Unpacking how Context Reinstatement aids Memory using Virtual Reality

Griffin E. Koch (griffinkoch@pitt.edu)
Department of Psychology, 3420 Forbes Ave
Pittsburgh, PA 15213 USA

Marc N. Coutanche (marc.coutanche@pitt.edu)
Department of Psychology, 3420 Forbes Ave
Pittsburgh, PA 15213 USA

Abstract

How does our environment impact what we will later remember? Early work in real-world environments suggested that a matching encoding / retrieval context improves memory. However, some laboratory-based studies have not replicated this advantageous context-dependent memory effect. Using virtual reality methods, we find support for context-dependent memory effects: participants remembered more when placed in the same context as during encoding. This advantage has a tradeoff of falsely 'recognizing' similar lures, however. In addition, we find that schema-consistency in terms of the object-environment relationship is beneficial for memory recall, but schema-inconsistency helps recognition. Lastly, we find that differences in the presence (or absence) of dynamic background components differentially elicit the benefits of context-dependent memory. These findings not only add to our understanding of when and how context affects our memory, but they also present an exciting and more naturalistic approach to studying such effects.

Keywords: episodic memory; context-dependent memory; virtual reality; recall; recognition

Introduction

Memories hold links to the past and are useful in our everyday lives. We are able to remember information that we both deliberately and incidentally encode. People encounter objects across different environments: on a bus, in the classroom, or walking through a park. Our ability to remember these objects is impacted both by where we encountered them, and where we try to remember them.

The 'context-dependent memory effect' is the phenomenon in which memories are more likely to be retrieved when the context of encoding matches that of retrieval (Smith & Vela, 2001). In a now classic example, Godden and Baddeley (1975) had participants recall a list of words, after learning them either underwater or on land. Participants remembered more words recalled in the same, compared to different, contexts (e.g., encoding and retrieval both underwater compared to encoding underwater and retrieval on land). Though such initial well-known studies supported the context-dependent memory effect, some laboratory-based studies have failed to replicate these initial findings, and we have yet to fully determine its underlying factors.

One of the earliest explanations for how memory declines after a change in environment is the encoding specificity principle (Tulving & Thomson, 1973). This principle stipulates that when retrieving something from memory, we draw on any information that may have been initially encoded in conjunction with the to-be-remembered item. This information can then later serve as a retrieval cue. There is, however, some ambiguity about the specificity required. For example, in Godden and Baddeley's classic study involving differences in retrieval between dry land and underwater (1975), there are a number of key featural differences between a land and underwater environment.

One such feature could be the relevance of the to-be-remembered items to their environment. A recent virtual reality (VR) study of context-dependent memory (Shin et al., 2020) had participants learn words while in one of two possible virtual environments: on Mars or underwater. Participants then were tasked with retrieving the words while either in the same or different environment. The study replicated context-dependent memory effects within VR, and found a greater effect for context-relevant words (e.g., net underwater). As participants were required to make judgments about the words' usefulness in the environment, it is not known if contemplating the relationship between objects and environment is necessary for this effect. This is a potentially important moderator of the context-dependent memory effect given that information consistent with current knowledge is oftentimes remembered better than is inconsistent information (van Kesteren et al., 2012).

The complexity of background features is also known to affect attention and visual processing of items within perceptually rich environments (Wang et al., 2021). Recent studies have suggested that adding visual richness to a context could be a contributor to context-dependent memory effects (Isarida & Isarida, 2014). In one such study, videos were used as background context for to-be-remembered words (Smith & Manzano, 2010), which more closely resemble the environments in which we typically encounter objects. A possible explanation for these findings is that videos provide more opportunities to encode the context (i.e., greater encoding specificity), leading to stronger context-dependent memories. Previous research has shown that emphasis placed on the context during encoding can moderate the context-reinstatement effect (Bjork & Richardson-Klavehn, 1989; Isarida & Isarida, 2014). Participants in Smith and Manzano's experiments were explicitly instructed to pay attention to the videos, limiting the conclusions that can be drawn about explicit versus incidental encoding (2010).

In M. Goldwater, F. K. Anggoro, B. K. Hayes, & D. C. Ong (Eds.), *Proceedings of the 45th Annual Conference of the Cognitive Science Society*.

Furthermore, the context-dependent memory effect has more often been observed when using free recall memory tests (Smith & Vela, 2001) compared to recognition tests. Since different forms of memory retrieval are differentially impacted by a variety of factors (including free recall and recognition; Coutanche et al., 2020), much could be learned from jointly studying both in a single paradigm.

Here we present a large VR study that asks whether and how recall and recognition of context-dependent memory is affected by schema and the dynamic (versus static) nature of the context. We hypothesized that schema-consistent object/context pairings and dynamic environments would lead to stronger context-dependent memory effects in both recall and recognition.

Methods

Participants

Participants were recruited until 240 contributed usable data evenly across four conditions. Participants self-identified as: being between the ages of 18 and 50, fluent in English, having normal or corrected-to-normal vision, not currently having a cognitive disability (such as a learning or attention disorder), and being able to stand without interruptions for approximately 1 hour. While progressing to the 240-participant target, eight participants' data were not included due to likelihood of low effort or attention in the encoding and distractor tasks (e.g., accuracy scores more than three standard deviations below the mean of the entire group). For four participants, data from five objects were excluded due to a technical issue. Sample size for each condition was based on an a priori power analysis using parameters from Wälti et al. (2019) when context-reinstatement had a beneficial effect on free recall memory performance. This sample size target for each condition was also in line with a recent virtual reality study investigating context-dependent memory (Shin et al., 2020). Upon completion of the tasks, participants were compensated for their time through either course credit or payment. See Table 1 for demographic information for all participants' data included in final analyses. The Institutional Review Board (IRB) approved all measures prior to data collection.

Procedure

All four conditions followed the same procedure, excepting modifications to the environments (described below). After eligibility screening and consent, participants started the session with a basic VR tutorial, which (along with the experimenter) provided them with guidance about how to move around and grasp objects in VR.

The experimenter then exited the lab room, and the participant was placed into a virtual hallway environment where they began the VR experiment by reading the instructions for the encoding task. A webcam and screen sharing system allowed the experimenter to see both the participant and what the participant was viewing while in VR, as well as communicate if any issues or questions arose throughout the session.

Table 1: Demographic Information

Condition	Age	Gender	First Experience in VR
S-S	20.1 (4.3)	F: 32, M: 27, NB: 1	Yes: 26, No: 34
M-S	20.5 (5.2)	F: 37, M: 23, NB: 0	Yes: 23, No: 37
S-M	20.0 (2.5)	F: 34, M: 25, NB: 1	Yes: 25, No: 35
M-M	19.4 (1.7)	F: 37, M: 21, NB: 2	Yes: 25, No: 35

Table 1: Demographic information for participants included in memory analyses. One of the virtual environments differed between conditions in terms of its background components being static (S) or containing motion (M). These varied in whether they were present during encoding or recognition (e.g., static during encoding and motion during recognition (S-M)). Female (F), Male (M), Non-binary (NB) abbreviations used. *Non-binary* includes individuals identifying as non-binary or gender-fluid. Standard deviations in parentheses.

During each of the two encoding sessions, participants were introduced to a set of 30 individual objects (details below), some of which were typically found in each environment, with others that were not. Participants were introduced to the objects without explicitly drawing their attention to any type of relationship between the environment and objects nor told of any future memory tasks. Participants incidentally encoded the objects through a sorting procedure in which an individual object appeared (on a countertop in the kitchen or desk in the classroom) and participants placed the object into one of two virtual boxes (labeled "More than \$20" and "Less than \$20") placed on the opposite side of the room. After sorting the object, participants returned back to find a new object to sort. After sorting all 30 objects in one environment, participants were relocated to a new virtual environment to complete the same sorting procedure, but with a new set of 30 objects. This procedure ensured that participants interacted with the objects both physically (by picking them up and placing them) and semantically (by categorizing them based on perceived cost), while also physically moving within the environment. On average, participants spent 6.8 (Standard Deviation (*SD*)=1.8) minutes completing the two encoding sessions.

Upon completion of the two encoding sessions, participants completed a 5-minute distractor task consisting of vocabulary and math questions back in the same hallway environment where they first started the VR experiment. Participants were presented with either a word or a math equation. Using either hand, participants selected the closest synonym (for vocabulary questions) or numerical answer (for math questions) from a set of three choices in text boxes. After 5 minutes of the distractor task, participants were relocated to one of the two earlier encoding environments (specific environment counterbalanced across participants) to perform a free recall test in which they were instructed to "describe out loud as many of the objects you had categorized into the boxes earlier as you can remember". On average, participants spent 2.4 (*SD*=1.4) minutes attempting to recall objects.

Next, participants were relocated to the other (counterbalanced) encoding environment for testing recognition memory based on the Mnemonic Similarity Task (Stark et al., 2013). In this test, an object was placed in the same location as encoding. Participants indicated if the object was "old", "similar", or "new" by pressing the corresponding label with their hand or the grabbed object. The stimuli were objects that had been presented in both environments, similar lures, and novel foils. Participants were instructed that they could grab and pick up the objects if that would help them make their decision. On average, participants spent 11.4 (*SD*=2.4) minutes completing the recognition memory test.

Participants were then removed from the virtual space and completed a survey of questions about demographics, VR experience (e.g., frequency of use of VR), feelings of presence within each virtual environment (e.g., "Please rate your sense of being in the kitchen, on the following scale from 1 to 7, where 7 represents your normal experience of being in a place"; adapted from Usoh et al., 2000), and object/environment consistency (e.g., likelihood of finding it in a typical kitchen and typical classroom). The entirety of the study (including VR and non-VR sessions) lasted approximately 1 hour.

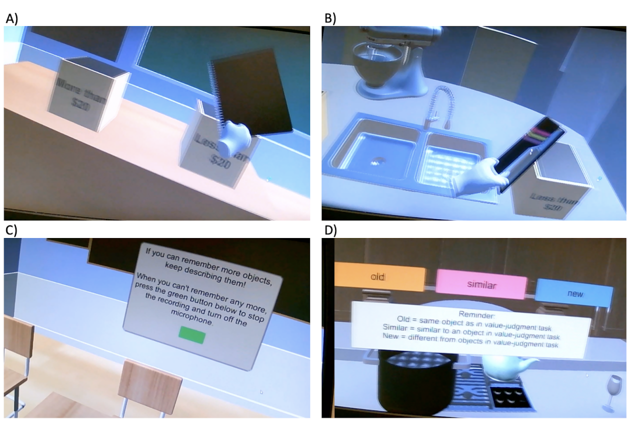

Figure 1: A and B: two virtual encoding environments. C: free recall task within one of the environments. D: recognition task within one of the environments; participants decided whether the presented object was "old", "similar", or "new".

Materials

Environments During initial instructions, distractor task, and ending instructions, participants were placed into a virtual hallway with few background features. For the encoding and retrieval tasks, two virtual environments were used: a classroom and a kitchen. The classroom environment consisted of background items such as desks, chairs, a bookshelf, windows with curtains, a blackboard, a clock, etc. The kitchen environment consisted of kitchen cabinets, chairs, windows and curtains, sink, kitchen appliances, tea kettle and pot of water on the stove, stand mixer, and a clock. For the static only condition, all background objects remained unchanging. For the conditions containing motion, we manipulated background objects within the kitchen to become dynamic. For example, throughout the session, the curtains appeared to be blowing in the wind through the window, the stand mixer span as if it were mixing something, steam emitted from the tea kettle and boiling pot of water on the stove, the hands on the clock rotated, and water ran from the sink faucet. The three dynamic conditions featured motion during encoding, retrieval, or both.

Objects A previous norming study guided our decisions in selecting 40 kitchen-objects (those expected to be typically found in a kitchen), 40 classroom-objects, and an additional 40 miscellaneous-objects (those expected to not be found in either environment). Results of ratings (on a 7-point scale;1 = not very likely, 7 = very likely) from the post-VR survey confirmed our design, see Table 2. An additional 120 objects of the same type were selected to serve as lures during the recognition memory test. These differed from the target objects in color, shape, or style (e.g., red blender and white blender). All target-lure object pairs were matched in orientation during presentation. Each participant saw a random subset of all available objects, with objects counterbalanced as target or lure.

Table 2: Object Schema Ratings

Object Schema	Kitchen Rating	Classroom Rating
Kitchen	6.6 (0.9)	1.3 (0.7)
Classroom	1.9 (1.3)	6.3 (1.2)
Miscellaneous	1.5 (1.0)	1.8 (1.3)

Table 2. Object schema ratings provided by participants included in memory analyses. Ratings on a 7-point scale of where an object would typically be found (1 = not very likely, 7 = very likely). Standard deviations shown in parentheses.

Virtual Reality

All VR tasks were completed by participants in a physical lab room while wearing an Oculus Rift S head-mounted display connected to either an HP Pavilion Gaming Desktop running Windows 11 Home, or an Alienware m15 laptop running Windows 10 Home. A custom hardware pulley set-up prevented the headset's cable from interrupting participants during the tasks. VR tasks were coded with the UXF framework (Brookes et al., 2019) within Unity (version 2018.3.14). Virtual environments and objects were downloaded from the Unity Asset store (https://assetstore.unity.com/) or Sketchfab (https://sketchfab.com/) and modified within Unity to cohesively match (e.g., realistic size) within the environments.

Statistical Analyses

To analyze our memory performance data, we conducted separate logistic mixed-effects regression models (Baayen, Davidson, & Bates, 2008). For memory recall, we predicted whether a participant recalled an object they had seen before or not. For memory recognition, we conducted three separate models to individually investigate hits, lure discrimination, and false alarms (following the approach used by Racsmány et al., 2021), unless otherwise noted. To investigate the effect of motion, we used orthogonal contrast coding between the conditions. We compared 1) environments containing no motion versus motion, 2) environments containing motion during both encoding and retrieval versus motion only during one, and 3) environments containing motion only during encoding vs motion only during retrieval. Additionally, we included orthogonal contrasts representing the relationship between the object and its encoding environment: 1) objects consistent versus inconsistent with the schema of the encoded environment; 2) for inconsistent objects, whether they were typically found within the other environment (e.g., spatula present in the classroom - rather than the more-typical kitchen) or not typically found in either (e.g., bicycle present in the classroom - not usually found in either classroom or kitchen). Each regression model also included random effects for participant and object. For ease of interpretation, figures depict averages at the participant-level.

Results

Memory Recall

We examined the context-dependent memory effect for objects learned within two separate virtual environments. We also investigated how schema and/or the presence of moving background components affect context-dependent memory. First, we found evidence supporting the context-dependent memory effect (β = 0.13, *SE* = 0.04, *Z* = 2.92, p = .004).

We observed trending-level support for an overall advantage in memory recall for objects that were learned in schema-consistent environments compared to inconsistent environments (β = 0.12, *SE* = 0.07, *Z* = 1.77, p = .077). This effect appeared to be driven by particularly poor performance on the schema-inconsistent objects that were unrelated to any encoding environment, as these were recalled less than the schema-inconsistent objects typically found in the other encoding environment (β = 0.25, *SE* = 0.12, *Z* = 2.17, p = .030). Schema consistency interacted with the context-dependent memory effect (β = 0.20, *SE* = 0.10, *Z* = 2.22, p = .026). We observed the context-dependent memory effect only within the schema-consistent objects (β = 0.25, *SE* = 0.07, *Z* = 3.43, p < .001), and not the schema-inconsistent objects (β = 0.06, *SE* = 0.05, *Z* = 1.03, p = .304), see Figure 2. We did not observe an interaction between the context dependent memory effect and whether the schema-inconsistent objects were typically found in the other encoding environment or not (β = -0.01, *SE* = 0.11, *Z* = -0.10, p = .919). There were no overall differences in memory recall for objects learned or retrieved in environments containing motion, nor effects that interacted with the presence of motion (all other *p*s > .211).

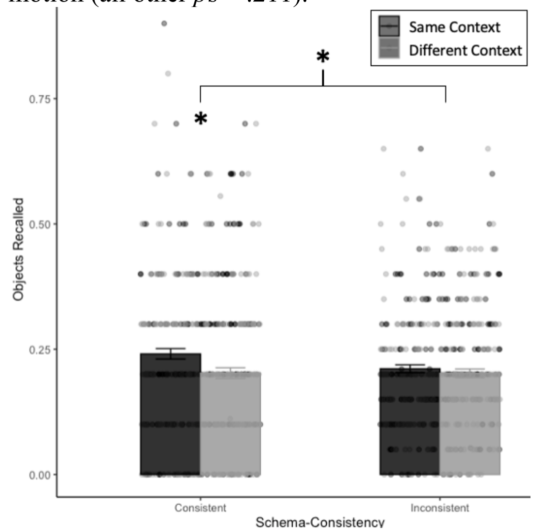

Figure 2: Average ratio of objects recalled when encoding and retrieval environments are the same or different and objects were consistent (or inconsistent) with their encoding environment. Error bars represent SEM. * represents p < .05.

Memory Recognition

Having examined memory recall, we next investigated memory recognition. Our design allowed us to investigate the specificity of participants' memory of the objects by testing their ability to recognize objects that were old versus similar (to previously seen items) versus new.

First, we investigated differences in hit rate (the ability to correctly identify an object as having been seen before). We found evidence supporting the context-dependent memory effect in recognition hit rate (β = 0.12, *SE* = 0.05, *Z* = 2.52, p = .012). Schema consistency also affected hit rate (β = -0.19, *SE* = 0.07, *Z* = -2.61, p = .009), such that schema-inconsistent objects were more accurately recognized than schema-consistent objects. Furthermore, we observed better hit rate for inconsistent objects that did not belong to either encoding environment compared to those which belonged to the other encoding environment (β = -0.30, *SE* = 0.13, *Z* = -2.39, p = .017). Neither of these effects interacted with the context-dependent memory effect (Schema consistency: β = -0.16, *SE* = 0.10, *Z* = -1.61, p = .108; Schema-inconsistent with other environment or not: β = 0.11, *SE* = 0.12, *Z* = 0.90, p = .370). We observed a trending effect of better recognition hit rates when participants experienced motion in zero environments compared to at least one (β = -0.20, *SE* = 0.12, *Z* = -1.72, p = .086). This effect did not interact with the context-dependent memory effect (β = 0.13, *SE* = 0.11, *Z* = 1.10, *p* = .270). We did observe an interaction between the context-dependent memory effect and the contrast comparing motion in both encoding and retrieval versus motion in only one of these (β = -0.42, *SE* = 0.15, *Z* = -2.73, *p* = .006), see Figure 3 for visual depictions of this interaction effect and Table 3 for more details on hit rates. There was no support for an interaction effect between context-dependent memory and whether motion occurred in only encoding or only retrieval (β = -0.06, *SE* = 0.13, *Z* = -0.43, *p* = .668), nor any other effects involving the presence of motion (all other *p*s > .127).

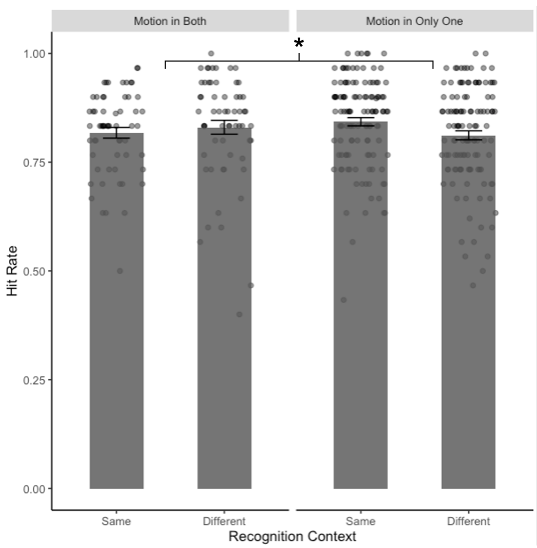

Figure 3: Average rate of correctly indicating an object was "old" when the object was indeed "old" and when encoding and retrieval environments are the same or different across conditions when motion was present during both encoding and recognition, or only one. Error bars represent SEM. * represents $p < .05$.

Table 3: Recognition Hit Rates

Environment	S-S	M-M	M-S	S-M
Same	0.85 (0.11)	0.82 (0.10)	0.85 (0.10)	0.83 (0.11)
Different	0.85 (0.11)	0.83 (0.12)	0.83 (0.11)	0.80 (0.12)

Table 3: Recognition hit rates. The columns reflect the order of motion (M) and static (S) in encoding and retrieval. The rows reflect whether the encoding/retrieval environments are the same or different. Standard deviations in parentheses.

Being able to recognize an object that had been seen before is only one way to represent memory ability. We next investigated lure discrimination following the approach outlined in Racsmány et al. (2021), by testing participants' ability to recognize an object as being similar to an object they had seen earlier. Detection rates were not affected by whether the encoding and retrieval environments were the same (or different) for the old objects used to generate each lure (β = -0.03, *SE* = 0.04, *Z* = -0.71, *p* = 0.480). Similar objects to those seen in schema-inconsistent environments were better identified as similar (rather than new or old) than those in schema-consistent environments (β = -0.28, *SE* = 0.08, *Z* = -3.44, *p* < 0.001). Additionally, similar objects to those which are typically not found in either encoding environment were better identified than those found in the other (β = -0.44, *SE* = 0.14, *Z* = -3.05, *p* = 0.002). There was no evidence of an interaction between the context-dependent memory effect and schema consistency (β = -0.08, *SE* = 0.09, *Z* = -0.93, *p* = 0.352), nor with the schema-inconsistent objects found in the other environment or not (β = -0.06, *SE* = 0.11, *Z* = -0.51, *p* = 0.608). We observed trending level support for the interaction between the schema-inconsistent objects typically found in the other encoding environment or neither and environments with motion present during both encoding and recognition (versus just one of these): β = 0.29, *SE* = 0.17, *Z* = 1.65, *p* = 0.099. Additionally, it appeared this interaction effect was driven by better identification of the schema-inconsistent similar objects typically not found in either encoding environment when motion was present only during encoding (not present during only recognition), β = 0.32, *SE* = 0.15, *Z* = 2.11, *p* = 0.035). See Table 4 for more details on lure discrimination rates based on object and motion conditions. In addition, we observed trending level support for a 3-way interaction involving context-dependent memory effects, schema consistency, and environments with and without motion (β = 0.41, *SE* = 0.21, *Z* = 1.95, *p* = 0.051). We also observed support for a 3-way interaction involving context-dependent effects, schema consistency, and whether motion was present during both encoding and recognition (or only during one): (β = 0.63, *SE* = 0.29, *Z* = 2.15, *p* = 0.032). See Table 4 for more details on lure discrimination rates based on context, object, and motion conditions. No other effects were observed relating to lure discrimination (all other *p*s > .120).

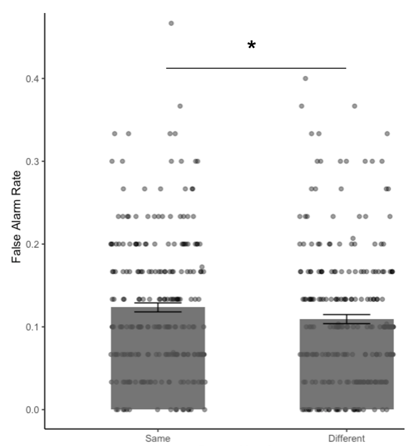

Figure 4: Average rate of incorrectly indicating an object was "old" when the object was "similar" when encoding and retrieval environments are the same or different. Error bars represent SEM. * represents $p < .05$.

Lastly, we investigated false alarm rate for identifying similar objects as old. Performing the recognition test in the same environment that held the object used to generate a lure led to higher false alarm rates ($\beta = 0.15$, $SE = 0.06$, $Z = 2.57$, $p = 0.010$), see Figure 4. Put another way, reinstatement of a context led participants to over-generalize recognition to a similar (but never-before-seen) object. Schema consistency did not have an effect on false alarm rate ($\beta = -0.06$, $SE = 0.12$, $Z = -0.5$, $p = .606$), or interact with the same or different encoding/retrieval environment ($\beta = 0.09$, $SE = 0.13$, $Z = 0.72$, $p = .473$), though we did observe a trending level 3-way interaction between these two factors and the presence of motion (versus no motion): $\beta = -0.49$, $SE = 0.29$, $Z = 1.69$, $p = .092$. See Table 4 for more details on specific false alarm rates. There was also a trending level effect of greater false alarms when motion was present in both encoding and retrieval compared to being present in just one ($\beta = 0.37$, $SE = 0.19$, $Z = 1.92$, $p = .055$). Furthermore, this contrast interacted with the context-dependent memory effect at a trending level ($\beta = -0.32$, $SE = 0.19$, $Z = -1.72$, $p = .086$), such that there was a greater difference in false alarm rate between same and different encoding/recognition contexts when motion was present in only one case (compared to motion present during both). Additionally, we observed an interaction between motion present only during encoding (versus only during retrieval) and the inconsistent objects typically found in the other encoding environment or not ($\beta = -0.44$, $SE = 0.21$, $Z = -2.11$, $p = .035$). See Table 4 for more details on specific false alarm rates relating to this finding. No other effects related to false alarm rate (all other *p*s > .153).

Table 4: Lure Discrimination and False Alarm Rates

	Lure Discrimination				False Alarm			
	S-S	M-M	M-S	S-M	S-S	M-M	M-S	S-M
SI Other E	0.74 (0.13)	0.72 (0.15)	0.75 (0.12)	0.73 (0.17)	0.11 (0.08)	0.12 (0.08)	0.10 (0.09)	0.11 (0.09)
SI Neither E	0.81 (0.12)	0.77 (0.16)	0.79 (0.12)	0.82 (0.12)	0.11 (0.10)	0.15 (0.12)	0.13 (0.10)	0.11 (0.10)
SRC – SC	0.70 (0.17)	0.74 (0.18)	0.71 (0.15)	0.73 (0.17)	0.14 (0.14)	0.13 (0.13)	0.12 (0.12)	0.11 (0.11)
SRC – SI	0.78 (0.12)	0.74 (0.16)	0.78 (0.12)	0.77 (0.14)	0.12 (0.08)	0.14 (0.08)	0.12 (0.09)	0.12 (0.09)
DRC – SC	0.75 (0.14)	0.69 (0.20)	0.73 (0.16)	0.74 (0.20)	0.10 (0.09)	0.13 (0.15)	0.10 (0.09)	0.10 (0.13)
DRC - SI	0.78 (0.13)	0.75 (0.15)	0.76 (0.12)	0.79 (0.14)	0.10 (0.09)	0.13 (0.11)	0.11 (0.10)	0.10 (0.08)

Table 4: Lure discrimination (left) and false alarm (right) rates. The columns reflect the order of motion (M) and static (S) in encoding and retrieval. The rows reflect schema-consistency of object (SC = schema-consistent, SI = schema-inconsistent) and whether the schema-inconsistent objects would typically be found in the other encoding environment (Other E) or not (Neither E). Additionally, we also group based on whether the encoding/retrieval environment is the same (SRC) or different (DRC). Standard deviations shown in parentheses.

Discussion

Here we have provided evidence of context-dependent memory effects in two forms of memory retrieval: recall and recognition. Our studies provide a more detailed understanding of context-dependent memory effects, and particularly identify when the object-environment relationship is advantageous for memory.

Importantly, we observed differences in the schema-consistency advantage between recall and recognition. Schema-consistent objects were better recalled (but not recognized). Schema-inconsistent objects (particularly not typically found in one of the encoding environments) were more often correctly recognized (but not recalled).

In addition, we also present mixed findings regarding the role of motion and increased contextual richness on context-dependent memory. While we expected that the presence of motion would lead to overall better memory, this was not entirely the case. The context-dependent memory effect was evident when it coincided with a switch in dynamic versus static background components between encoding and retrieval (e.g., motion during encoding but not retrieval). This was the case regardless of whether those components were only present during encoding or retrieval. No such benefit was evident when motion was present during both encoding and retrieval contexts.

Our work can shed light on some of the mixed findings of previous literature. The context-dependent memory effect has more often been found in free recall memory tests (Smith & Vela, 2001). We build upon prior findings by Racsmány et al. (2021) in showing that contexts can be both helpful, and harmful, for memory. While retrieving in the same context as encoding was beneficial for recall of objects, it also led to a disadvantage in making incorrect false alarms in recognition. This suggests that people may over-generalize or overestimate their knowledge about an item they think they had seen before. The matching context may be introducing a false sense of confidence due to familiarity, therefore, leading to worse detection of subtle differences in items. When contexts are different, we no longer have as many (if any) matching contextual cues, and we must rely only on our knowledge of the object to correctly recognize it.

This work continues an exciting avenue of immersive and realistic settings (Smith, 2019) in which to better learn about human behavior and cognition.

Acknowledgements

The authors thank Grace Lim, Tatyana Olevich, Amir Oueid, Amy Padia, Amy Qi, and Kelsey Wang for their assistance with data collection. We also thank Scott Fraundorf for consultation with statistical analyses. This work was made possible through support from the Behavioral Brain Research Training Program through the National Institutes of Health (grant number T32GM081760 to G.E.K.)

References

Baayen, R. H., Davidson, D. J., Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. Journal of Memory and Language, 59(4), 390–412.

Bjork, R. A., & Richardson-Klavehn, A. (1989). On the puzzling relationship between environmental context and human memory. In C. Izawa (Ed.), Current issues in cognitive processes: The Tulane Flowerree Symposium on Cognition. Lawrence Erlbaum Associates, Inc.

Brookes, J., Warburton, M., Alghadier, M., Mon-Williams, M., Mushtaq, F. (2020). Studying human behavior with virtual reality: The Unity Experiment Framework. Behavior Research Methods, 52, 455–463.

Coutanche, M. N., Koch, G. E., & Paulus, J. P. (2020). Influences on memory for naturalistic visual episodes: Sleep, familiarity, and traits differentially affect forms of recall. Learning & Memory, 27(7), 284-291.

Godden, D. R., & Baddeley, A. D. (1975). Context-dependent memory in two natural environments: on land and underwater. British Journal of Psychology, 66(3), 325–331.

Isarida, T, & Isarida, T. K. (2014). Environmental context-dependent memory. In A. J. Thirnton (Ed.), Advances in experimental psychology research (pp. 115–151). NOVA Science Publishers.

Racsmány, M., Bencze, D., Pajkossy, P., Szóllósi, Á., & Marián, M. (2021). Irrelevant background context decreases mnemonic discrimination and increases false memory. Scientific Reports, 11.

Shin, Y. S., Masís-Obando, R., Keshavarzian, N., Dáve, R., & Norman, K. A. (2020). Context- dependent memory effects in two immersive virtual reality environments: On Mars and underwater. Psychonomic Bulletin & Review.

Smith, S. A. (2019). Virtual reality in episodic memory research: A review. Psychonomic Bulletin & Review, 26(4), 1213–1237

Smith, S. M., & Manzano, I. (2010). Video context-dependent recall. Behavior Research Methods, 42(1), 292–301.

Smith, S. M., & Vela, E. (2001). Environmental context-dependent memory: A review and meta-analysis. Psychonomic Bulletin & Review, 8(2), 203–220.

Stark, S. M., Yassa, M. A., Lacy, J. W., & Stark, C. E. L. (2013). A task to assess behavioral pattern separation (BPS) in humans: Data from healthy aging and mild cognitive impairment. Neuropsychologia, 51(12), 2442–2449.

Tulving, E., & Thomson, D. M. (1973). Encoding specificity and retrieval processes in episodic memory. Psychological Review, 80(5), 352–373.

Usoh, M., Catena, E., Arman, S., & Slater, M. (2000). Using presence questionnaires in reality. Presence: Teleoperators and Virtual Environments, 9(5), 497-503.

van Kesteren, M. T. R., Ruiter, D. J., Fernández, G., & Henson, R. N. (2012). How schema and novelty augment memory formation. Trends in Neurosciences, 35(4), 211–219. https://doi.org/10.1016/j.tins.2012.02.001

Wang, Y., Yan, J., Yin, Z., Ren, S., Dong, M., Zheng, C., Zhang, W., & Liang, J. (2021). How native background affects human performance in real-world visual object detection: An event-related potential study. Frontiers in Neuroscience, 15.