

In press at *Journal of Experimental Psychology: General*

Precise schemas amplify memory biases:

Extending Bayesian models of reconstructive memory

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Author note

This work was supported by the National Science Foundation SBE Postdoctoral Research Fellowship 2313703 to Michelle Ramey. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Findings from Experiments 1 and 2 were shared at the 2024 Psychonomic Society meeting.

Author Contributions

Michelle Ramey: Conceptualization, Methodology, Software, Validation, Investigation, Formal analysis, Funding acquisition, Resources, Data Curation, Writing – Original draft, Writing – Review and editing, Visualization, Supervision, Project Administration

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OSF: https://osf.io/c5y8e/overview?view_only=58fb8393e0244cd8ba443d36f65ddb13

Abstract

Semantic knowledge in the form of *schemas*, such as expectations about typical object locations, consistently biases episodic memory. Bayesian reconstruction models propose that this results from strategic recruitment of schemas at retrieval, which are integrated with memory to guide responses. However, these models have been challenged for lacking direct empirical support and not specifying cognitive mechanisms. Across five studies (n s=85-203), we tested a unique prediction of Bayesian reconstruction models: that more precise schemas increase the extent to which schemas bias memory. We also proposed and tested a novel framework of underlying cognitive mechanisms, in which simple heuristics produce a Bayesian-like response pattern. Participants searched for target objects in schema-congruent and incongruent scene locations. During later retrieval, participants saw the background scenes and provided both target location recall responses and scene recognition responses. Schema precision for each scene was quantified via a rating task in which participants selected all schema-congruent locations for the target object; fewer schema-congruent locations reflected higher schema precision. We found that higher schema precision dramatically increased schema bias of recall, which supported Bayesian reconstruction predictions. However, underlying memory--but not schema precision--determined *reliance on* schemas; higher schema precision increased schema bias by improving performance in congruent scenes without influencing incongruent scene performance. That is, schema precision simply determined how helpful schemas could be when used, without affecting reliance on schemas versus memory. These results indicate that memory is prioritized above schemas, and a Bayesian-like response pattern results from schemas filling in the gaps in imprecise memories.

Keywords: episodic memory, semantic knowledge, recognition, recall, schemas

Public Significance Statement

Our expectations about the world influence our memories: we are likely to remember our past experiences as being more in line with our *schemas*--that is, more average or typical--than they actually were. The causes of this phenomenon are debated. We tested a theory that proposes that this effect occurs because people strategically use schemas to try to improve the accuracy of their memory responses. Specifically, we tested the prediction that more precise, or specific, schemas will increase reliance on schemas in our memory responses. For example, if we always put our keys in the same location, then when looking for those keys later, we do not need to rely on our specific memory for where we last put the keys--we can instead assume they are in the usual key location. We found that more precise schemas can help improve the accuracy of memory responses, but they do not actually increase reliance on schemas. Instead, individuals assess how strong their memory is in order to decide how much to rely on schemas when making a memory response.

Precise schemas amplify memory biases:

Extending Bayesian models of reconstructive memory

One of the most powerful and well-established influences on episodic memory is prior semantic knowledge in the form of *schemas*, which can range from stereotypes about people to expectations regarding where objects tend to be located in the world (Bartlett, 1932; Ghosh & Gilboa, 2014). Schemas lead us to remember events as being more average or typical (i.e., in line with our schemas) than they actually were; that is, schemas bias our memories (Bartlett, 1932; Hemmer & Steyvers, 2009; Huttenlocher et al., 1991; Ramey, 2026; Ramey et al., 2022; Tompary et al., 2020; Tompary & Thompson-Schill, 2021; Zhang, 2022). This has important societal consequences: schema bias of memory increases in aging (Castel, 2005; Castel et al., 2013; Hay & Jacoby, 1999; Ramey et al., 2024; Umanath & Marsh, 2014), and schemas in the form of stereotypes bias eyewitness memory (Greenberg et al., 1998; Osborne & Davies, 2013). However, despite the ubiquity and real-world significance of these schema effects on memory, the mechanisms of how schemas bias our memories are still unclear. A class of models has been developed--rational reconstruction models--that propose that we strategically leverage schema knowledge to reconstruct our memories during retrieval (Hemmer & Steyvers, 2009; Huttenlocher et al., 1991; Xu et al., 2024). That is, given that our memories are typically imprecise, these models propose that we use schemas to help fine-tune and fill in gaps in our memory. These models can successfully account for schema bias of memory, but they have been challenged for lacking direct empirical support and for not specifying underlying cognitive mechanisms (i.e., algorithmic-level explanations; Bowers & Davis, 2012; Griffiths et al., 2015; Jones & Love, 2011; Xue & Rahnev, 2026). In the present studies, we conduct a critical test of core predictions of rational reconstruction models, and we also propose and test a new

framework that characterizes the cognitive mechanisms that give rise to rational reconstruction effects.

There is a large literature examining how schemas influence episodic memory, but many of the mechanisms are still unknown. A longstanding finding is that schema incongruency, such as a coffee cup on the floor, improves memory (Rojahn & Pettigrew, 1992), which has been attributed to prediction error (e.g., being surprised) strengthening memory encoding (Greve et al., 2017, 2019; Lampinen et al., 2001; van Kesteren et al., 2012). Recent theories based on neurocognitive work have emerged that propose that schema congruency, such as a coffee cup on a coffee table, also improves memory encoding and consolidation (Ghosh & Gilboa, 2014; van Kesteren et al., 2012). These theories propose that the function of memory strength across schema congruency forms a U-shaped curve in which memory is best for incongruent and congruent information, and worst for schema-neutral information (e.g., a coffee cup on a shelf). However, results are conflicting: some studies find this U-shaped curve (Greve et al., 2019; Kafkas & Montaldi, 2018; Quent et al., 2022), others do not (Frank et al., 2018; Ortiz-Tudela et al., 2018), and many even find the opposite (i.e., advantages for neutral stimuli over congruent and/or incongruent stimuli; Bayen et al., 2000; Dodson et al., 2008; Ortiz-Tudela et al., 2023; van Kesteren et al., 2013). In fact, even studies demonstrating the predicted U-shaped curve find that the types of memory involved are not in line with extant theories (Quent et al., 2022).

Perhaps one reason for these conflicting findings is that attempts to investigate the effects of schemas on memory encoding and consolidation can be confounded by the effects of schemas on memory retrieval and reconstruction in some cases. Rational reconstruction theories have long proposed that schemas are leveraged to compensate for imprecise episodic memories during retrieval and reconstruction, such that schemas bias memory responding (Bartlett, 1932; Hemmer

& Steyvers, 2009; Huttenlocher et al., 2000; Zhang, 2022). When this is not controlled for, memory is spuriously better for congruent information (Rojahn & Pettigrew, 1992). For example, imagine that your partner verbally gave you a grocery list and you forgot to write it down, and your memory for it is fuzzy. In this scenario, you will likely draw on your schema for your household's typical grocery list to guide your memory decision (i.e., what to buy). As a result, your schema for your typical grocery list is integrated with imprecise episodic memory for the specific list your partner gave you to reconstruct the most likely list, such that the estimated list will be biased towards the schema. For example, if your partner typically asks for bread, you are likely to buy bread even if you do not specifically recall them asking for bread this time. If the list your partner gave you was indeed typical (i.e., schema-congruent), then this schema bias would improve memory performance--it may even appear like you successfully remembered the list. Importantly, this bias reflects schema influences on responding (i.e., the result of reconstruction), not influences on underlying episodic memory itself; schemas improve performance for congruent information even when stimuli are new (i.e., when one has no episodic memory; Ramey, 2026). Thus, better memory performance for congruent information does not necessarily reflect better underlying episodic memory for congruent information.

Bayesian Reconstruction Models

Although they are often overlooked, the biasing effects of schemas on memory reconstruction are so consistent that they have been mathematically formalized by some rational reconstruction theories, in the form of Bayesian reconstruction models (Hemmer & Steyvers, 2009; Huttenlocher et al., 1991; Macias & Persaud, 2024). These models propose that schemas and memory are rationally combined during reconstruction in a Bayesian fashion. That is, schemas act as a prior, underlying episodic memory acts as current evidence, and these two

sources of information are integrated in the final memory decision by weighting each according to their relative precision. The result of this process is that memory responses are biased by schemas in order to reduce overall error. Given that our underlying memory representations are often imprecise, incorporating schema information typically improves accuracy because schemas represent the most probable occurrence. These models stand in contrast to longstanding theories that schema bias of memory is a result of detrimental (i.e., irrational) distortion (for review see Alba & Hasher, 1983). Across both short-term and long-term memory tasks, Bayesian reconstruction models have provided a good fit to data (Bae et al., 2015; Duffy et al., 2006, 2010; Hemmer & Persaud, 2014; Hemmer & Steyvers, 2009; Huttenlocher et al., 1991; Huttenlocher & Hedges, 1992; Macias & Persaud, 2024; Persaud et al., 2021; Persaud & Hemmer, 2014, 2016; Xu et al., 2024).

Despite their success in modeling investigations, however, Bayesian reconstruction models have been challenged for not specifying underlying cognitive mechanisms (i.e., lacking an algorithmic level of analysis; Marr & Poggio, 1976). In particular, Bayesian cognitive operations--which in this case require assessments of the relative precision of memory versus schemas, and a Bayesian integration of these two sources--have been criticized for being too computationally intensive to be feasible as a cognitive mechanism (e.g., Bowers & Davis, 2012; Ortega & Braun, 2013). Bayesian reconstruction models have also been challenged for being too flexible, allowing them to account for a large variety of potential response patterns (Bowers & Davis, 2012; Jones & Love, 2011). These challenges cast doubt on whether schema bias of memory is driven by rational reconstruction processes. To resolve this debate, computationally tractable mechanisms that are feasible given limited cognitive resources need to be explored (Griffiths et al., 2015; Jones & Love, 2011), and *critical tests* of Bayesian reconstruction models

are needed to determine whether their core, unique predictions are supported in direct empirical tests (Roberts & Pashler, 2000).

A core, unique prediction of Bayesian reconstruction models is that schemas and underlying memory are weighted in memory decisions according to their relative precision (Hemmer & Steyvers, 2009; Huttenlocher et al., 1991). When underlying memory and schemas are similar in precision, one should rely on each to a similar extent. As underlying episodic memory becomes more precise, one should rely relatively less on schemas; for example, if one remembers exactly where they last placed their keys, there is no need to search in other typical locations. Recent findings have confirmed this prediction, such that as underlying memory precision increases, the influence of schemas on memory decisions (e.g., spatial recall) decreases (Ramey, 2026; Ramey et al., 2022).

Bayesian reconstruction models also predict an analogous effect for schema precision: as schema precision increases, the influence of schemas on memory decisions--that is, schema bias--should increase. However, this has not yet been tested directly. A particularly intriguing implication of this prediction is that more precise schemas should reduce reliance on otherwise intact and available episodic memory traces. For example, if one has a precise schema (e.g., always leaving their keys in the same specific place; Rips, 1989), then they should rely less on episodic memory than if they have an imprecise schema (e.g., a tendency to leave their keys at various locations throughout the house). Determining whether higher schema precision increases schema bias, and reduces episodic memory reliance, is critical for testing Bayesian reconstruction models. Elucidating the effects of schema precision is also important for advancing our broader understanding of schema-memory interactions and informing future

experimental designs, given that potential effects of schema precision have been largely overlooked to date.

As alluded to above, another challenge to Bayesian reconstruction models is how their dynamics might be implemented cognitively (Bowers & Davis, 2012; Jones & Love, 2011). Bayesian reconstruction models, like other Bayesian models of cognition, operate primarily within the computational level of Marr's levels of analysis (Griffiths et al., 2015; Marr & Poggio, 1976). This means that these models characterize the computational problem that the brain solves: They propose that the computational problem that produces schema bias of memory is a rational integration of schemas with memory at retrieval. These models do not operate at the algorithmic level, which characterizes the specific underlying cognitive operations involved. Thus, it is not necessarily proposed that participants conduct Bayesian computations when combining schemas and memory. Rather, the Bayesian response pattern is an emergent property of underlying cognitive mechanisms, which are generally proposed to include consideration of the relative utility of schemas versus memory, with schemas serving as a prior (that is, serving as a default response; Hemmer & Steyvers, 2009). The specific cognitive mechanisms--for example, how individuals assess the relative utility of schemas versus memory, and integrate the two sources--that might produce these Bayesian response patterns are unknown, and theories are lacking. It is also unclear whether and how Bayesian reconstruction dynamics might apply to real-world contexts in which schemas are not always relevant or useful for the memory decision at hand. For example, when trying to remember the atypical location in which one last placed their keys, any influence of schemas (for the typical key location) would impair performance. However, model-fitting efforts have focused on tasks in which the schema is always relevant and

useful for the memory decision at hand (Hemmer & Steyvers, 2009; Huttenlocher et al., 2000; Xu et al., 2024).

Current Proposed Framework

To address these issues, we test the core schema precision prediction of Bayesian reconstruction models described above, and we also propose and test an algorithmic-level extension of Bayesian reconstruction models that can flexibly apply to a variety of real-world settings. The rationale for doing so is to advance towards a more comprehensive theory of schema bias of memory by bridging computational and algorithmic levels of analysis (Griffiths et al., 2015). In our algorithmic-level extension, we propose that the combination of schemas with memory during reconstruction might proceed via (at least) two stages: 1) the decision to use a schema, followed by 2) the integration of schemas with memory if a schema is used. We specifically propose that if a relevant schema is identified for the memory decision at hand, that schema is used by default to guide responding¹ unless there is episodic memory evidence that contradicts or refines the schema. Based on recent findings (Ramey et al., 2022; Ramey, 2026), we propose that if memory contradicts the schema (e.g., “I remember my keys were somewhere unusual”) or is highly precise (e.g., “I remember exactly where my keys are”), the schema is not used. If memory refines the schema but is not highly precise (e.g., “I remember my keys were somewhere in the living room”), the schema is integrated with memory to guide the response (e.g., checking schema-congruent surfaces in the living room, like the tables). Importantly,

¹ This is equivalent to the Bayesian reconstruction proposal of schemas acting as the prior--the prior is used by default. Note that we use “memory decision” to refer to any behavior for which accuracy or efficiency can be improved by using memory and/or schemas, which is a very common use of memory in the real world (e.g., recall, search, prediction). For clarity, we focus on situations in which the decision must be made (e.g., you need to find your keys). However, our framework can also apply to situations in which one would opt out of the decision entirely if there were insufficient episodic memory: responding would simply not proceed without sufficient (subjectively assessed) episodic memory. The target confidence judgments in Experiment 4 reveal the dynamics involved when participants are guessing.

schema precision should not influence the decision of whether to use a schema, because schema-based responding simply serves as a default fallback when memory is insufficient. Put differently, schema precision should not influence the extent to which one relies on schemas versus memory. Rather, we propose that subjective assessments of underlying memory are the critical determinant of whether to use a schema. If a schema is used, then schemas are integrated with any available memory--which is the second stage we propose--such that both schema precision and memory precision influence the accuracy of responses. These simple heuristics we propose could produce the approximately Bayesian pattern of responses that has been observed (Hemmer & Steyvers, 2009; Huttenlocher et al., 1991; Xu et al., 2024).

Arguably the most notable aspect of our framework, which best differentiates it from extant models, is the initial stage in which one decides whether and how much to use a schema. This allows Bayesian reconstruction dynamics--which have, to date, almost invariably relied on the assumption that a schema will always be used--to be applied to a wider variety of contexts than has been possible. Our proposal also reconciles prior findings that were incompatible with a Bayesian reconstruction process: A strictly Bayesian computation requires that one always incorporate schemas to some extent regardless of memory strength (it is a fundamental facet of Bayes' theorem broadly speaking; Ortoleva, 2024), but prior findings indicate that schema bias is eliminated when memory is strong (Ramey et al., 2022; Ramey 2026). This is expected behavior in our framework. Thus, our framework provides an algorithmic-level theory--that is, underlying cognitive mechanisms--that could support and extend Bayesian reconstruction models.

To summarize, Bayesian reconstruction models propose that schemas and underlying memory traces are rationally combined at retrieval to influence memory decisions. The predictions of these models have been supported both in the consistently strong biasing effects of

schemas on memory responses, and in the fact that increases in underlying memory precision reduce this schema bias. However, the effects of schema precision--and whether the schema precision predictions of Bayesian reconstruction models are supported--are unknown. Moreover, how these Bayesian reconstruction dynamics might be implemented in terms of cognitive mechanisms is unknown. We propose that achieving a comprehensive understanding of schema effects on memory reconstruction requires consideration of the different mechanisms through which these dynamics could unfold: the decision of whether (or how much) to use a schema in a memory decision, and the effect of that schema when it is used. We hypothesized that higher schema precision would produce larger schema bias of memory responses, as predicted by Bayesian reconstruction models. In terms of the cognitive mechanisms underlying this effect, we expected that schema precision would not influence the extent to which one relies on schemas versus underlying memory, but would determine the effectiveness of the schema when a schema is used. We expected that underlying memory would be the primary determinant of schema reliance. We outline these hypotheses, and how we test them, in more detail below. Whether these predictions are supported has important implications not only for testing and extending Bayesian reconstruction theories, but for debates surrounding schema-memory interactions more broadly; for example, longstanding theories propose that memories are irrationally distorted by (rather than rationally combined with) schemas (for review see Alba & Hasher, 1983). Finding support for these predictions would advance rational reconstruction theories broadly speaking--which can account for schema bias without recourse to irrational distortion--and imply that reconstruction effects may be strong and ubiquitous enough to help explain prior conflicting results with respect to schema-memory interactions (e.g., tests for the U-shaped curve proposed by the SLIMM model; van Kesteren et al., 2012).

Current Research

We addressed these questions across five memory studies ($n=85-203$) and a scene rating task ($n=144$) by concurrently assessing schema precision and underlying memory. To do this, we designed extensions of a recently developed memory paradigm that separates underlying episodic memory from the final schema-influenced memory decision (Ramey et al., 2022), and we designed a novel schema precision task. In the memory task, participants searched for target objects embedded in real-world scenes. Half of the target objects were located in schema-congruent locations, and the other half were in schema-incongruent locations. In a later test phase, participants saw the background scenes without the target objects and made a recognition memory judgment for each background scene, allowing us to assess underlying memory that could not be systematically influenced by schemas at retrieval.² That is, schemas (in particular, the object schemas) could not be used to reconstruct whether a particular background scene was shown earlier in the experiment. Participants also made a spatial recall judgment for the object location, which is known to be strongly influenced by schemas at retrieval (Ramey et al., 2022). Experiments 1-3 comprised the key tests of the schema precision prediction. Experiments 4-5 changed the test format to further probe the effects from Experiments 1-3.

In a separate scene rating task, a different group of participants rated the schema precision of each scene-object pairing that was present in the memory tasks; specifically, they clicked on the locations in each scene where they would expect the object to be located in the real world. More regions clicked indicated a less precise schema for that scene, because the

² Note that retrieving scene memory was necessary for, but not sufficient for, object location memory. That is, because a given object appeared in multiple scenes, one could not remember an object's location in a scene without some memory for the scene itself. Scene memory was not considered to be a direct measure of object location memory, but rather indexed the availability of memory for the episode overall that could not be reconstructed using schema information.

schema was less diagnostic of a congruent target's true location. This definition of schema precision is directly derived from the prevailing Bayesian reconstruction model (Hemmer & Steyvers, 2009): Schema precision is the extent to which a schema can constrain congruent responses for a given stimulus. Combining the memory tasks and schema rating task, the effects of schema precision were assessed by determining how each scene's schema precision predicted schema-memory interactions in the memory tasks. (With the exception of Experiment 3, which accounted for individual differences by examining participants' own schemas.)

Hypotheses about Underlying Task Dynamics

We expected to find the typical signature of schema bias of memory decisions (Berens et al., 2020; Dodson et al., 2008; Greve et al., 2019; Ramey et al., 2022; Tompary & Thompson-Schill, 2021): Spatial recall accuracy for the target object locations should be better for congruent than incongruent scenes overall, including within new scenes. Congruency effects in new scenes demonstrate the presence of schema bias of responding--that is, schema influences on reconstruction that occur during retrieval, rather than schema influences on encoding or consolidation processes--because participants have no episodic memory for new scenes. We additionally expected to find more direct evidence in Experiment 5 that schema bias in this task is driven by reconstruction processes, by changing the test format to reduce the utility of schema bias. We also predicted that any observed schema bias effects would not be driven simply by schema-based guessing when memory is absent (Experiment 4); rather, we expect that schema bias effects are also driven by integration of available (but imprecise) memory traces with schemas.

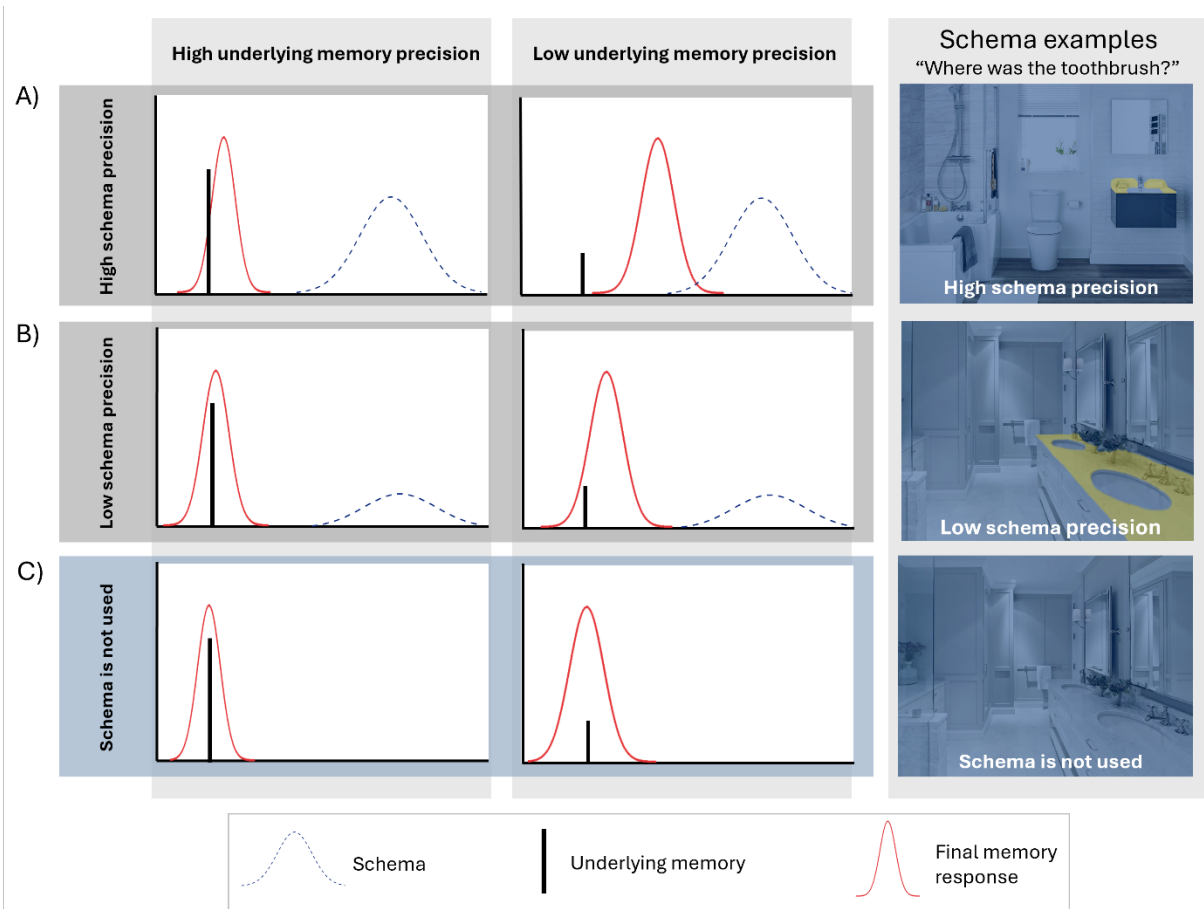
Key Hypotheses for Current Question

In terms of our key hypotheses, we expected the predictions of Bayesian reconstruction models to be supported in terms of recall accuracy outcomes: Schema bias of recall should be larger when schemas are more precise. In our task, this means that the spatial recall accuracy advantage for congruent relative to incongruent scenes--the congruency effect--should be larger for scenes with more precise schemas. In terms of instantiation within Bayesian reconstruction models, higher schema precision should 1) reduce the variability of the prior (i.e., schema), and 2) shift the posterior (i.e., responses) towards the prior (Figure 1). Such an effect would increase accuracy for congruent scenes,³ thus producing a larger congruency effect.

Figure 1

Predicted Effects within a Bayesian Reconstruction Model, for Congruent Scenes

³ Given that Bayesian reconstruction theories focus on cases in which all stimuli are schema-congruent, they do not make direct predictions about how schema precision should influence accuracy in incongruent scenes in this task. Our novel extension does make direct predictions about incongruent scenes in this task, outlined below.



Note. Our predicted effects, situated within a Bayesian reconstruction model (Hemmer & Steyvers, 2009). Given that these models specifically focus on congruent stimuli, this plot only illustrates congruent stimuli (but see our novel framework's predictions regarding incongruent stimuli below). The manner of representing each source of information is adapted from Hemmer and Steyvers (2009). The precision of underlying memory is represented via the height of the black lines. The schema distribution is the prior, the underlying memory is the evidence, and the final memory response is the posterior. Panel A) and B) represent the dynamic that occurs when a schema is used: schema information is combined with underlying episodic memory traces, such that the final response is a blend of schemas and memory. This dynamic, in which a schema is always used, is what is typically assumed by Bayesian reconstruction models. The yellow shading on the scenes represents the schema-congruent region(s); fewer regions corresponds to higher schema precision. A) The dynamic when schema precision is high, which causes the final memory responses to fall closer to the center of the schema distribution. B) The dynamic when schema precision is low, which causes schemas to have less of an influence on responses. C) The dynamic when there is no schema or schemas are not used. In this case, schema precision is irrelevant because there is no prior (i.e., uninformative prior). (We of course expect other schemas, such as gravity, to be employed, but that is beyond the scope of the present question; we consider this further in the discussion.) Note that the scenes were presented to participants in full color (as in Figure 2); the coloring in this figure is for illustration only.

Our next set of novel hypotheses pertained to our proposed cognitive mechanisms (i.e., algorithmic-level extension) underlying schema bias and schema precision effects in this task. As outlined above, Bayesian reconstruction models operate primarily at the computational level, such that they do not make strong claims about cognitive operations (i.e., the algorithmic level). However, given the success of these models thus far in predicting behavioral outcomes (Hemmer & Steyvers, 2009; Persaud & Hemmer, 2014; Xu et al., 2024), the most direct algorithmic extension to them would be to assume that Bayesian operations are applied at the algorithmic level. (In fact, many assume that Bayesian models claim that Bayesian operations are applied, so these are the generally assumed predictions of these models.) We therefore contrast the predictions derived from applying Bayesian operations at an algorithmic level with the predictions from our proposed cognitive mechanisms. A Bayesian cognitive mechanism--that is, if participants performed Bayesian computations when combining schemas with memory--entails that more precise schemas would increase reliance on schemas relative to underlying memory. Put differently, higher schema precision would decrease reliance on memory even if memory is accurate and available. Returning to the keys example, imagine that you specifically remember that your keys are somewhere in the living room (an imprecise memory). However, imagine that you also have a very precise schema that your keys are almost always on a hook in the kitchen. A Bayesian computation might result in you reporting your keys as being on the kitchen hook even though it conflicts with your memory, because the highly precise schema ends up more heavily weighted than the imprecise memory. That is, the highly precise schema would cause you to rely on your schema instead of your memory. This dynamic would result in higher schema precision increasing schema bias of memory; that is, recall performance would be better for congruent (keys on hook) than incongruent (keys in living room) stimuli. Importantly, this mechanism

predicts that higher schema precision will decrease accuracy for incongruent stimuli, because higher schema precision increases the likelihood that schemas are prioritized above memory in guiding memory decisions.

Our novel algorithmic proposal also predicts that higher schema precision will increase schema bias of memory, but does not predict that higher schema precision will decrease accuracy for incongruent stimuli. We do not propose that higher schema precision increases reliance on schemas relative to underlying memory. If you remember that your keys are in the living room, we propose that you would jettison your kitchen-key-location schema and look in the living room instead (and that you would use other relevant, non-conflicting schemas that could help inform your living room search). We propose that higher schema precision will increase schema bias at the aggregate level because a more precise schema provides better constraint of responses. The reason for this is simple: when there are fewer schema-congruent options (i.e., schemas are more precise), then any given schema-guided response is more likely to be accurate for congruent stimuli. To explain this, we will return to the keys example, but for the sake of simplicity, imagine the kitchen-key-hook-schema does not exist and the living room is a common key location. Imagine that you remember that your keys are somewhere in the living room. In this example, your keys are in a congruent location in the living room (i.e. on a table), and your living room only has one small table (i.e., very precise schema for where keys could be in that living room). If you use your schema to refine your memory decision (i.e., narrow down your memory response to tables in the living room), this precise schema will dramatically improve accuracy relative to an imprecise schema: you would choose that one table. If the schema were imprecise such that there were many tables to choose from, using the schema would not be as helpful for improving accuracy. On the other hand, if your keys were somewhere incongruent

(i.e., on the floor), then the precision of the schema would have little to no bearing on your accuracy--either way, you would be incorrect because you would be choosing a congruent location.

In the context of our task, we predict that a more precise schema should improve recall accuracy for congruent stimuli without influencing accuracy for incongruent stimuli. This would produce more schema bias (i.e., higher accuracy for congruent than incongruent stimuli) with higher schema precision, and an approximately Bayesian outcome in recall accuracy, without affecting reliance on schemas versus underlying memories. Rather, we propose that schemas are simply used to “fill in the gaps” in imprecise or missing memories, and more precise schemas cause what is essentially a statistically inevitable (if we assume reconstruction processes are at play) fine-tuning of schema-based responses. Our framework therefore bridges the computational and algorithmic levels by proposing that a Bayesian pattern of recall accuracy outcomes can be achieved via very simple, computationally tractable cognitive mechanisms rather than assuming that the brain performs actual Bayesian computations.

As a result, schema precision should not influence the likelihood of using a schema (our proposed first stage); that is, schema precision should not influence the probability that participants recall the object as having been in a congruent region. Instead, participants’ subjective assessment of their memory should be the primary determinant of whether schemas are used. This should appear as recognition confidence interacting with congruency condition to determine the likelihood of clicking on a congruent region (and schema bias of spatial recall accuracy decreasing as recognition confidence increases; Ramey et al., 2022). In particular, the likelihood of clicking on a congruent region should be high for all new scenes, indicating reconstruction-related schema bias of responding, and should specifically decrease within

incongruent scenes as recognition confidence increases, indicating that underlying memory decreases schema usage. The influence of schema precision should be limited to a fine-tuning of schema-based responses by providing more constraint of responses. This would be instantiated as higher schema precision improving spatial accuracy when a congruent region is clicked on a congruent scene, but having no effect on incongruent scene accuracy.

Experiments 1 and 2

Experiments 1 and 2 tested these questions using three nonoverlapping groups of participants. One group of participants completed a rating task in which they rated schema precision for all of the scenes, which produced a schema precision score for each scene. These schema precision scores were used for both Experiments 1 and 2 (and 4). The other two groups of participants completed a memory task. In Experiment 1, we used the memory task data from Ramey & Zabelina (2024), which was included solely to provide an additional replication sample. In Experiment 2, we collected memory task data from a new group of participants specifically for the present paper. Thus, the methods for Experiments 1 and 2 were identical, but involved different memory task participants.

Experiments 1 and 2 Method

Memory Task

Participants. For Experiment 1, 250 local undergraduate participants (mean age = 19.28 years, age range 18-37 years; 158 female, 89 male, 3 non-binary) completed the study and successfully passed all pre-experimental attention checks to ensure they understood the instructions. These participants were the same as in Ramey & Zabelina (2024). (There were no data collected nor analyses conducted related to schema precision or clicking on congruent regions.) None of these participants participated in the other experiments. Because the study was

conducted online, stringent exclusion criteria were used to ensure participants were attending to the task. Participant data were eliminated from analysis for failing any attention checks at any point throughout the experiment, clicking on the objects during the study phase less than 90% of the time, or having atypical mouse coordinates that did not conform to the typical browser output (e.g., from using a tablet rather than computer). After these exclusions, the final sample consisted of 203 participants. A sample size of 170 participants was needed to provide 99% power in a two-tailed test to detect the effect of recognition confidence on schema bias in a prior experiment ($\beta=.32$; Ramey et al., 2022 Experiment 1). Power analyses were conducted in G*Power 3.1 (Faul et al., 2007). All participants provided informed consent prior to participating. All procedures were approved by the university Institutional Review Board.

For Experiment 2, a power analysis of the Experiment 1 effect of schema precision on spatial accuracy in congruent scenes, $\beta=.30$,⁴ indicated that 195 participants were needed to achieve 99% power in a two-tailed test. We expected a similar rate of exclusions as in Experiment 1, so we collected a sample of 246 local undergraduate participants (mean age = 19.27 years, age range 18-38 years; 151 female, 92 male, 3 non-binary). After applying the same exclusions as in Experiment 1, the final sample consisted of 183 participants. None of these participants participated in the other experiments.

Aside from the participants, all other aspects of the experiment were equivalent between Experiments 1 and 2.

Apparatus. Experiments 1 and 2 were conducted online using JavaScript via jsPsych (de Leeuw, 2015). Participants were instructed to use a computer with a browser size of at least 800x600px; any participants who tried to use a phone or small tablet were not able to get past

⁴Note that this effect size is not the scene-averaged effect size presented in the results section, but rather the effect size from a subject-level model to allow us to assess the number of participants needed.

this requirement. The experiment would not begin if a participant's browser size was less than 800x600px but allowed them to continue once they expanded it sufficiently. Participants were able to see their cursor throughout the experiment.

Stimuli. Stimuli were 80 photographs of real-world scenes. This stimulus set is the same as in Ramey et al. (2022). All scenes were presented in color at a resolution of 800x600px. Of these 80 scenes, 60 were presented at study and test (i.e., old scenes), and 20 were presented only at test (i.e., new scenes). We included more old scenes than new scenes to ensure that an adequate number of old scenes was recognized at each level of confidence for analysis. (Note that our analytic method, linear mixed effects modeling, is robust to differences in trial count per bin.) Stimulus presentation was counterbalanced, such that the scenes appeared in different conditions (i.e., presented at both study and test, or used as a new lure during test) for different participants to mitigate stimulus effects.

Five scene categories were used, and a single type of target object was used for each category. Each scene category was equally represented (16 scenes per category). The categories and targets consisted of kitchens (target: frying pan), dining rooms (target: wine glass), bedrooms (target: alarm clock), living rooms (target: coffee mug), and bathrooms (target: toothbrush cup). Eight different object exemplars were used per category, such that the visual features of the target object varied across different scenes within a category. This entailed that objects were repeated across different scenes. These exemplars included a variety of angles and lighting options for each type of object, which allowed us to select the exemplar that fit most naturally into a given scene during the Photoshop process (e.g., the object perspective and lighting matched the perspective and lighting in the scene). In each scene, only one exemplar of the target object was present, and this was kept consistent across presentations. For example, in each living room

scene, there was only one coffee mug present. Importantly, for a given scene viewed by a given participant, the target was always visually identical and in the same location across repeated study phase viewings (note that targets were never present in the test phase).

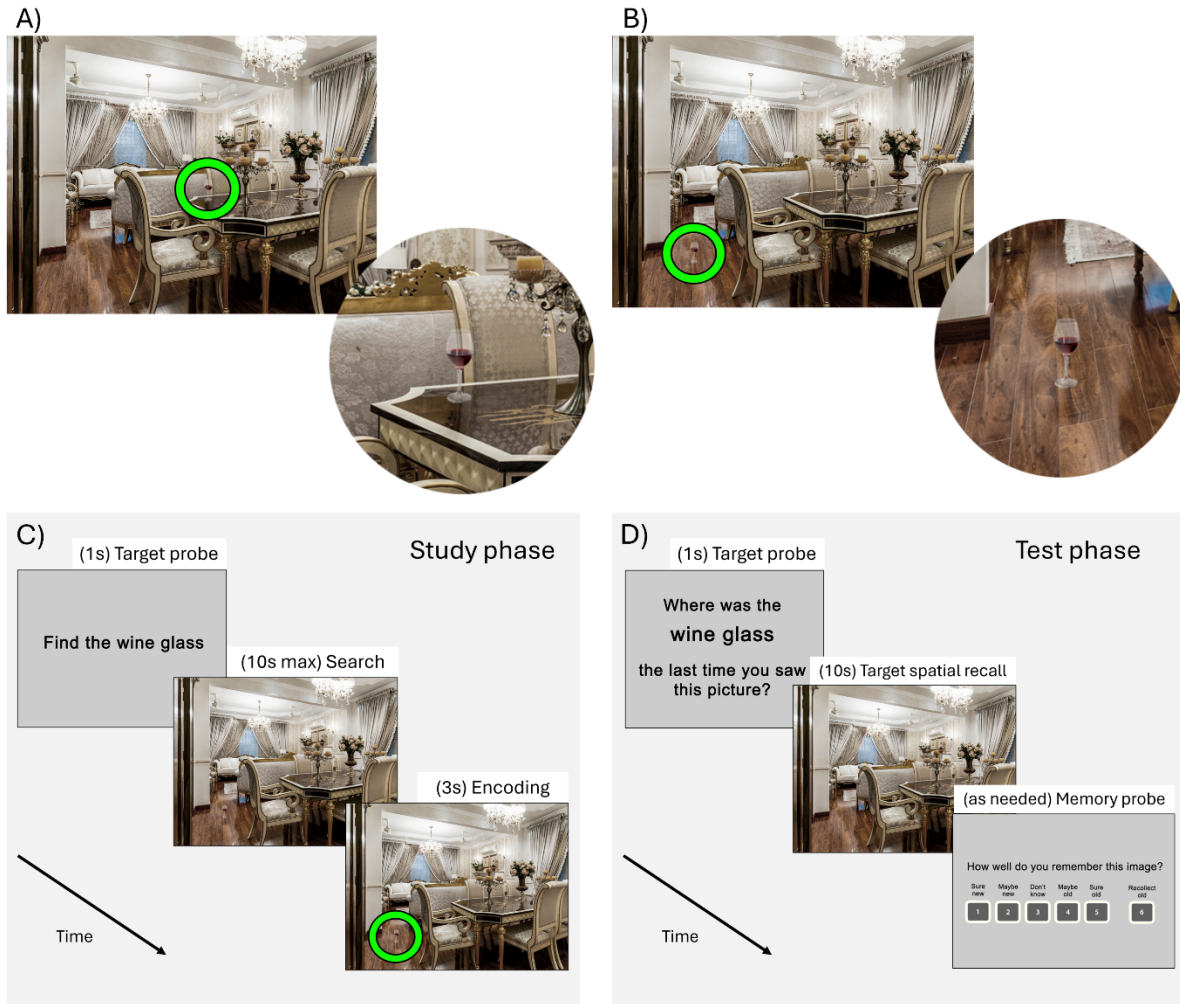
Two versions of each scene were created using Adobe Photoshop (Figure 2A-B): one with the target object in a schema-congruent location, and one with the target in a schema-incongruent location. Following prior work, the congruent location was consistent across all scenes in a category, such that targets were placed relative to larger objects with which the target objects co-occur with highest probability in daily life (Boettcher et al., 2018; Võ et al., 2019). Specifically, the congruent locations were as follows: in bathroom scenes, the toothbrush cups were located next to sinks; in dining room scenes, the wine glasses were located on tables (within arm's reach of a chair); in kitchen scenes, the pans were on stove burners; in bedroom scenes, the alarm clocks were on bedside night stands; and in living room scenes, the coffee mugs were on coffee tables. Note that the congruent locations were consistent within each scene category because this best approximates the type of paradigm used to examine Bayesian reconstruction to date (e.g., remembering the locations of objects on a blank background, with the schema being how those objects clustered together during encoding; Tompary & Thompson-Schill, 2021). High interference is a feature of this paradigm, because schema-congruent stimuli typically have high interference in the real world; by definition, if something is congruent, it represents a commonly encountered situation. In incongruent scenes, on the other hand, the objects were arbitrarily placed in unexpected but physically plausible locations (i.e., on floors, shelves, chairs, etc.). The types of surfaces on which incongruent targets were placed varied between scenes, both within and between categories. The goal of the incongruent condition was to create a condition in which schema information--whether pre-existing schemas or within-

experiment schemas--could not improve accuracy at retrieval. The surface areas of the locations, and the distributions of target locations, were similar between conditions (see Ramey et al., 2024, 2025). To validate the congruency manipulation, we also had a separate group of participants ($n=25$) rate each scene for the congruency of its target object on a continuous scale. Specifically, participants were asked to rate how normal or unusual a target's location was on a 1-6 scale. These scores were averaged together to produce a congruency score for each scene. As expected, congruent scenes ($M=5.60$, $SD=.32$) were rated as significantly more congruent than were incongruent scenes ($M=2.85$, $SD=.99$), $SMD=1.76$, $p<.0001$. These results verify that the congruency manipulation had the intended effect.

Scene congruency was manipulated within-subjects such that each participant was presented with half incongruent scenes and half congruent scenes. The congruent and incongruent versions of the scenes were also counterbalanced such that half of the participants saw the congruent version of a given scene, whereas the other half saw the incongruent version of that same scene. Importantly, a given scene was always congruent or incongruent within a given counterbalance, such that the target was always in the same place in a scene across study repetitions for a given participant.

Figure 2

Sample Stimuli and Procedure



Note. Procedure for Experiments 1-2. A) The congruent version of a sample scene, with the target object (wine glass) on the dining table. The green ring appeared around the target after participants clicked on the scene in the study phase. (The close-up is for visualization only; this was not part of the experiment). B) The incongruent version of the scene. C) The trial sequence in the study phase, which consisted of 60 scenes presented two times each (120 trials). In each trial, a target probe appeared (e.g., “Find the wine glass”), followed by the scene with target object. Participants were required to click on the target object within 10s. After clicking or after 10s, whichever occurred first, a green ring appeared around the target for 3s. D) The trial sequence in the test phase, which consisted of 80 scenes, 20 of which were new (80 trials). A target probe appeared, followed by the scene without the target object, and participants were given 10s to click on the scene location that they thought had contained the target when the scene was presented in the study phase. After 10s or clicking, whichever occurred first, participants gave a confidence-based recognition memory response for the scene.

Procedure. The experiment lasted approximately 45 minutes and consisted of a study phase followed by a test phase (Figure 2C-D). There was a 2-minute break between the study and

test phases. Before each phase, participants were given instructions as well as three practice trials to familiarize them with the procedure. Participants were given a break midway through each phase. All procedures were approved by the university Institutional Review Board.

Study Phase. Participants were told that they would be searching for and clicking on target objects and were asked to try to remember the scene and object locations for a later memory test. During the study phase, participants were presented with 60 unique scenes that were each shown twice, for a total of 120 trials. The repetitions were randomly intermixed throughout the study phase, with the requirement that the same scene did not appear twice in a row. In each trial, participants were first given a 1s probe alerting them to the target object they would need to search for. For example, for dining room scenes, the probe was “Find the wine glass.” After the probe, the scene appeared, and participants had 10s to click on the target object in the scene. After clicking on the scene, or after 10s had elapsed, a green ring appeared around the target object and remained for 3s to allow participants to encode the scene and target object location (Figure 2A-B).

Test Phase. Participants saw each scene once during the test phase, for a total of 80 test trials (60 old scenes, 20 new scenes). Participants were asked to give two types of memory judgments for each scene. First, participants completed a spatial recall judgment for the target object location in the scene. This began with a 1s target probe (e.g., “where was the wine glass the last time you saw this picture?”), followed by the presentation of the scene without its target object. Participants were given 10s to click on the location in the scene where they remembered having seen the target object in the study phase. Participants were told that even if they thought that a scene was new (i.e., not presented in the study phase), they should make their best guess for where the target object might have been if the scene had in fact been shown in the study

phase--that is, if their recognition memory had failed and it actually was an old scene. After the spatial recall judgment (i.e., the clicking task), a recognition memory response scale appeared in which participants were asked to determine whether, and how much, they recognized the background scene (the scale is described in more detail in the next paragraph). Participants were given time as needed to complete this recognition judgment. Then the trial ended.

The recognition memory response scale was intended to index underlying memory for the episode overall. The recognition probe assessed memory for the scene itself, because background scene recognition could not be systematically influenced by schemas at retrieval. On this scale, participants rated memory confidence for each background scene on a 6-point scale that has been extensively validated in prior work (Ramey et al., 2019; Yonelinas, 2002; Yonelinas et al., 2024). Response options included “Recollect old (6),” “I’m sure it’s old (5),” “Maybe it’s old (4),” “I don’t know (3),” “Maybe it’s new (2),” and “I’m sure it’s new (1).” Participants were instructed and tested on how to use this scale prior to beginning the test phase.

Data Aggregation. There were two outcomes of interest. The first was *target distance*: the Euclidean distance between the location clicked by participants during the spatial recall portion of the test phase and the actual location of the target object when the scene was presented in the study phase. This was measured in pixels between the mouse position during the click, recorded in terms of coordinates on the 800x600px scene, and the center of the target object. The target distance measure was skewed, so it was log-transformed. The second measure of interest was whether participants clicked on a congruent region. This was computed as a binary measure indicating whether or not a participant’s spatial recall response fell on a congruent surface, as defined earlier in the Method. A congruent click reflects a potentially schema-based response, whereas a click on a non-congruent region reflects a non-schema-based response. Trials in which

participants did not provide a recall response in time were excluded from analysis (Experiment 1: 1.3% of congruent trials, 1.2% of incongruent trials; Experiment 2: 1.4% of congruent trials, 1.3% of incongruent trials).

New scenes were assessed for comparison with old scenes. Given that new scenes were never presented with a target object, they were not inherently congruent nor incongruent and did not have a true target location. Whether a new scene was classified as congruent or incongruent--and therefore, which target location was used for computing target distance--was determined by the condition in which participants in the opposite counterbalance saw the scene during study (i.e., if participants in counterbalance 1 saw the target as congruent in a scene during the study phase, that scene was considered to be congruent in counterbalance 2 in which participants saw it as a new scene). Thus, to measure target distance in new scenes, we calculated the distance between the clicked location in the test phase and the target location when it was shown in the study phase for participants in the opposite counterbalance. That is, the target location for new scenes is where the target *would have been* had participants viewed that scene during study. It is functionally equivalent to randomly assigning congruency conditions to new scenes. This provides a direct baseline of memory-less performance for comparison with old scenes, allowing us to control for stimulus effects (e.g., if participants are likely to correctly guess the object's location in a particular scene). Participants' clicks on new scenes represented their best guess for where the target object might have been located based on their schema knowledge and their knowledge of the experiment.

Transparency and Openness. For all experiments, we report how we determined our sample sizes, all data exclusions, all manipulations, and all measures in the studies. The studies were not preregistered. The data and code are available on OSF (Redacted, 2026):

https://osf.io/c5y8e/overview?view_only=58fb8393e0244cd8ba443d36f65ddb13. Data were analyzed using R.

Schema Precision Rating Task

Participants. The most relevant previous rating task, in which participants were asked to click on a single location in a scene in which they would expect an object to be, used a group of 15 participants (Vö & Wolfe, 2013). To ensure we could obtain highly reliable measurements, we aimed to exceed this number; we determined the sample size based on the number of participants that we could recruit over the course of one semester. As a result of this, a total of 144 local undergraduate participants (mean age = 19.10 years, age range 18-29 years; 100 female, 43 male, 1 declined to state) completed the task for course credit. These participants came from the same pool but did not participate in the memory tasks in any of the experiments.

Apparatus. The same apparatus was used as in the memory task, along with custom JavaScript.

Stimuli. The background scenes (i.e., without the target objects) from the memory task were used.

Procedure. Participants were instructed to click on the regions of the scenes where they would expect to find a given target object in the real world. Each pairing of scene category with target object type was the same as for the memory task described above; for example, for bathroom scenes, participants were only asked about toothbrush locations. Specifically, participants were asked to place circles with a radius of 15px each on each scene by clicking on the scene (Figure 3A). Participants were encouraged to place the circles directly on top of each other if needed (e.g., if they thought the object would only appear in a small, highly specific region). They were also able to remove and re-place circles if needed.

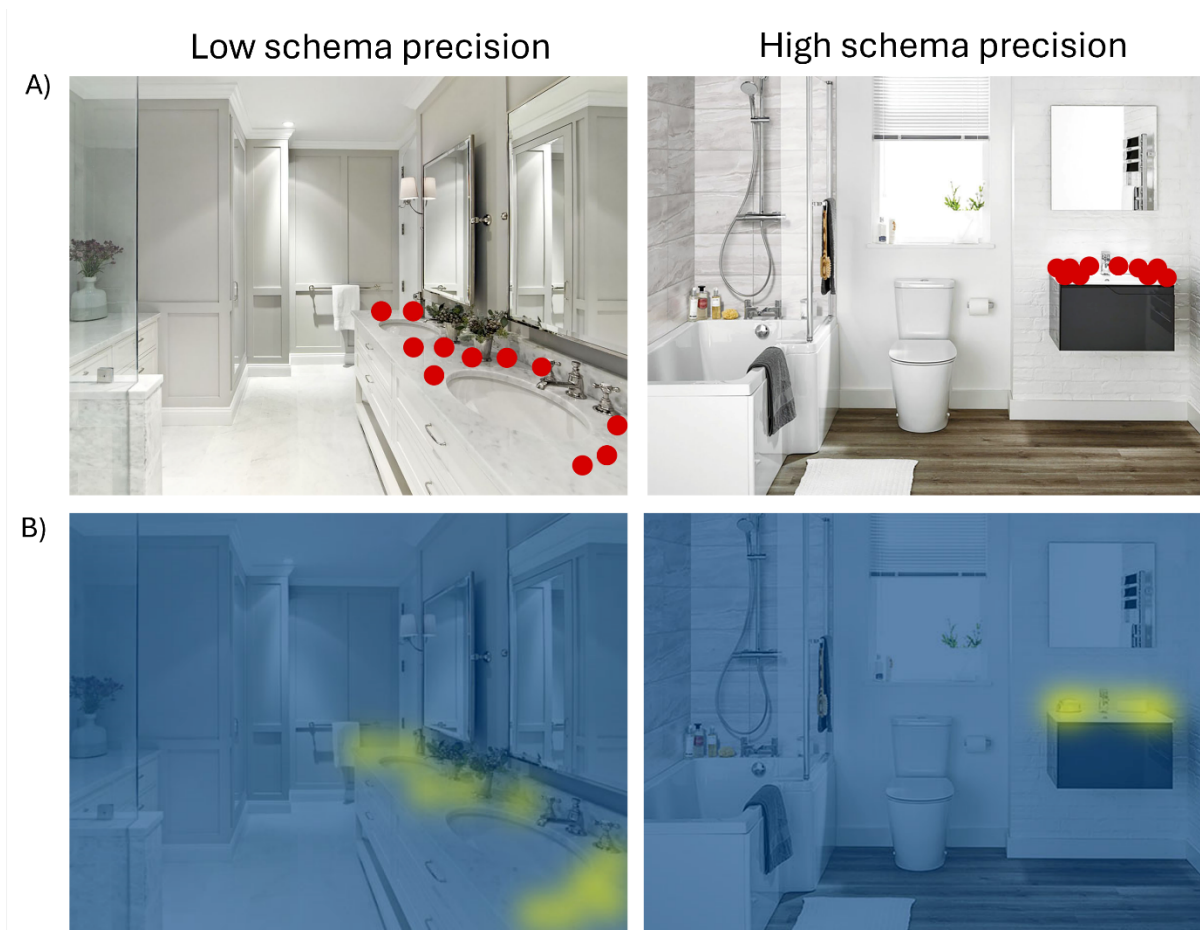
There were two blocks: in the first block, participants were asked to place exactly 10 circles. Participants could only continue to the next trial if 10 circles were placed, and they were not able to place more than 10 circles. This block was of primary interest in order to equate the number of clicks, such that every scene for every participant had 10 circles that were placed.

In the interest of refining our measurement of schema precision, we also had participants complete a second block that always occurred after the first block. In this second block, participants saw all of the same scenes again and were told that they could now place any number of circles they wanted to; they were instructed to place circles in a way that covered all of the regions in which they would expect to find the target object. On the one hand, this second measurement had the potential to provide a more sensitive measure of schema precision, but on the other hand, increased noise from individual differences and effort effects (e.g., some participants will place fewer clicks to finish the study more quickly) could reduce reliability.

In the end, the schema precision measure from the two blocks were almost perfectly correlated, $r=.97$. Analyses focused on the 10-click condition, but we re-ran all analyses with the unlimited-click condition and the pattern of results was unchanged.

Figure 3

Examples of Schema Precision Measure



Note. Examples of scenes with high and low schema precision. Schema precision was indexed via the proportion of the scene that was clicked. In this case, the schema in each scene is the same (the fact that toothbrush cups are usually on bathroom counters), and precision was manipulated via how constrained the schema-congruent region was. That is, if the target had been in a congruent region at study, spatial accuracy would be higher on average for schema-based responses (i.e., clicking anywhere on the counter) for the high precision than low precision scene. A) The top panels illustrate an example of what the participants saw during the rating task after placing their 10 circles. B) The bottom panels illustrate Gaussian-smoothed heatmaps of the clicked regions (overlaid on the scenes), which allowed for a more sensitive measure of proportion clicked. (Results were equivalent regardless of smoothing.)

Data Aggregation. We assessed schema precision as the total proportion of the scene covered by the circles that participants placed, such that higher values corresponded to more congruent regions and therefore lower schema precision. This was computed separately for each scene for each participant, and then the scores were aggregated by scene to produce a single

value per scene. To maximize use of the information provided by the click locations, a Gaussian kernel was used based on prior work (Ramey et al., 2020). Specifically, for each scene, a heatmap of all locations that a given participant clicked was created, and Gaussian smoothing was applied to allow for interpolation between click locations (Figure 3B). For example, 10 circles (with their 15-px radii) were not enough to cover a large dining table in most scenes, so participants evenly spaced the clicks out across the table (as instructed); the Gaussian smoothing allowed the entire table to be highlighted as a congruent region if sufficient circles were placed on it. The proportion of the scene that was covered by the Gaussian-smoothed regions was used as the index of schema precision, with fewer regions indicating higher precision. However, note that simply calculating schema precision as the area covered by the 10 circles exactly as the participants saw them (i.e., no Gaussian smoothing or other transformations of the data) did not change the results.

Statistical Analysis

All analyses of the memory task used data from the test phase. Because each scene had a single schema precision value across all participants, data were aggregated by scene. (But note that the pattern of effects was equivalent when trial-level multilevel modeling with no averaging was used, as in the Experiment 3 approach.) When an analysis involved only one score per scene (i.e., no repeated measures), standard linear regression was used. When an analysis involved multiple scores per scene, statistical analyses were conducted using multilevel modeling with a random intercept of image. Random slopes were also included when appropriate (i.e., when there were sufficient repeated measures for them to be identifiable). We tested models with an additional random intercept and slope for scene category (e.g., living room, kitchen), but found

that model fits were not improved or were in fact worsened by including them; regardless, the pattern of results was unchanged when these category random effects were included.

The dependent variable in each model was the spatial recall measure of interest, which could be either target distance or whether the spatial recall response was on a congruent region (i.e., congruent click). Depending on the specific analysis, as specified in the Results section, the fixed variables could be schema precision, old versus new status of scenes at test, recognition response, and/or congruency condition. Continuous predictors were scaled. When the outcome of analysis was continuous, linear mixed effects models were used (Kuznetsova et al., 2017); effect sizes are reported as β for continuous fixed effects and standard mean difference (*SMD*) for categorical fixed effects. When the outcome of analysis was binary, logistic mixed effects models were used, and effect sizes are reported as *B*. (Note that all reported effect sizes simply reflect the model estimate with continuous variables scaled.)

Experiments 1 and 2 Results

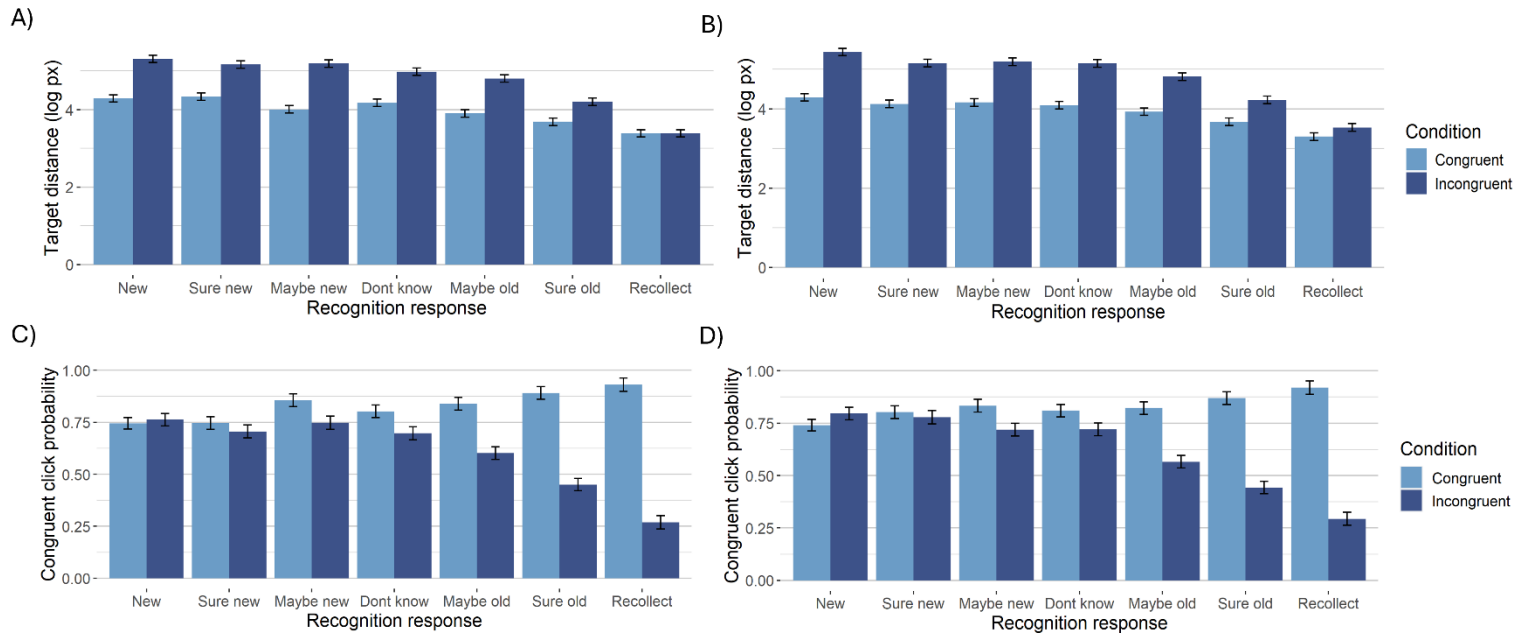
First, we determined whether the pattern of schema effects indicated that schema bias occurred during memory reconstruction. As outlined earlier, perhaps the most diagnostic test for schema bias of memory responding is examining schema effects in new scenes, such that any schema effects in new scenes must be due to effects of schemas on retrieval/reconstruction rather than effects of schemas on episodic memory itself. Given that new scenes had no true congruency condition, congruency condition was assigned in analysis using the congruency condition (and therefore target location) for that scene when it was shown during the study phase in the opposite counterbalance (see Method). These analyses of new scenes therefore examine participants' guessing patterns. Spatial recall accuracy for the target object locations, measured via target distance, was higher for congruent than incongruent new scenes, *SMD*=1.31, $p<.0001$

(Experiment 2: $SMD=1.34$, $p<.0001$). Moreover, participants clicked on congruent regions in new scenes 78% of the time (79% in Experiment 2), despite congruent regions comprising only 6.5% of the scenes on average (one-sample t-test against .065, Experiment 1: $t(39)=25.52$, $p<.0001$; Experiment 2: $t(39)=27.20$, $p<.0001$). Both of these findings indicate robust schema bias of responding: participants were more likely than chance to click on congruent regions. When all scenes were considered, rather than just new scenes, spatial accuracy was still better for congruent than incongruent scenes, $SMD=.73$, $p<.0001$ (Experiment 2: $SMD=.82$, $p<.0001$).

As expected, underlying memory for the episode overall--indexed via recognition confidence for the scenes--also strongly influenced spatial recall accuracy (Figure 4A-B). Spatial recall accuracy increased as recognition confidence increased, $\beta=-.45$, $p<.0001$ (Experiment 2: $\beta=-.42$, $p<.0001$). Moreover, we found that as recognition confidence increased, the effects of schema congruency on spatial recall accuracy decreased, $\beta=-.30$, $p<.0001$ (Experiment 2: $\beta=-.28$, $p<.0001$). Histograms of recognition confidence responses for all experiments are presented in the Supplementary Materials (Figure S1). Thus, the effects identified in prior work were replicated, such that underlying memory modulated the extent to which schemas biased responses.

Figure 4

Effects of Underlying Memory on Schema Bias



Note. Underlying memory for the overall episode in these studies is indexed via scene recognition confidence. A) Target distance by recognition response in Experiment 1. Higher values reflect lower spatial accuracy. All new scenes are included in the “New” bar for comparison; all other bars include old scenes only. B) Target distance by recognition response in Experiment 2. C) Congruent click probability by recognition response in Experiment 1. D) Target distance by recognition response in Experiment 2. For all plots, the estimated marginal means derived from a linear mixed effects model with random effects of scene are plotted, and the error bars represent the standard error of these estimated means from the model.

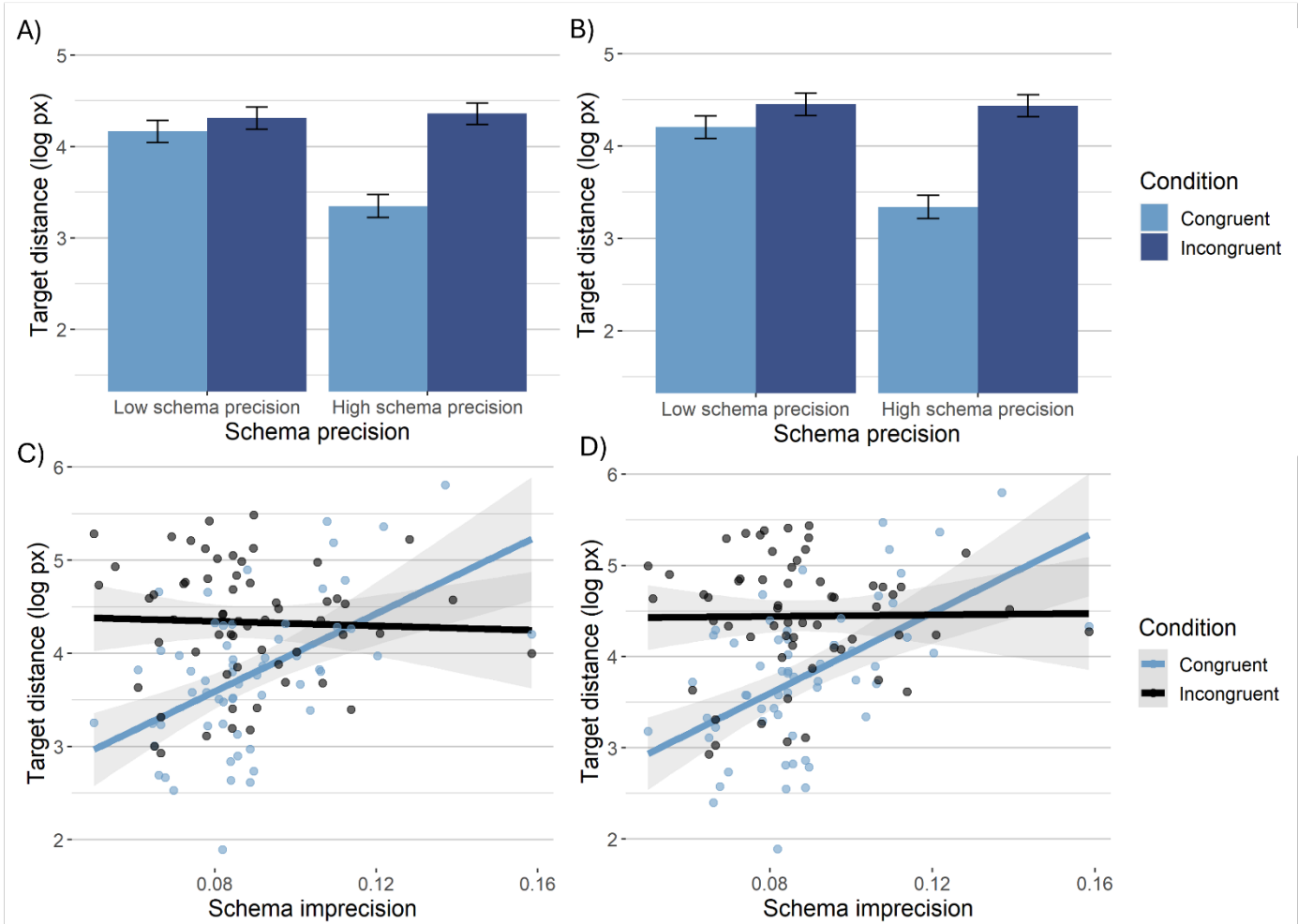
We next turned to effects of schema precision, which was measured via the proportion of each scene that was congruent according to the separate group of raters (with a lower proportion corresponding to higher schema precision). First, to directly test Bayesian reconstruction model predictions, we examined whether schema precision predicted schema bias in spatial recall accuracy (Figure 5 A-B). We found an interaction between congruency condition and schema precision, $\beta = -.56$, $p < .001$ (Experiment 2: $\beta = -.54$, $p < .001$), such that higher schema precision predicted larger schema congruency effects on spatial recall accuracy. That is, according to the typical metric of schema bias used in prior work (differences in accuracy between congruent and incongruent stimuli; Berens et al., 2020; Greve et al., 2019; Ramey et al., 2022; Tomparry &

Thompson-Schill, 2021), schema bias of memory was higher when schema precision was higher. In fact, the influence of schema precision was so strong that at low levels of schema precision, schema bias (i.e., congruency effect) was eliminated, even beginning to reverse at the extreme end (Figure 5). Overall, this supports the predictions of Bayesian reconstruction models.

Further examination (Figure 5 C-D) indicated that the effect was driven by higher schema precision predicting better spatial accuracy for congruent scenes, $\beta=.51$, $p<.0001$ (Experiment 2: $\beta=.53$, $p<.0001$), with no effect in incongruent scenes, $\beta=-.04$, $p=.77$ (Experiment 2: $\beta=.01$, $p=.92$). This supports the mechanism we proposed, in which schema precision improves accuracy for congruent scenes without influencing accuracy for incongruent scenes. We next decompose these effects by our two proposed stages of reconstruction.

Figure 5

Effects of Schema Precision on Overall Spatial Accuracy



Note. Higher target distance values reflect poorer spatial accuracy. A) Bar plot of target distance by schema precision across all scenes in Experiment 1, to illustrate the schema bias effect as it is typically illustrated in prior work (performance difference between congruent and incongruent stimuli). Dichotomization of schema precision (by least-squares) is used only for illustration. B) Bar plot of target distance by schema precision across all scenes in Experiment 2. C) Scatterplot of target distance by schema *imprecision* across all scenes in Experiment 1, to decompose the schema bias effects. Schema imprecision, rather than precision, is plotted to directly reflect the raw measure used. D) Scatterplot of target distance by schema imprecision across all scenes in Experiment 2. Note that the schema imprecision score for a given scene is the same between studies.

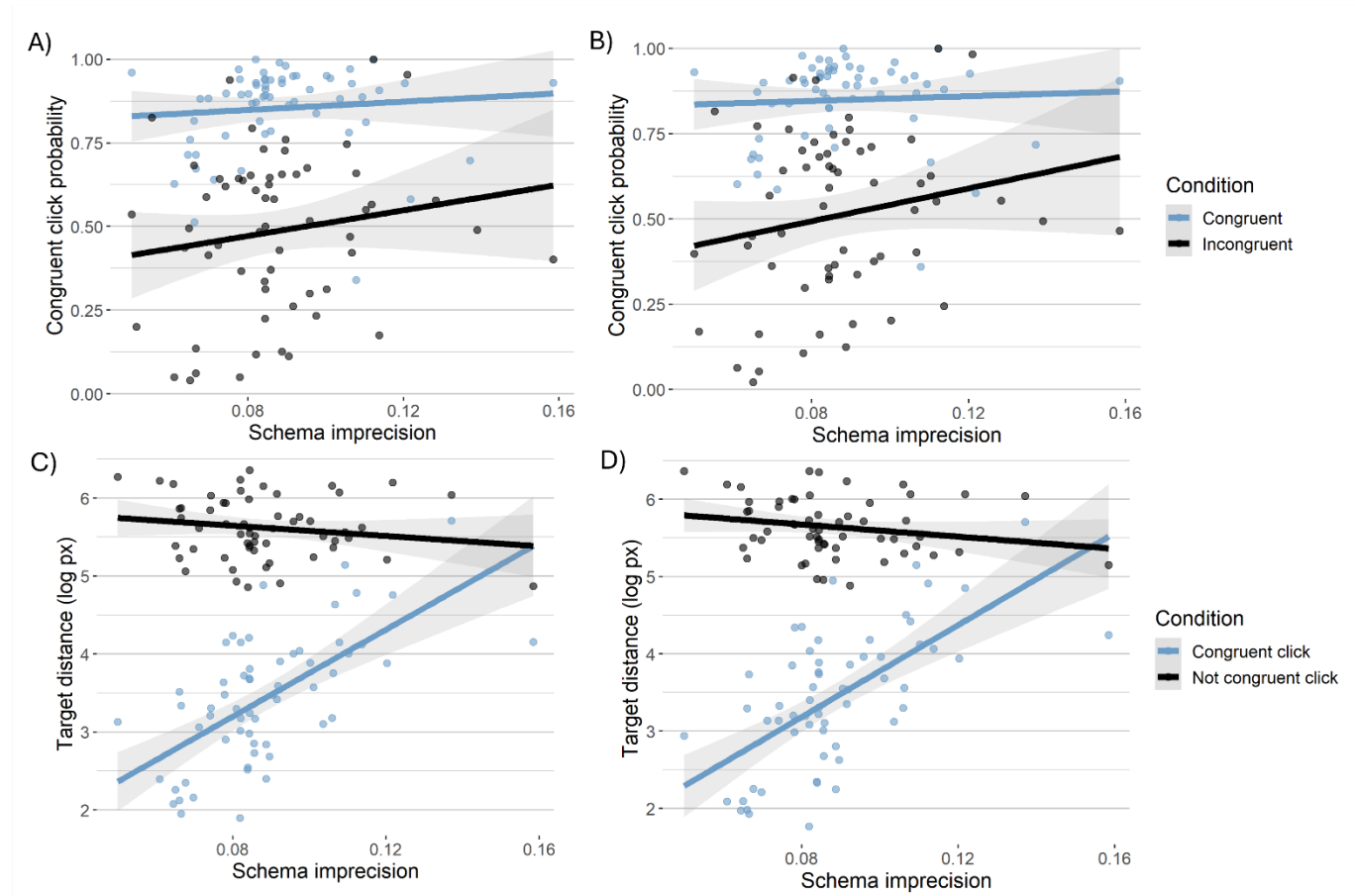
To examine the first proposed stage, in which one decides whether to use a schema, we assessed the probability of making a schema-based response (Figures 4C-D and 6). We hypothesized that underlying memory, but not schema precision, would determine whether schemas were used to guide responding. To test this, we first examined how the likelihood of clicking on a congruent region varied with recognition confidence. (We controlled for spatial accuracy in order to examine schema-based responding more directly, but the pattern of results was unchanged.) As noted earlier, participants were highly likely to click on congruent regions in new scenes. As predicted, underlying memory strength interacted with congruency condition to predict the probability of clicking on congruent regions, $\beta = -.67$, $p < .0001$ (Experiment 2: $\beta = -.65$, $p < .0001$), which was primarily driven by stronger memory decreasing congruent clicks for incongruent scenes (Figure 4 C-D). This same interaction effect was observed when comparing old to new scenes overall irrespective of memory response, $SMD = -1.59$, $p < .0001$ (Experiment 2: $SMD = -1.44$, $p < .0001$), such that previous experience with a scene decreased schema-based responding for incongruent scenes. This indicates that underlying memory strongly modulated the extent to which schemas were used to guide responses.

Next, we examined how schema precision predicted the probability of schema-based responding across all scenes (Figure 6 A-B). There was no significant relationship between schema precision and the probability of clicking on a congruent region, $\beta = .18$, $p = .11$ (Experiment 2: $\beta = .20$, $p = .08$). This suggests that higher schema precision did not increase reliance on schemas; in fact, the relation was numerically in the opposite direction. Thus, although higher underlying memory precision decreased reliance on schemas, higher schema precision did not decrease reliance on memories (i.e., did not increase reliance on schemas).

As for the second proposed stage, in which memory is combined with any schema knowledge that is recruited, we predicted that effects of schema precision on spatial recall would be contingent on the decision to use a schema (which was made in the first stage). We therefore expected that schema precision would influence accuracy for congruent scenes specifically when one chooses to make a schema-based response, simply by providing constraint of the response (Figure 6 C-D). As expected, higher schema precision predicted better spatial accuracy in congruent scenes when participants clicked on a congruent region, $\beta=.64, p<.0001$ (Experiment 2: $\beta=.64, p<.0001$), but not when they did not click on a congruent region, $\beta=-.16, p=.23$ (Experiment 2: $\beta=-.20, p=.13$), and the interaction was significant, $\beta=.46, p<.0001$ (Experiment 2: $\beta=.49, p<.0001$). In combination with the results above, this suggests that the influence of schema precision on spatial recall accuracy and schema bias is simply a result of more precise schemas being more effective in guiding schema-based responses (for congruent scenes). That is, schema precision acts via its capacity to fine-tune schema-based responses, rather than influencing reliance on schemas or memory.

Figure 6

Effects of Schema Precision on Probability and Accuracy of Schema-based Responses



Note. Schema imprecision, rather than precision, is plotted to directly reflect the raw measure and analysis. Schema imprecision did not decrease the probability of clicking on congruent regions; in fact, it nonsignificantly increased the probability. As predicted, schema imprecision exerted its effects on overall spatial accuracy by determining how effective schemas could be in fine-tuning schema-based responses within congruent scenes. A) Effect of schema imprecision on congruent click probability in Experiment 1. B) Effect of schema imprecision on congruent click probability in Experiment 2. C) Within congruent scenes, the effect of schema imprecision on target distance for schema-based responses (congruent clicks) versus non-schema-based responses in Experiment 1. D) Within congruent scenes, the effect of schema imprecision on target distance for schema-based responses versus non-schema-based responses in Experiment 2.

One potential consideration is that schema precision may have influenced memory encoding; for example, more precise schemas could have produced stronger or weaker underlying memory. To determine whether our results could be driven by encoding effects, we

re-ran the schema precision analyses with a covariate of scene recognition response. That is, we re-examined all schema precision effects such that they were conditionalized on the strength and type of underlying memory for the overall episode that had already resulted from encoding.

Schema precision continued to predict larger schema congruency effects on overall spatial accuracy, $\beta = -.48$, $p < .001$ (Experiment 2: $\beta = -.44$, $p < .001$). Schema precision again did not predict the probability of clicking on a congruent region, $\beta = .10$, $p = .23$ (Experiment 2: $\beta = .08$, $p = .41$).

When participants made a schema-based response in congruent scenes, higher schema precision predicted higher accuracy, $\beta = .61$, $p < .0001$ (Experiment 2: $\beta = .59$, $p < .0001$). This further indicates that the effects we identified were likely retrieval processes (as is assumed under the Bayesian reconstruction framework) rather than encoding processes, but this certainly does not preclude the possibility of separate encoding effects that are beyond the scope of the present studies.⁵ We also conduct a more direct test for encoding effects in Experiment 5.

Experiments 1 and 2 Discussion

Experiments 1 and 2 comprise the first direct test, to our knowledge, of the Bayesian reconstruction model prediction that higher schema precision should increase schema bias of memory responses. In line with this prediction, we found that as schema precision increased, the size of congruency effects on spatial recall accuracy (i.e., schema bias) increased. In terms of the mechanisms giving rise to this effect, we found support for our novel algorithmic proposal in that we observed dissociable effects of schema precision on the probability of using a schema versus

⁵ Note that we also mitigated congruency effects on encoding, including attention, via our experimental design: all participants study the (circled) target object and scene after search (Figure 2). Regardless, however, note that known influences of congruency on encoding--in which incongruent scenes produce stronger recognition and more detailed memory when corrected for reconstruction bias (Lampinen et al., 2001; Rojahn & Pettigrew, 1992)--would only weaken our effects, not cause them, given that our data clearly show better performance for congruent than incongruent scenes due to reconstruction bias.

the effects of schemas when they are used. That is, schema precision did not influence the decision of whether or not to use a schema, and did not influence accuracy in incongruent scenes. Schema precision influenced accuracy only in congruent scenes: For schema-based responses in congruent scenes, higher schema precision predicted higher accuracy. Underlying memory was the key determinant of whether a schema was used in responding. Together, these results support our algorithmic-level extension to Bayesian reconstruction models, such that underlying memory is used to determine reliance on schemas in responses, and schema precision helps constrain responses when a schema is used. Importantly, this indicates that the Bayesian-like pattern of spatial recall responses we identified is not driven by prioritization of schemas over underlying memory, such that changes in schema precision do not influence the likelihood of relying on available memories. Rather, our results suggest that schemas serve as a default fallback to fill in gaps in episodic memories.

Although every effect (or lack thereof) replicated between Experiments 1 and 2, we sought to further verify the robustness of these effects, in particular whether individual differences in schemas might change the results. In Experiments 1 and 2, we used scene-level schemas that were determined via aggregated responses from a separate group of raters. However, given that schemas are built from statistical learning over a lifetime of experiences, there are likely to be individual differences in scene schemas resulting from unique experiences (e.g., cultural differences). To address this, we conducted a third experiment in which every participant's own schema precision was measured individually for every scene. We expected to replicate the effects we found, but perhaps with weaker effects given that individual schema precision scores would be subject to more noise than the aggregated scene-level schema precision scores.

Experiment 3

Experiment 3 Method

The method was largely the same as Experiments 1 and 2, with the exception that the experiment was conducted in person, with fewer participants but more scenes.

Participants

A power analysis of the effect of schema precision on spatial accuracy in congruent scenes in Experiment 1, $\beta = .30$, indicated that 92 participants were needed to achieve 90% power in a one-tailed test. However, Experiment 3 increased the number of trials by 50%, and the study was completed in-person rather than online, so reliability (and therefore effective power) was likely higher. A total of 92 local undergraduate participants (mean age = 19.08 years, age range 18-25 years; 58 female, 31 male, 3 non-binary) successfully completed the experiment for course credit. None of these participants participated in the other experiments. Participant data were eliminated from analysis for failing attention checks throughout the experiment or clicking on the objects during the study phase less than 90% of the time. After these exclusions, the final sample consisted of 85 participants.

Apparatus

The experiment was conducted in person. Stimuli were displayed on a monitor 58 cm from the participants' eyes, at a resolution of 1920x1080 px. Participants' eyes were tracked during the memory task to address an unrelated question. Both the memory task and schema precision rating task were programmed in Python.

Stimuli

Stimuli were created in the same way as in Experiments 1 and 2. The only difference is that they were presented at 1440x1080 px rather than 800x600 px. Given that these participants participated in person, we were able to extend the study length, and so we used 120 unique scenes instead of 80 scenes. Of these 120 scenes, 90 were old, and 30 were new. Each scene category was equally represented (24 scenes per category, which refers to bedroom, bathroom, etc.). Full randomization of scenes to conditions was used (including congruency condition in new scenes), rather than counterbalances.

Procedure

The memory task was the same as that used in Experiments 1 and 2. The key difference in Experiment 3 is that all participants completed the schema precision rating task for all scenes after the memory task concluded. That is, they completed the memory task in its entirety, then saw the scenes again for the schema rating task. Specifically, for each scene, participants were asked to click on (i.e., place circles on) 10 locations they would expect to find the object in the real world, just as in the first block of the schema precision rating task in Experiments 1 and 2. Participants were again instructed that they could place the circles on top of each other to convey that the expected object locations were less than the total area that could be covered by the circles. The size of the circles was scaled to the scene size to be the same relative size as those used in Experiments 1 and 2.

Data Aggregation and Analysis

Measures were computed in the same way as for Experiments 1 and 2. The statistical modeling approach was modified to account for the fact that schema precision for each scene now varied by participant. Therefore, statistical analyses were again conducted using multilevel

modeling, but with the trial-level data. To do this, we included random intercepts and slopes of the effects by subject for all analyses. Note that random effects of stimulus were not used in analyses examining schema precision, because doing so at the trial level would partial out most scene-level schema precision variance such that the schema precision fixed effect would be considerably less interpretable. (However, the conclusions were supported when stimulus random effects were included; see Supplementary Materials.) All effect sizes reported followed the same conventions as those used in Experiments 1 and 2. Trials in which participants did not provide a recall response in time were excluded from analysis (1.3% of congruent trials, 1.1% of incongruent trials).

Experiment 3 Results

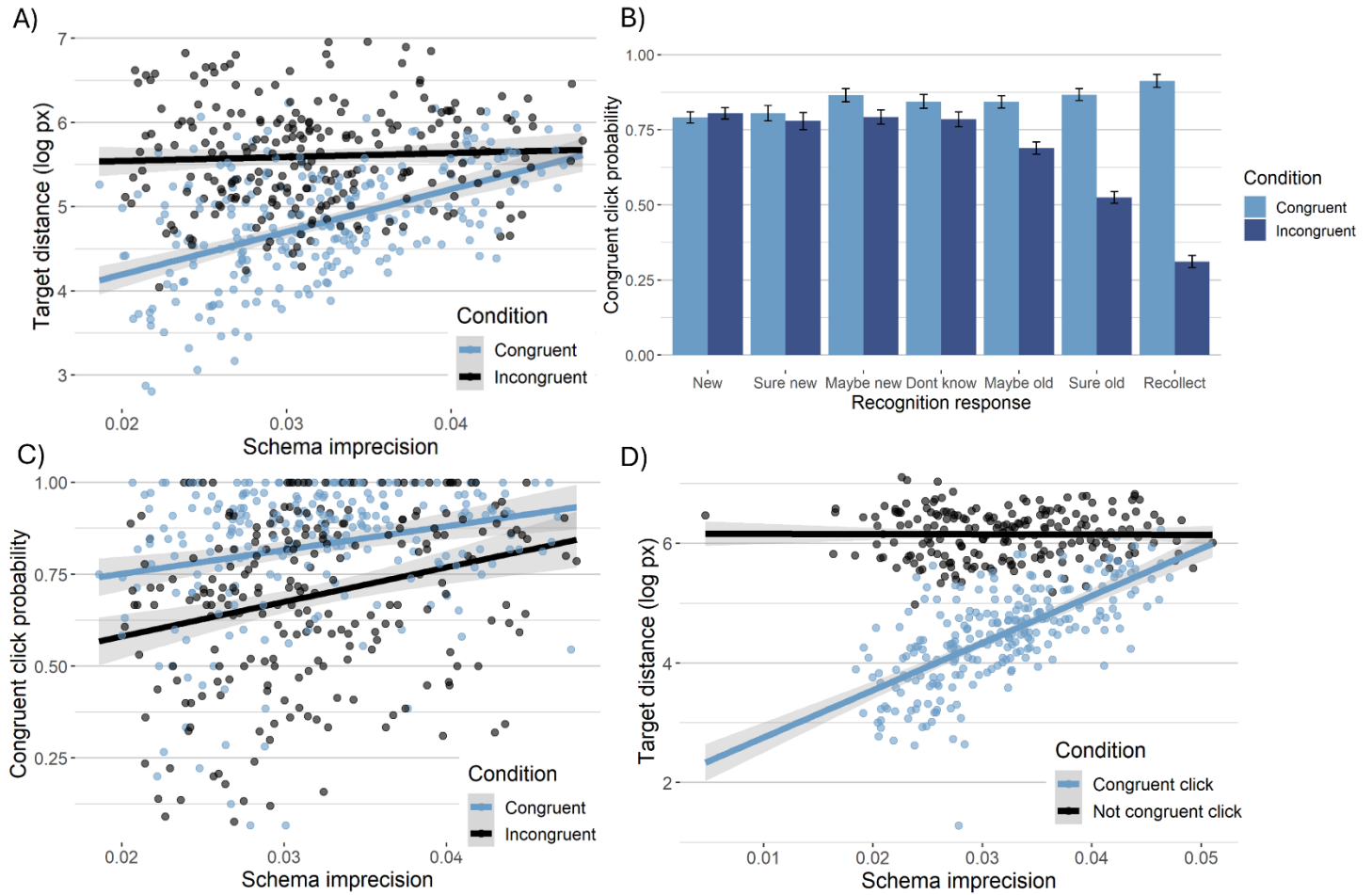
To foreshadow the results, the analyses from Experiments 1 and 2 were repeated, and all conclusions from Experiments 1 and 2 were supported in Experiment 3.

There was again strong evidence that congruency effects in this task were driven by schema bias of memory responding during retrieval and/or reconstruction: in new scenes, participants clicked on congruent regions 78% of the time, and spatial accuracy was higher for congruent than incongruent new scenes, $SMD=.92$, $p<.0001$. With both old and new scenes included, we again found that spatial accuracy was higher for congruent scenes, $SMD=.60$, $p<.0001$. Spatial recall accuracy improved with stronger underlying memory for the episode overall (recognition confidence) in old scenes, $\beta = -.27$, $p<.0001$. We also replicated the interaction between recognition confidence and congruency, in which an increase in underlying memory confidence predicted a decrease in congruency effects on spatial accuracy, $\beta = -.24$, $p<.0001$.

In terms of schema precision, there was a significant interaction between congruency and schema precision, $\beta = -.25$, $p < .0001$ (Figure 7A), such that higher schema precision predicted increased schema bias of spatial recall accuracy. This again occurred via schema precision predicting accuracy in congruent scenes, $\beta = .28$, $p < .001$, but not incongruent scenes, $\beta = .01$, $p = .51$.

We next examined the probability of making a schema-based response. Underlying memory strength interacted with congruency condition to predict the probability of clicking on a congruent region, $B = -1.04$, $p < .0001$ (Figure 7B). In contrast, higher schema precision again did not increase the probability of clicking on a congruent region; in fact, higher schema precision predicted a lower chance of clicking on a congruent region, $B = .19$, $p < .0001$ (Figure 7C). (Note that this effect was null, as in Experiments 1 and 2, when random effects of stimulus were included, $p = .92$; see Supplementary Materials.) Echoing the conclusions of Experiments 1 and 2, this demonstrates that underlying memory strongly influenced reliance on schemas in recall, whereas higher schema precision did not increase reliance on schemas.

Lastly, we examined the effects of schema precision on performance in congruent scenes, contingent on one choosing to make a schema-based response (Figure 7D). We again found that schema precision significantly predicted spatial accuracy when a congruent region was clicked, $\beta = .43$, $p < .0001$, but not when a congruent region was not clicked, $\beta = .02$, $p = .61$ (interaction by congruent click: $\beta = .37$, $p < .0001$). This indicates that schema precision primarily exerts its effects on spatial accuracy via a fine-tuning of responses once one has decided to use schema information in their response.

Figure 7*Experiment 3 Results*

Note. A) Effect of schema imprecision on spatial accuracy. B) Effect of recognition response on the likelihood of making a schema-based response. C) Effect of schema imprecision on the likelihood of making a schema-based response. D) Within congruent scenes, the effect of schema imprecision on spatial accuracy for schema-based responses (congruent click) and non-schema based responses. For visualization purposes only, the points for all scatterplots in this figure reflect scene averages to allow for more direct comparison with the figures from Experiments 1-2. Analyses were conducted on trial-level data.

Experiment 3 Discussion

Experiment 3 replicated the findings from Experiments 1 and 2: Higher schema precision predicted increased schema bias of recall accuracy, but did so through fine-tuning of schema-based responses rather than increasing reliance on schema information. This indicates that the effects of schema precision do not fundamentally differ when schema precision is assessed at an aggregated scene level across many individuals versus when each individual's own schema precision is assessed. This is likely because scene schemas tend to be quite stable across different individuals (e.g., Torralba et al., 2006). However, in cases where schemas are expected to vary more widely (e.g., samples consisting of participants from a variety of countries; other types of schemas that are subject to more individual differences), assessing each individual's schemas is likely best practice.

A remaining open question is whether the effects we identified were driven by a true integration of schemas with memory traces, as assumed by Bayesian reconstruction models, or whether they resulted from a simple guessing strategy when memory was absent. It is not debated that schemas are used to support guessing when memory is missing (e.g., Bayen et al., 2000). For example, if a participant fails to retrieve memory for where the object was, it is rational to make a schema-based guess and click on a congruent region. The Bayesian reconstruction proposal is that schemas are not *only* leveraged for making informed guesses when memory is missing, but are also leveraged when some episodic memory is available and successfully retrieved. It is possible that the results we observed could be driven simply by guessing trials, rather than a true Bayesian reconstruction effect of schemas being integrated with memory. To examine this possibility, and further probe the mechanisms underlying the schema precision effects we identified, we ran a fourth experiment examining target recall confidence.

Experiment 4

The main aim of Experiment 4 was to determine whether participants used schemas solely when they were guessing in the absence of memory. To directly assess when participants were guessing, we collected participants' confidence in their spatial recall judgment (i.e., *target confidence*). If schemas only influence recall responses when participants are guessing (i.e., when they cannot retrieve any memory relevant to the object location), then congruency effects and schema precision effects should only arise at the lowest levels of target confidence. In contrast, if schemas influence recall responses even when some memory is available, then congruency effects and schema precision effects should arise across all but the highest levels of target confidence. (As outlined earlier, when memory is precise, we expect that there will be little to no schema effects; Figure 4A-B.) To foreshadow, the results make clear that the effects are not simply due to guessing, and they provide new insights into how schema precision influences performance at different levels of recall confidence.

Experiment 4 Method

The apparatus, stimuli, and procedure were identical to Experiments 1 and 2, but with the addition of a target confidence probe. The same schema precision scene rating data from Experiments 1 and 2 were used in the present analyses.

Participants

The power analysis from Experiment 3 was used to determine sample size ($N=92$ for 90% power), and a total of 124 local undergraduate participants (mean age = 19.22 years, age range 18-47 years; 93 female, 29 male, 2 non-binary) completed the study and successfully passed all pre-experimental attention checks to ensure they understood the instructions. None of these participants participated in the other experiments. Participant data ($n=23$) were eliminated from

analysis for failing attention checks throughout the experiment, or clicking on the objects during the study phase less than 90% of the time. After these exclusions, the final sample consisted of 101 participants.

Procedure

The memory task was largely the same as that used in Experiments 1 and 2. The only difference in Experiment 4 is that a target confidence probe was added after the two memory judgments in the original task. Specifically, for each test phase trial, participants first gave their spatial recall response and then their scene recognition response, as in Experiments 1 and 2. After the scene recognition response, participants also gave an additional target location confidence response. The probe asked “How confident are you that the location you clicked is where the object was located earlier?”, and included a 1-5 scale ranging from “completely uncertain” to “completely certain.” Participants were given as much time as needed to respond. The target confidence probe screen had a blue background to more clearly distinguish it from the scene recognition probe, which had a grey background.

Data Aggregation and Analysis

Data aggregation and analyses were identical to Experiments 1 and 2, except for the use of the additional variable of target location confidence. Analyses focused on old scenes. Trials in which participants did not provide a recall response in time were excluded from analysis (2% of congruent trials, 1.8% of incongruent trials).

Experiment 4 Results

Participants distributed their responses across the target confidence scale, indicating that the scale was sensitive to continuous variations in target placement confidence (Figure 8a).

Higher target confidence predicted higher spatial recall accuracy (i.e., lower target distance) as expected, $\beta = -.50$, $p < .0001$ (Figure 8b). Schema bias--that is, better spatial recall accuracy for congruent than incongruent scenes--was present in every target confidence response, $SMDs \geq .64$, $ps \leq .0003$ (Table 1), except the most confident response (5), $SMD = .09$, $p = .61$, as expected (Figure 8b). The presence of schema bias in moderate- and high-confidence recall responses indicates that schema bias of recall was not simply driven by guessing trials. Consistent with Bayesian reconstruction models, increases in target confidence predicted decreases in the congruency effect on spatial recall accuracy, $\beta = -.30$, $p < .0001$. Target confidence also interacted with congruency condition to predict the likelihood of clicking on a congruent region, $\beta = -.66$, $p < .0001$. Thus, higher subjective recall precision predicted less schema bias of recall responses, converging with our findings with respect to scene recognition confidence.

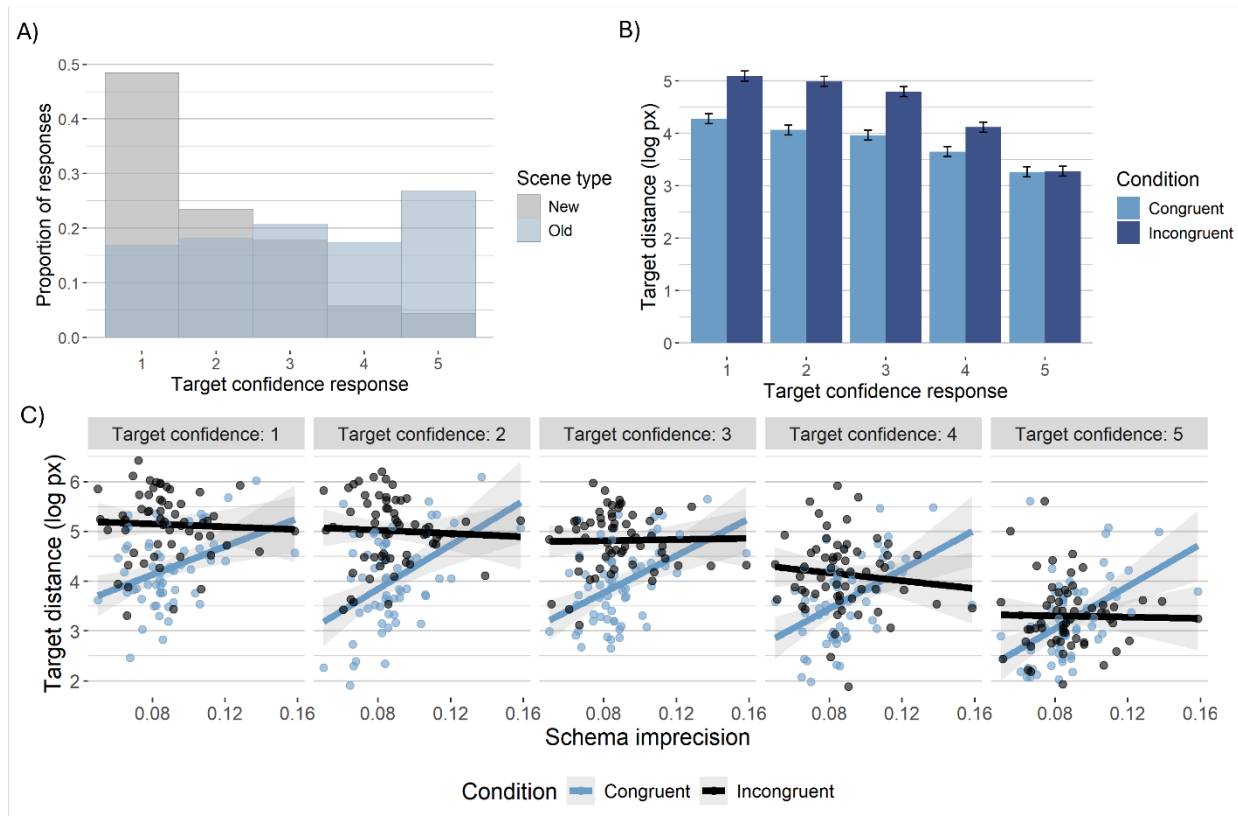
The key schema precision effect from Experiments 1-3--higher schema precision predicting better spatial recall accuracy for congruent scenes--was present in every target confidence response, $\beta s \geq .37$, $ps \leq .004$ (Figure 8c; Table 1). The interaction of schema precision by congruency condition on spatial recall accuracy was also significant in all target confidence responses, $SMDs \leq -.37$, $ps < .02$ (Table 1). This further demonstrates that the schema precision effects were not driven by guessing trials. Interestingly, the presence of a robust schema precision effect at the highest target confidence level (5) suggests that participants may have often confidently remembered that the object was on a congruent surface, and thus higher schema precision helped fine-tune those responses. This is well explained by previous findings that participants may recollect the congruency status of stimuli and integrate that with schemas to guide responses (Ramey et al., 2022, 2025), which fits with our framework.

Table 1*Experiment 4 Results for Each Level of Target Confidence*

Model	Target confidence	Effect size	<i>p</i> value
Spatial recall accuracy ~ congruency condition	1	1.06	<.0001
Spatial recall accuracy ~ congruency condition	2	1.02	<.0001
Spatial recall accuracy ~ congruency condition	3	1.09	<.0001
Spatial recall accuracy ~ congruency condition	4	0.64	0.0003
Spatial recall accuracy ~ congruency condition	5	0.09	0.61
Spatial recall accuracy ~ schema precision (for congruent scenes)	1	0.37	0.004
Spatial recall accuracy ~ schema precision (for congruent scenes)	2	0.46	0.0002
Spatial recall accuracy ~ schema precision (for congruent scenes)	3	0.46	0.0002
Spatial recall accuracy ~ schema precision (for congruent scenes)	4	0.47	0.0002
Spatial recall accuracy ~ schema precision (for congruent scenes)	5	0.49	<.0001
Spatial recall accuracy ~ schema precision × congruency condition	1	-0.37	0.018
Spatial recall accuracy ~ schema precision × congruency condition	2	-0.48	0.001
Spatial recall accuracy ~ schema precision × congruency condition	3	-0.43	0.004
Spatial recall accuracy ~ schema precision × congruency condition	4	-0.57	0.0009
Spatial recall accuracy ~ schema precision × congruency condition	5	-0.57	0.001

Note. Effect size is β for continuous predictors, and *SMD* for categorical predictors.

Figure 8*Experiment 4 Results*



Note. A) Scaled histogram of target confidence responses for old and new scenes. B) Target distance (higher values = lower spatial recall accuracy) by target confidence response for each congruency condition. The estimated marginal means derived from a linear mixed effects model with random effects of scene are plotted, and the error bars represent the standard error of these estimated means from the model. The reduction in congruency effects across target confidence responses is a distinct prediction of Bayesian reconstruction models. C) Target distance by schema imprecision for each level of target confidence.

Experiment 4 Discussion

Experiment 4 demonstrated that schema bias of spatial recall was present, and schema precision affected spatial recall, even when participants' recall responses were not guesses. This precludes the possibility that our findings are simply driven by trials in which participants were guessing in the absence of memory. Rather, these findings suggest that underlying memory and schemas were likely integrated to guide responses. These findings also provide additional converging evidence for the Bayesian reconstruction model prediction that higher underlying

memory precision reduces schema bias of memory decisions (Figure 8B), by more directly assessing subjective underlying memory precision for the target locations.

Separately from guessing, there is another possible dynamic that could undermine a straightforward interpretation of the present results: schema effects on encoding. Based on the Experiments 1-3 analysis of new scenes, as well as the analyses controlling for the type and strength of memory that already resulted from encoding (and any rapid consolidation) processes, we concluded that the schema bias effects we observed were most likely a result of reconstruction processes. That is, they are a strategy effect occurring during test, in which schemas are leveraged to inform responding. There is prior work that supports this interpretation by demonstrating that congruency advantages for memory performance result from retrieval and/or reconstruction processes rather than processes occurring prior to retrieval (Bayen et al., 2000; Dijksterhuis & Van Knippenberg, 1995; Dodson et al., 2008; Greve et al., 2019). However, given theories that schemas influence memory encoding and consolidation (van Kesteren et al., 2012) and distort memory traces themselves (Alba & Hasher, 1983), we sought to provide a more direct test of whether the dynamics we observed were driven by reconstruction processes, which is a foundational assumption of Bayesian reconstruction models.

Experiment 5

To assess converging evidence that the schema effects we observed occurred during test, we changed the test task. Specifically, in Experiment 5, we ran the same task as Experiments 1-2 but changed the test format so that schemas were less effective in constraining responses. Instead of a free response in which participants could click anywhere on the scene, participants completed a four-alternative forced-choice (4AFC) task in which they chose which of four locations had contained the target during the study phase. The four alternatives always contained

two congruent options and two incongruent options. The distance between the congruent options was equated with the distance between incongruent options, and both options for a given congruency condition were located on the same object (e.g., the toilet; Figure 9a). Given that the four provided alternatives already provided strong constraints on response options, schemas were rendered less useful for constraining responses during retrieval.

If non-reconstruction processes were the cause of the effects we observed in the prior experiments--for example, if more precise schemas improved encoding of congruent information--then schema precision and schema bias effects in Experiment 5 should be similar to the prior experiments. That is, performance for the congruent condition should be better than the incongruent condition, especially when schema precision is higher. In contrast, if the effects in the previous experiments were due to strategy effects of schemas on responding (i.e., reconstruction processes), schema bias and schema precision effects should be reduced or eliminated in Experiment 5.

Experiment 5 Method

Participants

Based on the same power analysis as Experiments 3 and 4 ($n=92$ for 90% power), a total of 112 local undergraduate participants (mean age = 19.77 years, age range 18-36 years; 88 female, 22 male, 2 non-binary) completed the study and successfully passed all pre-experimental attention checks to ensure they understood the instructions. None of these participants participated in the other experiments. Participant data ($n=22$) were eliminated from analysis for failing attention checks throughout the experiment, clicking on the objects during the study phase

less than 90% of the time, or having at- or below-chance accuracy in terms of forced-choice accuracy. After these exclusions, the final sample consisted of 90 participants.

Materials

A subset of 80 scenes from Experiment 3 was used. Specifically, 80 scenes were selected that allowed the foil target objects for each condition to be placed on the same object type and equally far apart in each condition. The studied target locations were unchanged from Experiment 3. The schema precision scores that participants provided in Experiment 3 were averaged for each scene, and were used as the scene schema precision scores in the present analyses.

Procedure

The experiment was identical to Experiments 1 and 2 except for two differences. First, the test phase no longer included a continuous spatial recall judgment. Instead, participants were shown the background scene, then after 2s, the numbers 1-4 appeared on the scene (Figure 9a). The 2s delay was included to give participants an opportunity to view the scene and retrieve memory without interference from the numbers. Two of the numbers were always in an incongruent location, and the other two were always in a congruent location. One of the numbers corresponded to the true studied target location (for old scenes). The numbers were assigned to the locations from left to right, such that the leftmost location in a scene was always 1, and the rightmost location was always 4 (see Figure 9a). Participants were given 10s to use the numbers on their keyboard to select which location they thought the target had been in during the study phase. After they selected a location, they provided a recognition confidence judgment for the scene itself as in the prior experiments. The second change was that the experiment consisted of

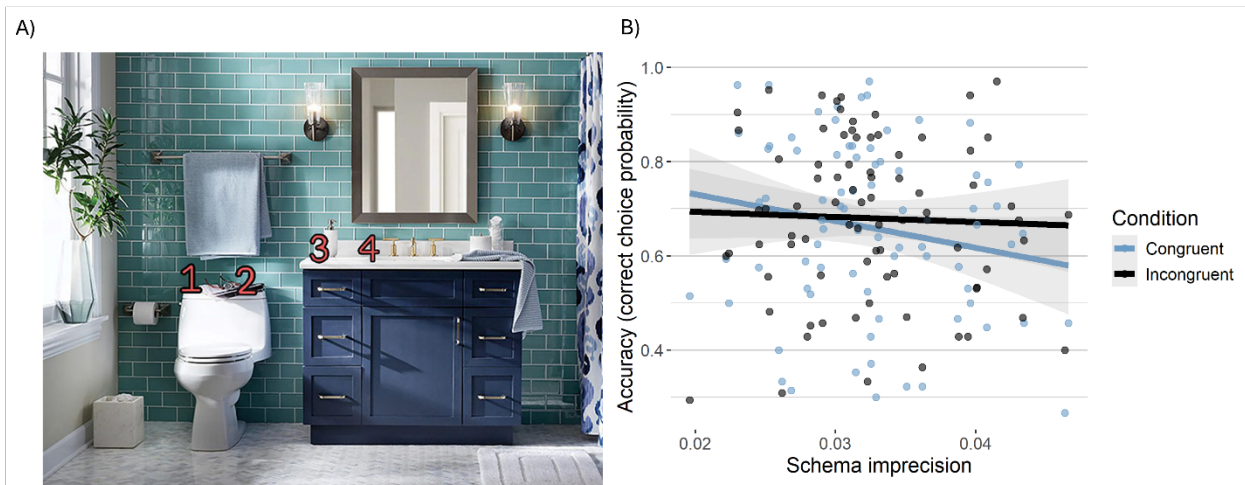
two study-test blocks to better equate difficulty with the prior tasks, because the 4AFC judgments were expected to be more difficult (e.g., having to judge between very similar alternatives).

Data Aggregation and Analysis

Data aggregation and analyses were identical to Experiments 1 and 2, except the key outcomes were no longer target distance or congruent click probability. Instead, we examined the likelihood of selecting the correct location, as well as the likelihood of selecting either of the two congruent locations from among the four options. Analyses focused on old scenes. Trials in which participants did not provide a recall response in time were excluded from analysis (0.4% of congruent trials, 0.2% of incongruent trials).

Figure 9

Experiment 5 Methods and Results



Note. A) A sample 4AFC test stimulus. The studied target locations for this scene were 1 (for incongruent condition) and 4 (for congruent condition). Location 2 was the foil for incongruent scenes, and location 3 was the foil for congruent scenes. All participants saw all four options at test; that is, whenever participants saw this bathroom scene at test, these four options were always the same regardless of the scene's congruency condition. Congruency condition simply determined which option was correct (i.e., which version of the original scene they had encoded). B) Accuracy, in terms of the probability of selecting the correct location, by schema imprecision and congruency condition.

Experiment 5 Results

Participants were well above chance (.25) in selecting the correct target location in a one-sample t-test, $M=.67$, $t(79)=25.28$, $p<.0001$. This was the case for both congruent scenes, $M=.66$, $t(79)=20.1$, $p<.0001$, and incongruent scenes, $M=.68$, $t(79)=22.6$, $p<.0001$. As hypothesized, the new test format reduced schema bias. Accuracy was no longer higher for congruent than incongruent scenes; in fact, accuracy was numerically higher for incongruent scenes, $SMD=.11$, $p=.34$ (Figure 9b). This elimination of schema bias with a change in test format implies that the schema bias effects observed in Experiments 1-4 were most likely driven by processes occurring during test (i.e., reconstruction).

Moreover, as expected, schema precision no longer had significant effects on accuracy in congruent scenes, $\beta=-.19$, $p=.10$, nor incongruent scenes, $\beta=-.04$, $p=.74$ (Figure 9b). Schema precision also did not influence the probability of choosing a congruent location, $\beta=-.05$, $p=.68$. There were still robust, expected effects of recognition response, with higher recognition responses predicting higher accuracy, $\beta=.50$, $p<.0001$, and an interaction such that higher recognition responses increased the likelihood of congruent choices for congruent scenes but decreased the likelihood of congruent choices for incongruent scenes, $\beta=-.67$, $p<.0001$.

Experiment 5 Discussion

In Experiment 5, we probed the same type of memory as Experiments 1-4--spatial recall for the target object locations--but changed the test format so that schemas were rendered less useful in constraining responses during test. As a result, schema precision no longer significantly influenced spatial recall performance. Instead, underlying memory was the only significant determinant of performance. In fact, the influence of congruency condition on accuracy was

eliminated and even numerically reversed such that accuracy was numerically higher for incongruent scenes.

A limitation of this manipulation is that it may not have *selectively* influenced the utility of schemas in constraining responses. The difficulty of the task may have increased given the fine-grained discriminations required. Although we used two study-test blocks to mitigate this potentially increased difficulty, doing so may have influenced performance in other ways. Additionally, even though the change in test format could not *influence* encoding processes, it is possible that the change in test format could have obscured encoding processes such that they were unable to be detected. However, the robust replication of the recognition confidence findings does indicate adequate power to detect the effects of interest, especially given that the schema bias effects in the prior experiments were larger than the recognition confidence effects.

The goal of Experiment 5 was to provide a converging test for reconstruction processes in our task, to complement the other evidence. Specifically, prior studies have demonstrated that schema bias results from processes occurring after encoding and consolidation (Bayen et al., 2000; Dijksterhuis & Van Knippenberg, 1995; Dodson et al., 2008; Greve et al., 2019), and our analyses of new scenes and controls for encoding/consolidation effects in Experiments 1-2 provide converging evidence that the present effects most likely occurred during reconstruction. Thus, although it may not be definitive on its own, the reduction in schema bias in Experiment 5 provides additional evidence for this. However, the nonsignificant trend towards better accuracy with higher schema precision in Experiment 5 does suggest that there could be subtle non-reconstruction-related effects of schema precision on memory (in addition to reconstruction effects), which is an interesting new possibility to explore in future studies. In sum, these results

converge to suggest that the present effects of interest, namely schema bias and schema precision effects, were primarily driven by effects occurring during retrieval and reconstruction.

General Discussion

In the present studies, we tested and extended Bayesian reconstruction models of memory (Hemmer & Steyvers, 2009; Huttenlocher et al., 1991; Xu et al., 2024), which propose that schemas bias memory because schemas are rationally integrated with memory traces at retrieval to guide responding. These models have been challenged because their unique predictions have not been empirically verified, and the cognitive mechanisms that could give rise to Bayesian reconstruction dynamics have not been specified (Bowers & Davis, 2012; Jones & Love, 2011). To address this debate, we tested a key prediction of these models that has not, to our knowledge, been tested previously: that higher schema precision increases schema bias of memory responses. We also proposed and tested a novel framework for the cognitive mechanisms that give rise to Bayesian-like recall patterns, which provides an algorithmic-level extension to Bayesian reconstruction models. Across five experiments, participants searched for congruently and incongruently located target objects in scenes. In a later retrieval phase, participants were shown the background scenes only and provided spatial recall responses for the target object locations (indexing a memory decision that could be influenced by both underlying memory and schemas at retrieval) as well as scene recognition responses (indexing underlying memory for the episode overall). In a separate rating task, a different group of participants (Experiments 1, 2, 4, and 5) or the same group of participants (Experiment 3) provided the precision of their schema for each scene by clicking on the potential congruent regions for each target object. In short, the results indicated that 1) schema precision is a critical determinant of schema bias of memory: schema bias was high when schema precision was high, but absent when schema precision was

low, 2) Bayesian reconstruction models correctly predicted the influence of schema precision and memory confidence on recall accuracy response patterns, with schema precision increasing schema bias and memory confidence decreasing schema bias, and 3) the underlying cognitive mechanisms that give rise to this Bayesian-like response pattern appear to be a simple heuristic in which schema *reliance* is determined by underlying memory precision rather than schema precision. These results indicate that schema precision does not influence whether schema information is used; rather, schema precision determines how effective schemas can be when they are used.

The dynamics underlying schema bias in this task were consistent with what is assumed by Bayesian reconstruction models. Recall responses were heavily schema biased in all experiments in which schemas could strategically be leveraged to constrain responding during test (Experiments 1-4): Participants clicked on congruent regions well above chance in new and old scenes, and spatial recall accuracy was substantially higher for congruent than incongruent scenes. The fact that schema bias was strongest in new scenes, and changing the test format in Experiment 5, suggested that the schema bias observed in this task was likely driven by direct influences of schemas on memory responding during retrieval (i.e., reconstruction). Experiment 4 further suggested that schema bias was driven by integration of schemas with episodic memory, rather than being driven solely by schema-based guessing when memory failed.

As predicted by Bayesian reconstruction models, we found that higher schema precision increased schema bias of memory decisions, such that the spatial recall advantage for congruent over incongruent scenes was larger when schemas were more precise. The cognitive mechanisms underlying this effect, however, were not consistent with a Bayesian computation: Schema precision did not influence the likelihood of using a schema (i.e., the probability of clicking on a

congruent region). Thus, although higher schema precision increased schema bias of responses, it did not do so by increasing reliance on schemas relative to memory. Rather, higher schema precision simply improved accuracy for congruent scenes when participants chose to use a schema, without influencing accuracy for incongruent scenes. Underlying memory, on the other hand, did influence reliance on schemas versus memory, in that scene recognition confidence (Experiments 1-3), and target recall confidence (Experiment 4), interacted with scene congruency to predict schema bias and whether participants clicked on a congruent region. These results support our proposed framework for the cognitive mechanisms that give rise to a Bayesian reconstruction response pattern in recall accuracy: Schemas are used to fill in the gaps in imprecise memories, such that underlying memory is the ultimate determinant of whether and how much schemas are used to guide responding. This indicates that the integration of schemas with memory is more asymmetric than what would result from a Bayesian computation, such that underlying memory traces are prioritized over schemas to guide memory decisions.

In terms of the theoretical advance afforded by the present findings, we not only tested and found support for a novel prediction of Bayesian reconstruction models, but we also proposed, tested, and found support for an algorithmic extension to these models. That is, Bayesian reconstruction models only make claims at the computational level, which characterizes the computational problem being solved by the brain (Griffiths et al., 2015; Marr & Poggio, 1976). The major advance of Bayesian reconstruction models is that they propose that schemas and memory are rationally integrated to guide responses, with schemas serving as a prior and the precision of each source of information playing an important role in determining accuracy (Hemmer & Steyvers, 2009; Huttenlocher et al., 2000; Xu et al., 2024). They do not specify the underlying cognitive operations that solve the computational problem they propose;

that is, they do not make claims at the algorithmic level. There has been extensive debate about the utility of Bayesian models of cognition, and it has been proposed that a potential resolution to these debates is to better test and extend these theories to integrate across levels of analysis (Griffiths et al., 2015; Jones & Love, 2011). The present work does just this, by putting forth an algorithmic framework specifying the cognitive operations that produce the pattern of recall accuracy outcomes described by Bayesian reconstruction models. Our framework follows from Bayesian reconstruction models in that we assume the same computational problem structure, and we also assume that the processes involved are rational (given cognitive limitations). The cognitive mechanisms we propose are simple and computationally tractable: schema precision is not actually considered when deciding how much to rely on memories versus schemas. Instead, individuals conduct a metacognitive assessment of memory, and schemas are recruited as needed to fill in missing information or refine imprecise memories. Higher schema precision simply makes schemas more useful, which produces the pattern of schema precision effects on recall accuracy predicted by Bayesian reconstruction models. Our framework overcomes a major challenge to Bayesian reconstruction models, which is that Bayesian operations (i.e., applying Bayesian assumptions to the algorithmic level) are too computationally intensive to serve as an actual cognitive mechanism (Bowers & Davis, 2012). The present findings and novel framework bridge the computational and algorithmic levels, which is important for advancing theory and generating novel predictions (Griffiths et al., 2015; Jones & Love, 2011).

Our framework adds to a growing body of work extending and refining Bayesian reconstruction models. For example, recent extensions have begun to consider incongruent stimuli (Macias & Persaud, 2024; Zuo et al., 2026), as well as within-experiment schemas nested within real-world schemas (Macias & Persaud, 2024). Recent extensions have also been able to

account for findings that the typicality of items within their schema can influence schema bias of memory (Tomparry & Thompson-Schill, 2021; Xu et al., 2024). Our framework represents a different type of extension by characterizing the underlying cognitive mechanisms that can give rise to the Bayesian behavior predicted by these models, and also allows these reconstruction effects to be examined in diverse circumstances in which schemas may be irrelevant or detrimental. Specifically, we propose that the cognitive heuristics for combining schemas with memory during reconstruction proceed via (at least) two stages: 1) an assessment of schema utility (which is in part based on episodic memory availability and precision) is conducted and the decision is made of whether and how much to use schemas in the memory decision, and 2) if a schema is used, schemas are integrated with any available memory traces. The first stage of our framework, in which one decides whether and how much to use schemas, solves at least two issues confronting Bayesian models in the past. First, the first stage can explain prior findings that schemas are often not used, or are even inverted such that congruent locations are avoided, when memory is precise or potentially conflicting with schemas (Ramey et al., 2022; Ramey, 2026). These findings are expected in our framework because underlying memory that conflicts with schemas, or underlying memory that is highly precise, should cause one to opt out of using (or even invert) schemas. Second, the first stage facilitates the application of Bayesian reconstruction dynamics to real-world contexts in which schemas are not always relevant or useful, because it incorporates an assessment of schema utility that precedes any schema usage. Mathematically, our proposal could be built into Bayesian models either via 1) the weighting parameter (w), such that high memory precision can cause the weight of the prior to go to zero in a threshold-like fashion irrespective of prior precision, or 2) using a set of second-order priors that are influenced by underlying memory and determine which schema to use, if any. This latter

approach follows suit with recent Bayesian models of decision-making in the economics literature (Ortoleva, 2012, 2024). Such an extension could perhaps be directly incorporated into the recent Bayesian reconstruction model by Xu et al. (2024), in which individuals reconstruct memory by first inferring and selecting the most relevant schema based on the stimulus category. For example, our findings and prior findings suggest that if participants remember that a stimulus was incongruent, they may select and combine schemas to constrain their response to any physically plausible location that is not congruent (Ramey et al., 2022; Zuo et al., 2026). Our proposal could be directly integrated into the process proposed by Xu et al. by 1) building in a role for episodic memory in the schema selection process, and 2) allowing for the possibility that no schema is selected, even if a relevant schema is available.

In addition to providing a critical test and extension of Bayesian reconstruction models, the present results also have implications for our understanding of schema-memory interactions more broadly. In particular, these results indicate that rational reconstruction processes occurring during retrieval create robust memory performance benefits for congruent information that are not restricted to guessing trials. In fact, Experiment 5 indicated that the congruency advantage in this task could potentially be fully accounted for by reconstruction processes: Reducing the ability to strategically use schemas at retrieval eliminated the congruency advantage (i.e., eliminated schema bias) and in fact numerically reversed it. This adds to prior work finding that congruency advantages for memory performance often result from retrieval/reconstruction processes (e.g., Bayen et al., 2000; Dijksterhuis & Van Knippenberg, 1995; Dodson et al., 2008; Greve et al., 2019). This also makes a strong case against theories that schema bias is driven by irrational distortion of episodic memory traces during encoding and/or maintenance (for review see Alba & Hasher, 1983). Moreover, although it is quite clear that there are also congruency

effects on memory encoding--in particular, it is well established that incongruency improves memory when bias-corrected outcomes are used (Rojahn & Pettigrew, 1992)--these findings indicate that studies need to carefully control for potential reconstruction effects to be able to investigate schema effects on encoding, consolidation, or non-reconstruction-related retrieval effects. This has particularly important implications for tests of the U-shaped curve proposed by the SLIMM theory (van Kesteren et al., 2012), in which memory encoding/consolidation is proposed to be best for congruent and incongruent information relative to schema-neutral information.

The present findings regarding schema precision, on their own, also have important implications for future work. To date, the role of schema precision has been largely overlooked in studies of schema bias. The present effect of schema precision was so strong that schema bias effects were eliminated entirely at low levels of schema precision. Experiment 4 further indicated that schema precision effects on recall occur at all levels of memory confidence, such that they are ubiquitous. Our findings therefore suggest that schema precision is an important consideration for designing experiments, and for attempts to compare results between different experiments, given that schema bias outcomes appear to be dependent on schema precision.

Limitations and Constraints on Generality

There are a number of considerations to be made with respect to generalizing these findings to other tasks. First, we leveraged a common real-world situation in which schema effects can exhibit thresholds (e.g., choosing to search in a congruent location or not); that is, the schemas we used had clear boundaries. This binary metric of schema-based responding allowed us to tease apart the probability of using schemas from the influence of schemas when they are used. However, we expect that the first stage of our two-stage model, in which one determines

schema reliance, should be continuous rather than binary in many situations. In such cases, we expect this process would involve determining the extent of schema reliance, perhaps via weighting. For example, in continuous paradigms such as Tompary and Thompson-Schill (2021), in which participants recalled locations of objects clustered on a blank background, a continuous weighting process is likely involved. In that case, we would propose that participants use schemas most of the time given that most stimuli were schema congruent in their task, and that memory precision is the ultimate determinant of how heavily those schemas are weighted. When participants specifically remember that the target was incongruently located, they would not integrate the schema into their response. We also expect that continuous variations in schema congruence (e.g., some congruent locations are more congruent than others), separately from precision of schemas for congruent items, could affect this process. Our general proposition is that an assessment of schema relevance and expected utility is conducted, and that underlying memory plays an important role in this process whereas schema precision plays a lesser role (if any). Additionally, it is likely that other factors, such as inhibition and attention, also influence this decision (Macias & Persaud, 2024). A second consideration is that the boundary conditions on what exactly schema precision entails are not yet clear. We selected our measure of schema precision by directly deriving it from the mathematics of Bayesian reconstruction models (i.e., how much the schema can constrain congruent responses; Hemmer & Steyvers, 2009; Huttenlocher et al., 1991). Other aspects of schema strength or relevance, such as trial statistics in terms of how many scenes were congruent versus incongruent at study, could have different effects. Relatedly, in rare cases where schemas are so precise that they are deterministic rather than probabilistic (e.g., people cannot fly), underlying memory may not be prioritized over schemas (e.g., if one has a memory of someone flying, one's gravity schema might lead them to

assume the memory was a dream and discount it). A third consideration is that the order of the memory probes, with recall followed by recognition, may have impacted the metacognitive processes involved in making these memory decisions. This possibility is a potentially interesting question for future work. A fourth consideration is that in contexts that do not require explicit episodic memory responses (e.g., navigation; visual search), schemas may often be used instead of episodic memory given that episodic memory retrieval is generally characterized as being a more effortful process.

The possibility of alternative mechanistic accounts of schema bias also warrants consideration. One possibility is that schemas may scaffold memory retrieval, which would primarily improve memory for congruent information (for recent discussion of this dynamic, see Yacoby et al., 2026). In this context, schemas serve as a retrieval cue that facilitates retrieval of episodic memories, and more precise schemas would provide more precise cues. For example, the generate-and-recognize strategy, in which one generates plausible options using a schema (in this example) and reports the options that trigger a sense of recognition, can aid recall (Watkins & Gardiner, 1979). Although this dynamic likely contributes to schema bias in some circumstances, it is unlikely to explain schema bias in the present task. Most notably, schema bias was largest in new scenes, when there was no episodic memory to retrieve, and schema precision effects were similar regardless of memory availability (see Figure 8C). A second possible alternative account relates to prediction. Based on recent findings that congruency-related prediction has unique effects on memory separately from congruency itself (Huang et al., 2025), it is possible that participants may remember the prediction they made during encoding. This could lead to two episodic traces for a given scene: one that represents the true target location, and one that represents the predicted target location based on schema expectations. A

more precise schema would produce a more precise prediction. This could cause schema bias of memory and schema precision effects. However, prior findings that schema bias is similar even when the schema is introduced after encoding (Bayen et al., 2000; Dijksterhuis & Van Knippenberg, 1995; Dodson et al., 2008), along with the fact that the strongest schema bias occurred in new scenes in our task and decreased with stronger memory for the episode, makes it unlikely that this dynamic substantially contributes to the type of schema bias we observed in our task.

A limitation of this set of studies is that the current results cannot definitively establish causality with respect to schema precision, given that we used real-world scenes rather than directly manipulating schema precision for a given stimulus (whereas we did manipulate schema congruency for a given scene). The possibility of reverse causality is mitigated by Experiments 1, 2, 4, and 5, given that a participant's spatial recall response could not have influenced a separate participant's assessment of which regions were congruent in the rating task. However, it is possible that a third factor is responsible for the observed relation between schema precision and spatial recall. Future studies directly manipulating schema precision in a highly controlled fashion would be useful to follow up on the presently identified effects.

In terms of target population, undergraduate students were recruited given that this was an initial investigation of the basic effects of schema precision. Future studies recruiting more diverse populations to examine cultural differences in schemas, as well as age-related changes, would be fruitful for extending these findings.

Conclusion

In sum, our results indicate that schemas bias our episodic memory responses via reconstruction processes, in which schemas are strategically leveraged to try to improve response accuracy. This causes us to report that prior experiences were more typical or average than they actually were. We found that underlying memory traces are prioritized over schemas: When our underlying memories are precise, we reduce or eliminate the use of schemas in our responses. When our schemas are precise, our memory responses appear to be more strongly influenced by schemas--but this is not because of higher reliance on schemas. Rather, this is simply because we fall back on schemas to fill in the gaps in our memories, and more precise schemas provide more helpful constraint of responses.

Acknowledgements

We would like to thank [redacted] for consulting on the custom JavaScript for the schema precision rating task. We would also like to thank the undergraduate research assistants who helped collect data for Experiment 3: [redacted]

AI disclosure

No artificial intelligence tools were used for any aspect of this work.

References

- Alba, J. W., & Hasher, L. (1983). Is memory schematic? *Psychological Bulletin*, 93(2), 203–231.
<https://doi.org/10.1037/0033-2909.93.2.203>
- Bae, G.-Y., Olkkonen, M., Allred, S. R., & Flombaum, J. I. (2015). Why some colors appear more memorable than others: A model combining categories and particulars in color working memory. *Journal of Experimental Psychology: General*, 144(4), 744–763.
<https://doi.org/10.1037/xge0000076>

Bartlett, F. C. (1932). *Remembering: A study in experimental and social psychology* (pp. xix, 317).

Cambridge University Press.

Bayen, U. J., Nakamura, G. V., Dupuis, S. E., & Yang, C.-L. (2000). The use of schematic knowledge about sources in source monitoring. *Memory & Cognition*, 28(3), 480–500.

<https://doi.org/10.3758/BF03198562>

Berens, S. C., Richards, B. A., & Horner, A. J. (2020). Dissociating memory accessibility and precision in forgetting. *Nature Human Behaviour*, 4(8), 866–877.

<https://doi.org/10.1038/s41562-020-0888-8>

Boettcher, S. E. P., Draschkow, D., Dienhart, E., & Vö, M. L.-H. (2018). Anchoring visual search in scenes: Assessing the role of anchor objects on eye movements during visual search.

Journal of Vision, 18(13), 11. <https://doi.org/10.1167/18.13.11>

Bowers, J. S., & Davis, C. J. (2012). Bayesian just-so stories in psychology and neuroscience.

Psychological Bulletin, 138(3), 389–414. <https://doi.org/10.1037/a0026450>

Castel, A. D. (2005). Memory for grocery prices in younger and older adults: The role of schematic support. *Psychology and Aging*, 20(4), 718–721. [https://doi.org/10.1037/0882-](https://doi.org/10.1037/0882-7974.20.4.718)

[7974.20.4.718](https://doi.org/10.1037/0882-7974.20.4.718)

Castel, A. D., McGillivray, S., & Worden, K. M. (2013). Back to the future: Past and future era-based schematic support and associative memory for prices in younger and older adults.

Psychology and Aging, 28(4), 996–1003. <https://doi.org/10.1037/a0034160>

de Leeuw, J. R. (2015). jsPsych: A JavaScript library for creating behavioral experiments in a Web browser. *Behavior Research Methods*, 47(1), 1–12. [https://doi.org/10.3758/s13428-014-](https://doi.org/10.3758/s13428-014-0458-y)

[0458-y](https://doi.org/10.3758/s13428-014-0458-y)

- Dijksterhuis, A., & Van Knippenberg, A. (1995). Timing of schema activation and memory: Inhibited access to inconsistent information. *European Journal of Social Psychology*, 25(4), 383–390. <https://doi.org/10.1002/ejsp.2420250403>
- Dodson, C. S., Darragh, J., & Williams, A. (2008). Stereotypes and retrieval-provoked illusory source recollections. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 34(3), 460–477. <https://doi.org/10.1037/0278-7393.34.3.460>
- Duffy, S., Huttenlocher, J., & Crawford, L. E. (2006). Children use categories to maximize accuracy in estimation. *Developmental Science*, 9(6), 597–603. <https://doi.org/10.1111/j.1467-7687.2006.00538.x>
- Duffy, S., Huttenlocher, J., Hedges, L. V., & Elizabeth Crawford, L. (2010). Category effects on stimulus estimation: Shifting and skewed frequency distributions. *Psychonomic Bulletin & Review*, 17(2), 224–230. <https://doi.org/10.3758/PBR.17.2.224>
- Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191. <https://doi.org/10.3758/BF03193146>
- Frank, D., Montaldi, D., Wittmann, B., & Talmi, D. (2018). Beneficial and detrimental effects of schema incongruence on memory for contextual events. *Learning & Memory*, 25(8), 352–360. <https://doi.org/10.1101/lm.047738.118>
- Ghosh, V. E., & Gilboa, A. (2014). What is a memory schema? A historical perspective on current neuroscience literature. *Neuropsychologia*, 53, 104–114. <https://doi.org/10.1016/j.neuropsychologia.2013.11.010>
- Greenberg, M. S., Westcott, D. R., & Bailey, S. E. (1998). When Believing Is Seeing: The Effect of Scripts on Eyewitness Memory. *Law and Human Behavior*, 22(6), 685–694. <https://doi.org/10.1023/A:1025758807624>

Greve, A., Cooper, E., Kaula, A., Anderson, M. C., & Henson, R. (2017). Does prediction error drive one-shot declarative learning? *Journal of Memory and Language*, 94, 149–165.

<https://doi.org/10.1016/j.jml.2016.11.001>

Greve, A., Cooper, E., Tibon, R., & Henson, R. N. (2019). Knowledge is power: Prior knowledge aids memory for both congruent and incongruent events, but in different ways. *Journal of Experimental Psychology: General*, 148(2), 325–341. <https://doi.org/10.1037/xge0000498>

Griffiths, T. L., Lieder, F., & Goodman, N. D. (2015). Rational Use of Cognitive Resources: Levels of Analysis Between the Computational and the Algorithmic. *Topics in Cognitive Science*, 7(2), 217–229. <https://doi.org/10.1111/tops.12142>

Hay, J. F., & Jacoby, L. L. (1999). Separating Habit and Recollection in Young and Older Adults: Effects of Elaborative Processing and Distinctiveness. *Psychology and Aging*, 14(1), 122.

Hemmer, P., & Persaud, K. (2014). Interaction between categorical knowledge and episodic memory across domains. *Frontiers in Psychology*, 5. <https://doi.org/10.3389/fpsyg.2014.00584>

Hemmer, P., & Steyvers, M. (2009). A Bayesian Account of Reconstructive Memory. *Topics in Cognitive Science*, 1(1), 189–202. <https://doi.org/10.1111/j.1756-8765.2008.01010.x>

Huang, J., Furness, E., Liu, Y., Kenmoe, M.-J., Elias, R., Zeng, H. T., & Baldassano, C. (2025). Accurate Predictions Facilitate Robust Memory Encoding Independently From Stimulus Probability. *Open Mind*, 9, 940–958. <https://doi.org/10.1162/opmi.a.14>

Huttenlocher, J., & Hedges, L. V. (1992). Reconstructing the Past: Category Effects in Estimation. In *Psychology of Learning and Motivation* (Vol. 28, pp. 251–280). Elsevier. [https://doi.org/10.1016/S0079-7421\(08\)60492-2](https://doi.org/10.1016/S0079-7421(08)60492-2)

Huttenlocher, J., Hedges, L. V., & Duncan, S. (1991). Categories and particulars: Prototype effects in estimating spatial location. *Psychological Review*, 98(3), 352–376. <https://doi.org/10.1037/0033-295X.98.3.352>

Huttenlocher, J., Hedges, L. V., & Vevea, J. L. (2000). Why Do Categories Affect Stimulus Judgment?

Journal of Experimental Psychology: General, 129(2), 220–241.

Jones, M., & Love, B. C. (2011). Bayesian Fundamentalism or Enlightenment? On the explanatory status and theoretical contributions of Bayesian models of cognition. *Behavioral and Brain Sciences*, 34(4), 169–188. <https://doi.org/10.1017/S0140525X10003134>

Kafkas, A., & Montaldi, D. (2018). Expectation affects learning and modulates memory experience at retrieval. *Cognition*, 180, 123–134. <https://doi.org/10.1016/j.cognition.2018.07.010>

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, 82(13). <https://doi.org/10.18637/jss.v082.i13>

Lampinen, J., Copeland, S., & Neuschatz, J. (2001). Recollections of Things Schematic: Room Schemas Revisited. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, 27, 1211–1222. <https://doi.org/10.1037//0278-7393.27.5.1211>

Macias, C., & Persaud, K. (2024). From silos to synergy: Integrating approaches to investigate the role of prior knowledge and expectations on episodic memory. *Psychonomic Bulletin & Review*. <https://doi.org/10.3758/s13423-024-02505-4>

Marr, D., & Poggio, T. A. (1976). *From Understanding Computation to Understanding Neural Circuitry*. <http://hdl.handle.net/1721.1/5782>

Ortega, P. A., & Braun, D. A. (2013). Thermodynamics as a theory of decision-making with information-processing costs. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 469(2153), 20120683. <https://doi.org/10.1098/rspa.2012.0683>

Ortiz-Tudela, J., Milliken, B., Jiménez, L., & Lupiáñez, J. (2018). Attentional influences on memory formation: A tale of a not-so-simple story. *Memory & Cognition*, 46(4), 544–557. <https://doi.org/10.3758/s13421-017-0784-2>

- Ortiz-Tudela, J., Nolden, S., Pupillo, F., Ehrlich, I., Schommartz, I., Turan, G., & Shing, Y. L. (2023). Not what u expect: Effects of prediction errors on item memory. *Journal of Experimental Psychology: General*, 152(8), 2160–2176. <https://doi.org/10.1037/xge0001367>
- Ortoleva, P. (2012). Modeling the Change of Paradigm: Non-Bayesian Reactions to Unexpected News. *American Economic Review*, 102(6), 2410–2436. <https://doi.org/10.1257/aer.102.6.2410>
- Ortoleva, P. (2024). Alternatives to Bayesian Updating. *Annual Review of Economics*, 16(Volume 16, 2024), 545–570. <https://doi.org/10.1146/annurev-economics-100223-050352>
- Osborne, D., & Davies, P. G. (2013). Eyewitness identifications are affected by stereotypes about a suspect's level of perceived stereotypicality. *Group Processes & Intergroup Relations*, 16(4), 488–504. <https://doi.org/10.1177/1368430212454927>
- Persaud, K., & Hemmer, P. (2014). The Influence of Knowledge and Expectations for Color on Episodic Memory. *Proceedings of the Annual Meeting of the Cognitive Science Society*.
- Persaud, K., & Hemmer, P. (2016). The dynamics of fidelity over the time course of long-term memory. *Cognitive Psychology*, 88, 1–21. <https://doi.org/10.1016/j.cogpsych.2016.05.003>
- Persaud, K., Macias, C., Hemmer, P., & Bonawitz, E. (2021). Evaluating recall error in preschoolers: Category expectations influence episodic memory for color. *Cognitive Psychology*, 124, 101357. <https://doi.org/10.1016/j.cogpsych.2020.101357>
- Quent, J. A., Greve, A., & Henson, R. N. (2022). Shape of U: The Nonmonotonic Relationship Between Object–Location Memory and Expectedness. *Psychological Science*, 33(12), 2084–2097. <https://doi.org/10.1177/09567976221109134>
- Ramey, M. M. (2026). Prior knowledge biases episodic memory by filling in the gaps in imprecise memories: Simulating aging effects in younger adults. *Cognition*.

- Ramey, M. M., Henderson, J. M., & Yonelinas, A. P. (2020). The spatial distribution of attention predicts familiarity strength during encoding and retrieval. *Journal of Experimental Psychology: General*, 149(11), 2046–2062. <https://doi.org/10.1037/xge0000758>
- Ramey, M. M., Henderson, J. M., & Yonelinas, A. P. (2022). Episodic memory processes modulate how schema knowledge is used in spatial memory decisions. *Cognition*, 225, 105111. <https://doi.org/10.1016/j.cognition.2022.105111>
- Ramey, M. M., Henderson, J. M., & Yonelinas, A. P. (2025). Episodic memory and semantic knowledge interact to guide eye movements during visual search in scenes: Distinct effects of conscious and unconscious memory. *Psychonomic Bulletin & Review*. <https://doi.org/10.3758/s13423-025-02686-6>
- Ramey, M. M., Yonelinas, A. P., & Henderson, J. M. (2019). Conscious and unconscious memory differentially impact attention: Eye movements, visual search, and recognition processes. *Cognition*, 185, 71–82. <https://doi.org/10.1016/j.cognition.2019.01.007>
- Ramey, M. M., Yonelinas, A. P., & Henderson, J. M. (2024). How schema knowledge influences memory in older adults: Filling in the gaps, or leading memory astray? *Cognition*, 250, 105826. <https://doi.org/10.1016/j.cognition.2024.105826>
- Ramey, M. M., & Zabelina, D. L. (2024). Divergent thinking modulates interactions between episodic memory and schema knowledge: Controlled and spontaneous episodic retrieval processes. *Memory & Cognition*. <https://doi.org/10.3758/s13421-023-01493-5>
- Redacted. (2026). *Schema precision and episodic memory revision*. https://osf.io/c5y8e/overview?view_only=58fb8393e0244cd8ba443d36f65ddb13
- Rips, L. J. (1989). Similarity, typicality, and categorization. In *Similarity and analogical reasoning* (pp. 21–59). Cambridge University Press. <https://doi.org/10.1017/CBO9780511529863.004>

- Roberts, S., & Pashler, H. (2000). How persuasive is a good fit? A comment on theory testing. *Psychological Review*, 107(2), 358–367. <https://doi.org/10.1037/0033-295X.107.2.358>
- Rojahn, K., & Pettigrew, T. (1992). Memory for schema-relevant information: A meta-analytic resolution. *British Journal of Social Psychology*, 31, 81–109.
- Tompary, A., & Thompson-Schill, S. L. (2021). Semantic Influences on Episodic Memory Distortions. *Journal of Experimental Psychology: General*, 150(9), 1800–1824.
- Tompary, A., Zhou, W., & Davachi, L. (2020). Schematic memories develop quickly, but are not expressed unless necessary. *Scientific Reports*, 10(1), 16968. <https://doi.org/10.1038/s41598-020-73952-x>
- Torralba, A., Oliva, A., Castelhana, M. S., & Henderson, J. M. (2006). Contextual guidance of eye movements and attention in real-world scenes: The role of global features in object search. *Psychological Review*, 113(4), 766–786. <https://doi.org/10.1037/0033-295X.113.4.766>
- Umanath, S., & Marsh, E. J. (2014). Understanding How Prior Knowledge Influences Memory in Older Adults. *Perspectives on Psychological Science*, 9(4), 408–426. <https://doi.org/10.1177/1745691614535933>
- van Kesteren, M. T. R., Beul, S. F., Takashima, A., Henson, R. N., Ruiter, D. J., & Fernández, G. (2013). Differential roles for medial prefrontal and medial temporal cortices in schema-dependent encoding: From congruent to incongruent. *Neuropsychologia, Special Issue on Functional Neuroimaging of Episodic Memory*, 51(12), 2352–2359. <https://doi.org/10.1016/j.neuropsychologia.2013.05.027>
- 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>

- Võ, M. L.-H., Boettcher, S. E., & Draschkow, D. (2019). Reading scenes: How scene grammar guides attention and aids perception in real-world environments. *Current Opinion in Psychology, Attention & Perception*, 29, 205–210. <https://doi.org/10.1016/j.copsyc.2019.03.009>
- Võ, M. L.-H., & Wolfe, J. M. (2013). The interplay of episodic and semantic memory in guiding repeated search in scenes. *Cognition*, 126(2), 198–212. <https://doi.org/10.1016/j.cognition.2012.09.017>
- Watkins, M. J., & Gardiner, J. M. (1979). An appreciation of generate-recognize theory of recall. *Journal of Verbal Learning and Verbal Behavior*, 18(6), 687–704. [https://doi.org/10.1016/S0022-5371\(79\)90397-9](https://doi.org/10.1016/S0022-5371(79)90397-9)
- Xu, Z., Hemmer, P., & Zhang, Q. (2024). Towards a Generalized Bayesian Model of Reconstructive Memory. *Computational Brain & Behavior*. <https://doi.org/10.1007/s42113-024-00222-8>
- Xue, K., & Rahnev, D. (2026). The explicit-Bayes hypothesis for cognition. *Nature Reviews Psychology*. <https://doi.org/10.1038/s44159-026-00570-1>
- Yacoby, A., Greve, A., Schaverien, E., Shtoots, L., Henson, R. N., & Levy, D. A. (2026). Dissociable effects of schema congruency on item recognition and source memory across levels of expectedness and surprise. *Memory & Cognition*. <https://doi.org/10.3758/s13421-026-01930-1>
- Yonelinas, A. P. (2002). The Nature of Recollection and Familiarity: A Review of 30 Years of Research. *Journal of Memory and Language*, 46(3), 441–517. <https://doi.org/10.1006/jmla.2002.2864>
- Yonelinas, A. P., Ramey, M. M., Riddell, C., Kahana, M., & Wagner, A. (2024). Recognition memory: The role of recollection and familiarity. In *The Oxford Handbook of Human Memory* (1–2). Oxford University Press. <https://academic.oup.com/edited-volume/57928/chapter-abstract/475476914>

Zhang, Q. (2022). How And Why Does Schematic Knowledge Affect Memory? In *The Cognitive Science of Belief: A Multidisciplinary Approach*. Cambridge University Press.

Zuo, S., Ramey, M. M., & Hemmer, P. (2026). A Hierarchical Bayesian Model of Memory for Natural Scenes. *SSRN (Preprint)*.