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Traversing Minecraft Through Story: Examining Fictional Story as a Cognitive Structuring Tool for Spatial Memory

A Dissertation submitted in partial satisfaction
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in

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by

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Dedication

This dissertation is dedicated to my family, mentors, students, friends, and everyone who supported me throughout this journey. To my parents and family, thank you for your unconditional love, sacrifices, and belief in me long before I believed in myself. To my students, this work is also for you. Your curiosity, resilience, and perspectives continually reminded me why educational research matters and why creating more equitable learning environments is so important.

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ABSTRACT OF THE DISSERTATION

Traversing Minecraft Through Story: Examining Fictional Story as a Cognitive Structuring Tool for Spatial Memory

by

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Doctor of Philosophy, Graduate Program in Education
University of California, Riverside, June 2026
Dr. Kinnari Atit, Chairperson

Spatial memory and navigation are critical for learning and interacting within complex environments, yet less is known about tools and conditions that support specific processes involved in the encoding and organization of large-scale spatial information. The present study investigated whether fictional story could serve as a cognitive structuring tool to support object-location memory in a large-scale virtual environment. A total of 120 undergraduate students completed the Minecraft Memory and Navigation (MMN) task and were randomly assigned to a fictional story, non-fictional narrative, or silent condition during passive route learning. Outcomes included object accuracy, object sensitivity (d′), spatial location accuracy, and object-location binding accuracy. Results indicated that fictional story did not significantly improve overall spatial memory performance relative to the other conditions. However, a marginal effect emerged for spatial location accuracy, with participants in the fictional story condition demonstrating

numerically higher memory for the learned locations. Across analyses, performance was strongly associated with spatial working memory, perspective-taking ability, and prior gaming experience. These findings contribute to a more nuanced understanding of how structured learning conditions may influence large-scale spatial memory processes.

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Chapter 1
Introduction

Spatial skills refer to a set of cognitive processes that enable individuals to perceive, represent, and reason about spatial relationships among objects and within environments (Newcombe & Shipley, 2014; Verdine et al., 2017). These skills are engaged in everyday tasks such as driving, arranging dishes in the dishwasher, interpreting maps, and rearranging furniture (Liben & Titus, 2012; Ormand et al., 2017), and they support learning, problem-solving, and performance across domains that require reasoning about spatial relationships in complex environments, including navigation, spatial visualization, and the construction of spatial representations (Kell & Lubinski, 2013; Lowrie et al., 2017; Newcombe, 2010; Wai et al., 2009). However, much of this work has focused on small-scale spatial skills, which involve the manipulation of objects or representations within confined, fully visible spaces and are typically assessed using controlled laboratory tasks (Hegarty et al., 2006; Newcombe & Shipley, 2014; Uttal et al., 2013). This emphasis limits our understanding of how spatial cognition operates in real-world contexts that require integrating spatial information across movement, perspective, and experience.

In contrast, large-scale spatial cognition refers to the ability to learn, navigate, and construct representations of environments that extend beyond a single viewpoint (Montello, 1993; Newcombe & Shipley, 2014), thereby requiring the integration of spatial information over time and across changing viewpoints (Kraemer et al., 2017; Montello et al., 2004). These processes support the formation of coherent spatial representations that enable individuals to orient themselves, identify relevant environmental features, and use spatial information flexibly, making large-scale spatial cognition fundamental to how individuals learn and interact with complex, real-world environments.

Despite extensive research on spatial skills, less is known about how large-scale spatial processes are structured and how they differ from one another. While small-scale spatial abilities have been more extensively characterized and decomposed into distinct components, such as mental rotation and spatial visualization (Hegarty et al., 2006; Lohman, 1979; Uttal et al., 2013), a comparable level of conceptual clarity has not been consistently achieved for large-scale spatial cognition. As a result, it remains unclear which large-scale spatial processes are distinct, which operate together, and how they collectively support the formation and use of spatial representations in complex, real-world environments (Nazareth et al., 2019). This gap limits our ability to explain how learning and performance emerge from the coordination of multiple spatial processes in large-scale environments and, in turn, constrains our ability to determine which forms of scaffolding most effectively support specific spatial processes.

One contributing factor is that large-scale spatial cognition is inherently difficult to study in controlled experimental contexts. Real-world environments are complex, dynamic, and challenging to standardize, which has historically limited the ability to isolate the cognitive mechanisms underlying large-scale spatial thinking (Heth et al., 1997; Hölscher et al., 2011; Schinazi et al., 2013). Unlike small-scale tasks, which allow for the isolation of specific processes, large-scale spatial tasks require the integration of multiple processes across movement, perspective, and time. Recent advances in virtual environments have begun to address these challenges, enabling more precise examination and disentanglement of the cognitive processes underlying large-scale spatial learning and performance (Schinazi et al., 2013; Simon et al., 2022; Weisberg et al., 2014).

A more precise understanding of large-scale spatial cognition requires examining the underlying mechanisms that support how spatial information is encoded, organized, and retained over time (Montello, 1993; Postma et al., 2004). While large-scale spatial tasks are often evaluated through navigation performance, successful interaction with complex environments depends on these underlying processes as the foundation of spatial representations (Kuipers, 2000; Wolbers & Hegarty, 2010). One key mechanism is spatial memory, which provides the initial basis for encoding, storing, and organizing spatial information to construct spatial representations of environments that enable flexible navigation (Burgess, 2006; Ekstrom et al., 2014; Epstein & Vass, 2014). Advancing this understanding also requires identifying forms of scaffolding that can differentially engage and isolate these processes. As such, examining spatial memory provides a critical entry point not only for disentangling the cognitive processes underlying large-scale spatial cognition, but also for determining how different forms of scaffolding may support specific aspects of spatial learning and performance.

Spatial Memory in Large-Scale Environments

Within the broader framework of large-scale spatial cognition, spatial memory serves as a critical mechanism for learning, representing, and interacting with complex environments. Spatial memory refers to the ability to encode, store, and retrieve information about the spatial layout of environments, including the locations of objects, landmarks, and pathways within large-scale spaces (Burgess, 2006; Epstein & Vass, 2014; Ishikawa & Zhou, 2020). This capacity allows individuals to form internal spatial representations of large-scale, open environments that support navigation, orientation, and the flexible use of spatial knowledge (Burgess, 2006; Ekstrom et al., 2014). Therefore, spatial memory provides a foundation for examining how distinct spatial processes contribute to large-scale spatial learning and performance, and how different forms of support may shape these processes.

Spatial memory involves a sequence of cognitive processes, including encoding, storage, and retrieval. During encoding, spatial information, such as the location of objects or the configuration of environmental features, is transformed into a mental representation that can be retained over time (Baddeley & Hitch, 2000; Shelton & McNamara, 2001). Storage refers to the maintenance of this information within memory systems, while retrieval involves accessing these stored representations to guide behavior, such as recalling the location of a landmark or navigating a previously learned route (Maguire et al., 1999; Spiers & Maguire, 2007; Tulving, 1984). In large-scale environments, these processes are particularly complex, as individuals must encode and store spatial information across movement, shifting perspectives, and incomplete viewpoints. Remembering this more complex and integrated spatial information supports the construction of coherent, large-scale representations of environments that extend beyond an individual's immediate perception (Jacobs, 2003; Montello, 1993).

These representations play a central role in navigation, and although spatial memory and navigation have historically been treated as closely intertwined and not clearly dissociable processes (O'Keefe & Nadel, 1978), more recent work emphasizes that they are conceptually and functionally distinct (Ekstrom et al., 2017; Chrastil & Warren, 2012; Madl et al., 2015; Simon et al., 2022). This distinction is reflected in their differing roles in behavior and representation: navigation involves moving through an environment, often relying on sequential, route-based knowledge and real-time decision-making (Foo, Warren, Duchon, & Tarr, 2005), whereas spatial memory refers to the underlying representation of the environment, including knowledge of object locations, spatial relationships, and environmental structure (Ekstrom et al., 2017).

Although navigation relies on spatial memory, it can also be supported by route-based or procedural strategies that depend on sequential knowledge and place fewer demands on integrated spatial representations (Chrastil & Warren, 2012). As a result, successful navigation performance may not always directly reflect the quality or coherence of underlying spatial representations. Consistent with this distinction, emerging evidence suggests that navigation ability can diverge from the accuracy of spatial representations (Simon et al., 2022), supporting the need to examine spatial memory independently from navigation in order to more precisely characterize the mechanisms underlying large-scale spatial learning and performance.

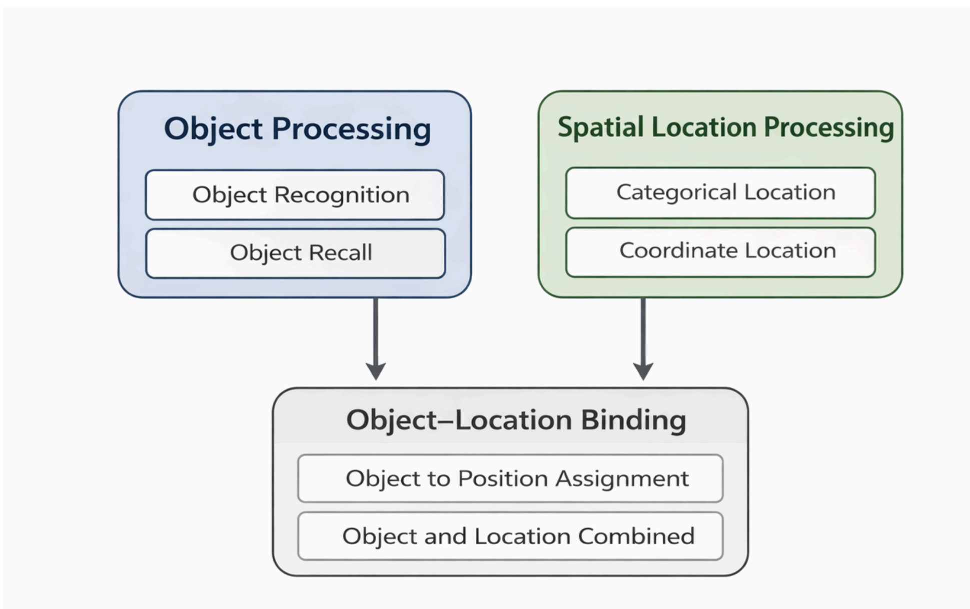
Importantly, spatial memory is not a fixed capacity but rather a malleable cognitive system shaped by experience, context, and individual differences. Research has shown that spatial memory performance varies with factors such as familiarity with an environment, opportunities for exploration, and the conditions under which spatial information is learned (Allen, 2004; Baddeley & Lieberman, 2017; Uttal et al., 2013; Voyer et al., 2017). This suggests that spatial memory may be particularly responsive to targeted learning conditions, indicating that different learning conditions may play a meaningful role in the encoding, storage, retrieval, and organization of spatial information. Furthermore, recent work clarifying the distinction between spatial memory and navigation provides a promising avenue for more closely examining the component processes that underlie spatial memory. In particular, focusing on foundational spatial memory processes that support the development of spatial representations provides a useful approach for understanding how spatial memory mechanisms can be supported during the learning of large-scale spatial environments.

Object-Location Memory

One such process is object-location memory, which supports the encoding and integration of information about what is present in an environment and where it is located, serving as a core building block of spatial representations (Burgess, 2006; Ekstrom et al., 2014; Postma et al., 2004). Recalling the locations of objects within large-scale environments involves multiple functional stages that are best understood through cognitive frameworks. One prominent framework is the model proposed by Postma et al. (2004), which characterizes these stages in terms of three processing components: object processing, spatial location processing, and object-location binding. These components are depicted in the figure below:

Figure 1

Cognitive Model of Object-Location Memory (Postma et al., 2004)

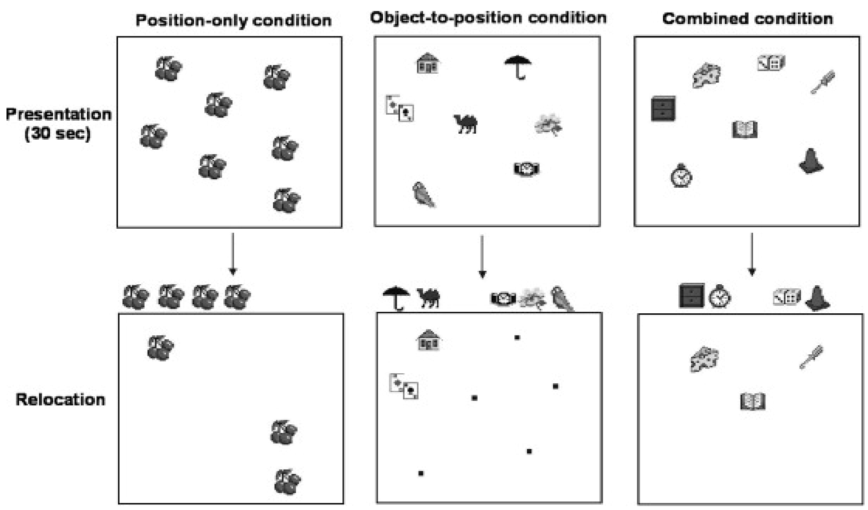


As illustrated by the Cognitive Model of Object-Location Memory, the first component, object processing, involves encoding and storing the visual features of objects within an environment and is reflected in the ability to identify, visualize, and recall those objects (Joseph, 2001; Logothetis & Sheinberg, 1996; Postma et al., 2004). The second component, spatial location processing, involves encoding and storing the positions of objects and operates at two levels: categorical and coordinate (Kosslyn, 1992; Postma et al., 2004). Categorical spatial location processing captures the general or relational position of an object (e.g., "in the left corner"), representing its location within a broader spatial framework without specifying precise placement. Coordinate spatial location processing involves encoding fine-grained spatial information to capture the exact position of an object relative to other elements in the environment (e.g., on the floor to the right of another object). The final component, object-location binding, involves integrating object identity with spatial location information to form associations between what is present in an environment and where it is located. Research has demonstrated that these components can be dissociated, which indicates that object processing, spatial location processing, and object to location binding rely on partially distinct cognitive mechanisms (Fu et al., 2023; Postma et al., 2004).

In alignment with this framework, object-location memory has typically been examined using paradigms that isolate each of these components. Various experimental paradigms have been employed to measure object-location memory (Allen, 2004). However, the general procedure for measuring object-location memory has been consistent across these various paradigms. Object-location memory is typically assessed by examining its three individual components (Postma et al., 2004). The general procedure for doing so involves administering three separate spatial tasks, with each task corresponding to a specific component of object-location memory (Postma et al., 2004).

Figure 2

Example displays of object processing, spatial location, and object-location binding measures (Postma et al., 2004).



These paradigms enable the independent examination of object processing, spatial location processing, and object-location binding, thus providing a means of investigating how distinct components of object-location memory contribute to performance across individuals and contexts. However, these tasks are most often implemented in small-scale settings in which spatial information is fully visible at encoding. By comparison, large-scale environments introduce additional demands, including movement through space, shifting perspectives, and incomplete viewpoints (Interrante & Anderson, 2007; Zimmermann & Eschen, 2017). Therefore, extending these approaches to large-scale contexts provides an important opportunity to examine how these foundational processes of spatial memory operate under more ecologically relevant learning conditions

In summary, because object-location memory relies on the encoding and integration of multiple types of information, including object identity, spatial location, and their associations, it may be particularly sensitive to how information is structured during learning. Differences in how spatial information is organized during encoding may influence how these components are processed and integrated. Given that object-location binding requires integrating information about what and where, it may be particularly sensitive to encoding conditions that promote relational and structured integration - such as those provided by fictional story. Therefore, examining how cognitive structuring tools shape the encoding and organization of object-location information may offer a useful approach for understanding how these foundational processes can be supported during spatial learning. One key dimension of cognitive structuring is temporal organization, which has been shown to play a central role in how information is prioritized, integrated, and retained in memory (Howard & Kahana, 2002).

The Role of Temporal Structure in Memory Encoding

Building on the distinction between spatial memory and navigation, an important next step is to examine how scaffolding strategies shape the encoding and organization of spatial information during learning. Prior research demonstrates that the structure of information during encoding plays a critical role in how it is organized and retained over time (Bransford & Johnson, 1972; Eichenbaum, 2017; Sabo & Schneider, 2025; van Kesteren et al., 2018). In particular, structured input, such as narratives, supports the formation of more coherent and durable memory representations compared to unstructured input (Robin & Moscovitch, 2017; Zacks, 2020). These effects are thought to arise because structured temporal frameworks guide how information is segmented, prioritized, and integrated during encoding (Ghosh & Gilboa, 2014; Radvansky & Zacks, 2017), supporting the formation of coherent representations that can be more easily retrieved (Eichenbaum, 2017; Moscovitch et al., 2016). In the context of spatial learning, this suggests that the temporal structure imposed during encoding may influence how spatial information is organized and integrated into memory.

Narratives represent a particularly relevant form of structured input because they organize information into a coherent temporal sequence. This temporal organization shapes how information is processed across a sequence, as memory is sensitive to the order in which information is encountered. For example, items presented earlier or later in a sequence are often remembered better than those in the middle, reflecting differences in how information is encoded and retained over time (Atkinson & Shiffrin, 1968; Cowan, 2019). These serial position effects highlight how temporal structure can differentially support encoding processes at various points within a sequence. In spatial learning contexts, such temporal structuring may guide attention and sequencing during encoding, influencing which spatial elements are prioritized and how they are integrated into a broader representation of the environment.

In addition to organizing information across time, narrative structure may also reduce cognitive load by providing a coherent framework that allows information to be encoded as part of an integrated sequence rather than as isolated elements (Sweller, 1988; Paas et al., 2003). This may be particularly important in large-scale spatial learning tasks, where individuals must encode multiple spatial elements across movement and changing perspectives. By structuring information temporally, narrative may support the encoding, integration, and retrieval of spatial information, ultimately shaping the quality of spatial memory representations formed during learning.

Fictional Story as a Cognitive Structural Tool

Fictional stories represent a highly structured form of input that organizes information into coherent sequences of events involving characters, settings, and actions (Abbott, 2020; Chatman, 1978; Herman, 2009). Rather than simply presenting information, fictional stories provide a framework that shapes how information is encoded by organizing elements through temporal, relational, and causal structure. Therefore, three key mechanisms may explain why fictional story supports memory: (1) providing temporal structure, (2) supporting relational and associative encoding, and (3) promoting integration into coherent representations.

First, fictional stories provide a temporal structure that organizes information into a coherent sequence with a defined beginning, middle, and end. This structure supports the segmentation of continuous experience into meaningful events and facilitates the integration of these events over time (Radvansky & Zacks, 2017; Zacks et al., 2007). Importantly, fictional stories extend beyond simple sequencing by embedding events within a plot that links earlier elements to later outcomes through causal dependencies

(Gander & Gander, 2022; Graesser et al., 1999; Thorndyke, 1977). These plot-driven connections often introduce elements such as goals, conflict, and resolution, which increase engagement and help sustain attention across the unfolding sequence of information. This temporally unfolding and causally structured framework guides attention across a sequence and supports the integration of information over time.

Second, fictional stories support relational and associative encoding by embedding information within a network of meaningful relationships. Unlike less structured forms of input in which elements may be encountered as discrete or unrelated units, fictional stories connect elements through causal, temporal, and semantic links, which constrain and organize encoding (Graesser et al., 2003; Thorndyke, 1977; Zacks & Swallow, 2007). This relational structure promotes associative encoding processes, whereby multiple elements are linked together, enhancing both retention and retrieval (Bellezza, 1996; Eichenbaum, 2017). By organizing information within these interconnected relationships, fictional stories also support sense-making by allowing individuals to interpret new information in relation to an unfolding context rather than as isolated details.

Consistent with schema and relational memory frameworks, organizing information within a meaningful context allows individuals to integrate otherwise disconnected elements into structured representations, which reduces fragmentation in memory and facilitates retrieval (Ghosh & Gilboa, 2014; Schacter & Addis, 2007). More recent work on event cognition and situation models similarly suggests that coherent contextual frameworks support comprehension and memory by guiding the integration of information across events and experiences (Radvansky & Zacks, 2017; Zacks, 2020). Thus, fictional stories enhance memory by structuring encoding around meaningful relationships, which supports both the interpretation and integration of information into more cohesive and retrievable representations.

Additionally, fictional stories promote the integration of information into coherent representations. Narrative comprehension research suggests that individuals construct situation models, integrated mental representations that track characters, spatial context, temporal structure, and causal relationships across events (Barnett & Bellana, 2025; Radvansky & Zacks, 2017). These models are continuously updated as new information is encountered, while event boundaries prompt the reorganization of the representation (Zwaan, 2025). Coherent narrative structure facilitates this process by aligning causal, temporal, and relational links across events, allowing new information to be incorporated into an existing framework rather than encoded independently (Nguyen, 2024; van Kesteren et al., 2014). This integration results in more stable and accessible memory representations. Furthermore, situation models explicitly include spatial information to link what is present in an environment with where it occurs (Zwaan, 2025), suggesting that fictional stories may support the coordinated encoding of objects and their locations within a unified representation.

Converging evidence from neuroscience further supports these mechanisms, indicating that processing information within a story structure engages distributed brain systems involved in perception, action, and memory, including hippocampal-cortical networks that support the integration of information across time (Ekstrom & Ranganath, 2018; Hsu et al., 2015; Speer et al., 2009; van Kesteren et al., 2014). This pattern of activation aligns with broader evidence that the brain is neurologically wired to process information in temporally unfolding, causally structured sequences (Nguyen et al., 2024; Zwaan, 2009).

In conclusion, fictional stories are not just structured but they also actively guide how information is interpreted and connected. By embedding spatial information within a coherent sequence of events, fictional story helps individuals organize that information as part of an unfolding experience rather than as isolated details. This structure supports more cohesive encoding by linking elements within a meaningful context. For object-location memory in particular, where successful performance depends on binding objects to their locations, this kind of relational and contextual support may be especially useful. However, despite these potential benefits, the role of fictional story in supporting spatial cognition has not yet been directly examined.

Current Study

Despite extensive evidence that narrative structure enhances memory for events and information (Barnett & Bellana, 2025), it remains unclear whether these benefits extend to the encoding and integration of spatial information, particularly in large-scale environments. Although narrative comprehension research suggests that story structure supports the organization of information across multiple dimensions (Graesser & Klettke, 2003; Radvansky & Zacks, 2017), including spatial information (Pagkratidou et al., 2026), this has not been directly examined within spatial memory paradigms. This gap is particularly evident in research on large-scale spatial memory, where component processes such as object processing and spatial location processing must be integrated through memory binding, yet the role of fictional story as a cognitive structuring tool has rarely been examined in this context. As a result, it remains unclear whether fictional story can meaningfully influence spatial memory processes.

To address this gap, the current study examines the efficacy of fictional story as a cognitive structuring tool for enhancing object-location memory within a large-scale virtual environment. Using a between-subjects experimental design, participants in all conditions completed a spatial memory task in a Minecraft-based environment in which they learned 12 object-location combinations presented within a 10-minute video. Participants were randomly assigned to one of three conditions: a fictional story condition, in which object-location information was embedded within a fictional story; a non-fictional narrative condition, in which the same information was presented within a descriptive, non-fictional narrative; and a silent condition, in which object-location information was presented without narration to establish a baseline for learning. Comparing fictional story to non-fictional narrative isolates plot-based, causally structured narratives from a descriptive, informational narrative with no causal links, thereby enabling the present study to test whether this added structure supports the encoding and integration of spatial information.

Object-location memory was assessed using Postma et al.'s (2004) framework across three component processes: object processing, spatial location processing, and object-location binding. Following the task, participants completed a qualitative interview to provide insight into the mental effort they exerted during the task. By examining how fictional story influences the encoding and integration of object identity and spatial location, this study aims to provide a more precise understanding of how presenting spatial information within a fictional story may support spatial memory. This investigation is guided by the following research question: *Is fictional story more effective than non-fictional narrative in enhancing participants' spatial memory? Specifically, does this difference occur in participants' object processing, spatial location processing, and/or their ability to bind objects to locations?*

Informed by prior research indicating that fictional stories facilitate associative encoding and relational integration (Bellezza, 1996; Eichenbaum, 2017), it was hypothesized that the fictional story condition would preferentially enhance object-location binding. Since both fictional stories and non-fictional narratives provide temporal structure that supports the sequential organization of information, no significant differences were expected between these two conditions for object processing or spatial location processing. However, because fictional story uniquely supports the causal integration of information (Zacks et al., 2007), it was expected to more strongly support the formation of object-location associations. Accordingly, participants in the fictional story condition were predicted to demonstrate stronger object-location binding, the central process in object-location memory that determines whether objects are remembered in their correct locations, than those in the non-fictional narrative and silent conditions. This research question and associated predictions guided the study.

Chapter 2
Methods

This study was approved by the Institutional Review Board at the University of California, Riverside (IRB #HS-22-205). The data examined in this dissertation were collected as part of a larger study examining the effect of fictional narrative on spatial memory and navigation.

Participants

An a priori power analysis was conducted using G*Power (Faul et al., 2007). Based on prior research demonstrating a large effect of digital storytelling on visual memory ($f = .40$; Sarıca & Usluel, 2016), the analysis indicated that a minimum sample of 64 participants would provide 80% power to detect effects in a between-subjects design with three groups and four covariates ($\alpha = .05$). As no prior studies to our knowledge have examined the effect of fictional story on spatial memory in large-scale environments, this estimate served as a conservative benchmark for planning the study. To further ensure adequate statistical power and allow for balanced group sizes, a total of 120 undergraduate students (*female = 60, male = 60*) between the ages of 18 and 31 (*Mean age = 20.49, SD age = 3.85*) were recruited and participated in this study.

Participants were recruited from the University of California, Riverside through undergraduate education courses and campus-wide recruitment flyers. Once informed consent was provided, each participant was randomly assigned to one of three experimental conditions: 1) silent, 2) fictional story, or 3) non-fictional narrative. Once the experiment was complete, each participant received a $25 Amazon e-gift card for their time and participation in the study.

Consistent with prior research conducted at the same institution (Simon et al., manuscript under review), the sample reflects the broader demographic composition of the University of California, Riverside, which includes a large proportion of students identifying as Hispanic/Latinx and Asian/Asian American. In the present sample, 33% of participants identified as Hispanic/Latinx and 43% identified as Asian/Asian American, which reflects the university's overall demographic profile.

Measures and Materials

Demographics and Video Game Questionnaire

The Demographics and Video Game questionnaire includes 7 demographic and background items, 2 items about video game experience, and 2 items about participants' behavior and interests regarding movies and books. Questions about video game experience were adapted from a prior study that used the Video Game Experience Questionnaire to assess participants' video game playing habits (Chrastil et al., 2013). The full Demographics and Video Game Questionnaire is provided in Appendix A.

Guay's Visualization of Views

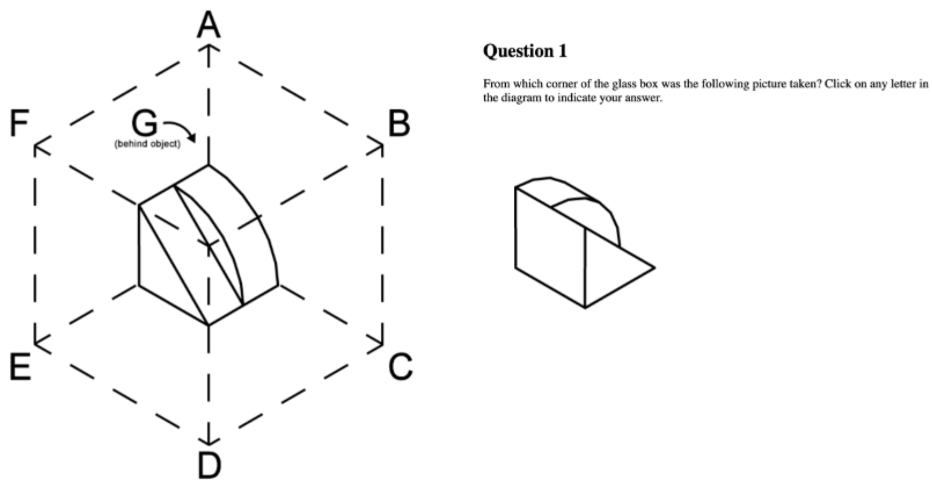
Participants completed a researcher-created virtual version of Guay's Visualization of Views (Guay & Daniels, 1976, as modified by Lippa et al., 2002).

Guay's Visualization of Views is a timed spatial task that assesses an individual's visual perspective-taking abilities. Participants had eight minutes to complete all 24 items. For each item, participants were shown a figure "hovering in the middle" of a transparent cube, followed by a second image of the same figure presented from a different perspective (i.e., the target figure). Participants were asked to identify the correct corner of the cube that would display the figure from the same perspective as the target figure. Following Hegarty et al.'s (2009) scoring procedure, incorrect or skipped items were assigned a score of "0," whereas correct items were assigned a score of "1." An example of a visual perspective-taking question from Guay's Visualization of Views is provided in Figure 3.

Participants' total scores were then calculated by the number of correct items minus the number of incorrect items, divided by 6 (to correct for guessing). The maximum possible score on the assessment is 24. Internal consistency for the present sample was acceptable (Cronbach's $\alpha = .71$), consistent with expectations for timed spatial ability measures.

Figure 3

Example question from Guay's Visualization of Viewpoints.



Corsi Block Task

An online version of the Corsi Block task (Corsi, 1972) was administered through PsychToolkit (Stoet, 2010, 2017). The Corsi Block task is a short term spatial memory task that measures an individual's short term encoding, storage, and retrieval of spatial information through a block tapping task. The virtual Corsi Block task displays nine squares in one color against a black background. When the task begins, a subset of the blocks blink in a different color in a random sequence. When the sequence of blinking blocks is complete, the participant is instructed to recreate the sequence of blocks they saw light up. When the participant is finished clicking the block sequence they remember, they hit the "done" button and get feedback about their performance. Sequence length starts at two blocks and increases after each correct trial until the participant's response is no longer accurate. If the participant provides the incorrect block sequence twice in a row, the task ends and they receive their final score. The final score is the participant's

Corsi block span, which is the number of blocks in the longest correctly remembered sequence. The Corsi Block Task is presented in Appendix B.

Passive Instructional Route Video

Three passive instructional videos were created, one for each experimental condition: fictional story, non-fictional narrative, and silent. In all three videos, participants observed a Minecraft avatar navigating a route through the Minecraft world to locate 12 objects placed in specific chest locations. The visual content of the videos was identical across conditions; only the narration differed. Furthermore, the fictional and non-fictional scripts were matched for length, word count, and spatial information. The key distinction across conditions was the degree of relational and causal structure imposed on the object-location information.

Nonfictional Narrative Condition. In the non-fictional narrative condition, object and chest location information was embedded within a narrative about the history of Minecraft that presented factual information in a structured format with a beginning, middle, and end, but without a cohesive plot linking events across the narrative. Instead, the object-location combinations were linked to 12 separate factual statements about Minecraft or the objects. The full script for the non-fictional narrative condition is provided in Appendix C.

Fictional Story Condition. In the fictional story condition, the object and chest location information were embedded within a fictional, first-person fantasy plot-driven story centered on the avatar as the main character. The fictional story follows the narrative framework of the Hero's Journey, a storytelling structure first described by

Joseph Campbell (1968) and widely observed in myths, legends, and modern narratives. This framework follows a protagonist as they embark on a transformative adventure, confront challenges, and ultimately experience personal growth. The Hero's Journey consists of 12 stages and in this condition, each of the 12 object-locations was embedded within each stage of the story structure. A table detailing the structure of a Hero's Journey is provided in Appendix D. The fictional story script is provided in Appendix E.

Silent Condition. In the silent condition, no verbal narration was provided, and participants observed the avatar locating the objects and corresponding chest locations without accompanying audio narration. The silent condition provides a baseline for encoding in the absence of structured narrative support.

<u>Minecraft Memory and Navigation Task 2 and Outcome Measures</u>

Minecraft Memory and Navigation Task-2

The Minecraft Memory and Navigation (MMN) task (Simon et al., 2022) was adapted to assess the three components of object-location memory. The MMN task is a large-scale spatial memory and navigation task conducted within an open-field Minecraft environment. The original version of the task was designed to measure spatial memory during active navigation. For the purposes of the present study, the task was modified to specifically measure the three components of object-location memory (i.e., memory for object identity, memory for spatial location, and memory for object-location associations).

The adapted task, the Minecraft Memory and Navigation Task-2 (MMN-2), requires participants to retrieve objects from an inventory, place them into a chest, and transport the chest to the location in the environment where the object was originally encountered during the passive learning phase. Participants are presented with an inventory containing 24 objects, including the 12 objects encountered during the passive learning video and 12 distractor objects that were not previously shown. Participants must identify the objects they remember learning and navigate to the locations where those objects were originally presented while recreating the route. This task structure enables simultaneous measurement of the three components of object-location memory. Figure 4 shows a bird's-eye view of the Minecraft environment used in the MMN-2 task.

Figure 4

Bird's-eye view of the Minecraft environment used in the MMN-2 task.

Note. *The image illustrates the terrain of the Minecraft environment in which participants navigated to locate object locations during the MMN-2 task.*

Minecraft Server and Data Tracking

The Minecraft environment was hosted on a custom server that houses the experimental environment. The server was equipped with custom plugins, which are programs that modify the game environment to support the experimental task and automatically record participant behavior. The MMN-2 task plugin records the objects participants select from the inventory and the exact coordinates at which participants place each object in the environment. An additional tracking plugin records participants' step-by-step movement trajectories throughout the environment. These systems allow comprehensive behavioral data related to spatial memory and navigation to be automatically logged during task completion.

Post-Task Interview

Following completion of the MMN-2 task, participants completed a brief post-task interview. Participants were first asked to report their perceived mental effort during the task using a 9-point subjective rating scale, where 1 indicated very, very low mental effort and 9 indicated very, very high mental effort. This measure was adapted from the Cognitive Load Theory mental effort rating scale, which is commonly used to assess the amount of cognitive resources invested in a learning task (Paas, 1992). Participants were then asked a follow-up question prompting them to briefly explain the reasoning behind their rating. An additional open-ended question was asked to better understand participants' experiences during the passive learning phase. Participants in the fictional story and non-fictional narrative conditions were asked to describe what they remembered from the narration while watching the video. Participants in the silent condition were asked to describe what they were thinking about while observing the avatar navigate the environment. These questions were included to provide contextual insight into how participants attended to and processed the information presented during the learning phase. The interview script in its entirety is presented in Appendix F.

MMN-2 Task Outcomes

Object Accuracy. Object accuracy was defined as the number of correctly identified target objects selected from the inventory, regardless of sequence. This measure was operationalized as a count score ranging from 0 to 12 to indicate the total number of correctly selected objects.

Object Sensitivity (*d′*). In addition to the object accuracy score, object processing performance was also assessed using a signal detection measure (d') to provide a bias-corrected estimate of participants' ability to discriminate between previously encountered objects and distractor objects. To compute d′, correctly selected target objects were classified as hits, failures to select previously encountered objects were classified as misses, and incorrectly selecting a distractor object was classified as a false alarm. The d′ score was calculated as the difference between the z-transformed hit rate and the z-transformed false alarm rate (i.e., $d' = z(\text{hit rate}) - z(\text{false alarm rate})$). Values of d′ near 0 indicate chance-level performance, values around 1 indicate modest sensitivity, values around 2 indicate good sensitivity, and values of 3 or higher indicate strong sensitivity; negative values indicate a greater tendency toward false alarms than hits.

Therefore, higher d' values indicate greater discrimination between target and distractor objects and therefore reflects stronger object processing.

Node Accuracy. In the present study, spatial location memory was assessed by measuring participants' ability to correctly return and identify previously encountered locations. In the MMN-2 task, participants navigated through the Minecraft environment and placed chests at the locations where objects had previously appeared during the passive learning video. This metric measures the direct spatial distance between the participant's placement location and the true object location, independent of the path taken to reach that position. Node accuracy was calculated as the number of correct locations participants navigated to, regardless of the object placed at that location or the sequence in which locations were visited. Thus, this measure reflects participants' memory for spatial positions independently of object identity.

Node accuracy was scored on a binary (1/0) scale, with one point awarded for each spatial location correctly identified, regardless of whether the correct object was placed at that location. Euclidean distance was used to determine whether a placement was classified as correct. Specifically, Euclidean distance represents the straight-line distance between two points in three-dimensional space based on their coordinate positions in the Minecraft environment. In the present study, a placement was classified as accurate if it occurred within 20 blocks of any of the 12 correct object locations, based on the Euclidean distance between the participant's placement coordinates and the true object coordinates (Simon et al., manuscript under review). This threshold was informed by prior work using the MMN paradigm, which initially applied a 10-block threshold (Simon et al., manuscript under review); however, this threshold proved to be overly strict, resulting in limited variability in performance. Accordingly, a more lenient 20-block threshold was adopted in the present study to better capture meaningful variation in node accuracy. Placements within this range were classified as correct, whereas placements outside the threshold were classified as incorrect. Therefore, higher node accuracy scores indicate stronger spatial location processing.

Object-Location Accuracy. Object-location accuracy refers to the ability to correctly bind objects with their corresponding spatial locations within an environment (Postma et al., 2004). In the present study, object-location binding was assessed using a behavioral metric referred to as object-location binding precision. This metric was calculated only for placements involving correctly selected objects, allowing spatial precision to be evaluated specifically for instances in which participants attempted to return a correct object to its learned location.

Following the spatial scoring procedure described for node accuracy, placements were evaluated using the same 20-block spatial tolerance threshold based on Euclidean distance between the participant's placement coordinates and the true object coordinates (Simon et al., 2024). Object-location binding precision was quantified as the average Euclidean distance between participants' placement locations and the true locations of the corresponding objects for all correctly selected objects. This provides a continuous measure of spatial precision in associating objects with their learned locations, with smaller average Euclidean distance values indicating greater object-location binding precision.

Figure 5

Object-location placement and route within the Minecraft environment.

Note. *The "×" marks the starting location, lines indicate the navigation route taken through the environment, and yellow dots represent the true object locations.*

Procedure

The study was conducted during a single 90-minute in-person session in the STEM Teaching and Learning Lab. Upon arrival, participants were seated at a desktop computer and provided with access to the study's Canvas course site, which contained all study materials. Participants first reviewed and completed the informed consent form. After providing consent, participants completed a demographic questionnaire followed by two individual difference measures assessing spatial ability: Guay's Visualization of Views (VoV) task and the Corsi Block Task. These measures were completed on laboratory computers and required approximately 30 minutes in total. Following the completion of these measures, participants were given a five-minute break while the researcher prepared the Minecraft environment for the experimental task.

The second portion of the session consisted of the Minecraft Memory and Navigation task (MMN-2) and lasted approximately 60 minutes. Participants first received a brief tutorial introducing the Minecraft interface and the controls required to navigate the environment (e.g., movement, camera control, accessing inventory, and placing chests). Participants then completed a practice version of the task in a separate Minecraft environment. During this practice session, participants navigated the environment, opened several chests containing objects, and practiced returning chests to their original locations. The practice task allowed participants to become familiar with the navigation controls, inventory system, and object placement mechanics they needed to use in the experimental task.

After completing the practice task, participants moved to a second computer to view the passive learning video corresponding to their assigned experimental condition (fictional story, non-fictional narrative, or silent). Participants were instructed to pay close attention to the objects, their locations, the sequence in which they appeared, and the route taken by the avatar. Participants were not permitted to pause the video or take notes. Immediately after viewing the video, participants returned to the Minecraft environment to complete the MMN-2 task. Participants were given 10 minutes to complete the task after which participants then completed the post-task interview. Participants' responses were recorded using a lab-provided audio recorder for later transcription. After completing the post-task questions, participants were debriefed about the purpose of the study, given the opportunity to ask questions, and thanked for their participation.

Chapter 3
Results

Analytic Sample

The final analytic sample consisted of 120 undergraduate students. Participants were randomly assigned to one of three conditions (fictional story, non-fictional narrative, or silent), with 40 participants per condition. Each condition was balanced for participant sex, with 20 female participants and 20 male participants in each condition.

Participants reported varying levels of video game experience (see Table 1). Most participants indicated prior experience playing Minecraft (n = 106, 88%), while a smaller proportion reported no prior Minecraft experience (n = 14, 12%).

Participants also reported their broader video game experience and self-identified their gaming skill level (e.g., novice, intermediate, expert). Based on these self-reports, the sample included 23 novice gamers (19%), 55 intermediate gamers (46%), and 41 expert gamers (34%), with one participant (1%) indicating that they did not play video games at all.

Table 1

Participant Demographic and Experience Characteristics (N = 120)

Variable	*Category*	*n (%)*
Sex at Birth	Male	60 (50%)
	Female	60 (50%)
Minecraft Experience	No	14 (12%)
	Yes	106 (88%)
Video Game Experience	Novice	23 (19%)
	Intermediate	55 (46%)
	Expert	41 (34%)
	Does not play video games	1 (1%)
Race/Ethnicity	Hispanic/Latinx	40 (33%)
	Asian/Asian American	52 (43%)
	White/European	10 (8%)
	Black/African American	10 (8%)
	Multiracial	7 (6%)
	Prefer not to answer	1 (1%)

***Note*.** Values are count with percentages in parentheses. Video game experience reflects self-reported skill level.

Screening and Assumptions

Prior to primary analyses, data were screened for accuracy, missing values, outliers, and adherence to statistical assumptions. No extreme univariate outliers were identified during outlier screening, and multivariate outliers assessed using Mahalanobis distance did not exceed critical values based on the number of predictors included in the models (Penny, 1996; Tabachnick et al., 2007). This indicates that no participants exhibited unusual patterns of scores across variables that would bias the ANCOVA results.

Assessment of distributional assumptions using the Shapiro-Wilk test indicated significant deviations from normality for object accuracy ($W = 0.91$, $p < .001$), node accuracy ($W = 0.97$, $p = .010$), and d' ($W = 0.97$, $p = .008$), but not for object-location binding ($W = 0.99$, $p = .42$). Visual inspection of Q-Q plots of model residuals indicated slight deviations from normality for object accuracy and node accuracy, primarily at the tails, whereas object-location binding residuals closely approximated a normal distribution. Overall, these departures were modest, and the assumption of normality was considered acceptable (see Appendix G).

Homogeneity of variance was supported by Levene's tests for all outcome variables (object accuracy: $F(2, 117) = 0.40$, $p = .67$; d': $F(2, 117) = 0.63$, $p = .532$; node accuracy: $F(2, 103) = 1.39$, $p = .25$; object-location binding: $F(2, 103) = 0.07$, $p = .93$). The assumption of homogeneity of regression slopes was met, as interactions between condition and covariates were not significant for object accuracy (Condition × VOV: $p = .86$; Condition × Corsi: $p = .40$), d' (Condition × VOV: $p = .807$; Condition × Corsi: $p = .200$), node accuracy (Condition × VOV: $p = .21$; Condition × Corsi: $p = .26$), or object-location accuracy (Condition × VOV: $p = .29$; Condition × Corsi: $p = .12$). Residual and scatterplot inspection indicated generally linear relationships between covariates and outcome variables, with no systematic curvature observed (see Appendix H). Multicollinearity was not evident (VIF values ranged from 1.01 to 1.03 across all models), and independence of observations was supported by study design and non-significant Durbin-Watson tests across all outcome variables (DWs = 1.74–2.11, *p*s = .057–.651). Overall, the assumptions were adequately met. A summary of the statistical assumption checks for primary analyses is provided in Table 2.

Table 2

Summary of Statistical Assumption Checks for Primary Analyses

Assumption	Test/Method	Statistic	Result
Normality of Residuals	Shapiro-Wilk Test	$W = 0.91$, $p < .001$; $W = 0.97$, $p = .010$; $W = 0.99$, $p = .42$; W = 0.97, $p = .008$	Minor deviations; assumption considered met
Linearity	Residual Plots; Scatterplots	—	No substantial deviations; assumptions met
Homogeneity of Variance	Levene's Test	$F(2, 117) = 0.40$, $p = .67$ $F(2, 103) = 1.39$, $p = .25$ $F(2, 103) = 0.07$, p = .93 $F(2, 117) = 0.63$, $p = .532$	Assumption met
Homogeneity of Regression Slopes	Condition x Covariate Interactions	Condition × VOV: $p = .86$; $p = .21$; $p = .29$; $p = .807$ Condition × Corsi: $p = .40$; $p = .21$; $p = .29$; $p = .200$	Assumption met
Multicollinearity	VIF	1.01–1.03	Assumption met
Independence of Observations	Durbin–Watson test	$DW = 1.74–2.11$ $p = .057–.651$	Assumption met

In sum, these results indicate that all assumptions were adequately satisfied, and analyses were therefore conducted using the full analytic sample.

Descriptive Statistics

Descriptive statistics for the primary outcome variables and individual difference measures of spatial ability are presented in Table 3. Across the full sample (*N* = 120), participants demonstrated a mean object accuracy score of 7.68 (*SD* = 2.76), a mean node accuracy score of 5.53 (*SD* = 2.88), and a mean object sensitivity (*d′*) score of 1.76 (*SD* = 0.83). Object-location accuracy had a mean of 71.10 (*SD* = 32.81). For the individual difference measures, participants demonstrated a mean spatial working memory score of 6.22 (*SD* = 1.26) and a mean visual perspective-taking score of 13.83 (*SD* = 7.36).

Table 3

Descriptive Statistics and Participant Characteristics

Variable	*N*	*M*	*SD*	*Minimum*	*Maximum*
Object Accuracy	120	7.68	2.76	1.00	12.00
Object Sensitivity (d′)	120	1.76	0.83	-0.62	3.54
Node Accuracy	120	5.53	2.88	0.00	12.00
Object-Location Accuracy	120	71.10	32.81	1.14	146.90
Spatial Working Memory	120	6.22	1.26	0.00	9.00
Visual Perspective-Taking	120	13.83	7.36	-3.17	24.00

Note. Values represent means (*M*), standard deviations (*SD*), and ranges.

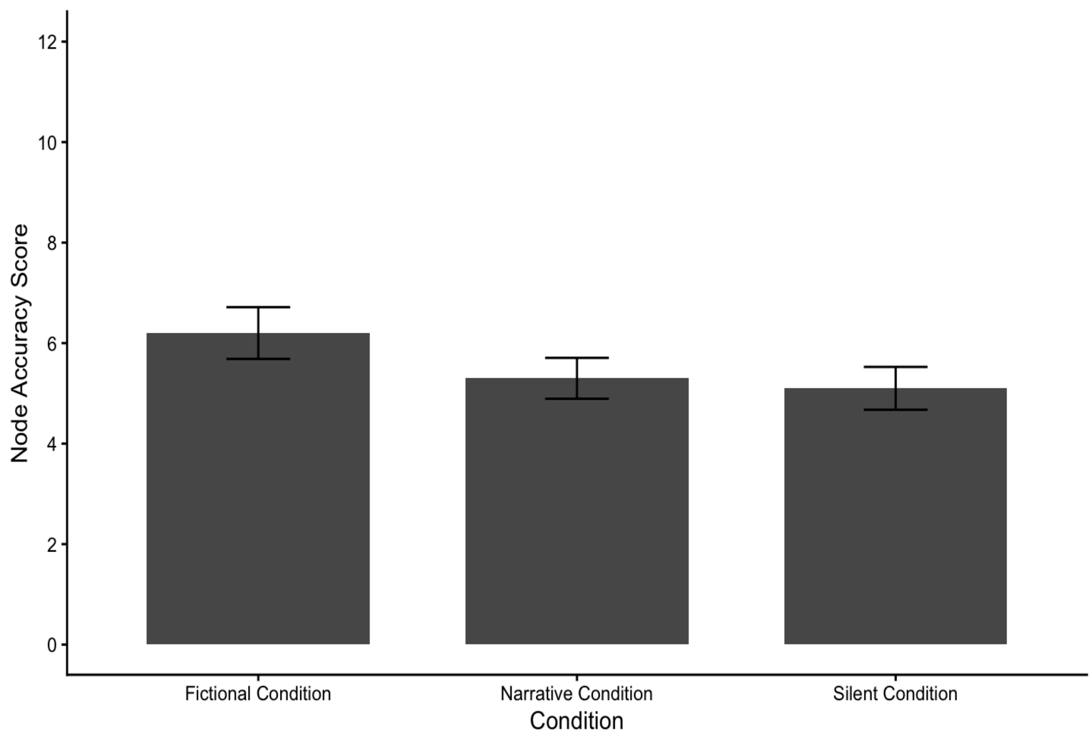
Descriptive Patterns Across Experimental Conditions

Descriptive comparisons across experimental conditions revealed modest differences in performance across the spatial memory outcome measures. For object accuracy, participants in the silent condition demonstrated numerically higher mean performance (*M* = 7.85, *SD* = 2.73) relative to the non-fictional narrative condition (*M* =

7.75, *SD* = 2.64) and the fictional story condition (*M* = 7.45, *SD* = 2.95), although these differences were small. This pattern is illustrated in Figure 6.

Figure 6

Object Accuracy Across Experimental Conditions

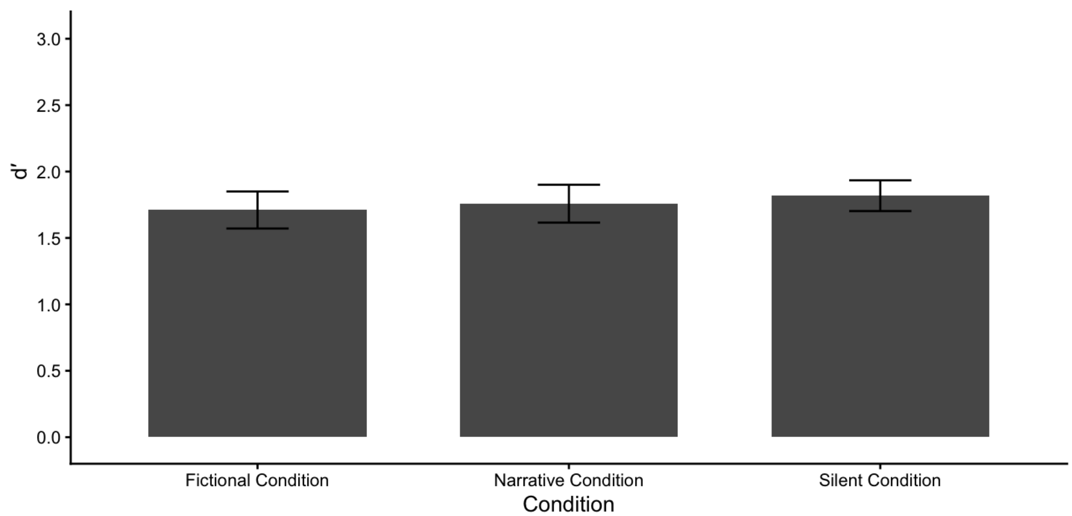


Note. Error bars represent standard errors of the mean.

For object sensitivity (*d′*), participants in the silent condition showed numerically higher mean performance (*M* = 1.82, *SD* = 0.72) relative to the non-fictional narrative condition (*M* = 1.76, *SD* = 0.90) and the fictional story condition (*M* = 1.71, *SD* = 0.88). This pattern is illustrated in Figure 7.

Figure 7

Object Sensitivity (d') Across Experimental Conditions

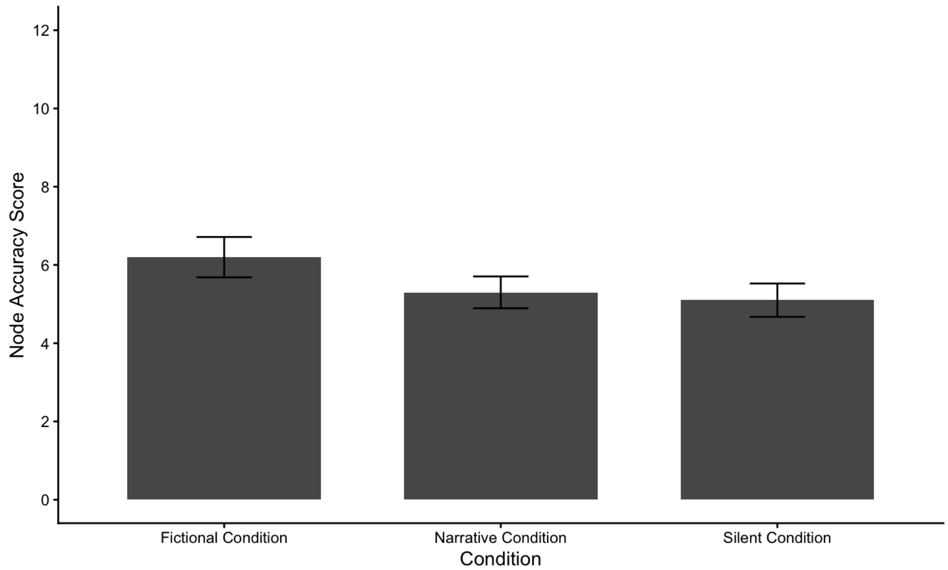


Note. Error bars representing standard errors of the mean.

In contrast, node accuracy was numerically highest in the fictional story condition (*M* = 6.20, *SD* = 3.26), followed by the non-fictional narrative condition (*M* = 5.30, *SD* = 2.57) and the silent condition (*M* = 5.10, *SD* = 2.70). This pattern is illustrated in Figure 8.

Figure 8

Node Accuracy Across Experimental Conditions.

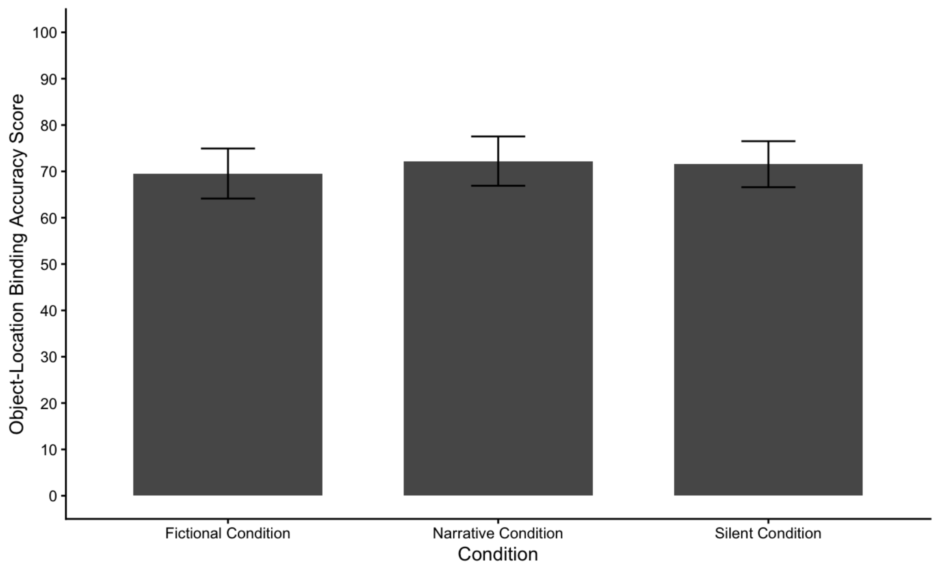


Note. Error bars represent standard errors.

A similar pattern was observed for object-location binding, with the non-fictional narrative condition (*M* = 72.20, *SD* = 33.60) numerically exceeding both the silent condition (*M* = 71.50, *SD* = 31.40) and the fictional story condition (*M* = 69.50, *SD* = 34.20). This pattern is illustrated in Figure 9. A more detailed breakdown of these values is provided in Table 4.

Figure 9

Object-Location Binding Accuracy Across Experimental Conditions



Note. Error bars represent standard errors of the mean. The greater the value, the less accurate their object-location binding accuracy.

Table 4

Descriptive Statistics by Experimental Condition

Condition	*N*	**Object Accuracy** *M (SD)*	**Object Sensitivity (d′)** *M (SD)*	**Node Accuracy** *M (SD)*	**Object-Location Accuracy** *M (SD)*
Fictional Story	40	7.45 (2.95)	1.71 (0.88)	6.20 (3.26)	69.50 (34.20)
Non-fictional Narrative	40	7.75 (2.64)	1.76 (0.90)	5.30 (2.57)	72.20 (33.15)
Silent	40	7.85 (2.73)	1.82 (0.72)	5.10 (2.70)	71.50 (31.40)

Note. Values are presented as means (*M*) with standard deviations (*SD*) in parentheses.

Descriptive and Exploratory Analyses of Qualitative Interview Data

In regard to the qualitative interview data in which participants rated the mental effort required during the MMN-2 task, ratings across conditions generally indicated moderate-to-high mental effort during the task overall (*M* = 7.00, *SD* = 1.24). Participants in the fictional story condition reported the highest average ratings (*M* = 7.30, *SD* = 1.07), followed by the narrative condition (*M* = 6.98, *SD* = 1.03) and the silent condition (*M* = 6.72, *SD* = 1.45). Exploratory inspection of interview responses further suggested variability in how participants attended to and processed the audio conditions during encoding. Some participants in the fictional story condition reported that the story supported the organization of environmental information, whereas others described the audio as distracting or cognitively demanding. Similarly, participants in the non-fictional narrative condition frequently reported focusing on isolated facts at the expense of spatial information. These results are illustrated in Table 5.

Table 5

Descriptive Statistics for Participant Ratings of Mental Effort Across Conditions

Condition	*N*	*Mean*	*SD*	*Minimum*	*Maximum*
Overall Sample	120	7.00	1.24	2.00	9.00
Fictional Story	40	7.30	1.07	3.50	9.00
Non-fictional Narrative	40	6.98	1.03	4.50	9.00
Silent	40	6.72	1.45	2.00	9.00

Note. Values represent means (*M*), standard deviations (*SD*), and ranges.

Exploratory coding of interview responses suggested that participants frequently described dividing attention between spatial information and auditory information. Participants in the fictional story condition more often described the narrative as either supportive of remembering locations or as cognitively demanding, whereas participants in the non-fictional narrative condition more frequently characterized the factual narration as distracting.

To further examine whether participants subjectively experienced the experimental conditions differently, an exploratory one-way ANOVA was conducted to examine differences in mental effort ratings for the MMN-2 task across the fictional story, non-fictional narrative, and silent conditions. Results indicated that ratings did not significantly differ across conditions, $F(2, 100) = 2.22$, $p = .114$. Results are presented in Table 6.

Table 6

One-Way ANOVA Examining Differences in Task Ratings Across Experimental Conditions

Source	**df**	**SS**	**MS**	***F***	***p***
Condition	2	6.63	3.32	2.22	0.114
Residuals	100	149.61	1.50		

Note. SS = sum of squares; MS = mean square.

Associations Among Primary Outcomes and Covariates

Pearson correlation analyses were conducted to examine relationships among the primary outcome variables, spatial cognitive measures, and participant characteristics.

These analyses were conducted to provide insight into how the three object-location memory components relate to one another and to individual difference variables relevant to the study's research questions. The full correlation table is presented in Table 7.

Table 7

Variable	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Object Accuracy	—								
2. Object Sensitivity (d′)	**.84*** **	—							
3. Node Accuracy	**.53*** **	**.36*** **	—						
4. Object-Location Accuracy	-.12	**-.24** **	**-.35*** **	—					
5. Spatial Working Memory	**.19***	.15	**.21***	-.06	—				
6. Visual Perspective-Taking	**.28** **	**.21***	**.29** **	-.17	.11	—			
7. Sex at Birth	.02	-.02	-.10	**-.29** **	-.05	**-.34*** **	—		
8. Minecraft Experience	**.23***	**.29** **	**.21***	**-.19***	-.03	.06	**-.24** **	—	
9. Gaming Experience	.09	.10	**.23** **	**-.28*** **	.13	**.27** **	**-.54*** **	.11	—

Pearson Correlations Among Study Variables ***Note.*** *p* < .05*, p < .01**, *p* < .001***

Object accuracy was positively associated with node accuracy ($r = .53, p < .001$). Object sensitivity (d') was strongly positively associated with object accuracy ($r = .84, p < .001$) and was also positively associated with node accuracy ($r = .36, p < .001$). Object accuracy was additionally positively associated with visual perspective-taking ($r = .28$, $p = .002$), spatial working memory ($r = .19$, $p = .030$), and Minecraft experience ($r = .23$, $p = .010$), but was not significantly associated with sex at birth ($r = .02$, $p = .840$) or gaming experience ($r = .09$, $p = .340$).

Node accuracy was positively associated with visual perspective-taking ($r = .29$, $p = .001$), spatial working memory ($r = .21$, $p = .020$), Minecraft experience ($r = .21$, $p = .020$), and gaming experience ($r = .23$, $p = .010$), but was not significantly associated with sex at birth ($r = -.10$, $p = .280$). Object-location accuracy was negatively associated with node accuracy ($r = -.35$, $p < .001$), object accuracy ($r = -.12$, $p = .180$), object sensitivity (d') ($r = -.24$, $p = .009$), Minecraft experience ($r = -.19$, $p = .040$), and gaming experience ($r = -.28$, $p = .002$), but was not significantly associated with spatial working memory ($r = -.06$, $p = .490$) or visual perspective-taking ($r = -.17$, $p = .070$).

Among the individual difference variables, visual perspective-taking was positively associated with gaming experience ($r = .27$, $p = .004$) and negatively associated with sex at birth ($r = -.34$, $p < .001$). Gaming experience was also negatively associated with sex at birth ($r = -.54$, $p < .001$). All other correlations were not statistically significant. These correlational findings were used to inform the selection of covariates included in subsequent analyses to isolate the effects of condition.

Effects of Condition on Object–Location Memory Components

To address the research question of whether fictional story enhances performance relative to the non-fictional narrative and silent conditions across object processing, spatial location processing, and object-location binding, four separate analyses of covariance (ANCOVAs) were conducted. Each model examined the effect of condition on the respective outcome while controlling for covariates that were significantly associated with that component in prior analyses. The first ANCOVA, shown in Table 8, examined the effect of condition on object accuracy while controlling for spatial working memory, visual perspective-taking, and Minecraft experience.

Table 8

ANCOVA Results for Object Accuracy

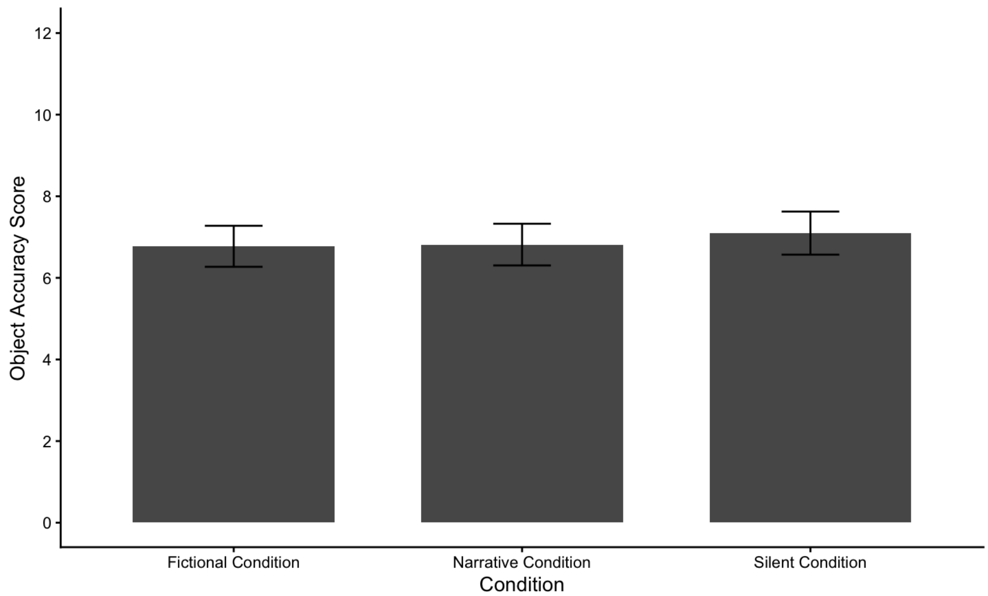
Source	**df**	**SS**	***F***	***p***
Intercept	1	17.20	0.07	.795
Condition	2	2.37	0.18	.839
Spatial Working Memory	1	21.68	3.21	*.076†*
Visual Perspective-Taking	1	52.28	7.73	**.006****
Minecraft Experience	1	41.11	6.08	**.015***
Residuals	112	757.39		

Note. †$p < .10$, $p < .05$*, $p < .01$**

The effect of condition on object accuracy was not statistically significant, $F(2, 112) = 0.18$, $p = .839$. With respect to covariates, visual perspective-taking was statistically significant, $F(1, 112) = 7.73$, $p = .006$, whereas spatial working memory was not statistically significant, $F(1, 112) = 3.21$, $p = .076$. Minecraft experience was also statistically significant, $F(1, 112) = 6.08$, $p = .015$. Adjusted means across conditions are presented in Figure 10.

Figure 10

Adjusted Object Accuracy Across Experimental Conditions



Note. Error bars represent standard errors of the mean.

A second ANCOVA, shown in Table 9, was conducted to examine the effect of condition on object sensitivity (d') while controlling for visual perspective-taking and Minecraft experience.

Table 9

ANCOVA Results for Object Sensitivity (d')

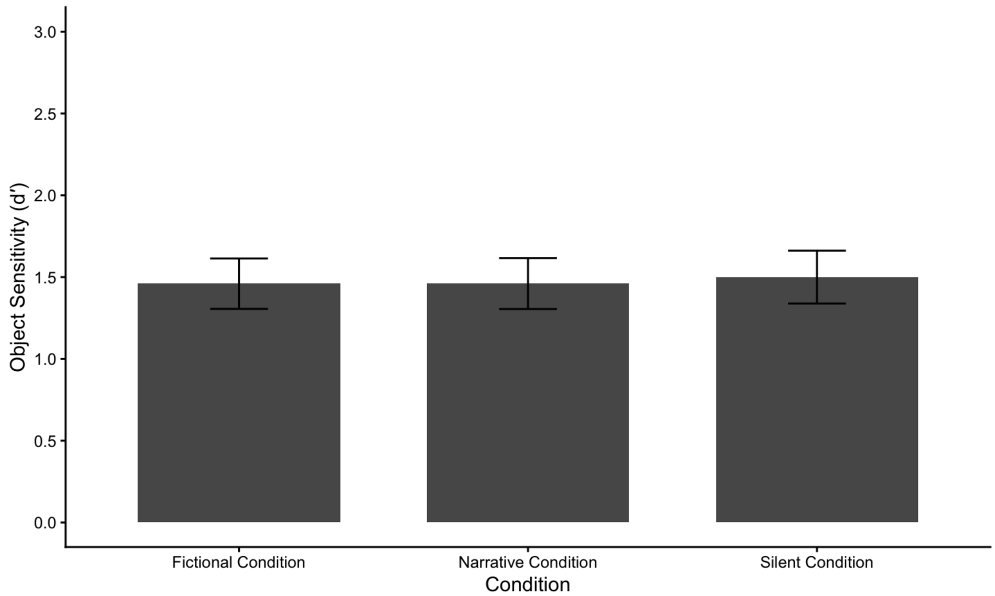
Source	**df**	**SS**	***F***	***p***
Intercept	1	5.48	8.65	**.004****
Condition	2	0.04	0.03	.968
Visual Perspective-Taking	1	2.94	4.64	**.033***
Minecraft Experience	1	5.74	9.06	**.003****
Residuals	112	70.92		

Note. *p < .05, **p < .01, ***p < .001.

As Table 9 shows, the effect of condition was not statistically significant, $F(2, 112) = 0.03$, $p = .968$, indicating that object sensitivity did not differ across the fictional story, non-fictional narrative, and silent conditions after accounting for relevant covariates. With respect to covariates, visual perspective-taking was a significant predictor of object sensitivity, $F(1, 112) = 4.64$, $p = .033$, as was Minecraft experience, $F(1, 112) = 9.06$, $p = .003$. Adjusted object sensitivity scores across conditions are presented in Figure 11.

Figure 11

Adjusted Object Sensitivity (d') Across Experimental Conditions



Note. Error bars represent standard errors of the mean.

A third ANCOVA, illustrated in Table 10, was conducted to examine the effect of condition on spatial location processing (node accuracy) while controlling for visual perspective-taking, spatial working memory, Minecraft experience, and gaming experience. The effect of condition on node accuracy was marginally significant, $F(2, 111) = 2.84$, $p = .063$.

Table 10

ANCOVA Results for Node Accuracy

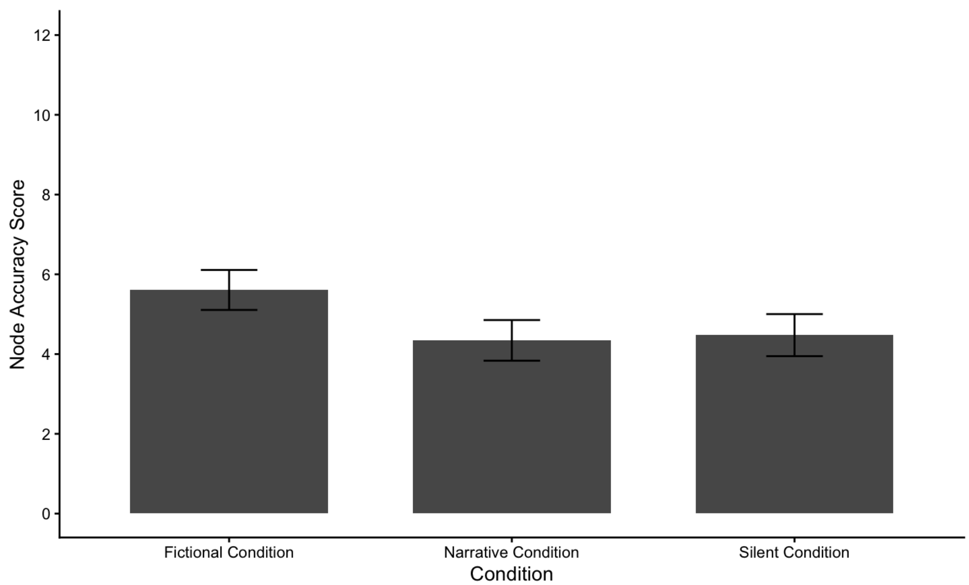
Source	**df**	**SS**	***F***	***p***
Intercept	1	2.06	0.31	.581
Condition	2	38.05	2.84	*.063†*
Visual Perspective-Taking	1	50.02	7.47	**.007****
Spatial Working Memory	1	19.72	2.95	*.089†*
Minecraft Experience	1	30.66	4.58	**.035***
Gaming Experience	1	14.76	2.20	.14
Residuals	111	743.22		

Note. †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$.

Adjusted node accuracy across conditions is presented in Figure 12, which shows that participants in the fictional story condition demonstrated marginally higher adjusted node accuracy scores relative to the non-fictional narrative and silent conditions.

Figure 12

Adjusted Node Accuracy Across Experimental Conditions



Note. Error bars represent standard errors of the mean.

Among the covariates, as shown in Table 10, visual perspective-taking was statistically significant, $F(1, 111) = 7.47$, $p = .007$, and Minecraft experience was also statistically significant, $F(1, 111) = 4.58$, $p = .035$. Spatial working memory was marginally significant, $F(1, 111) = 2.95$, $p = .089$, whereas gaming experience was not statistically significant, $F(1, 111) = 2.20$, $p = .140$.

A fourth ANCOVA was conducted to examine the effect of condition on object-location accuracy, measured as the average Euclidean distance between participants' placement of correct objects and the objects' true locations, while controlling for Minecraft experience and gaming experience. The effect of condition on object-location binding was not statistically significant, $F(2, 115) = 0.09$, $p = .912$. Results are presented in Table 11.

Table 11

ANCOVA Results for Object-Location Accuracy

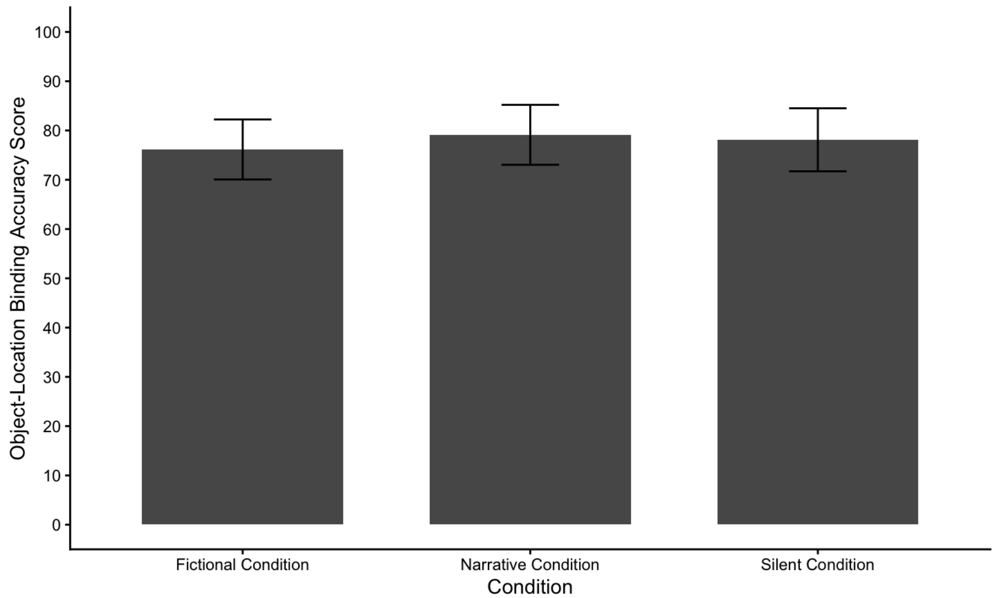
Source	**df**	SS	***F***	***p***
Intercept	1	92160	92.76	**<.001*** **
Condition	2	183	0.09	.912
Minecraft Experience	1	3325	3.35	*.070†*
Gaming Experience	1	8941	9.00	**.003** **
Residuals	115	1114251		

Note. †$p < .10$, **$p < .01$, ***$p < .001$.

Minecraft experience was marginally significant, $F(1, 115) = 3.35$, $p = .070$, and gaming experience was also statistically significant, $F(1, 115) = 9.00$, $p = .003$. Adjusted object-location binding across conditions is presented in Figure 13.

Figure 13

Adjusted Object–Location Accuracy Across Conditions



Note. Error bars represent standard errors of the mean.

In sum, across the four ANCOVA models, learning condition did not significantly influence object processing, spatial location processing, or object-location binding, although a marginal effect was observed for spatial location processing.

Further Exploratory Analyses

Given the absence of significant differences between the fictional story, non-fictional narrative, and silent conditions in the initial ANCOVA models, a secondary analysis was conducted to examine whether the presence of verbal information during learning, rather than narrative type, influenced spatial memory performance. Specifically, the fictional story and non-fictional narrative conditions were combined into a single “language” condition and compared to the silent “no language” condition. This approach is analytically motivated by the possibility that both the fictional story and non-fictional narrative conditions share a common underlying feature, the presence of verbal input alongside visual spatial input during encoding, which may itself support or hinder spatial memory processes independent of narrative condition. As this comparison resulted in unequal group sizes (language: $n = 80$; no language: $n = 40$), the assumption of homogeneity of variance was re-evaluated. Levene’s tests indicated that this assumption was met for all outcome variables ($ps > .50$).

To examine if the presence of language during instruction influenced participants’ memory for objects learned, an ANCOVA was conducted to assess whether there was a difference between language and no language on object accuracy while controlling for spatial working memory, visual perspective-taking, and Minecraft experience. Results are presented in Table 12.

Table 12

ANCOVA Results for Object Accuracy by Language Condition

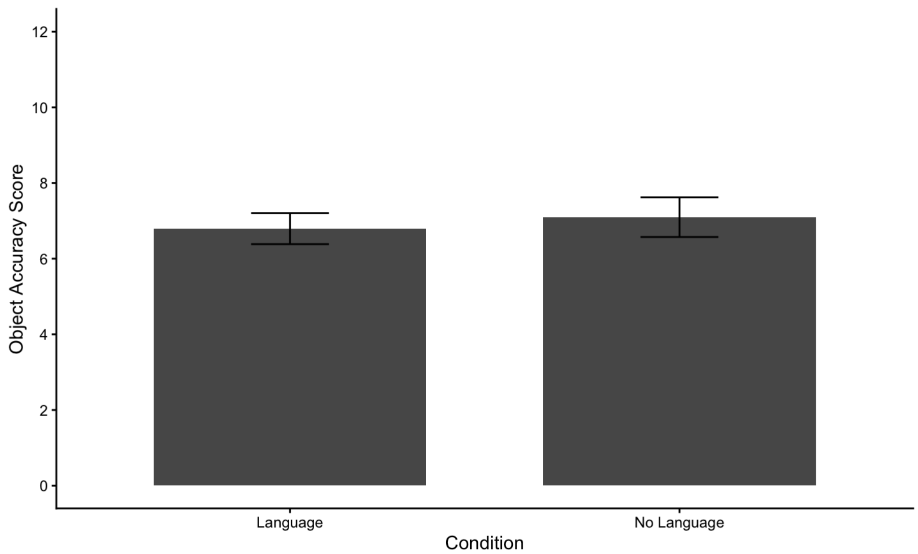
Source	**df**	**SS**	***F***	***p***
Intercept	1	17.71	2.64	.107
Language Condition	1	2.34	0.35	.556
Visual Perspective-Taking	1	52.36	7.81	**.006****
Spatial Working Memory	1	21.91	3.27	*.073* †
Minecraft Experience	1	41.90	6.13	**.015***
Residuals	113	757.42		

Note. †$p < .10$, *$p < .05$, ***$p < .001$

The effect of language condition on object accuracy was not statistically significant, $F(1, 113) = 0.35$, $p = .556$. Visual perspective-taking was statistically significant, $F(1, 113) = 7.81$, $p = .006$, whereas spatial working memory was not, $F(1, 113) = 3.27$, $p = .073$. Minecraft experience was also statistically significant, $F(1, 113) = 6.13$, $p = .015$. Adjusted object accuracy across language conditions is presented in Figure 14.

Figure 14

Adjusted Object Accuracy by Language Condition



Note. Error bars represent standard errors of the mean.

Another ANCOVA, shown in Table 13, was conducted to examine the effect of language condition (language vs. no language) on object sensitivity (d') while controlling for visual perspective-taking and Minecraft experience. The effect of language condition was not statistically significant, $F(1, 113) = 0.07$, $p = .798$, indicating that object sensitivity did not differ between the language and no language groups after accounting for relevant covariates.

Table 13

ANCOVA Results for Object Sensitivity (d') by Language Condition

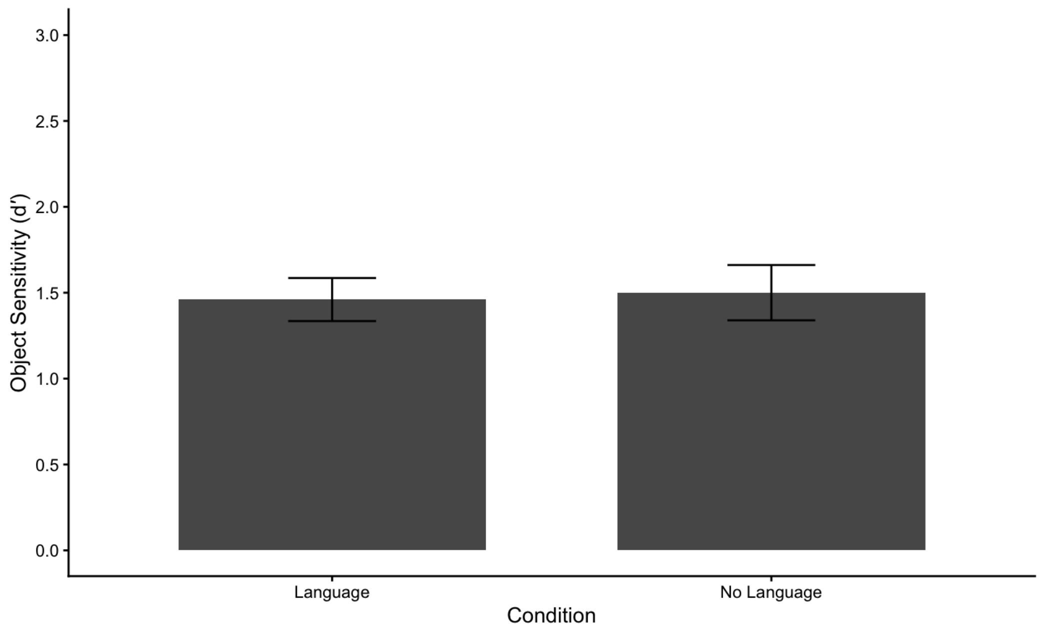
Source	**df**	**SS**	***F***	***p***
Intercept	1	6.09	9.71	**.002****
Language Condition	1	0.04	0.07	.798
Visual Perspective-Taking	1	2.94	4.68	**.033***
Minecraft Experience	1	5.74	9.14	**.003****
Residuals	113	70.92		

Note. *$p < .05$, ***$p < .001$

With respect to covariates, visual perspective-taking was a significant predictor of object sensitivity, $F(1, 113) = 4.68$, $p = .033$, as was Minecraft experience, $F(1, 113) = 9.14$, $p = .003$. Adjusted object sensitivity scores across language conditions are presented in Figure 15.

Figure 15

Adjusted Object Sensitivity (d') Across Conditions



Note. Error bars represent standard errors of the mean.

An ANCOVA was also conducted to examine the effect of language condition on node accuracy while controlling for visual perspective-taking, spatial working memory, Minecraft experience, and gaming experience, as shown in Table 14.

Table 14

ANCOVA Results for Node Accuracy by Language Condition

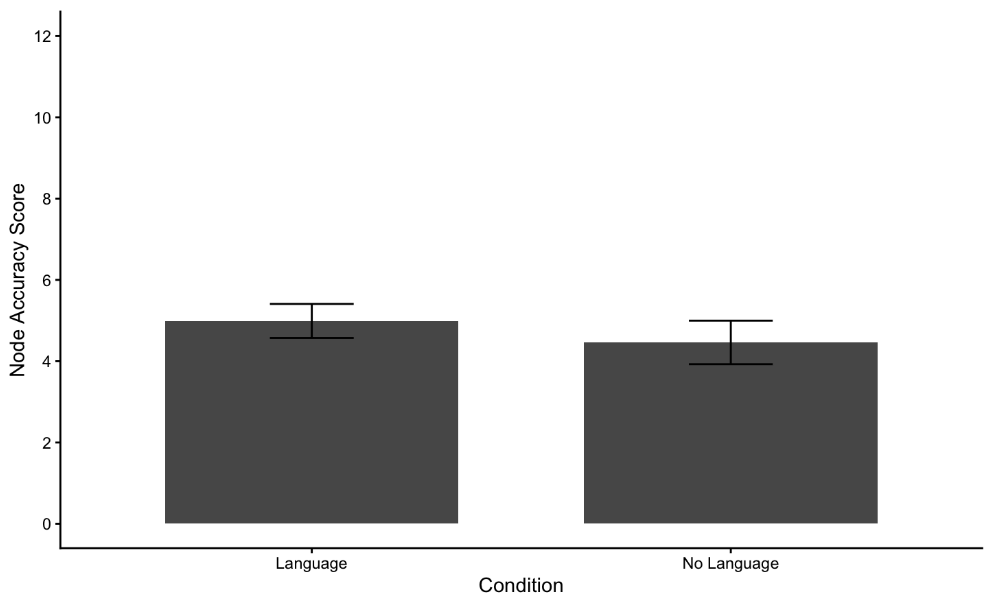
Source	df	SS	F	*p*
Intercept	1	0.50	0.07	.789
Language Condition	1	7.08	1.02	.314
Visual Perspective-Taking	1	48.35	6.99	**.009****
Spatial Working Memory	1	16.45	2.38	.126
Minecraft Experience	1	31.11	4.50	**.036***
Gaming Experience	1	15.09	2.18	.142
Residuals	112	774.19		

Note. †$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$.

The effect of language condition on node accuracy was not statistically significant, $F(1, 112) = 1.02$, $p = .314$. Visual perspective-taking was statistically significant, $F(1, 112) = 6.99$, $p = .009$, and Minecraft experience was also statistically significant, $F(1, 112) = 4.50$, $p = .036$, whereas spatial working memory, $F(1, 112) = 2.38$, $p = .126$, and gaming experience, $F(1, 112) = 2.18$, $p = .142$, were not statistically significant. Adjusted node accuracy across language conditions is presented in Figure 16.

Figure 16

Adjusted Node Accuracy Across Language Conditions



Note. Error bars represent standard errors of the mean.

Lastly, an ANCOVA was conducted to examine the effect of language condition on object-location accuracy while controlling for Minecraft experience and gaming experience. Results are reported in Table 15.

Table 15

ANCOVA Results for Object-Location Accuracy by Language Condition

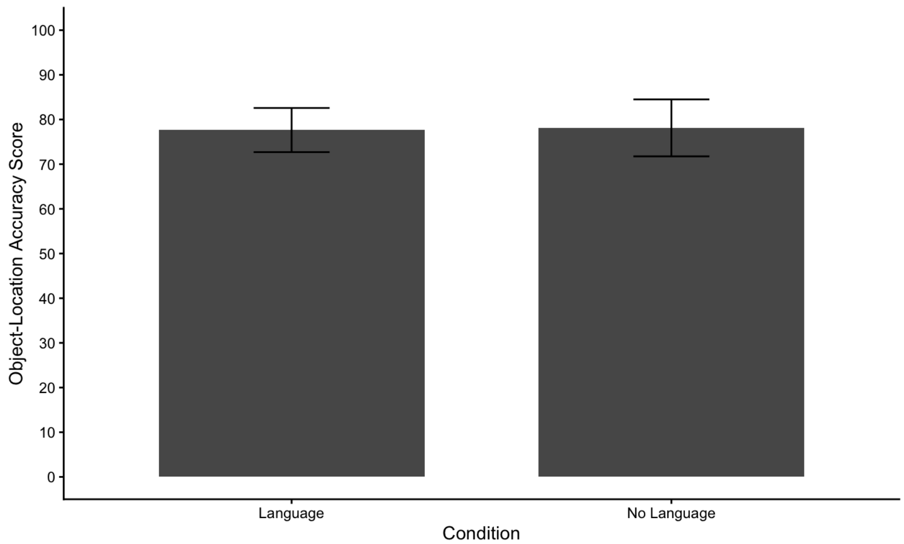
Source	**df**	**SS**	***F***	***p***
Intercept	1	107280	108.75	**<.001*** **
Language Condition	1	6.00	0.01	.937
Minecraft Experience	1	3327	3.37	*.069* †
Gaming Experience	1	8907	9.03	**.003** **
Residuals	116	1144280		

Note. †p < .10, **p < .01, ***p < .001.

As shown in Table 15, the effect of language condition on object-location accuracy was not statistically significant, $F(1, 116) = 0.01$, $p = .937$. With respect to covariates, Minecraft experience was marginally significant, $F(1, 116) = 3.37$, $p = .069$, and gaming experience was also statistically significant, $F(1, 116) = 9.03$, $p = .003$. Adjusted object-location accuracy across language conditions is presented in Figure 17.

Figure 17

Adjusted Object–Location Accuracy Across Language Conditions



Note. Error bars represent standard errors of the mean.

The collapsed analyses revealed a consistent pattern across all four outcome measures. The presence of language during encoding did not significantly influence object accuracy, object sensitivity (d'), node accuracy, or object-location accuracy. This indicates that verbal input during encoding was not associated with differences in spatial memory performance in the present study.

Chapter 4
Discussion

The present study examined whether fictional story, as a cognitive structuring tool that organizes spatial information temporally and meaningfully, enhances object-location memory in an open, large-scale environment. This prediction was grounded in theories of narrative structure and associative encoding, which suggest that organizing information within a coherent sequence of events can support spatial information integration and retrieval. Consistent with predictions, object processing and spatial location processing did not significantly differ between the fictional story and non-fictional narrative conditions and were also comparable to the silent condition, although a marginal effect emerged for spatial location processing. However, contrary to the main hypothesis, there were no significant differences between the fictional story and non-fictional narrative conditions in object-location binding performance.

Although the overall effect of condition on spatial location processing did not reach conventional levels of statistical significance, a marginal effect emerged, with adjusted mean comparisons indicating that participants in the fictional story condition demonstrated numerically higher node accuracy scores relative to the non-fictional narrative and silent conditions. This pattern suggests that fictional story may have modestly supported participants' memory for spatial locations, even though this effect was not robust. Furthermore, no significant differences emerged when the fictional story and non-fictional narrative conditions were collapsed and compared to the silent condition, which suggests that the presence of audio or narrative input alone did not significantly influence spatial memory performance in the present task. These findings indicate that these components of memory were largely not influenced by the presence or structure of verbal information.

Overall, these findings suggest that, in the context of passive route learning, object-location memory may be more strongly impacted by the visuospatial processing demands of a large-scale environment than by temporal or relational structure, thus limiting the extent to which narrative-based organization can influence encoding. Exploratory interview findings further support this interpretation, as participants frequently described dividing attention between spatial information and the accompanying audio during encoding. Although some participants in the fictional story condition reported that the story supported remembering locations, others described the narration as cognitively demanding or distracting, suggesting that narrative structure may not uniformly support spatial encoding across learners.

Prior work in narrative comprehension and associative learning demonstrates that organizing information within a coherent sequence supports integration and retrieval, particularly for semantic and event-based information (Cohn-Sheehy et al., 2021; Ghosh & Gilboa, 2014; Radvansky & Zacks, 2017). However, the current findings contrast with this literature by showing no significant advantage of fictional story over non-fictional narrative or silent conditions for object processing or object-location binding. At the same time, the marginal pattern observed for spatial location processing may suggest that fictional story provided a modest benefit specifically for remembering spatial locations within the environment. One possible explanation is that object-location memory and its component processes, as measured here, may be too fine-grained or mechanistic to capture the broader integrative benefits of narrative structure. In this view, narrative may operate at the level of more global cognitive processes rather than discrete component mechanisms, thus supporting the construction of integrated spatial representations rather than directly enhancing individual elements such as memory binding alone. As a result, its influence may not be detectable when spatial memory is assessed through isolated components, but may instead emerge in measures that capture the formation of intricate spatial representations, such as cognitive maps.

Research on cognitive map formation suggests that spatial representations are constructed through the integration of information across experiences, viewpoints, and relational structures, rather than through the accumulation of discrete elements alone (Ekstrom & Ranganath, 2018). In this context, processes that support integration, such as fictional story, may contribute more to the organization of these higher-level representations than to performance on individual component measures. Therefore, if narrative and story structure are not examined at the level of spatial processing where their effects can be meaningfully captured, comparisons across narrative conditions may substantially underestimate their influence. Support for this interpretation is further reflected in the relationships observed among the outcome measures. The strong association between object sensitivity (d'), object accuracy, and node accuracy suggests that successful spatial memory performance depends not only on recognizing relevant elements but also on effectively discriminating them from irrelevant information during encoding. These relationships reflect the coordinated functioning of multiple components of object-location memory, indicating that performance may emerge more from their interaction rather than from isolated processes.

In addition to the limited condition effects, individual differences in spatial cognition consistently predicted performance across object-location memory components.

Visual perspective-taking, spatial working memory, Minecraft experience, and gaming experience emerged as significant or marginal predictors across multiple analyses, suggesting that performance in large-scale spatial environments may depend more strongly on underlying spatial cognitive abilities and prior experience navigating virtual environments than on narrative structure alone. These findings are consistent with prior research demonstrating that perspective-taking and spatial working memory support the encoding and integration of spatial information across viewpoints, while experience with video games and virtual environments may strengthen navigation strategies, spatial attention, and the ability to track object-location relationships during exploration (Chrastil, 2013; Green & Bavelier, 2003; Weisberg & Newcombe, 2016; Wolbers & Hegarty, 2010).

Given the substantial body of research demonstrating its memory benefits, these findings do not necessarily indicate that fictional story fails to support spatial memory or spatial cognition, but rather suggest that its influence may be more subtle, context-dependent, or may emerge under conditions not fully reflected in the current task design. Although most condition effects were not statistically significant, the marginal effect observed for spatial location processing raises the possibility that fictional story may facilitate some aspects of spatial organization or environmental structuring, even if these effects are not strong enough to broadly enhance all components of object-location memory. In the context of large-scale spatial learning, these results are more consistent with research emphasizing the role of visuospatial processing constraints and cognitive resources, such as spatial working memory and perspective-taking, in supporting navigation and the formation of spatial representations (Bao et al., 2025; Gittinger et al., 2024; Weisberg & Newcombe, 2016). From this perspective, spatial memory in navigational contexts may be more strongly shaped by the coordination of perceptual and spatial processes than by higher-level narrative structure, which may reduce the extent to which narrative and story-based organization influence encoding and integration under these conditions.

Limitations

Several limitations of the present study should be considered, particularly related to task design. First, the use of a passive learning paradigm may have reduced sensitivity to condition effects, as participants were not actively navigating or interacting with the environment during learning. Prior research suggests that active, embodied navigation supports deeper spatial encoding and integration, and the absence of such engagement may have limited the extent to which participants processed or utilized narrative structure during learning (Cheng, 2023; Chrastil & Warren, 2012; Tuena et al., 2024). This design limitation may have reduced the extent to which differences between learning conditions could emerge within the MMN-2 task.

Second, participants were not required to select all 12 target objects, which may have reduced engagement with the full set of object-location associations. Although this design decision was intended to align with established object-location memory paradigms (e.g., Postma et al., 2004), the present task adapted this approach by separating object identification from spatial placement, such that participants first selected objects and then completed object placements one by one within a single phase. In hindsight, this translation may have made object placements less meaningful, as it may have allowed participants to selectively place only the objects they felt most confident locating, even though this was not the task instruction or intended strategy. As a result, object-location accuracy may reflect a subset of items participants believed they remembered rather than a comprehensive representation of all object-location associations, which could potentially reduce sensitivity to differences across conditions.

Additionally, the narrative manipulation itself may have introduced unintended complexity. The use of a Hero's Journey structure, while theoretically rich, may have been overly complex for the task context, potentially diluting or obscuring the specific story elements that could support object-location memory. This complexity may have made it more difficult for participants to extract and utilize the causal and temporal structure of the story during encoding. Finally, the study assessed immediate memory performance only, and fictional story structure may exert stronger effects on delayed retention or consolidation over time. The study also did not directly assess participants' engagement with or processing of the narration presented during the learning video, which raises the possibility that differences in narrative structure were not fully attended to or utilized during the task.

Implications and Future Research Directions

These findings have important implications for research on spatial cognition, learning, and STEM education. Prior work has identified spatial skills as a critical pathway for supporting student success in STEM (Nazareth et al., 2019; Newcombe, 2010; Uttal & Cohen, 2012; Wai et al., 2009), yet much of this research has also focused primarily on small-scale spatial skills (Sorby, 2009; Uttal et al., 2013), leaving important gaps in our understanding of how individuals learn, organize, and navigate large-scale spatial environments. Many STEM disciplines require students to reason about complex spatial systems, integrate information across viewpoints and representations, and mentally manipulate structures that cannot be directly observed. These findings suggest that educators may support the development of large-scale spatial thinking within STEM instruction by intentionally designing learning environments that foster visual perspective-taking and spatial working memory processes. This may be particularly valuable in disciplines such as chemistry, engineering, physics, and biology, where students must coordinate multiple spatial representations and reason across scales to understand complex systems and structures. Future research should continue examining how instructional approaches that target visual perspective-taking, spatial working memory, and large-scale spatial reasoning can support STEM learning and transfer across disciplinary contexts.

Building on this work, much further research is necessary to understand the nuances of how fictional story could be used as a cognitive tool to support STEM learning. This line of work may have important implications for supporting spatial cognition and promoting equity in STEM education. Because disparities in spatial skills are associated with barriers to access and success in STEM fields (Bachman, 2022; Kell & Lubinski, 2013; Wai et al., 2009), developing accessible approaches to support large-scale spatial memory and navigation may represent an important pathway for reducing inequities in STEM learning. Although the present study did not find significant condition effects across all outcomes, the marginal difference observed for spatial location processing suggests that fictional story may modestly support aspects of environmental organization and spatial learning. Future research should therefore examine whether story-based approaches are more effective in active navigation paradigms and immersive STEM learning environments, such as field-based instruction, where learners must continuously integrate spatial, temporal, and relational information during navigation.

Additionally, exploratory analyses of the interview data suggested that participants often divided attention between spatial information and the accompanying audio during encoding, with some participants describing the narration as supportive and others describing it as cognitively demanding or distracting. Future research should therefore examine how individual differences in attention allocation, cognitive load, and emotional and imaginative engagement with the story shape the effectiveness of fictional story as a cognitive structuring tool. Future work may also benefit from incorporating process-oriented measures, such as eye tracking, think-aloud protocols, or physiological measures of cognitive load, to better understand how learners attend to and integrate the story and spatial information during encoding. These directions may provide a more nuanced understanding of the conditions under which fictional story supports large-scale spatial learning.

From a cognitive science and navigation research perspective, future research should more directly examine how story structure interacts with the cognitive and neural mechanisms underlying spatial memory and navigation. In particular, future research on fictional story as a tool for enhancing spatial cognition should investigate whether its effects emerge through underlying spatial cognitive processes, such as spatial working memory, perspective-taking, and the integration of spatial information into coherent representations, rather than solely through behavioral performance outcomes. Future work should also examine how narrative structure influences the encoding, organization, and retrieval of spatial information, including object-location binding, sequence memory, and the integration of information across viewpoints.

Additionally, future studies should investigate how story-based cognitive structuring interacts with systems supporting spatial representation, such as hippocampal-dependent relational memory and cognitive map formation, to better understand whether narrative facilitates the construction of coherent spatial representations or situation models. Future work could also examine whether embedding spatial information within meaningful sequences enhances memory for routes, landmarks, and spatial relationships, as well as how narrative interacts with navigation strategies such as egocentric and allocentric processing. This line of research may be especially promising within active navigation and embodied exploration paradigms, as prior work demonstrates that active navigation supports stronger spatial encoding and integration than passive observation through self-motion cues and spatial updating processes (Chrastil & Warren, 2012; Ruddle et al., 2011; Shelton & McNamara, 2004). Overall, these directions may provide greater insight into how fictional story can support spatial cognition and navigation in STEM learning environments.

Conclusion

In conclusion, the present study does not provide evidence that fictional story preferentially enhances spatial memory in a large-scale environment. Across most analyses, spatial memory performance was not significantly influenced by condition but was instead more consistently associated with individual differences in cognitive ability and prior experience. However, a marginal effect emerged for spatial location processing, with participants in the fictional story condition demonstrating numerically higher node accuracy scores relative to the non-fictional narrative and silent conditions. This suggests that fictional story may modestly support certain aspects of environmental organization or spatial processing, although future research is needed to clarify the conditions under which these effects emerge and the cognitive processes through which they operate. In particular, performance was linked to underlying cognitive processes such as spatial working memory and perspective-taking, which provide further evidence for their central role in supporting object-location memory in complex spatial environments. Furthermore, the association between video game experience and task performance supports prior research suggesting that engagement with interactive spatial environments can support the development of spatial cognitive skills (Feng et al., 2007; Green & Bavelier, 2003; Weisberg et al., 2014).

These findings further suggest important boundary conditions on when and how fictional story may facilitate learning, particularly in tasks that place high demands on visuospatial processing. Exploratory interview findings further suggested that learners varied in how they attended to and experienced the accompanying narration, with some participants describing the audio as supportive and others described it as cognitively demanding or distracting during encoding. Although fictional story did not robustly enhance any components of object-location memory, the marginal effect observed for spatial location processing suggests that fictional story may still support aspects of environmental organization under certain conditions. These findings illuminate the importance of examining not only whether fictional story supports spatial cognition, but also the specific cognitive processes and learning contexts through which these effects emerge. More broadly, this work contributes to a more nuanced understanding of spatial cognition by emphasizing the role of domain-general cognitive processes and highlights the importance of aligning instructional supports with the cognitive demands of the task. In doing so, this study provides a foundation for future research aimed at identifying the conditions under which fictional story or other narrative-based forms of cognitive scaffolding may effectively bolster spatial learning.

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Appendix A: The Demographic and Activity Questionnaire

Please respond to the following items in regards to yourself.

1. Gender:

Male	Female	Non-binary	Self-describe:	Prefer not to say

2. Current Age:

3. Race/Ethnicity:

American Indian/Native American/Alaska Native
Asian/Asian American
Black/African American
Hispanic/Latinx
Native Hawaiian/Other Pacific Islander
White/European
Prefer not to say
Other: __________________________

4. What is your undergraduate major/concentration?

5. What year are you in your undergraduate education?

a. Freshman

b. Sophomore

c. Junior

d. Senior

e. Unmatriculated Student

6. Are you a first-generation college student (i.e., your parents or guardians did not earn a four-year degree)?

Yes	No

7. Is English your first language?

Yes	No

8. Do you play video games for fun/leisure? (Yes/No) If yes:

a) At what age did you start playing video games?

b) What video games are you currently playing? (ex: Fortnite, Call of Duty: Warzone, Angry Birds, Minecraft, Roblox)

c) Circle your top three favorite types

of video games:

Action	Maze	Role-playing
Adventure Fighting	Military	Simulators
Arcade	Music	Space
City-building games	Pinball	Sports
Economic simulation games	Platform	Stealth
Educational	Puzzle	Strategy war games
First-person shooter	Strategy	Survival/Horror
Flight	Racing	Vehicular combat
God games	Real-time and turn-based tactical	
Mass. Multi. Online Games	Real-time and turn-based strategy	
Other (specify):		

d) If you had to rate your skill level for playing video games, what would you choose:

i) Novice

ii) Intermediate

iii) Advanced

iv) Expert

9. Do you have experience playing Minecraft? (Yes/No)

If yes:

a) What is your skill level on Minecraft?

i) Novice

ii) Intermediate

iii) Advanced

iv) Expert

b) How many years have you been playing Minecraft?

10. Do you enjoy watching movies/tv shows? (Yes/No)

a) If yes, what type of movies/tv do you like to watch?

i) Documentary

ii) Fantasy/Sci-Fi

iii) Horror

iv) Action/Adventure

v) Comedy

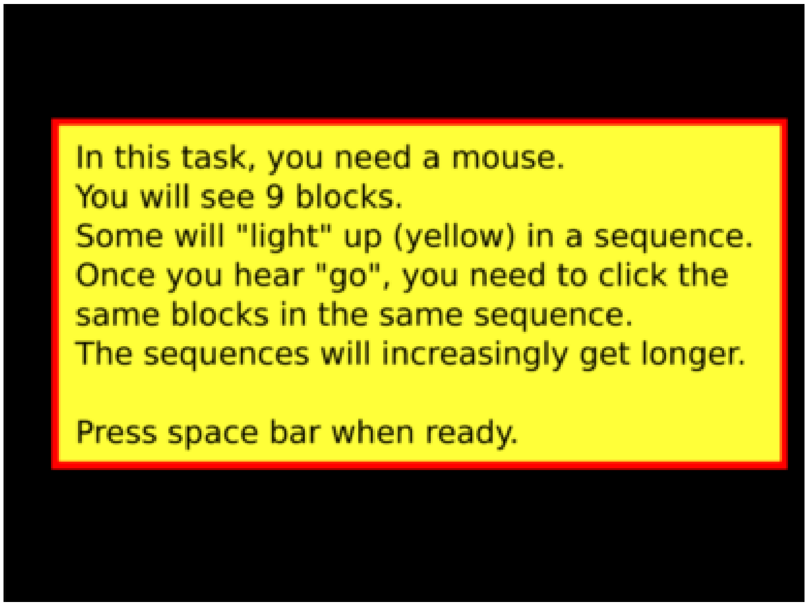
vi) Drama

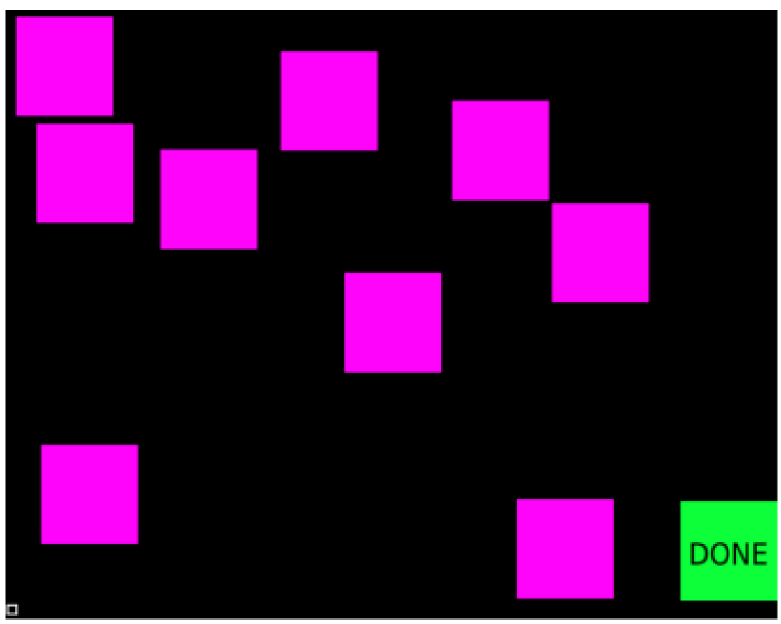
b) How many movies/episodes do you typically watch a week?

11. Do you engage in creative writing for fun/leisure?

Yes	No

Appendix B: Corsi Block Task





Link to task:
https://www.psytoolkit.org/experiment-library/corsi.html

Appendix C: Non-Fictional Narrative Script

Minecraft is an open sandbox game created by Markuss Persson using Java programming language. Mojang Studios first released Minecraft to the public in 2009 and Minecraft is now the best-selling video game in history. As of 2021, there are nearly 140 million monthly active players. Clearly, Minecraft's popularity is still going strong.

Gamers from around the world enjoy exploring Minecraft's blocky, three-dimensional world with an infinite amount of terrain to explore freely. In the Minecraft environment, players can discover and extract different objects, craft tools and items, and build structures. Depending on what game mode is chosen, players can fight, compete against other players or work with other players. In Minecraft, the player has the power to choose the type of game they want to play each time they play!

Over the years, Minecraft has received critical acclaim, winning several awards and even being cited as one of the greatest video games ever created. The annual Minecon convention, which is a livestream and Minecraft fan convention, plays a big role in sustaining Minecraft's popularity. If you have not yet played Minecraft, I highly recommend you try it!

Block opens, the avatar enters the environment, and the task begins.

1. The starting point is at the top of Sunflower Mountain. Go towards the edge of the mountain and jump off the mountain. Land and find a buried chest and retrieve the crossbow. A crossbow is a wooden medieval bow and arrow which was used as a weapon.
2. Walk straight towards the large blades of grass. Once inside the tall grass, find a buried chest and retrieve the blue candle. Candles were first made by the Romans in 500 B.C.
3. Walk straight towards Malabar Hill, and turn right by the gate. Behind the gate, find a buried chest and retrieve the magenta candle. Candles were used in medieval times for the goddess Artemis' birthday.
4. Walk straight ahead towards a patch of a red and a white flower. Here, you find a buried chest with a green candle inside. In the old days, candles were mainly made out of animal products like beef fat or beeswax.
5. Then turn left, and the abandoned castle bridge can be seen from afar. Walk straight towards it and then turn left behind the large blades of grass. Find the buried chest and retrieve the bamboo sapling. Bamboo is the fastest growing plant

on the planet.

6. Then, turn right towards the abandoned castle bridge, and once at the bridge, turn left and walk alongside the brick wall. Then, turn right and enter the bridge. Find the buried chest and retrieve the turtle egg. Turtles usually lay 100-150 eggs and this group of eggs is called a clutch.
7. Walk up the stairs towards the top of the bridge. Find a buried chest and retrieve the coral brain. Coral reefs are sea animals that protect wildlife.
8. Now, walk down the stairs and turn left out of the bridge, and jump down the hole. Find a buried chest and retrieve the twisting vines. In tropical forests, vine species represent more than 40% of the species diversity.
9. Jump out of the hole and walk straight ahead towards a pile of haystacks. Walk straight along the hay and then turn right to go behind the hay. Find the buried chest and retrieve the emerald. Emeralds were first mined by the ancient Egyptians.
10. Turn left and walk straight towards the forest. Then turn left again, walk straight down the steps and go inside the large blades of grass. Find the buried chest and retrieve the Nether Star. The average star is between 1 billion and 10 billion years old.
11. Walk straight up the stairs towards the lake and go down the stairs. Turn right and go under the large tree. Find a buried chest and retrieve the red mushroom. Mushrooms are the fruit of a predominantly underground organism.
12. Walk straight along the tree towards the end of the forest. At the end of the forest, find the buried chest and retrieve the spyglass. The spyglass was the first scientific instrument to amplify human eyesight.

Appendix D: The 12 Stages of the Hero's Journey Framework

Stage and Time Period	*Description*
Stage 1: The Ordinary World	The hero's monotonous daily life is established
Stage 2: The Call to Adventure	Where the hero is presented with a challenge
Stage 3: Refusal of the Call	Where the hero hesitates or initially rejects the challenge
Stage 4: Meeting the Mentor	Where the hero encounters a mentor figure who provides wisdom and guides the hero
Stage 5: Crossing the Threshold	Where the hero departs from their familiar world into a world unknown
Stage 6: Tests, Allies, and Enemies	Where the hero faces trials, forms alliances, and encounters adversaries
Stage 7: Approach to the Inmost Cave	The part of the journey where the hero must face their fears
Stage 8: The Ordeal	The hero faces the central obstacle in their journey.
Stage 9: The Reward	Where the hero gains new insights and achieves their goal
Stage 10: . The Road Back	Where the hero begins their journey back to their ordinary life
Stage 11: The Resurrection	The climactic moment of death and rebirth, which shows how the hero evolved during their journey
Stage 12: Return with the Elixir	Where the hero returns home, bringing newfound wisdom to their community.

Appendix E: Fictional Story Script

I was jogging along a wooded path when I ran right by a crooked old "*Do Not Enter*" sign. Before I could think twice, the ground beneath me gave way, and I was tumbling down into a hole. The fall seemed endless, the world above slipping further and further away.

Then I finally landed on an unfamiliar forest floor with my head hitting the ground in a loud *thump*! My head spun, and the world around me swirled with strange shadows and dappled light. When I finally got my bearings, I saw a beautiful blue Toucan flying above me. "*Finally, I've been waiting for a human to come to save our kingdom. Thank you*", the Toucan said with a peculiar air of authority as he perched himself on a nearby branch.

"*There's only one hope,"* the toucan explained, his voice dropping to a solemn whisper, "*Scattered across the now abandoned kingdom are enchanted chests, each holding magic, powerful enough to defeat the forest's evil beast. However, a misguided spell has ensured that only humans can open the chests. If you find all the magical objects, I will take you home. If you refuse, I will be forced to search for help elsewhere and you will be stuck in our world forever*".

Without much choice, I agreed to find the magical objects so that I could make it back home. The Toucan gleefully directed me down the mountain towards the kingdom. I set off on my mission, with a knot of unease coiling in my chest, each step feeling heavier than the last.

Block opens, the avatar enters the environment, and the task begins.

1. **Ordinary World**: Equipped with a knapsack and a list of the objects I should find that the Toucan gave me, I arrived at the kingdom. Just to the left side of me, I spotted a set of haybell stairs. This looked like an area worth exploring, so I hopped up onto the steps and saw a chest on top of the second haybell ledge. I opened it and found a sword inside, this mission might be easier than I thought.
2. **Call to Adventure**: I continued straight through the pile of hay bales, and walked down a set of steps when I saw a dark forest. Transfixed, I walked straight ahead towards a patch of blue flowers. I then heard faint sounds of birds chirping so I turned and jumped down some steps, and made my way through the green marshes to try to find where the birds were when I came upon a chest that was in front of the marshes to my left. I opened the chest and found a torch. The birds fell silent the moment I raised the torch, and the words "*question what you are*

told" materialized on its surface, as if the object itself were attempting to speak to me.

3. **Refusal of the Call:** I didn't think much of this message, and turned around to head out of the forest. I jumped up the set of grassy stairs like a joyful child. I continued to climb the steps until I made it back to the mountainous landscape. I walked around the mountain I was facing and headed towards a sand ledge. I jumped up onto the sand ledge where I found a chest on the left side of a grassy patch. I opened it to find kelp. Written on the kelp was another message that said "*Think critically*". I didn't have time to take these messages in, as I wanted to get home as quickly as possible.
4. **Meeting the Mentor:** I heard the mysterious birds chirping again, so I jumped down the sand ledge and walked towards a brown fence to follow the birds' songs, with each note pulling me closer to them. I walked past the gate and scaled the side of a mountain top, trying not to look down. I walked through a few sunflower patches searching for more chests but couldn't find anything, so I climbed down the mountain. I could hear the chirping getting louder, pulling me away from the mountain towards the open landscape. The birds' chirping abruptly stopped after I passed a hill full of sunflowers. Here is where I found a chest to my left below that sunflower hill. I opened the chest to find a turtle egg inside. On the turtle egg, I saw a message that said "*Trust birds that sing, not those that talk*". I then understood that the birds were speaking with me through the objects, and I felt compelled to let them guide me.
5. **Crossing the threshold:** I then hopped up the step in front of me and walked straight ahead towards the castle bridge in the distance. Before I could make it onto the castle bridge, I heard the birds singing in the opposite direction. So I turned around and headed straight towards a tree lined pathway. I walked through the first pair of trees and saw a chest on top of a ledge on the left hand side of the path. I opened the chest to find a tree sapling. On the tree sapling, I can read another message that said "*you will need to trust our melodies to face what comes next*". A shiver ran down my spine as I wondered what they were trying to warn me about.
6. **Tests, Allies, and Enemies:** I then turned and walked between two large trees. I hopped up on the ledge and walked straight towards a set of steps leading up to a steep hill. I climbed the steps until I got to the top. I then heard the birds chirping again, and followed their sounds between three tall stacks of hay, when suddenly the birds were drowned out by a terrifying roar. Frightened, I ran straight ahead and climbed down into a large hole. In my rush to escape I left my knapsack with all the objects inside behind. I glanced up and saw an ominous shadow rush past

the hole, snatching my knapsack. Confused and distraught, I tried to find a place to rest and catch my breath when I found another chest right in front of the opposite side of the hole hidden among long blades of grass. I opened it to find a glowing bundle of coral, with another message etched into it that said *"Go after the deceptive, and take back what was taken."*

7. **The Approach to the Inmost Cave**: Once the coast was clear, I turned around and leapt out of the hole from the same spot where I had entered. With my heart still pounding, I traced the beasts' tracks back through the same stacks of hay, heading toward a distant mountain crowned by a roaring waterfall. On my way to tracking down my stolen knapsack, I saw another chest to my right just before I got to the foot of the mountain. I opened the chest to find a thick cluster of vines, with a message in them that said "*Don't worry, the beast needs all the objects to take over our land, there is still time"*. Then, I heard a menacing howl coming from the mountain, so I decided to stop following the tracks and focus on finding the rest of the objects.
8. **The Ordeal**: I walked straight ahead and crossed a brick bridge to get far away from the beast. As I was fleeing the mountain, I saw the beasts' shadow reflecting off of the mountain. I watched the shadow transform from a larger than life beast into a Toucan. The Toucan was the beast the whole time. Frightened, I ran past the castle gate into a large grassy field. I walked straight to the other side when I saw a chest directly in front of the way out of the grassy field. I opened it to find coal, where a message appeared that said "*You trusted the wrong one. He captured you and tricked you, don't let him defeat you*".
9. **The Reward**: I can hardly fathom how easily I was tricked, trusting what a strange talking bird said without question out of desperation to get home. Suddenly I heard the birds chirping again so I turned left and walked out of the grassy field. I leapt up each ledge in front of me, each one rising higher than the last, as the sound of the birds grew louder. Once I reached the top, I saw four grass mounds and climbed down to the hill towards them. Once I got to the middle of the four mounds, I jumped up onto the mound to my right and the birds' chirping stopped. Here I found another chest, and I opened it to find a gleaming emerald. On the emerald it said "*We believe in you, you are strong enough to undo the Beast's cruel hold and restore the kingdom's safety."*
10. **The Road Back**: With a newfound determination and confidence, I turned around and walked towards vine-draped trees. As I reached the trees, the sound of the birds returned, so I turned right, pushed through the vines, and walked along the marshlands to follow their guidance. I followed the birds' sounds through more vine-draped trees out of the marshlands. Then I saw a chest on a ledge to my

right, and I opened it to find a Nether Star. A message appeared on the Nether Star that said "*you have one wish, you can either wish for the knapsack back or wish yourself home"*. I closed my eyes, made my wish, and felt the knapsack appear on my back with all the objects inside.

11. **The Return**: I continued straight ahead, jumped up two steps, and found myself back near the castle bridge. I started to hear the birds sing again, and veered left into another grassy field. As I walked straight, I found another chest in the middle of the field. I opened the chest and found a cactus, with a message that said "*The healing powers of the cactus will protect you from the beasts' vengeance. Continue on to make things right"*.
12. **Return with the Elixir**: I then walked straight ahead towards a cluster of brown hills, and could now hear a symphony of birds happily chirping, with new life coming back into their voices. I followed their melodies into a field with yellow and red flowers. I then discovered another hidden chest nestled near the right-hand corner at the base of the hill. I opened it to find a bowl, and a message appeared on it that said "*You've found all the magical objects, we'll take care of the beast. Once we capture him, you must return all the objects to their rightful places and restore the safety of the kingdom, then we can transport you home"*.

Appendix F: Post-Task Interview Script

To all groups: On a scale from 1 to 9, where 1 indicates very, very low mental effort and 9 indicates very, very high mental effort, how much mental effort did you put into this task. Why?

Follow-up question:

For the non-fictional narrative and fictional story groups*:* Do you remember what the narrator was saying as you were watching the video? Can you tell me what you remember about what they said?

For the silent control group (no narration): Do you remember what you were thinking as you were watching the video? Can you tell me what you remember about your thoughts?

Participant provides a response.

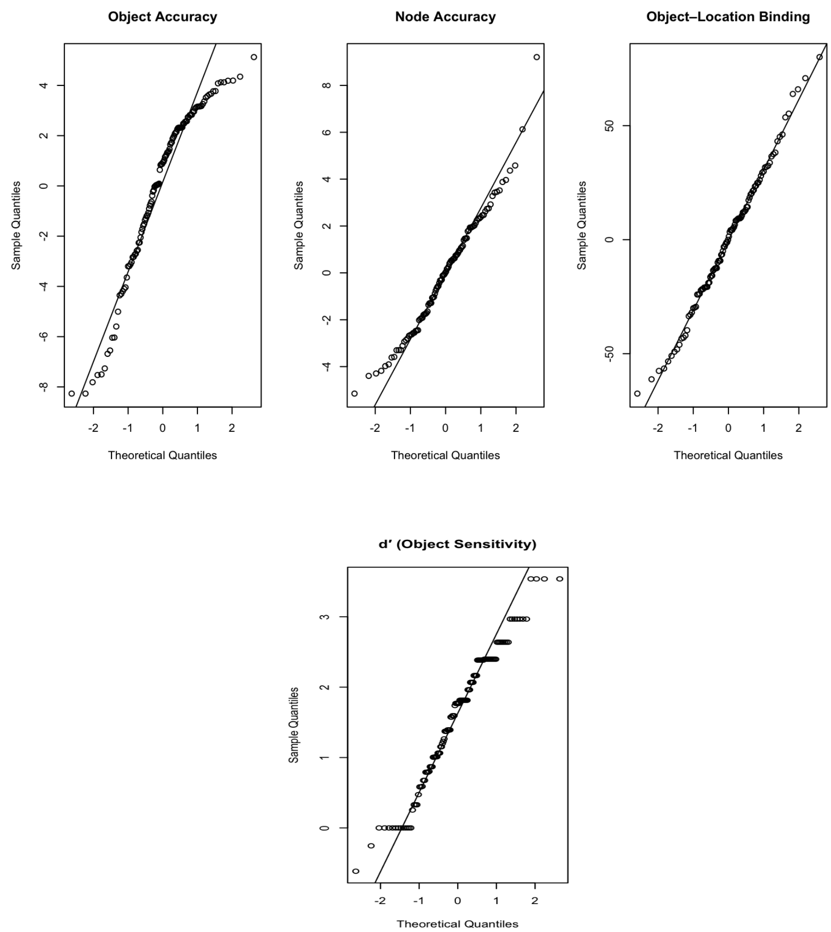
Thank you so much for your participation today! For your efforts, you will receive a $25 Amazon gift card. You will receive your gift card digitally via email within 1-2 weeks of completing the study today.

If you have any questions about the study you just completed after you leave here today, please email us at the address provided in the consent form.

Thank you again for your participation in the study, and I hope you have a lovely day!

Appendix G: Normal Q–Q Plots of Residuals for Primary Outcome Variables

Normal Q–Q plot of model residuals



Appendix H: Residuals Versus Fitted Values Plots for ANCOVA Models