conditions

Conditions refer to the cognitive and task resources and constraints learners encounter when interacting with instructional materials. *Cognitive conditions* can include the level of prior knowledge a learner has before engaging in a learning task. Typically, learners with greater prior knowledge engage in greater SRL strategies which contribute to higher learning outcomes (Bernacki et al., 2012; Yang et al., 2018). *Task conditions* refer to constraints imposed on a learner by their environment. These constraints can refer to the environment's (e.g., game-based learning environment) restriction on learners' agency throughout the task where agency refers to learners' control over their own actions. As such, restricted agency limits the number of choices and actions a learner can perform throughout the learning process, including their deployment of SRL strategies (Bandura, 2001; Martin, 2004; Code, 2020). While full agency has been hypothesized to increase learning outcomes due to increased interest and engagement related to discovery learning (Mayer, 2004; Kirschner et al., 2006), learners are notoriously incapable of engaging in effective SRL. This is perhaps due to the difficulty of information, learners' lack of metacognitive knowledge of which SRL strategy to apply, or the open-ended nature of most learning environments (de Bruin & van Merriënboer, 2017; Schunk & Greene, 2018; Seufert, 2018; Winne, 2018; Munshi & Biswas, 2019).

Operations

Learners' task and cognitive conditions can influence their *operations* which refer to the cognitive strategies a learner can employ when interacting with instructional materials. The operations that are enacted center around searching for information across different sources, monitoring the learned information and their relevance toward their goal (i.e., content evaluation; Azevedo & Cromley, 2004; Azevedo & Dever, 2022; Dever et al., 2020; Greene & Azevedo, 2009), assembling several different sources into a coherent representation of information, rehearsing information in working memory, and translating information that was collected into a different type of representation (e.g., mental representation vs. concept map; Winne, 2018). Operations deployed during SRL are essential to the synthesis, (mis)understanding of information, and memorization of information for situation transfer (e.g., from virtual to classroom) and information recall. As such, it is necessary to examine how learners interact with information during SRL to examine how behaviors influence learning outcomes. Specifically, we question:

How do learners' operations of selecting information throughout a complex learning task influence learning?

Products

Products, or the information that is formed using the instructional material from the environment, is perhaps the most straightforward process within the COPES framework. Simply, products can be represented by the changes in knowledge representation where products are a representation of learning. In using learning gains to represent the new knowledge learners obtain during the learning task, we can assess how the learners' task and cognitive conditions have influenced their (in)accurate deployment of operations that (dis)allowed learners to gain knowledge within a specific domain. As such, this study utilizes a formula developed by Marx and Cummings (2007; see Section 6.5) that identifies how much has been learned while accounting for learners' prior knowledge.

Defining SRL as a Complex System

SRL includes dynamically and accurately monitoring and regulating cognitive, affective, metacognitive, and motivational processes and adapting them to meet the internal (e.g., evolving understanding) and external demands and constraints of an activity (Azevedo et al., 2019). According to Favela (2020) and the assumptions of Winne's (2018) COPES model, complexity science offers a lens to understand and analyze cognitive and psychological processes that emerge as a function of complex systems. Complex systems theory describes how systems that demonstrate changing behavior due to interacting components can be explained and predicted (Favela, 2020). For the current study, we align this framework with SRL literature in which learners' conditions, operations, and products are components of SRL that change and interact with each other as learning occurs. Complex systems are generally characterized by three criteria: (1) self-organization; (2) interaction dominance; and (3) emergence (Favela, 2020; Haken, 2006).

According to these three criteria, this article argues that SRL qualifies as a complex system (see Li et al., 2022). Constraints such as cognitive resources fluctuate with the instructional content provided in the learning environment (i.e., prior knowledge on genetic diseases vs. viruses); Operations such as cognitive strategy use shift based on task demands and goals which may change over time (McCardle & Hadwin, 2015; Cloude et al., 2021); and products are also likely to change over time as learners acquire new knowledge incrementally (Shute & Sun, 2020). While existing literature supports SRL as occurring cyclically (Winne & Azevedo, 2014; Schunk & Greene, 2018), analytical methods used within current literature does not account for the non-linear, dynamic, and complex nature of self-regulatory behaviors during learning about a difficult topic (e.g., microbiology) with a game-based learning environment. As such, it is essential to start employing complex systems theory to SRL literature to explain how learners deploy SRL strategies during learning.

Self-organization refers to changing behavior from which order arises out of disorder but without the influence of a central controller or programmer (Haken, 2006; Heylighen, 2008). Consistent with the concept of self-organization, SRL components mutually coordinate and constrain each other to elicit order in executed SRL behaviors which would have otherwise been chaotic (Dale et al., 2013). Initially, one may presume the central controller is the individual learner or their executive and metacognitive control functions. However, various SRL processes mutually influence one another in the context of a complex environment that may include, for example, task conditions (i.e., environmental constraints) and standards imposed on learners' processes. Moreover, learners' prior knowledge (Cognitive Conditions) can restrict which SRL strategy a learner deploys during learning. Similarly, the affordance of full agency (Task Conditions) could contribute to an unsystematic deployment of (in)accurate SRL strategies, thereby minimizing learning outcomes. In this way, processes outside of executive control interact to support SRL.

Complex systems are also characterized by their *interaction dominance* in which behavioral order and control of a system arises from the interactions between system components, not just the additive value of the components (Holden, 2009). Relative to current models of SRL, and more specifically when dealing with COPES, this characteristic of complex systems denotes the importance in considering SRL components as interactive rather than independent. Studies examining SRL have traditionally examined the impact of one component on another (e.g., Bernacki et al., 2012; Yang et al., 2018), but rarely have SRL studies examined the dynamic relationship between components. Under the interaction dominance characteristic of complex systems, there is not just an additive or unidirectional relationship between system components which elicit a certain behavior. Rather, SRL is possible through the interaction between cognitive and metacognitive strategies across time and SRL phases. It is important to note that since SRL is theoretically aligned with complex systems, there is much to be gained from leveraging analytical techniques based in complex systems theory (i.e., NDST) that can extract the very nature of dynamically interacting components.

Similarly, although definitions vary, the criteria of *emergence* often refers to how the behavior of an entire system cannot be broken down into just the sum of the components (Favela, 2020). In other words, the behavior of the whole system supersedes the behaviors of the individual components. In the case of COPES, this means that SRL cannot be isolated into either conditions, operations, or products. Additionally, SRL cannot be broken into separate cognitive and metacognitive strategies as SRL requires the oscillation of all components and both types of strategies throughout the learning process. The conceptualization of SRL as a complex system is made increasingly evident when we consider non-traditional environments with high levels of learner-environment interactivity such as that found during game-based learning.

Supporting SRL During Game-Based Learning

The goal of a game-based learning environment (GBLE) is to make multimedia instructional materials accessible in a non-linear fashion which increases agency during learning via the deployment of SRL strategies while maintaining the interest, engagement, and motivation of a learner (Clark et al., 2016; Sawyer et al., 2017; Mayer, 2019; Plass et al., 2020; Shute & Sun, 2020; Taub et al., 2020c). Because of this, GBLEs are increasingly being used in order to support learning through their combination of (1) narrative to increase engagement and interest, (2) tasks to support domain learning, and (3) game elements to promote engagement with both the task and the instructional materials presented throughout the environment. This uniquely positions learners within GBLES, relative to other learning environments, to have the agency to control their learning progression and direction without having too much freedom they are overwhelmed by choice.

During game-based learning, it is essential for learners to engage in SRL strategies to meet the demands of learning activities and comprehend instructional materials essential for attaining domain knowledge in pursuit of a goal (Winne & Azevedo, 2014). Although, the open-ended nature of GBLEs both facilitates and limits the successful use of SRL strategies. On one hand, GBLEs allow learners agency to engage in and develop self-regulation through goal-setting and the use of monitoring and cognitive strategies (e.g., reading, note-taking, summarizing) and tools (e.g., instructional materials, help-seeking; Winne & Hadwin, 2013; Nietfeld, 2018). Alternatively, the open-ended nature may not provide the needed support for the learner to coordinate the several cognitive and metacognitive strategies required for successful SRL (Josephsen, 2017). Because of this, there is a need for GBLEs to be developed with scaffolds that guide learners' interactions with instructional materials to simultaneously support successful SRL and increase domain-specific learning gains. The balance between support and freedom provided by GBLEs calls for the incorporation of a complex systems theory concept, far-from-equilibrium.

Far-From-Equilibrium Systems

Adapting the concept of far-from-equilibrium from physical sciences, behavior can be described as learners' patterns of, or oscillations between, stable and unstable states (Veerman et al., 2021). That is, healthy cognitive systems, such as learners' SRL behaviors, are demonstrated by behaviors which maintain a balance between stability (i.e., rigidity) and adaptability (i.e., chaotic). To support this healthy behavior, the GBLE should promote the balance of SRL behaviors that are not too rigid (i.e., no agency) nor too chaotic (i.e., discovery-based learning). A too-rigid SRL system would demonstrate a greater repetition of SRL strategies during learning, such as only attending to one instructional material (i.e., book, research article, non-player character), perhaps promoted through the restricted agency imposed by the GBLE. Behaviors which could be too chaotic would demonstrate significantly greater novelty not conducive to content learning, potentially encouraged through full agency afforded to learners by the GBLE.

Applying the far-from-equilibrium concept of complex systems theory, healthy SRL behaviors should be demonstrated by learners' balance between stable and adaptable SRL strategies and actions during learning with a GBLE. This balance can be supported and maintained through cognitive conditions available to (i.e., prior knowledge) and task conditions imposed on (i.e., restricted agency) the learner. Task resources and constraints include the environmental features and mechanics that directly influence how a learner will interact with instructional materials within the GBLE. To guide learners' interactions with instructional materials, a GBLE may intentionally restrict the amount of agency learners have while still promoting their freedom in choosing the SRL strategies to be deployed. While agency as scaffolds (i.e., restricted agency as guiding learners throughout the GBLE) have been found to increase learning outcomes (Sawyer et al., 2017; Dever & Azevedo, 2019a; Dever et al., 2020), we must ask if agency promotes a healthy balance between rigidity and adaptability as learners deploy SRL strategies to interact with instructional materials in a GBLE. A methodological approach to study this question is to use a non-linear dynamical systems theory (NDST) analytical method for understanding learners' SRL behavioral shifts during learning with a GBLE.

A Non-linear Dynamical Systems Approach to Measuring SRL

NDST describes how numerous interacting components have a multiplicative effect on system-level behavior, where small changes in component processes can produce sudden (non-linear) behavioral shifts (Riley & Holden, 2012; Amon et al., 2019). Because of this, NDST can be used to evaluate and measure the repetition and predictability in learners' SRL strategy use, denoting the degree to which a learners' SRL strategy use throughout a GBLE follows the far-from-equilibrium concept. Due to the interdependent nature of non-linear dynamical systems, global behavior both constrains and is constrained by its underlying component processes, such that reciprocal feedback entrains processes at various levels (Amon et al., 2019). Because SRL behaviors change over time due to the constantly changing interactions with GBLEs as well as the acquisition of domain-specific knowledge, SRL can be measured using an NDST approach. While NDST has yet to be used to understand SRL with GBLEs from a complex systems theory stance, a study by Garner and Russel (2016) has applied NDST and sequence-oriented techniques to understand how learners deploy SRL while reading multiple texts. This study found differences of recurrent patterns between learners who took notes vs. those who did not while reading instructional materials. Building on the findings from this study, this article acknowledges the complex SRL strategies that occur during game-based learning and based on a GBLE's environmental affordances of agency.

This study utilizes auto-recurrence quantification analysis (aRQA), an NDST method, to examine how learners adaptively shift between repetitive and novel sequences of interactions with a GBLE. This method is also used to describe the relationship between these sequences and task conditions, learning gains, and SRL ability. aRQA quantifies the degree of repetition or “recurrence” within a single time series (Webber & Zbilut, 2005), indicating the extent to which a system returns to the same states across various time lags. Because NDST is a central part to studying the relationship between agency and SRL behaviors within this study, it is important to understand how learners' time series data is used to identify SRL behavioral patterns.

Figure 12A demonstrates the time series of the events in chronological order. Figure 12B shows how RQA first transforms a participant's time series—in this case, with categorical data—into the Figure 12B distance matrix representing the Euclidean distance between the values that represent areas of interest where participants were looking (i.e., Books, Posters, or NPC). When a participant is looking at the same area of interest at two different time points (e.g., time points t1 and t8), then the recurrent state is highlighted black. The diagonal represents the line of identity (LOI), where the time series is recurrent with itself at lag 0. Diagonal lines parallel to the LOI represent successively greater time lags between the points that are being compared in terms of distance. The Panel C recurrence matrix is created by applying a radius parameter that defines the threshold at which points are considered sufficiently similar enough to be considered recurrent. Thus, a very small radius value is used such that only exact matches are counted as recurrent, such that the recurrence matrix highlights points where the same area of interest is returned to at different time lags. Unique to the authors' approach (e.g., Amon et al., 2019; Necaise et al., 2021), we include an additional procedure to "color-code" the matrix (Figure 12D) to identify the distinct behaviors that underlie the recurrent points in the matrix.

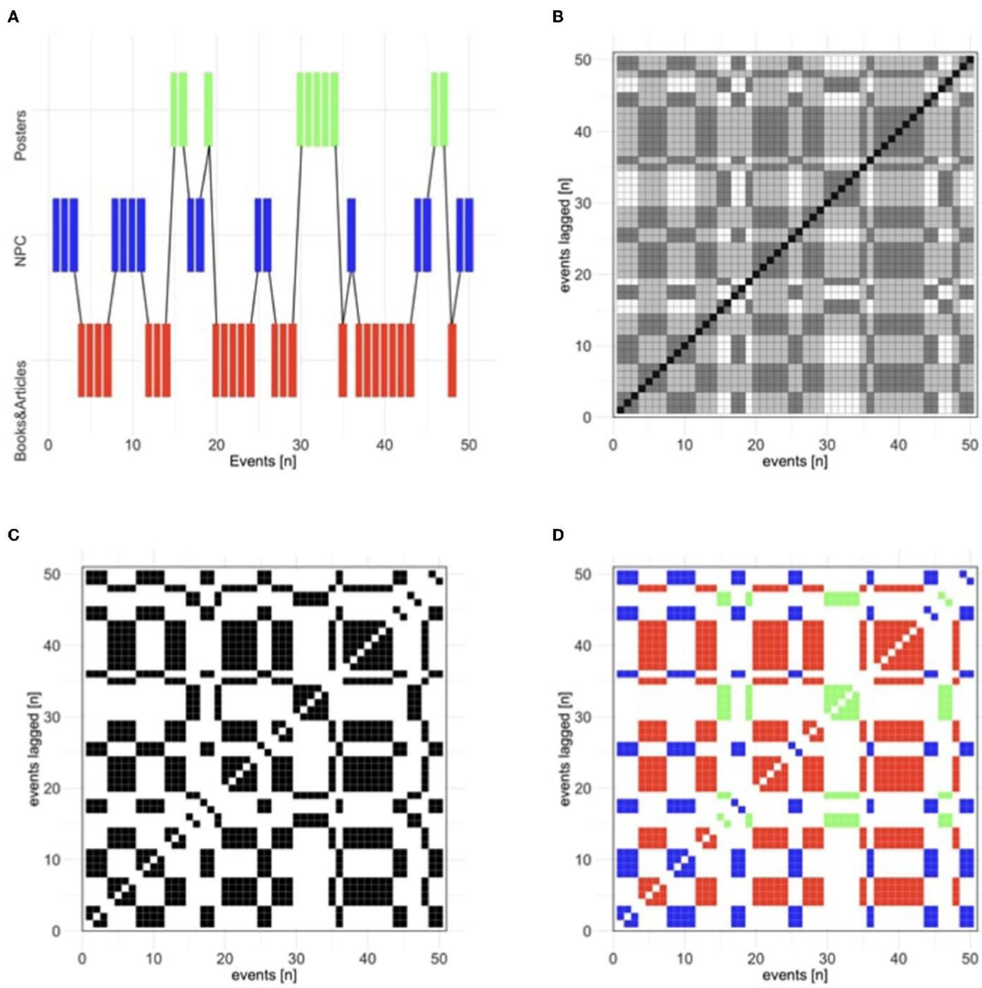

Figure 12: (A) Time series of events in the chronological order (or events on the main diagonal) that are transformed into the (B) distance matrix, (C) recurrence plot, and finally, into the (D) color-coded recurrence plot (Books in red, NPC in blue, and Posters in green).

We examine an RQA metric called percent determinism (DET), where determinism refers to the relative predictability of the system; i.e., the extent to which the system's future state can be predicted by the system's current state. In terms of RQA, DET technically refers to the percentage of the points that form diagonal lines, representing repeated sequences of behavior. For example, a time series with areas of interest *A, B, C, A, B, A* would include one recurrent sequence (A, B) depicted as a two-point diagonal on either side of the LOI. For this study, we use learners' interactions with instructional materials (i.e., books, research articles, posters, non-player characters) which hold all information needed to develop domain knowledge. Specifically, learners' interactions with these instructional materials are represented by learners' operations or time-evolving strategies that they deploy during gameplay and dynamically alter to fit their present needs. For the purposes of our study, more repetitive behavioral sequences of instructional material may give insight into how deployed SRL strategies interact with cognitive and task conditions to result in learners' products, or learning outcomes. Thus, aRQA provides a unique lens through which to understand SRL in terms of how task and cognitive conditions are related to how learners interact with instructional materials and the resulting learning gains.

Current Study

While previous studies have examined SRL using NDST methods (Garner and Russell, 2016), few studies in SRL literature: (1) examine how SRL strategies are deployed during game-based learning (Cloude et al., 2020; Taub et al., 2020a; Dever et al., 2021); (2) operationalize SRL as a sequence of dynamic, temporally unfolding processes and examine the direct relationships between these processes simultaneously using eye tracking data; and (3) use an NDST approach to analyzing how SRL occurs during learners' time in a GBLE. The goal of this study was to address these gaps in current literature by examining SRL using the lens of complex systems theory and analytically investigate how learners use SRL strategies within a GBLE through applying NDST methods. To address these gaps and further the SRL field conceptually, methodologically, and analytically, we propose three research questions:

Research Question 1: To what extent do learners' SRL behaviors and dwell times differ across instructional material throughout gameplay? This first research question examines how long a learner dwelled, or attended to, instructional materials, and how this duration varied as a function of relative game time, type of instructional material, and relevance of the instructional material to the pre-test. As prior studies have shown that learners are typically unable to engage in meaningful SRL and accurately deploy SRL strategies that will significantly increase their learning gains (Josephsen, 2017), we hypothesize that there will be significant main and interaction effects to explain within-person variability, but do not assume a direction. However, as individual differences (e.g., prior knowledge, task conditions, etc.) can significantly change how learners deploy SRL strategies during game-based learning, we propose that there will be significant between-person variability in the relevant vs. irrelevant instructional material dwell times.

Research Question 2: To what extent are learners' task and cognitive conditions, learning outcomes, and sequences of SRL behaviors with instructional material related to dwell times on instructional materials throughout gameplay? This second research question builds off of the first research question and aims to understand the full picture of how SRL processes can be examined and related to each other when examining eye gaze dwell times across relevant and irrelevant instructional materials. First, we hypothesize that learners with restricted agency will have greater learning gains than those with full agency, as supported by previous literature (Bradbury et al., 2017; Sawyer et al., 2017; Dever & Azevedo, 2019a; Dever et al., 2020). Further, we hypothesize that learners with restricted agency, greater prior knowledge, and greater learning gains will demonstrate increased dwell times on relevant instructional materials as they can better evaluate content relevance. It is possible that a relationship between the experimental manipulation and subsequent learning gains is a product of constrained interaction and, in turn, more repetitive eye gaze sequences. As such, we further hypothesize that learners with more repetitive sequences of SRL behaviors with instructional materials will have greater gaze dwell times on relevant, rather than irrelevant, instructional materials.

Research Question 3: How do learners' task conditions, cognitive conditions, and learning gains relate to their sequences of SRL behaviors? This research question is used to explore how learners differ in how often learners deploy repetitive sequences of SRL behaviors between task and cognitive conditions and its relationship with learning gains. For this research question, we hypothesize that learners with more repetitive eye-gaze sequences (i.e., more rigid behaviors), will be associated with restricted agency but related with higher learning gains. Further, we hypothesize that learners with higher prior knowledge will demonstrate more novel behaviors as they use instructional material interaction diversity as an SRL strategy to keep far-from-equilibrium interactions.

Methods

Participants and Materials

A total of 139 undergraduate students were recruited from a large public university based in the United States to learn with a narrative-centered, game-based learning environment called CRYSTAL ISLAND (Rowe et al., 2011; Dever et al., 2020a, 2021; Taub et al., 2020c). CRYSTAL ISLAND was designed to foster (1) higher-order thinking skills, such as effective problem solving and scientific reasoning, while also gaining knowledge about (2) microbiology content. For purposes of this article, a subsample of 82 undergraduates (68.3% female; Mage = 20.1, SDage = 1.69) were included in the analysis based on meeting the following criteria: (1) completed the entire study with CRYSTAL ISLAND; (2) were randomly assigned to either the full or partial agency conditions; (3) had no prior experience interacting with CRYSTAL ISLAND before participating in the study; and, (4) did not have missing data points across all converging data channels captured before, during and after game-based learning, including both log files and performance measures (e.g., pre/post-test assessments).

Most participants reported their race as “White/Caucasian”(68.30%; n = 56), while the remaining reported “American Indian or Alaskan Native” (1.22%; *n* = 1), “Asian” (12.20%; *n* = 10), “Black or African American” (7.32%; *n* = 6); “Hispanic or Latino” (7.32%; *n* = 6), and “Other” (3.66%, *n* = 3). The subsample also indicated that they “Did not play video games at all” (18.29%; *n* = 15), “Rarely played video games” (35.37%; *n* =29), “Occasionally played video games” (21.95%, *n* = 18), “Frequently played video games” (15.85%; *n* = 13), and “Very frequently played video games” (58.54%; *n* = 7). The subsample also reported having “No video game skills” (14.63%; *n* = 12), “Limited skills” (21.95%; *n* = 18), “Average” (37.80%; *n* = 31), “Skilled” (20.73%; *n* = 17), and “Very skilled” (4.88%; *n* = 4). The majority of the sample indicated they played a total of “0–2” (68.29%; *n* = 56), “3–5” (13.41%; *n* = 11), “5–10” (7.32%; *n* = 6), “10–20” (9.76%; *n* = 8), and “Over 20” (1.21%; *n* = 1) hours per week. This study was approved by the university's Institutional Review Board before recruiting participants and informed consent was gathered before collecting data.

To assess participants' understanding of microbiology, a 21-item, 4-option multiple choice, pre/post-test assessment was administered before and after game-based learning with CRYSTAL ISLAND see Figure 13, regardless of whether or not participants successfully solved the mystery. The assessments were designed with 12 factual (e.g., “What is the smallest type of living organism?”) and 9 procedural items (e.g., “What is the difference between bacterial and viral reproduction?”). Participants answered between 6 and 18 correct items across on the pre-test assessment (*Med* = 11, *M* = 55%, *SD* = 0.14), while participants answered between 9 and 19 correct items (*Med* = 14, *M* = 67%, *SD* = 0.12) on the post-test assessment (Rowe et al., 2011). In addition to the knowledge assessments, several self-report items were administered before and after the learning session but these data were not analyzed in this article. Game play duration ranged from 39.73 to 135 min (*M* = 85, *SD* = 19).

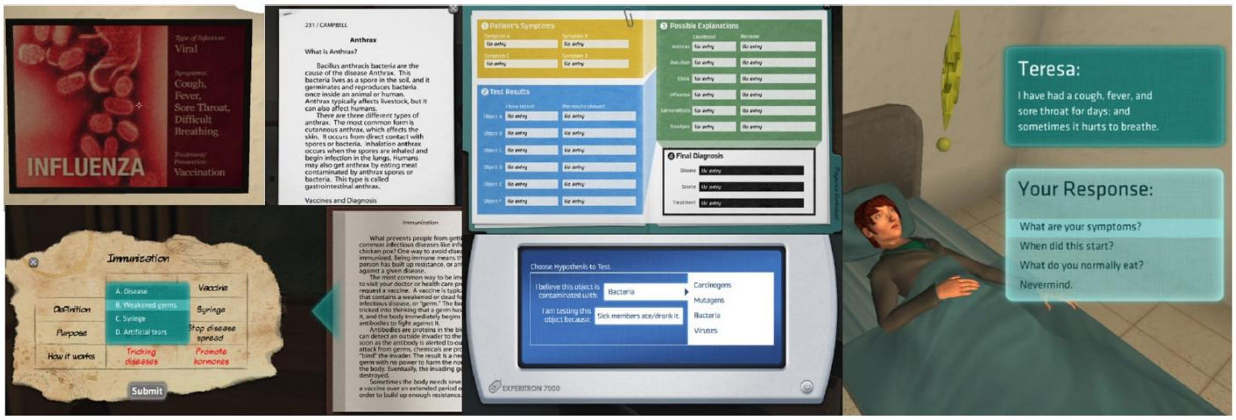

Figure 13: Elements within the CRYSTAL ISLAND Environment.

Experimental Design

In this study, participants were randomly assigned to one of two experimental conditions: (1) full agency (*n* = 47), and (2) partial agency (*n* = 35). These groups were built to experimentally manipulate the learners' level of control (i.e., agency) in the sequence of interactions with game features built into CRYSTAL ISLAND. In the control condition–i.e., full agency, participants were given complete control over their sequence of interactions with CRYSTAL ISLAND, or business-as-usual. Participants in the experimental condition–i.e., partial agency, were given restricted control over their sequence of interactions (e.g., first reading a book and then generating a hypothesis), meaning they were required to initiate a specific order of actions to progress with the learning session. For example, participants in the partial agency condition were required to first visit Kim, an NPC nurse in the camp infirmary. Once they entered the infirmary, the participant could not leave until all items within the building were interacted with (e.g., clicked on with no minimum time requirement). Once able to leave the infirmary, the next building was "unlocked." This experimental condition was designed around a particular sequence of interactions that scaffolded higher-order thinking skills such as effective problem solving and scientific reasoning activities via game features and restricted agency.

It is important to note that between the conditions, dwell times on instructional materials (i.e., how long participants looked at instructional materials indicated by eye-gaze behavior) were not restricted other than the requirement that learners in the partial agency interact with the material in some way (i.e., they could select the book, but not attend to it according to eye-tracking metrics). Additionally, all types of instructional materials were found in each building, so participants in the partial agency condition were not restricted to certain types of instructional materials as they progressed in the game.

Across all participants, participants spent an average of 86.0 min (*SD* = 19.5 minutes) in game where learners in the full agency condition spent an average of 80.2 min (*SD* = 20.1 min) and those in the partial agency conditions spent an average of 93 min (*SD* = 15.7 min).

Procedure

Participants were recruited using flyers across a large North American public university campus. Once participants were scheduled, they were instructed to come into the university laboratory space to obtain informed consent and complete the experiment for up to 2h. A CITI-certified researcher greeted the participant upon their arrival and instructed them to sit at the experimental station which consisted of a computer, keyboard, and mouse. After informed consent was obtained, they were randomly assigned to one of two conditions. Participants were then instructed to complete a series of questionnaires including the pre-test assessment to gauge their level of microbiology science content understanding and self-report items on emotions, motivation, and presence.

Afterwards, the researcher calibrated participants to three apparati: (1) SMI EYERED 250 eye tracker using a 9-point calibration to capture their eye movements during game-based learning (SMI, 2014), (2) facial recognition software to measure their facial expressions of emotions, as well as (3) electrodermal activity bracelet called Empatica 4 to capture their physiological arousal and stress response (iMotions, 2015). Specifically, the participant was required to view a gray screen with a neutral expression for approximately 10 s to establish a baseline for the facial recognition software and EDA bracelet. Once successful calibration was completed, participants started learning and problem solving with CRYSTAL ISLAND. Participants were given up to 90 min to solve the mystery. Once they completed the game, or they engaged with CRYSTAL ISLAND for 90 min, participants were instructed to stop what they were doing and complete a similar set of post-test items and self-report measures including the post-test assessment on microbiology. Upon their completion, participants were debriefed about the objectives of the study and their participation, thanked, and paid $10/h for their time.

Apparatus

Eye gaze behaviors were recorded using a table-mounted SMI EYERED250 eye tracker (sampling rate = 250 Hz). Participants were calibrated with a 9-point calibration. Participants' fixation durations, saccades, and regressions on different areas of interests (AOIs), which define the boundaries on the computer screen where specific elements or information are held. To be classified as a fixation duration, the participant was required to have relatively stable gaze behavior for at least 250 ms. These data were captured continuously using iMotions software (2015) as participants engaged in game-based learning.

Coding and Scoring

Reading dwell times and instances were established using gaze behaviors and log files. Log files collected as learners engaged with CRYSTAL ISLAND identified the times at which instructional materials were opened denoted by log file timestamps using event-based recording. As from just log files alone researchers cannot assume that learners were reading information from the instructional material, eye gaze behavior was used to supplement the identification of reading instances. Learners' total fixation durations on a single AOI while the instructional material was opened denoted by log files were aggregated into dwell times which identifies the total time learners spent fixating on a single AOI instance. These AOIs were laid overtop of each type of instructional material including books and research articles, posters, and the dialogue boxes as well as the NPC itself to identify NPC instances.

Learning gains were operationalized using normalized change scores (Marx & Cummings, 2007) which identified participants' differences in pre- and post-test scores proportional to the number of total points possible and controlling for participants' prior knowledge, or pre-test score.

Content evaluations were operationalized by first identifying the relationship between instructional materials and pre-test questions. Instructional materials which directly addressed a question on the pre-test were identified as relevant. If the information did not address a pre-test question, the instructional material was identified as irrelevant as the information within the text was not needed to increase learning gains. While content evaluations were not directly observable, we take the stance that learners who attend to relevant materials are making a correct content evaluation whereas attending to irrelevant instructional materials were incorrect content evaluations. This classification of relevant vs. irrelevant instructional materials is based on prior SRL (Azevedo et al., 2004) and priming literature (McNamara, 2005) where it is assumed that participants exposed to microbiology information on the pre-test may identify the same information within the GBLE as more important, and therefore more relevant to their learning. Across a total of 40 instructional materials spread throughout the CRYSTAL ISLAND environment, 19 were classified as relevant. Specifically, 33% (3/9) of NPCs, 57% (12/21) of books and research articles, and 40% (4/10) of posters were considered relevant to the pretest [see Dever et al., 2021].

Relative game time was calculated by taking the time at which an interaction occurred and dividing that by a participant's total time in game so that all interactions were scaled as occurring from Time = 0 to Time = 1. For example, if a participant opened a book at Time = 300s, and they spent 2382s in game, then the participant opened that book 12.6% into their game. This allows for a uniform comparison across all participants in terms of their total time spent interacting with the game.

Statistical Processing

To process the data and conduct analyses, several packages in R (R Core Team, 2017), including its base package, were used. For the multilevel modeling and basic reporting of statistics we used the "lme4" (Bates et al., 2015), "jtools" (Long, 2018), and "emmeans" (Lenth et al., 2018) packages. To conduct aRQA analyses and obtain the output, we utilized the "crqa" (Coco et al., 2020) package in R.

Model Building and Estimation

To examine how participants' sequences of SRL behaviors in reading and evaluating instructional material during game-based learning differs within and between learners, we constructed a multilevel growth model including several observation- and individual-level variables. Specifically, our overall model examined how dwell times on instructional materials (i.e., outcome variable) is influenced by observation- and individual-level variables. The dependent variable of dwell time was log transformed (with a base of 10) to normalize the data and reduce heteroscedasticity (skew and kurtosis < |2|). Due to the log transformation, reported estimates of the independent variables are geometric means where the estimates are exponentiated.

After transformation, several leveraging outliers (*N* = 72 out of 4,346 total observations) were removed from analyses as the dwell times of these instances fell outside a 1.5 interquartile range of the first and third quartiles of data. After the transformations and outlier removal, two-level multilevel linear growth models were used to analyze the hierarchically structured data where observations (*N* = 4,274) were nested within individual learners (*N* = 82). Throughout their time in game, each learner had an average of 52.12 observations (*SD* = 9.98with the number of observations ranging from 25 to 74 across all learners. Prior to exploration of observation- and individual-level variables, an unconditional means (null) model was estimated. This model demonstrated an intraclass correlation coefficient (ICC) of 0.05, suggesting that 5% of variation in instructional material dwell times is between learners [$t(82.6) = 2.99$, $p < 0.01$]. This justifies our use of multilevel linear growth models to examine the observation- and individual-level variables influencing dwell times on instructional materials.

Observation-Level Variables

These variables included relative game time, the type of instructional material, and the relevance of the material to the pre-test. Because participants varied in the total amount of time they interacted with the game, relative game time scales each participants' time in game from 0 to 1 where the raw game time a participant initiated an action was divided by the participants' total time in game. The values of relative game time were then forced to zero for each participant to interpret the model intercepts. In other words, participants' first initiation of an action was treated as a zero (with all other interactions adjusted accordingly) so that the growth model intercept, originally representing the dwell time where time was equal to zero which does not have a meaningful value, now represents the dwell time of participants' first time interacting with an instructional material. The type of instructional material included books and research articles (informative text, no visuals), non-player characters (informative text, uninformative visuals), and posters (informative and uninformative text and visuals) that provided information about microbiology concepts.

All types of instructional material were evaluated for their relevance in relation to microbiology concepts introduced in the pre-test. For example, an item on the pre-test asks "How do vaccines protect you?". For this question, a book or research article on the function of vaccines would be relevant to the pre-test whereas an instructional material on genetic diseases is irrelevant for this question. The classification of an instructional material is based on priming literature (McNamara, 2005) where participants are assumed to classify (either accurately or inaccurately) instructional material as either relevant or irrelevant in reference to the pre-test (Dever et al., 2020, 2021).

Individual-Level Variables

These variables include participants' condition, their prior knowledge, and the percent determinism of their sequences of instructional material interactions. Within the models, both variables were treated as fixed. Condition refers to either the full or partial agency conditions that participants were randomly assigned prior to interacting with the CRYSTAL ISLAND environment (see Section 6.2). Prior knowledge in microbiology was calculated using participants' raw pre-test scores on their microbiology content quiz before interacting with instructional materials in the CRYSTAL ISLAND environment. Percent determinism represents the proportion of recurrent sequences within a single time series, denoting the predictability of a system where a greater proportion of recurrent sequences indicates a system with higher behavioral predictability.

An unconditional means model was run to examine the variation of the dependent variable between individuals. The model found a 0.05% intraclass correlation coefficient; in other words, 5% of variation in the dwell times on instructional materials in CRYSTAL ISLAND is between learners [$t(82.6) = 2.99$, $p < 0.01$] and 95% is within learners. As such, several other multilevel models were constructed including: (1) an unconditional growth model with the latent time variable as an independent variable; (2) observation-level variables and their interactions; (3) significant predictors from (2) and individual-level variables; and (4) predictors from (3) and cross-level interactions.

Results

Research Question 1: To What Extent Do Learners' SRL Behaviors and Dwell Times Differ Across Instructional Material Throughout Gameplay?

For Research Question 1, we examined the unconditional growth model (i.e., Model 1) and the growth model with observational-level predictors (i.e., Model 2). Model 1 examined how time influenced the dwell time across all instructional materials. From this model, the dwell time on participants' initial interaction with instructional material was approximately 31.5s (SD = 52.7) which was significantly different from zero [$t(211.4) = 66.6$, $p < 0.01$]. However, dwell time across all instructional materials decreased by 68.0% (S.E. = 0.08) as participants' time in game progressed [$t(4236.1) = -14.4$, $p < 0.01$] from participants' initial interaction with instructional material. Model 1 fits the data significantly better than the unconditional means model [BIC = 14387.9, $D = 14{,}354$; $\mathcal{X}^2(1) = 202.1$, $p < 0.01$] where, by adding a latent time variable, the growth model explains approximately 4% of individual-level variance in dwell time.

Model 2 (BIC = 12,623, D = 12,506) incorporated observational-level variables (i.e., type of instructional material, relevance of the instructional material to the pretest) in addition to the latent time variable to examine the effect on the variation in participants' dwell times. This model was a statistically significant better fit than the unconditional growth model [$\mathcal{X}^2(10) = 1{,}848$, $p < 0.01$]. Holding all other variables constant, learners' average fixation durations on instructional materials was 104.6s (SE = 0.08). There were significant main and interaction effects for and between all variables. For every unit increase in relative game time, dwell times decreased by approximately 89.0% [S.E. = 0.16; $t(653.86) = -13.36$, $p < 0.01$].

Overall, participants had significantly greater dwell times on relevant (M = 48.4 s; SD = 56.5 s), rather than irrelevant (M = 37.1 s; SD = 48.8 s), instructional materials [$t(4186.7) = 3.37$, $p < 0.01$] by approximately 25.9% (S.E. = 0.07). Books and research articles (M = 77.3 s; SD = 64.3 s) had greater dwell times than dialogue with NPCs by 85.6% [S.E. = 0.07; M = 22.7; SD = 17.5; $t(4200.0) = -26.8$, $p < 0.01$] and posters by 91.5% [S.E. = 0.09; M = 8.96; SD = 5.33; $t(4210.6) = -28.3$, $p < 0.01$]. In relation to dwell times on instructional materials during participants' time in game, dwell times on books and research articles decreased by 88.9% (S.E. = 0.16) as time in game increased. Compared to books and research articles, dwell times on posters and dialogues on NPCs increased at a greater rate as the game progressed by 6-fold [S.E. = 0.20; $t(4209.54) = 8.86$, $p < 0.01$] and 9-fold [S.E. = 0.19; $t(4211.7) = 11.85$, $p < 0.01$], respectively.

When examining the relationship between participants' content evaluations, type of instructional material, and game time on dwell times, Model 2 found that participants' dwell time on pretest-relevant instructional materials decreased by 56% (S.E. = 0.18) as participants learned with CRYSTAL ISLAND [$t(4182.4) = -4.65$, $p < 0.01$]. When examining a three-way interaction and controlling for observation-level variables, dwell times on relevant posters [S.E. = 0.16; t(4180.0)

= 2.65, $p < 0.05$] and dialogues with NPCs [S.E. = 0.17; $t(4176.8) = 6.70$, $p < 0.01$] increased as participants engaged with CRYSTAL ISLAND by 98.5 and 97.1% respectively compared to dwell times on books and research articles.

Research Question 2: To What Extent Are Learners' Task and Cognitive Conditions, Learning Outcomes, and Sequences of SRL Behaviors Related to Dwell Times on Instructional Materials Throughout Gameplay?

Task and Cognitive Conditions

An independent samples t-test was first run to ensure that prior knowledge did not differ between experimental conditions. Results were not significant ($p > 0.05$), so we included both as individual-level variables. However, when running Model 3 which contained the observation-level variables from Model 2 and added prior knowledge and agency conditions as individual-level variables, there was not a main effect for either condition or prior knowledge ($p > 0.05$). When examining cross-level effects of prior knowledge and condition, only the interaction between condition and type of instructional material was significant where participants in the partial agency condition had significantly greater dwell times on posters than participants in the full agency condition by approximately 29% [S.E. = 0.10; $t(160.1) = 2.57$, $p < 0.01$]. No other interaction effects were significant. Therefore, we conclude that task and cognitive conditions do not significantly relate to the dwell time on both relevant and irrelevant instructional materials as the game progresses.

Learning Outcomes

Model 4 added normalized learning gain as an individual-level variable to Model 3. However, the model did not find a significant main effect or interaction effect when adding learning gains to the model. As such, we conclude the learning outcomes are not significantly related to the dwell time on either relevant or irrelevant instructional materials as the game progresses.

Sequences of SRL Behaviors

For Model 5, percent determinism was added as an individual-level variable to Model 3. Percent determinism has a significant main effect where, with all other variables constant, for every unit increase in percent determinism, dwell times decreased by approximately 2.0% [S.E. = 0.01; $t(113.0) = -2.68$, $p < 0.05$]. There was one cross-level interaction between percent determinism and type of instructional material where, compared to dwell times on books and research articles, for every unit increase of percent determinism, dwell times on posters increased by approximately 2.0% [S.E. = 0.01; $t(4097.2) = 2.62$, $p < 0.05$], with no significant relationship between NPC dialogue and percent determinism ($p > 0.05$). From these results, we conclude that there is a significant relationship between percent determinism and the dwell times spent on instructional materials regardless of participants' content evaluations.

Research Question 3: How Do Learners' Task Conditions, Cognitive Conditions, and Learning Gains Relate to Their Sequences of SRL Behaviors?

Information on the recurrent sequences of books and research article opens, NPC dialogues, and poster interactions were extracted from the lags outputted from aRQA analyses (see Figure 12 for example). This information was used to first calculate the total number of recurrent points across all participants and instructional material types (see

Table 8).

Table 8.
Proportional Means of Recurrence Points Across Lags 1-5 and Instructional Materials

Recurrent Action	Lag1	Lag2	Lag3	Lag4	Lag5
NPCs	0.212	0.231	0.262	0.275	0.264
Books and Research Articles	0.468	0.482	0.529	0.548	0.617
Posters	0.320	0.287	0.210	0.177	0.119

To examine how the dynamics (i.e., sequences) of instructional material interactions, cognitive conditions, and task conditions influence learning, frequencies of learners' recurrent points across Lags 1-3 were first correlated against each other to ensure multicollinearity does not affect the outcome of further comparisons. Several significant correlations existed between Lags 1–3 and across the instructional materials ($p < 0.01$), so Lag1 frequency counts of recurrent points across all instructional materials were used as variables for hierarchical clustering. Using this method, three clusters of participants were identified differing in the number of recurrent sequences of instructional materials on Lag1. Cluster 3 was removed from subsequent analyses as there were less than 10 participants ($N = 5$), the remaining clusters, Cluster 1 ($N = 34$) and Cluster 2 ($N = 43$), were used in further analyses. T-tests revealed that learners classified within Cluster 1 had significantly fewer book and research article recurrent points as well as poster recurrent points compared to learners classified within Cluster 2, but no significant difference in NPC dialog interaction recurrent points (see Table 9).

Table 9.
Recurrent Point Frequency between Clusters 1 and 2

Instructional Material	Cluster 1 [M(SD)]	Cluster 2 [M(SD)]	*t*-value; *p*-value
NPCs	1.35 (1.07)	1.33 (0.75)	$t_{(56.7)} = 0.13$; $p > 0.05$
Books and Research Articles	2.21 (0.77)	3.88 (1.10)	$t_{(74.1)} = -7.88$; $p < 0.01$
Posters	1.56 (0.82)	2.65 (0.98)	$t_{(74.3)} = -5.40$; $p < 0.01$

Using both Clusters 1 and 2 as a predictor, a multiple linear regression was run to understand how the cluster learners were classified within as well as their agency within CRYSTAL ISLAND influenced learning gains. Prior knowledge was not included as (1) prior knowledge does not differ between conditions; and (2) prior knowledge did not significantly interact with any variables in the hierarchical linear model (see RQ2). Overall, there was a significant multiple linear regression model [$F(3, 37) = 4.79$; $p < 0.01$] that accounted for 16% of variance. The multiple linear regression found a significant main effect of cluster where, keeping condition constant, participants classified as Cluster 2 ($M = 0.45$; $SD = 0.24$), with greater recurrent points on both books and research articles and posters, had significantly greater learning gains than those in Cluster 1 ($M = 0.33$; $SD = 0.28$) with less recurrent points ($t = 2.58$; $p < 0.05$). There was a second main effect of condition where, keeping cluster constant, participants in the partial agency condition (M = 0.48; SD = 0.25) had significantly greater learning gains than learners with full control over their own actions ($M = 0.33$; $SD = 0.26$; $t = 3.11$; $p < 0.01$). A significant interaction effect was also observed ($t = -2.05$; $p < 0.05$).

From this interaction, participants classified within Cluster 1 and with full agency had a significantly greater learning gains than participants in Cluster 2 with full agency. Specifically, participants within Cluster 1 with full agency had a mean learning gain of 0.23 ($SD = 0.26$) whereas participants in Cluster 2 with full agency had a mean learning gain of 0.43 ($SD = 0.23$). Meanwhile another significant effect was found where participants within the partial agency condition had a mean learning gain of 0.52 (*SD* = 0.23) if they were classified within Cluster 1, but a mean learning gain of 0.47 (*SD* = 0.26) if they were classified within Cluster 2.

In summary, results across all research questions have several main findings: (1) dwell times on instructional materials as a function of learners' content evaluations of instructional materials over gameplay where dwell time on pre-test relevant materials decrease; (2) the predictability of SRL behaviors, denoted by percent determinism, is related to learners' greater dwell times on instructional materials; and (3) learner profiles of recurrent instructional material sequences can be extracted and are related to both agency and overall learning outcomes where learning gains are greatest in participants who had restricted agency and greater recurrent interactions with instructional materials.

Discussion

As very few studies have provided a comprehensive analysis of unfolding SRL processes during game-based learning, the goal of this study was to examine the emergence of SRL from a complexity science perspective. This article investigated whether cognitive strategies, task conditions, and SRL behaviors, grounded within Winne's (2018) COPES model of SRL, moderated when and for how long learners gathered information during learning with a GBLE. This study viewed SRL through the lens of complex systems theory and analyzed SRL using an NDST technique to understand how SRL should be scaffolded within GBLEs through restricted agency.

The first research question examined how dwell times on both irrelevant and relevant instructional materials vary as a function of relative game time, type of instructional material, and relevance of the instructional material. Overall, hypotheses for the first research questions were supported where significant between- and within-person variability were identified. Further, dwell times across all instructional materials decreased over learners' time in game and there were generally greater dwell times on relevant than irrelevant instructional materials. This could potentially be due to the familiarity with materials over the course of gameplay, indicating more accurate metacognitive monitoring SRL behaviors. Even though dwell times on books and research articles were significantly greater than both NPC dialogues and posters, the dwell times on NPCs and posters increased at a greater rate compared to books and research articles as learners interacted with CRYSTAL ISLAND.

Of most interest is the interaction between relative game time and instructional material relevance. Specifically, dwell times on pre-test relevant materials generally decreased over learners' gameplay whereas dwell times on relevant NPCs and posters increased over learners' time in game. From these results, we conclude that while learners are initially able to accurately deploy SRL strategies for information-gathering by engaging with pre-test relevant instructional materials, as time engaging in game-based learning progressed, learners' ability to consult relevant information from irrelevant books and research articles decreased. Because dwell times on books and research articles did not change during learning but time on relevant books and research articles decreased, we infer that the long blocks of text without any supporting diagrams or conversational interactions did not support learners' deployment of accurate SRL monitoring strategies (i.e., content evaluations). However, learners were generally able to deploy accurate content evaluations when interacting with posters and NPCs as they learned with CRYSTAL ISLAND. Our results expand prior studies such as that by Dever et al. (2019b) and Taub et al. (2018) by including relative game time, dwell times, and content evaluations based on relevance to domain knowledge acquisition. These results support SRL as a complex system through and add to Winne's (2018) IPT of SRL model by examining how operations can affect how learners interact with their learning environment and how this can be captured and measured using eye-tracking and log-file data.

The second research question expanded previous results to understand how SRL processes can be examined and related to each other when examining eye gaze dwell times across relevant and irrelevant instructional materials. Hypotheses were partially confirmed where results did not find that task conditions, cognitive conditions, or learning outcomes were significantly related to dwell times on either relevant or irrelevant instructional materials during learning with CRYSTAL ISLAND. However, hypotheses regarding SRL sequencing behaviors were partially confirmed where the models found that as percent determinism increases, the dwell times on instructional materials increase regardless of material relevance to the pre-test. This effect may have implications for the oscillation between accurate and inaccurate use of SRL strategies due to the non-significance in dwell times on relevant and irrelevant instructional materials. Further, this result is interesting as learners who repeat sequences of information-gathering behaviors with instructional materials tend to have greater dwell times on these materials. To fully explore this effect, future analyses should examine the differences in repeated behaviors for each type of instructional material.

From these results, we conclude that SRL systems with greater predictability and less novel behaviors typically have greater dwell times across instructional materials. The findings contradict research conducted on task conditions, cognitive conditions, and overall learning which found these constructs to significantly interact. This is potentially due to how SRL within this study was measured using an NDST method to examine the stability vs. rigidity of SRL behaviors individually rather than aggregating using typical parametric methods. However, these results contribute to the dynamic and complex conceptualization of SRL as we were able to identify a positive relationship between the predictability of SRL behaviors and learning outcomes. Specifically, this result has implications for (1) Winne's (2018) model to include learners' recursive interactions with GBLE elements as an operational strategy for SRL, and (2) scaffolding design through the lens of far-from-equilibrium concept within complex systems theory. For example, treating SRL systems as complex should extend to theory as well as how GBLEs are designed. From the results of the study, GBLEs should increase the minimum time of instructional material interaction and promote learners' use of several different types of representations while still structuring their approach to how learners interact with the environment. Scaffolds within GBLEs should be designed to balance learners' exploratory behaviors with the structure provided by scaffolds to encourage behaviors that follow the far-from-equilibrium concept.

To further explore learners' sequences of instructional material interactions and how they relate to task conditions, cognitive conditions, and learning gains, the third research question extracted information from the aRQA output. In doing so, we were able to explore how learners differ in (1) the distribution of novel behavioral sequence indices over different instructional materials; and (2) the novelty of behavioral sequences between task and cognitive conditions and its relationship with learning gains. For this third research question, we hypothesized that learners with more repetitive eye gaze sequences would be present in learners with restricted agency and related with higher learning gains. Further, we hypothesized that learners with higher prior knowledge would demonstrate more novel behaviors as they used instructional material interaction diversity as an SRL strategy. Specifically, more novel behaviors denote a healthier SRL system, and as such, the use of multiple different types of materials can be considered a learning strategy employed by learners.

Overall, our hypotheses were not confirmed as prior knowledge was not included within our analyses due to previous non-significant relationships. However, when clustering all participants according to the frequency of recurrent points on Lag 1 and between all instructional materials, hypotheses were confirmed. First, we were able to identify differences between learners where two clusters identified learners as having greater books and research article recurrence (Cluster 2) or fewer recurrence in these interactions (Cluster 1) with no differences in the frequency of NPC recurrent points. From our analyses, learners who had restricted control over their own actions (i.e., the partial agency condition) demonstrated significantly greater learning gains, regardless of classified cluster profiles than learners with full control. However, when ranking the significant clusters and conditions in reference to overall learning, we conclude that learners with partial agency in Cluster 1 had greater learning gains, **demonstrating novel behavior while engaging in guided game-based learning increases overall learning gains**. These results are parallel to findings for the concept of agency (Sawyer et al., 2017; Dever et al., 2020; Taub et al., 2020c) but are novel by examining learners' recursive behaviors in gathering information during game-based learning. These results are consistent with the far-from-equilibrium concept of complex systems theory which promotes the balance between rigidity (i.e., partial agency) and chaos (i.e., novel SRL behavior).

Future Directions and Concluding Statement

Our findings have significant conceptual, theoretical, methodological, empirical, and design implications for future research on SRL and GBLEs. Conceptually, our use of NDST analytical methods to analyze SRL process data during game-based learning significantly contributes to the field of SRL and learning technologies by including complex systems theory (Lajoie et al., 2018; Järvelä and Bannert, 2019). While much has been published describing SRL as a dynamic, temporally unfolding process, there is no published research using complex systems theory as a theoretical grounding or dynamical systems in modeling as a method to examine the dynamics of SRL strategies, specifically information-gathering behaviors, during GBLEs (Azevedo et al., 2019; Favela, 2020; Plass et al., 2020). That is, SRL has theoretically been described as temporally dynamic, with some models assuming non-linearity as well, but we extend these assumptions by positing SRL as a complex system and used NDST analytics to empirically support this claim. To date, this article acts as one of the first studies to apply NDST methods to SRL using complex systems theory (see Garner and Russell, 2016; Li et al., 2022).

The use of non-linear dynamical systems techniques allows researchers to specify, operationally define, and make predictions about assumptions regarding the dynamics of SRL processes. More specifically, we can understand how the dynamics of each SRL process (within and across different data channels) are connected to specific complex SRL components described in Winne s COPES model. A dynamical systems approach ties each of the COPES together elegantly and produces testable hypotheses that need to be further explored by researchers (e.g., how do other cognitive conditions such as motivation or emotions relate to how learners oscillate between more recursive or novel operations?)

In addition, our findings using log-files and eye movements provide evidence of the dynamics of specific cognitive and metacognitive processes that, until recently, could only be described in an abstract manner using models such as Winne's (2018) theory of SRL. More specifically, our findings indicating that relationships between eye gaze dwell time and (1) the type of representation a learner gathers information from (i.e., large sections of text, poster, or dialogue); (2) the ability of the learner to distinguish relevant from irrelevant information; (3) learning gains; and (4) agency, could only have been established using the non-linear dynamical systems modeling and statistical techniques used in our study. As such, our findings, based on our use of multimodal data, can begin to augment current models of SRL (e.g., Winne, 2018) by adding the micro-level processes (e.g., judgments of learning, monitoring progress toward goals) that are currently hypothesized to predict learning and performance. Dynamical system modeling can be used to study task and cognitive conditions and affordances of the GBLEs (e.g., agency) as learners engage in SRL processes.

Future research should focus on how other multimodal data (e.g., physiological and facial expressions of emotions) contribute to our understanding of the dynamics of other key SRL processes such as affect and motivation. Can the dynamics capture subtle states or state transitions related to emotion regulation, emotion regulation efficacy, etc. (McRae & Gross, 2020)? What are the multimodal data that most accurately predict affective and motivational states? What specific indices can be extracted from each data channel to understand the temporal dynamics of affect and motivation during GBLE? Would non-linear dynamical modeling techniques and analytical approaches predict that the same states within and across data channels are predictive of learning, reasoning, performance, etc.? How would learning technology-specific affordances impact the dynamics of SRL across learning technologies? For example, how would the lack of autonomy embodied into an intelligent tutoring system impact the dynamics of cognitive, affective, metacognitive, and motivational SRL processes compared to a simulation?

Researchers should consider longer and different types of experiments to test how changing agency, number and types of relevant and irrelevant instructional materials, behavioral repertoire of the NPCs, etc. would impact learners' self-regulation and multimodal data. This new research strategy would also force researchers to isolate the exact dependent variables for each data channel and how they both individually and collectively contribute to our understanding of the dynamics of SRL across learners and contexts.

Our findings also have implications for the design of future GBLEs where NPCs can detect when, how, and why learners fluctuate in their accurate SRL strategy deployment. Further, complex systems theory lends support in the development of GBLEs to support the balance between rigid and complex SRL behaviors. The system's intelligence capability could lead the NPCs to engage in a conversation with the learners about why their ability to identify relevant text has changed. Further, this could serve as an opportune time to pedagogically intervene by providing different types of scaffolding or prompting to the learners. We see several innovative pedagogical interventions delivered by the NPCs. For example, "Your eye movements suggest that you are not spending enough time on the relevant textual cues. Would you like for me to model these processes? Or, would you like for me to show you your multimodal data to show you what, where, and how you have changed your overall strategy?". In summary, the use of non-linear dynamical system modeling has tremendous potential to advance the field of SRL, multimodal data, and GBLEs.

Data Availability Statement

The datasets presented in this article are not readily available because of written consent restraints. Requests to access the datasets should be directed to Daryn Dever, corresponding author.

Ethics Statement

The studies involving human participants were reviewed and approved by North Carolina State University International Review Board. The participants provided their written informed consent to participate in this study.

Author Contributions

DD significantly contributed to the conceptualization and construction of this manuscript as well as the analyses that were conducted. MA and HV contributed their expertise of complex systems and non-linear dynamical systems theory and the application of auto-Recurrence Quantification Analysis. MW contributed to the analyses and data extraction as well as to the editing of this manuscript. EC wrote the methodology section and provided edits. RA significantly contributed his expertise in SRL and supported the future directions and final conclusion section. All authors contributed to the editing of the manuscript.

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Conflict of Interest

EC was employed by SoarTechnology, Inc. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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CHAPTER 6: THEORETCIAL, METHODOLOGICAL, ANALYTICAL, AND APPLIED CONTRIBUTIONS AND IMPLICATIONS FOR FUTURE DIRECTIONS

Across all chapters of this dissertation, there are several theoretical, methodological, analytical, and applied/instructional issues, contributions, and implications for enhancing how the complexities of SRL are captured and scaffolded during game-based learning. Theoretically, this dissertation examines SRL not only within traditional educational literature but also across the learning, psychological, and complexity sciences. Specifically, SRL theory was expanded to explain how learners interacted with multiple types of instructional materials during learning and how learners' interactions with these materials dynamically changed over time in game. Methodologically, this dissertation used process data to capture learners' SRL use during game-based learning. Analytically, this dissertation extends how SRL is defined, measured, inferred, and interpreted. Specifically, we examine how SRL can be attributed to learners' actions contextualized within a GBLE and can be both analyzed and interpreted to preserve and account for the dynamics of how SRL may change over time. Finally, there are several applied contributions and implications of this dissertation, namely, how to scaffold SRL during learning. Throughout the chapters, we are able to see a common theme of effectiveness in restricting agency in GBLEs to promote learning and SRL use. However, there is a need to better support SRL use as it changes over time and as behaviors need to be contextualized to the environment (e.g., game-based, simulation, intelligent tutoring systems). As such, this dissertation ends with a review of how the theoretical, methodological, and analytical contributions and implications of the previous chapters lend themselves to future directions in applying adaptive agency-based scaffolds within GBLEs. It is important to note that all contributions and implications are intertwined. In other words, expanding SRL theory leads to new analytical techniques that require advance methodologies to further improve applied and instructional practices for capturing and scaffolding learners' SRL during game-based learning.

Theoretical Contributions and Implications

SRL literature seldom incorporate theories from other domains in combination with traditional SRL models. This limits current literature in explaining how learning occurs, especially within game-based learning environments which incorporate several elements, including reading text, interpreting diagrams, and dialoging with NPCs, especially as learners select these interactions according to goal and content relevance. For example, while Winne's COPES model may explain that learners deploy operations (e.g., searching, monitoring, assembling, rehearsing, translating) during learning, it does not explain how learners interact with specific instructional materials nor how learners discern between relevant information and irrelevant information.

This dissertation acknowledged this limitation and attempted to close this gap in SRL literature. Although Chapters 2 (Dever & Azevedo, 2019) and 3 (Dever et al., 2020) only use CTML as their theoretical grounding instead of in combination with an SRL model, the results from these studies demonstrate that learner interactions with instructional materials within GBLEs counters the assumptions of CTML where learners placed a higher value in texts that did not have supporting diagrams than interactions that provided a conversation or a diagram. Results from Chapter 3 specifically acknowledged that learners deploy metacognitive strategies, such as content evaluations, and that the type of instructional material determined learners' ability to accurately use SRL strategies. From this we can ask the question: Can the use of SRL models in combination with other learning theories explain the inconsistency of theory and analytical findings? Chapter 3 directly discusses this relationship in proposing that SRL is required within CTML to explain how learners select instructional materials in relevance to their learning goals as well as how the selection of materials are dynamically monitored. Further, Chapter 3 reflects on the contextualization of CTML to a game-based learning task in which learners' metacognitive competencies can determine the accuracy of learners' SRL strategies (i.e., evaluating content as relevant) over time, especially as learners are afforded full control over their actions.

The concerns and future directions in Chapters 2 and 3 are addressed starting in Chapter 4 (Dever et al., 2021). CTML is combined with COPES to examine the relationships between internal (i.e., prior knowledge) and external (i.e., level of restricted agency) conditions, learners' use of SRL strategies (i.e., content evaluations), and how learners use instructional materials to increase their products (i.e., domain knowledge) over time during game-based learning. The relationship between CTML and SRL is validated by the results of Chapter 4. Learners' external conditions imposed by the GBLE (i.e., agency) and their use of SRL in selecting relevant instructional materials are directly related to learners' products, or how much domain knowledge they learned in the environment.

Similar to Chapter 4, Chapter 5 (Dever et al., 2022) expands SRL theories to incorporate complex systems theory. This accounts for the dynamics of SRL, or how learners change in their deployment of SRL over time while learning with a GBLE. In using complexity science to theoretically ground and analyze SRL behaviors (i.e., the use of SRL strategies) exhibited by learners during game-based learning, we can understand the cognitive processes as they emerge over time. Chapter 5 aligned the COPES SRL framework with complexity. To situate learners' conditions, operations, and products as SRL components that interact with each other as learning occurs. Further, concepts from complex systems theory can be used to explain SRL behaviors. For example, Chapter 5 introduces the far-from-equilibrium concept as a way to measure the function or malfunction of learners' SRL. Specifically, this conceptualizes a balance in which SRL strategies should be used. Behaviors that are too rigid or repetitive as well as behaviors that are too chaotic or constantly changing denote a malfunction of SRL whereas a balance between repetition and chaos represents functional SRL.

All studies within this dissertation both impress a need for the use of multiple theories to explain SRL within GBLEs. While SRL literature can explain why and how learners deploy SRL during learning, the use of theories and models outside of SRL literature can improve how we contextualize learners' SRL behaviors to GBLEs and can explain which SRL strategies are appropriate to use in both a specific and broader sense. For example, the use of CTML in conjunction with COPES details the necessity of learners in using content evaluations to select, organize, and integrate information in relevance to learners' goals. Complex systems theory in conjunction with SRL models explain how SRL behaviors should occur in balance over time. In using both theories, and in the future incorporating other theories from both learning and other domains, researchers can theoretically ground and interpret learners' SRL behaviors to better support SRL in GBLEs. For example, intelligent and adaptive agency-based scaffolds driven by SRL can track, measure, and respond to manage learners' use of functional SRL. However, to do this, researchers should incorporate methodologies that are able to capture SRL during learning.

Methodological Contributions and Implications

Offline methods of data capture, i.e., interviews, retrospective think-alouds, self-report questionnaires, are largely used to capture learners' SRL use and competencies but these methods fail to detect the nuances and intricacies of SRL as time on task progresses (Veenman et al., 2006). When examining how SRL is used during game-based learning, these environments allow for data to be captured using online process data as the learner completes tasks. For example, as GBLEs are often computer-based, GBLEs offer a unique opportunity for log-file data to be captured both locally and remotely. However, critical gaps in current literature exist in using and comparing multimodal process data to quantify and evaluate the quality of SRL, comprehension, and learning during game-based learning. As such, this dissertation aimed to use process data, and specifically multimodal process data, to capture when SRL processes were used during game-based learning, for how long each SRL strategy was used, and how the use of SRL changed over time.

Chapter 2 (Dever & Azevedo, 2019) used one type of process data, eye tracking, to examine how learners interacted with instructional materials during game-based learning. In tracking learners' gaze movements, inferences can be made in understanding learners' decision-making processes, cognitive strategies used, and their attention allocation to materials in the environment. This is shown in Chapter 3 (Dever et al., 2020) where eye tracking and log files are compared against each other to see which process data are appropriate for capturing specific processes. This study showed differences between these process data in that eye tracking proved to be better at capturing how learners utilized their SRL processes within GBLEs. Chapters 4 (Dever et al., 2021) and 5 (Dever et al., 2022) also used multimodal process data through eye tracking and log files but in conjunction with each other to validate learners' interactions. For example, although log files may confirm that a learner interacts with an instructional material, eye-tracking data confirms that the learner's attention is on the material rather than off-task. In other words, in using multimodal process data, researchers can not only quantify the use of SRL but also ensure the quality of SRL processes as the use of multiple data streams can provide validation of interpretations and SRL behaviors can be triangulated by incorporating multimodal process data.

These studies also show that not only should study methodologies use multimodal process data but that researchers must discern how to use these process data to measure SRL behaviors post-hoc (Azevedo et al., 2019; Giannakos et al., 2022). For example, should log files be used instead of eye tracking when examining navigational data during game-based learning? What information can eye-tracking data provide researchers versus log-file data and how can this help our understanding of SRL? This understanding of how to use multiple methods of data collection will be useful for dictating how future GBLE systems capture learners' interactions and feed information back into the environment to scaffold SRL. For example, say a GBLE already has the knowledge, dictated by empirical research, that a learner should first engage in an SRL strategy, such as a content evaluation (Azevedo & Dever, 2022), when first entering a conversation with an NPC. We can imagine a GBLE system that, through real-time log-file data collection, can detect when a learner initiates a conversation. In feeding eye-tracking data from the learner into the GBLE system at that moment in time, a determination by the GBLE can be made that a learner (1) did not make a content evaluation, (2) accurately evaluated content as relevant, or (3) inaccurately evaluated content as irrelevant by detecting eye scanning behavior over the dialog choices and proceeding to engage in a conversation instead of closing out of the interaction. Should the learner make inaccurate evaluations, the GBLE can provide adaptive scaffolding for that specific learner to prompt them to engage in conversation with that NPC. Future directions in research extend beyond this dissertation to include more methods of data collection including concurrent verbalizations evaluated in real time using natural language processing. The use of more sophisticated methodologies in collecting multimodal process data during game-based learning allows for opportunities for research to use more advanced analytical techniques to understand and evaluate how SRL is used over time.

Analytical Contributions and Implications

Our current understanding of SRL within literature can be attributed to the limited analytical techniques used within empirical studies, contributing to a vicious cycle in which new analytical techniques are not used due to the theoretical grounding of variables and concepts which in turn leads to findings that do not contribute to large advances in SRL theory. In other words, the field of SRL will stagnate unless researchers incorporate new theories outside of SRL literature, capture SRL using process data, and appropriately use statistical analytical techniques that reflect these changes (Azevedo, 2020). While some studies have attempted to use more sophisticated techniques to understand and predict learner success during game-based learning (e.g., Emerson et al., 2023; Golsen et al., 2022), the majority of literature is still saturated with analytical limitations. This dissertation reflects these limitations and advancements within the field of SRL. Specifically, while Chapters 2 (Dever & Azevedo, 2019) and 3 (Dever et al., 2020) utilize theoretical groundings outside of the SRL field and incorporate multimodal process data to capture SRL processes, it is Chapters 4 (Dever et al., 2021) and 5 (Dever et al., 2022) that incorporate time to capture the dynamics and complexities of SRL during game-based learning.

Chapter 4 used growth modeling to show how learners' eye tracking data captured during learning with instructional materials changed over time. In using hierarchical growth modeling, this study showed how learners are unable to engage in SRL consistently and accurately over time. Chapter 5 serves as the focal point for the analytical contributions and implications of this dissertation in which multimodal process data were used and complexity science was connected with SRL theory to determine the statistical analyses utilized and how the interpretation of research findings furthers SRL theory. Specifically, Chapter 5 utilized facets of complex systems theory to guide the analytical techniques and interpretations. Auto-recurrence quantification analysis (aRQA) from non-linear dynamical systems theory (NDST) was used to understand how learners' SRL behaviors (i.e., the use of SRL strategies captured using process data) shift between repetitive and novel sequences of interactions. Because this analytical technique can provide insight as to how SRL is deployed over time and is related to learners' internal and external conditions and their learning outcomes, aRQA provides SRL researchers the unique opportunity to understand SRL in terms of how SRL behaviors dynamically change over time.

Additionally, by using the far-from-equilibrium concept from complex systems theory, which states that functional systems demonstrate a balance between repetitive and novel patterns of behavior, researchers can interpret quantified SRL behaviors in terms of functionality. This dissertation defines functioning SRL systems as containing behaviors which demonstrate a balance between the repetitious and novel deployment of SRL strategies. Conversely, malfunctioning SRL systems display behaviors that trend towards the extreme ends of the spectrum in which learners display too much repetitious SRL strategy use or too novel in which a large range of SRL strategies are being used within a short time period. Results from this dissertation contribute to conceptualizing the dynamics and complexities of SRL.

There are several implications for the scaffolding of SRL during game-based learning using restricted agency based on the findings from Chapter 5 which state that restricting agency during game-based learning helps to promote functional SRL systems. Future GBLEs should incorporate these analytical techniques into how SRL behaviors are prompted. For example, should a learner be engaging in repetitious behaviors in which the same patterns SRL strategies are being used throughout the learning task, the GBLE should prompt the learner to engage in a different strategy or provide training on how to use other types of SRL strategies to promote increased novelty of SRL behaviors. Additionally, future directions in research should ensure that they dynamics of SRL processes are reflected in the type of analytical methodologies used. While traditional parametric and nonparametric analytical techniques may prove to be more appropriate given specific research questions, when examining how SRL unfolds over time or how learners' use of

SRL during a learning task related to learning outcomes, researchers need to account for the interaction between the multiple components of SRL and how the overall behavioral patterns displayed by learners across their full time in game may affect this relationship. Being aware of and using these analytical techniques can have large implications for how SRL can be more accurately scaffolded within GBLEs.

Applied/Instructional Contributions and Implications

Learners are notoriously incapable of effectively and accurately deploying SRL during game-based learning, especially if the environment is open-ended. This dissertation argues that there are theoretical, methodological, and analytical limitations that currently exist in the field which make it difficult for researchers and developers to design and study GBLEs that can effectively scaffold learners. For example, empirical research has not extensively tested agency as a scaffold in supporting learning, comprehension, and problem solving. Chapters 2 through 5 within this dissertation provide possible pathways for SRL literature to improve the theoretical grounding of research and GBLE scaffolds, the methods in which learner data is captured, and the analytical techniques that can be used to measure the degree of functionality in learners' SRL behaviors. The goal for future GBLEs is to establish a balance between the agency provided to learners to encourage active participation and engagement while scaffolding learners' SRL to increase learning gains. This dissertation reviews four studies that have examined the relationship between agency-based scaffolds and SRL.

Across all chapters, it has been established that learners who received scaffolding via restricted agency while interacting with a GBLE demonstrated greater learning gains than learners who were afforded full control over their actions. Further, each chapter details that there are statistically significant differences in how learners deploy SRL strategies while interacting with instructional materials between learners who did and did not receive agency-based scaffolding. Findings from Chapter 4 (Dever et al., 2021) found differences in learners' interactions with instructional materials depending on agency where scaffolded learners engaged more with materials that contained both text and diagrams and less with large chunks of text than learners with full control over their actions where this relationship strengthened over time. Overall, this dissertation demonstrated that learners who received scaffolding via restricted agency efficiently employed SRL strategies as revealed through process data and higher learning gains. However, there is still significant room for improvement as demonstrated in Chapter 5 (Dever et al., 2022) which showed that even if learners are scaffolded during game-based learning, their ability to accurately deploy SRL strategies, specifically content evaluations, decreases as time on task progresses.

All studies included in this dissertation have several implications for how to scaffold SRL during game-based learning using agency scaffolds. First, scaffolds should be context-dependent in which the scaffold changes to reflect the type of activity enacted (e.g., prompting content evaluations when provided new instructional material versus coordinating multiple sources of information when problem-solving) or instructional material being interacted with (e.g., encouraging note-taking when reading a book versus inference-making when conversing with an NPC). Second, scaffolds need to be adaptive, changing over time as learners demonstrate increased competencies, familiarity with the environment, and accurate use of metacognitive judgments to select relevant information and engage in goal-directed activities. This adaptive scaffolding can be based on both theory and methodology. For example, this dissertation features far-from-equilibrium as a defining assumption of SRL where learners' behaviors should reflect a functional balance between repetitive and chaotic behaviors. In using this as a theoretical grounding, GBLEs can then identify which and when learners demonstrate more desirable behaviors and when scaffolding is needed. Methodologically, the learners' behaviors can only inform adaptive scaffolds if process data is captured in real time. In other words, constant information about learners' interactions and SRL behaviors needs to be fed into the GBLE in order for the system to determine the level of scaffolding needed to optimize learning outcomes. In summary, the use of new theoretical, methodological, and analytical techniques provide tremendous potential for the design and implementation of adaptive scaffolding for SRL during game-based learning.

APPENDIX A: IRB APPROVAL

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EXEMPTION DETERMINATION

June 21, 2022

Dear Daryn Dever:

On 6/21/2022, the IRB determined the following submission to be human subjects research that is exempt from regulation:

Type of Review:	Initial Study
Title:	Dissertation Approval
Investigator:	Daryn Dever
IRB ID:	STUDY00004446
Funding:	None
Grant ID:	None
Documents Reviewed:	• HRP-255-SR-FORM- Request for Exemption for Secondary Research.docx, Category: IRB Protocol; • Variables to Analyze.docx, Category: Test Instruments;

This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made, and there are questions about whether these changes affect the exempt status of the human research, please submit a modification request to the IRB. Guidance on submitting Modifications and Administrative Check-in are detailed in the Investigator Manual (HRP-103), which can be found by navigating to the IRB Library within the IRB system. When you have completed your research, please submit a Study Closure request so that IRB records will be accurate.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

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