Episodic memory, unlike semantic or procedural memory, is memory of a particular event or occasion. A key part of episodic memory is the context in which the event in question occurred. This contextual component of episodic memory is known as *source memory*, and its importance can be illustrated in a variety of ways. For instance, when identifying the suspect of a crime, a memory within the context of the crime scene itself will have very different implications than a memory of a chance encounter. To successfully complete such an identification task, the witness needs to: 1) encode information about the suspect and the context within their memory, 2) bind this information into an overall representation, 3) recognize the suspect at a later time, 4) retrieve the context in which the event occurred, and 5) make a response on the basis of the retrieved representation.

Characterizing each of these components and how they interact is an important question in memory research, and a variety of different models have been proposed to address it. Source memory research has been largely concerned with the memory retrieval process, specifically whether the strength of a retrieved memory varies continuously or must exceed a threshold value in order to be retrieved. Several classes of models exist in the literature that formalize these ideas about memory retrieval. Continuous models of source memory predict that retrieved information may be inaccurate but not absent, allowing for a gradual decline in the quality of information retrieved (Banks, 2000; Mickes, Wais & Wixted, 2009). In contrast, a threshold or discrete-state model holds that retrieval fails discretely, and so performance is made up of either precise responses, or guesses when the memory is subthreshold (Batchelder & Riefer, 1990; Klauer & Kellen, 2010). A third class of models can be described as a hybrid that draws upon elements of both continuous and threshold processes, known as dual-process models.

Our aim in this article is to compare continuous, threshold, and hybrid models of source memory using a continuous outcome decision task. We present a novel method of analysis of the results of this task using the circular diffusion model of Smith (2016), Our analysis allows us to distinguish the contributions of memory processes and retrieval processes to source memory performance in a precise way.

## Dual-Process Models in Recognition Memory

The debate between continuous and discrete models of source memory is situated in the wider recognition literature, which has proposed a range of models to account for memory performance across experimental paradigms. Although source memory is distinct from recognition memory, the two types of memory are often tested simultaneously, and models are developed accordingly to account for both types of tasks (Starns, Hicks, Brown & Martin, 2008). Dual-process models are a class of models which take this integrative approach, in which different kinds of retrieval mechanism support different kinds of memory (Bowers & Schacter, 1990).Specifically, in the dual-process model of Yonelinas (1994), episodic memory involves a mixture of two processes: a fast familiarity-based process and a slower recollection process. Familiarity, defined in this framework, is a quick judgment about whether or not an item has been encountered before based on the strength of its representation in memory (Yonelinas, 1994). Recollection is defined as a slower search process for qualitative information about the item (Atkinson & Juola, 1974). Recollection is assumed to be a thresholded retrieval process while familiarity is a continuous signal-detection process (Yonelinas, 1999). The basis for this theoretical assumption is that in recollection people either succeed or fail to retrieve information. While the level of detail above the threshold may vary, Yonelinas (1999) argues that there is a threshold below which there is no information retrieved.

Within a dual-process framework, performance on an item recognition task comprises both familiarity and recollection processes, where targets that were studied will be more familiar than lures which were not (Yonelinas, 1994). If successful, recollection enhances recognition by providing details of the study event. Critically, both targets and lures have familiarity, and differ continuously in the degree to which they are familiar, but only targets can be recollected because they are associated with a study event. In source memory tasks, however, familiarity cannot be used to determine the source of items as they have all been studied, and are all equally familiar. Consequently, Yonelinas (1994) conceptualized source memory as a pure recollection process, in that a correct response depends only on successful recollection of contextual details of the study event.

Given that source memory is dependent on recollection in this way, and that recollection according to the dual-process model is thresholded, the model implies that performance in source memory tasks should exhibit a retrieval threshold. When forced to make a source memory judgement in the case that recollection fails, participants can only guess in the absence of information. The dual-process model therefore predicts that overall performance on source memory tasks should be a mixture of two discrete components: informed responses and no-information guesses, depending on whether recollection succeeds or fails respectively.

# Recognition and Source Memory in Two-choice Tasks

## Source ROC Predictions

Traditionally, evidence both for and against a threshold in recollection has come from the examination of Receiver Operating Characteristic (ROC) curves (Yonelinas & Parks, 2007; Yonelinas, 1999; Slotnick & Dodson, 2005). In a two-choice paradigm with two possible sources of information, each source in a continuous model is associated with a normally distributed memory strength, and these distributions overlap. As the response criterion is varied, the ratio of hit rates to false alarms will be such that the resultant shape of the plot is curvilinear (Slotnick & Dodson, 2005). In contrast, in a discrete model, the strength of the memory representation fails to meet either response threshold in the overlap. As a result, the ratio of false alarms to hit rates across criterion points is constant, producing a linear ROC (Rouder, Morey, Cowan, Zwilling, Morey & Pratte, 2008). The dual process model, in which source memory is dependent on a thresholded process in recollection, also predicts linear source ROCs when familiarity is equivalent across both sources (Yonelinas, 1999).

### Conditioning Source Memory on Recognition Confidence

The premise that recollection is thresholded was challenged by a reanalysis of the Yonelinas (1999) data by Slotnick and Dodson (2005), which conditioned source performance on recognition confidence ratings for each item. This reanalysis demonstrated that if source ROCs were plotted separately for different levels of confidence reported in the item recognition task, the highest confidence source ROCs were in fact curvilinear, contrary to the predictions of the dual-process model. Performance for unrecognized items was at chance and these items were on the diagonal of the ROC. As items rated with lower recognition confidence were included in the original data, the shape of the overall source ROC were apparently increasingly linear, and more consistent with the predictions of the threshold model. The authors argued that only the items that were recognised with high confidence contained diagnostic source information, and that the linearity of source ROCs observed by Yonelinas (1999) was an artifact of collapsing across all recognition confidence ratings, and was thus not evidence for a recollection threshold.

Yonelinas and Parks (2007) responded to the Slotnick and Dodson (2005) analysis by proposing that source ROCs are typically linear, but become more curvilinear under a number of conditions. One such condition is when an item and a source are treated holistically as one item, known as *unitised familiarity*. We will return to this point in the Discussion. While this proposal represented a concession towards a continuous contribution under certain circumstances, Klauer and Kellen (2010) were later able to account for curvilinear ROCs using only discrete states by allowing for a variable mapping between recognition confidence ratings and source memory thresholds. At present, then, there is a lack of consensus about whether apparently linear or curvilinear ROCs reflect thresholded or continuous retrieval processes.

# Continuous Report

Harlow and Donaldson (2013) addressed the need for more diagnostic data by replacing binary decision outcomes with a continuous report paradigm. In the Harlow and Donaldson (2013) continuous report paradigm, source information was provided by a point located on the circumference of a circle, which represented the context, and which was paired with a word item. When later cued with that word, participants were required to reproduce the associated location. This procedure allowed for an objective measure of the error in the angle between the reported and true source locations. The researchers’ use of a continuous measure of source memory performance allowed them not only to measure the accuracy of source memory judgments, but also the distribution of response errors. Instead of categorizing responses as either correct or incorrect as in a two-choice task, their task, which captures an entire distributions of response accuracy, provides a more detailed picture of trial-to-trial variability in retrieval performance. The additional information in such distributions may be more diagnostic than ROC curves of the underlying retrieval processes. Critically, the threshold and continuous models of source memory make divergent predictions about the distributions of response errors in continuous report tasks.

Under the threshold model, any items that fall below the recollection threshold will be associated with guesses, which will be distributed uniformly across all possible response options. Items that exceed the threshold and are successfully retrieved will cluster, with some error, around the true value of the item source. This work is paralleled in the visual working memory literature, where Zhang and Luck (2008) argued on the basis of a mixture model using both von Mises and uniform components that the resolution of working memory representations beyond a certain memory array size was fixed, representing a discrete item limit within the memory system itself. Harlow and Donaldson (2013) took a similar approach in modelling performance in their source memory task, using a von Mises distribution to capture the shape of the marginal distribution of response error when items exceeded the retrieval threshold. The von Mises distribution is a circular analogue of the normal distribution and, like the normal distribution, has a bell-shaped density function. A mixture of these two processes then produces a high-peaked, heavy-tailed distribution (Harlow & Donaldson, 2013). Harlow and Donaldson (2013) found that source accuracy data was better fit by the threshold model better than its continuous counterpart, which instead predicts that responses made with moderate memory strength would reflect a wider spread of responses around the true location with no uniform guessing structure.

## Source Memory for Unrecognized Items

A potential confound in the experimental design used by Harlow and Donaldson (2013) was that they did not condition source memory performance on recognition confidence. The Slotnick and Dodson (2005) study discussed earlier showed how source-memory ROC shapes depend on recognition confidence in the two-choice paradigm, and it is possible that continuous source memory judgments are affected in a similar way. Hautus, MacMillan, and Rotello (2008) modeled performance in two-choice source memory tasks, and found that the best fits were attained by incorporating a guessing process for unrecognized items, mirroring the Slotnick and Dodson (2005) finding that source performance was at chance for items recognised with low confidence. The guessing process was preferred because continous model variants that lacked such a guessing process predicted that the performance decreases that occurred with decreasing recognition confidence were too gradual and could not capture the abrupt shift to chance performance when items were unrecognized.

A lack of source discriminability for unrecognized items has been replicated numerous times (Bell, Mieth, & Buchner, 2017; Malejka & Broder, 2016; Onyper, Zhang, & Howard, 2010), although these studies often employed a procedure where item and source ratings were obtained in the same test trials. When item recognition and source memory tests were in separate blocks, Osth, Fox, McKague, Heathcote, and Dennis (2018) observed reliable source memory for unrecognized items, but discriminability was still quite low (*d’* ~ .1).

If the lack of source memory for unrecognized items generalizes to a continuous report task, these guesses would result in a heavy-tailed error distribution, which would not necessarily reflect a threshold in memory retrieval, but a may simply reflect a state in which source retrieval is not attempted. Guessing behavior can arise either as the product of a retrieval threshold within source memory or without a threshold in source when either the participant does not attempt to retrieve the source memory or the source memory is absent. In the context of the findings of Harlow and Donaldson (2013), this latter account predicts that if unrecognized items are excluded, the heavy tails in the error distribution will disappear, and that a continuous model will be preferred in account for source performance.

# Decision-Making

In completing a source or recognition memory task, not only do participants need to retrieve information from memory, they must also make a decision on how to respond based on the information retrieved. In this sense, the information retrieved from memory can be thought of as evidence for entering a decision process. Much of the existing body of source memory research, particularly in the continuous report paradigm, lacks an explicit account of properties of this decision process. Past research in the recognition memory literature has shown that when such decision processes are accounted for, conclusions that can be made about recognition memory diverge from those made when decision-making is not explicitly considered (Dube, Starns, Rotello & Ratcliff, 2012; Osth, Bora, Dennis, & Heathcote, 2017; Ratcliff & Starns, 2013). Diffusion models have emerged as increasingly influential accounts of decision processes which predict both response time (RT) and response accuracy data, and which naturally explain well-documented phenomena like the speed-accuracy trade-off (Ratcliff, Smith, Brown & McKoon, 2016). Diffusion models have also been used extensively in the past to model memory retrieval, and more recent research has proposed a general theory of memory and decision-making in which decisions about stimuli within visual working memory are made using a diffusion process (Smith & Ratcliff, 2009). In the most common form of the diffusion model (Ratcliff, 1978), the decision process is modeled as noisy evidence accumulation between a pair of absorbing boundaries that represent the decision criteria for the task. Evidence is accumulated until the process reaches one or other boundary: The first boundary reached determines the response and the time to first reach a boundary is the decision time component of RT.

A close up of a map

Description automatically generated

The diffusion model assumes that multiple sources of variability affect the decision process, including moment-to-moment variability in the accumulation of evidence and trial-to-trial variability in the quality of evidence entering the decision process (Figure 6). The moment-to-moment variability reflects the noisiness of the evidence provided by the retrieval process, while the trial-to-trial variability reflects differences in the stimulus information on which the decision is based. The rate of evidence accumulation on any trial is known as the drift rate. Drift rates can vary across trials, with high drift rate trials resulting in high accuracy and fast RTs, while trials with lower drift rates result in slower and less accurate responses (Ratcliff, Smith & McKoon, 2015).

The relationship between accuracy and RT is intuitive: when evidence for the correct response is good, trial responses will be more accurate on average, and for each trial, the evidence accumulated will progress towards the correct boundary more than the error boundary, leading to faster RTs. On the other hand, decisions made on the basis of lower quality information will take longer to make, and will on average be less accurate. Consequently, when drift rate varies between trials, then the mean RT for correct responses will be shorter than mean RT for errors, because drift rates are higher in the former. This phenomenon, known as a *slow error* pattern,has been reliably observed when decision making is difficult (Ratcliff et al., 2016). A counterintuitive property of trial-to-trial variability in the drift rate of the diffusion model is that, without this variability, correct and error RT distributions will be the same, it is only when drift rates vary between trials that we obtain this slow error pattern.

In introducing the Circular Diffusion Model, Smith (2016) extended the standard Ratcliff (1978) diffusion model, which models decision-making as a one-dimensional evidence accumulation process (diffusion on a line), to account for continuous report tasks. In the circular model, the drift rate is defined as a vector in a two-dimensional (2D) space having both an identity component for the position of the stimulus on the circle, represented as the phase angle of the drift vector, and a magnitude component, representing the quality of the evidence for any particular response. When a response is made, the magnitude of the drift vector determines RT in the same way as does the scalar drift rate does in the standard Ratcliff model, while the point at which the evidence accumulation process exits the circle determines the response outcome.

Although the circular diffusion model does not categorize responses discretely as correct or incorrect, the same relationships between RT and response accuracy are predicted when RTs are considered as a continuous function of accuracy, quantifiable by the angle between the true and reported locations on the criterion boundary. Trial-to-trial variability in drift rate results in responses closer to the true stimulus location having faster RTs, while those further away will have slower RTs, producing the slow error pattern seen in the two-choice case. Variability in the criterion leads to the inverse, producing fast errors. Like the two-choice case, RT distributions conditioned on the response angle are identical without trial-to-trial drift or criterion variability, requiring drift or criterion variability to change this pattern of results.

An important prediction of the circular diffusion model for this study is that, while a fixed drift rate produces a von Mises response error distribution, the introduction of trial-to-trial variability in drift rate results in high, narrow peaks and broad shoulders in the error distribution. The high, narrow peaks reflect those trials with fast, accurate responses, and the subset of trials with low drift rates produce much wider error distributions. The effect of averaging across all trials is, therefore, an overall distribution that can have a narrow peak and raised tails (Smith, 2016). In this way, the circular diffusion model is able to produce heavy-tailed distributions which have, to this point, been thought to characterize an underlying memory retrieval threshold.

# The Current Study

There are two aims in the current study. The first is to explore the possibility that the heavy tails observed in the Harlow and Donaldson (2013) continuous report source memory task can be explained as source guessing for unrecognized items. If this is the case, then conditioning performance on the source memory task on high confidence in the recognition task should result in a distribution of response errors without the heavy tails predicted by the threshold model,

The second aim is to determine if incorporating a model of the decision-making process that allows for across-trial drift rate variability can capture the distribution of response error and RTs. If the heavy-tailed pattern in the Harlow and Donaldson (2013) data can be explained by across-trial variability in the drift rate of the circular diffusion model, then a threshold mechanism in the memory process is not necessarily implied by the heavy-tailed shape of the error distribution. Providing an elaborated model of decision-making in this manner offers additional constraint by jointly modelling response error and RTs. The across-trial drift rate variability account predicts a slow error pattern in the joint distribution.

Our experimental task also included a manipulation of the imageability and concreteness of the stimulus words, as rated on the MRC Psycholinguistic Database. Harlow and Donaldson (2013) selected words for low ratings on both metrics to prevent participants from visualizing a concrete object in a source location. In our study, we drew stimuli from pools of low and high imageability and concreteness words which allowed us to quantify and compare the effect of these attributes.

# Computational Modelling

**Simple Mixture Model**

To attempt to replicate the Harlow and Donaldson (2013) finding, we first used the Zhang and Luck (2008) mixture model to fit the marginal distribution of response error. The model had two free parameters, one for precision which described the spread of responses around the true location, and a mixing parameter *π*,which described the proportion of trials which were driven by information in a von Mises distribution, as opposed to guesses in a uniform distribution. To clearly distinguish this model from mixture variants of the circular diffusion model, this will be referred to as the Simple Mixture model.

## Diffusion Models

We test three alternative versions of the circular diffusion model that express different hypotheses about the process of memory retrieval. The first of these was designed to be analogous to the continuous model of source memory presented in Harlow and Donaldson (2013), and was implemented as a circular diffusion model with drift rate variability. This variant will subsequently be referred to as the *continuous diffusion* model. Drift rate variability was set to be equal in both dimensions of the 2-dimensional space, but different between imageability conditions. There were four parameters for mean drift rates (*μ1x*, *μ2x*, *μ1y*, *μ2y*),which characterize the components of the drift rate in the *x* and y directions in the low (*μ1*) and high (*μ2*) word imageability conditions. Because the model was fitted to the distribution of report errors, which is centered on zero degrees, the dominant component of the drift rate was expected to be in the *x* direction. The second component of drift was included to allow for the possibility of drift bias. The decision criterion was represented by *a.* The variability of the decision criterion uniform variability across trial with range sa across trials was represented by *sa*. There were also two standard deviation parameters *η1* and *η2*, which described the standard deviations of the drift rates in the low and high imageability conditions respectively. The standard deviations of the drift rates were assumed to be the same in the *x* and *y* directions. Finally, there was a non-decision time parameter, *Ter­*. Like the standard diffusion model, the circular model assumes that RT is the sum of the decision time and a time for other (encoding and response) processes. These parameters are summarised in Table 2.

The second model variant embodied the thresholded property favoured by Harlow and Donaldson (2013), and will be referred to as the *threshold diffusion* model. This was implemented as a mixture of two diffusion processes: one with positive drift and no between-trial drift variability, and a second component that was modelled as a diffusion process with zero drift. The zero-drift process provides a diffusion process implementation of a guessing process, in which the decision process is driven only by noise. Unlike “guessing” in its classical sense, which accounts for accuracy but not RT, the zero-driven process is able to predict both accuracy and RT. Mixing proportions for the two processes were allowed to vary between the word imageability conditions. This model had ten free parameters. Four mean drift rates parameters were shared with the continuous model (*μ1x*, *μ2x*, *μ1y*, *μ2y*), with the same interpretation, as well as *Ter­,* the non-decision time parameter. There were two parameters for the mixing proportions between information-driven and guessing components, one for the low imageability condition (*π1*) and another for the high imageability condition (*π2*). The decision criterion was estimated separately for the information-driven component (*a1*) and the guessing component (*a2*). Both processes shared a parameter for criterion variability (*sa*).

The third model was a synthesis of both the continuous and threshold diffusion models, which was identical to the threshold diffusion model, but also allowed for drift rate variability between trials, and can therefore be regarded as a mixture model which incorporates the continuous and threshold diffusion models. This, the *mixture diffusion* model, had 11 free parameters, all of which are displayed in Table X.

|  |  |
| --- | --- |
| Table X  Symbols and definitions of free parameters estimated in diffusion model variants | |
| Symbol | Parameter |
| *μ1x* | Mean drift, low condition, x direction |
| *μ2x* | Mean drift, high condition, x direction |
| *μ1y* | Mean drift, low condition, y direction |
| *μ2y* | Mean drift, high condition, y direction |
| *η1* | Drift variability, low condition |
| *η2* | Drift variability, high condition |
| *a1* | Decision criteria, information-driven component |
| *a2* | Decision criteria, guessing component |
| *π1* | Mixing proportion, low condition |
| *π2* | Mixing proportion, high condition |
| *Ter* | Non-decision time |
| *sa* | Criterion variability |

*Note.* Not all parameters were estimated for all three models. The continuous diffusion model did not include a mixed guessing process, and therefore lacked *a2*, *π1* and *π2.* The threshold diffusion model did not have drift variability and lacked *η1* and *η2*. The mixture diffusion model included all parameters listed.

## The Generalized von Mises Model

In addition to comparing the continuous, threshold and mixture variants of the circular diffusion model, we also allow for a non-linear relationship between physical distance between source locations and psychological confusability (Wixted citation). This was done by introducing flexible scaling of the phase angle component of drift in the circular diffusion model, which represents the identity of the stimulus in memory. The distribution of phase angles is described as a “generalized von Mises distribution” by Smith, Saber, Corbett and Lilburn (2019), where the probability of obtaining a drift rate with phase angle *θ* is given by the following equation:

We use a version of the circular diffusion model, which draws upon a generalized von Mises distribution of phase angles, to fit data in the same source memory task. This model will be referred to as the *generalized von Mises* model.

|  |  |
| --- | --- |
| Table X  Symbols and definitions of parameters in the Generalized von Mises Model | |
| Symbol | Parameter |
| *Nunorm1* | Mean drift rate vector length, low imageability |
| *Nunorm2* | Mean drift rate vector length, high imageability |
| *κμ1* | Precision, low imageability |
| *κμ2* | Precision, high imageability |
| *η* | Drift variability |
| *ρ* | Distribution of phase angle |
| *a* | Decision criterion |
| *sa* | Decision criterion variability |
| *Ter* | Non-decision time |
| *st* | Non-decision time variability |

The critical parameters in the model are *ρ* and *κμ*,which determine the shape of the generalized von Mises distribution of drift rate phase angles. When *ρ* = 1, the distribution described in Smith et al. (2019) is equivalent to a standard von Mises distribution. As *ρ* approaches zero, the shape of the distribution becomes increasingly leptokurtic, such that for very low values of *ρ* (e.g., *ρ* = .05), the distribution resembles a spike of probability mass superimposed on a uniform background.

The interaction between various values of *ρ* and *κμ* produces model variants which can be related to the competing theories of source memory. When *ρ*=1 and *κμ* is large, the model resembles a fixed precision model in VWM. As *ρ* decreases, the model becomes increasingly similar to either a variable-precision model, based on the value of *κμ*.

A picture containing text

Description automatically generated

Ultimately, this produces a flexible model that is able to gradually transition to resemble models like the continuous and threshold circular diffusion models presented earlier, simply by adjusting parameters that govern the shape of the distribution of phase angles.

# Method

## Stimuli and apparatus

Stimuli were presented on a 20’’ Dell 2009W LDC Monitor, set with a screen refresh rate of 60 Hz. Software written in MATLAB controlled stimulus presentation and recorded responses. Stimuli consisted of words generated from the MRC Psycholinguistic Database, selected/ for low concreteness (minimum 100, maximum 456) and imageability (minimum 100, maximum 481) in the low stimulus set, and high concreteness (minimum 543, maximum 611) and high imageability (minimum 545, maximum 609) in the high stimulus set. Words were displayed in size 24 point “Courier New” white font positioned in the center of a uniform mean luminance field.

## Participants

Twenty participants were recruited online through the University of Melbourne SONA system. Each participant was expected to complete four 60-minute sessions, for which they were paid $12 at the completion of each session. One participant who did not complete all four sessions was excluded from analysis (*N* = 19). All participants were provided with plain language statements and consent forms, and gave informed consent prior to data collection.

## Design

Participants completed the experimental tasks over four sessions, Each of the four sessions consisted of 180 trials, which was broken up into 18 blocks of 10 items each. Blocks were comprised of a study phase, followed by a test phase (Figure X).

In the study phase, participants were presented with a black cross on a dark grey circle outline at the start of each trial for (600 ms), which was followed by the display of a word in the centre of the screen (1500 ms). To ensure source information was attended to, participants then indicated the former location of the cross on a now-blank circle using a computer mouse. Responses made within 6 degrees of the true target location were classified as a successful verification of attention and advanced participants to the next item. Responses further away were deemed unsuccessful, and the words “TRY AGAIN” was displayed for 1000 ms, the location was then re-presented for 250ms, and the verification task was repeated. Participants were then instructed to complete a distractor task, which involved 30 seconds of arithmetic problems. Following this, participants were shown a scrambled list of 10 previously studied items and 10 foils, and asked to rate each item on a six-point confidence Old/New scale. Finally, in the source memory retrieval task, participants were cued with the words for 1500 ms, and then indicated the recalled location by a clicking a mouse on the circumference of a grey response circle. There was no time limit on the decision task. A schematic for one trial in each of the phases is shown in Figure X.

# Results

**Data Screening**

Preliminary inspection of the data suggested that a proportion of the participants were performing the task with very low accuracy. A Rayleigh test for uniformity identified two participants whose data did not indicate evidence for a departure from uniformity in at least one condition, interpretable as completely random responding (Table X; Fisher, 1993). These participants will be referred to as a *low response accuracy* subgroup, with the expectation that the data from the remaining *high response accuracy* group will be more diagnostic for the purposes of distinguishing between the models.

|  |  |  |
| --- | --- | --- |
| Table X  Rayleigh Test for Uniformity for Source Memory Response Error | | |
| Participant | Mean Resultant Length | *p* |
| 1 | 0.02 | .87\* |
| 2 | 0.69 | <.01 |
| 3 | 0.44 | <.01 |
| 4 | 0.51 | <.01 |
| 5 | 0.55 | <.01 |
| 6 | 0.21 | <.01 |
| 7 | 0.57 | <.01 |
| 8 | 0.87 | <.01 |
| 9 | 0.10 | .01 |
| 10 | 0.87 | <.01 |
| 11 | 0.35 | <.01 |
| 12 | 0.66 | <.01 |
| 13 | 0.07 | .24\* |
| 15 | 0.08 | .04 |
| 16 | 0.54 | <.01 |
| 17 | 0.09 | <.01 |
| 18 | 0.62 | <.01 |
| 19 | 0.29 | <.01 |
| 20 | 0.28 | <.01 |

\* *p* values greater than 0.05, indicating no evidence of a departure from uniformity for participants 1 and 13.

## Source Memory for Unrecognized Items

Data for each participant was split into three categories on the basis of participants’ confidence in the recognition phase of the experiment. Items which were rated three and below were deemed unrecognized by the participants, while successful recognition was defined by a rating of four and above. Of the recognized items, ratings of the maximum value of six are further specified as highly recognized items.

Rayleigh tests applied to source responses for unrecognized are displayed in Table X. These responses were uniform across all participants, which indicates that no source memory was present when recognition confidence was low.

|  |  |  |
| --- | --- | --- |
| Table X  Rayleigh Test on Source Memory for Unrecognized Items | | |
| Participant | Test Statistic | *p* |
| 1 | 0.06 | 0.46 |
| 2 | 0.24 | 0.38 |
| 3 | 0.17 | 0.16 |
| 4 | 0.11 | 0.48 |
| 5 | 0.04 | 0.96 |
| 6 | 0.13 | 0.30 |
| 7 | 0.08 | 0.75 |
| 8 | 0.33 | 0.17 |
| 9 | 0.11 | 0.80 |
| 10 | 0.38 | 0.07 |
| 11 | 0.40 | 0.01 |
| 12 | 0.18 | 0.40 |
| 13 | 0.10 | 0.62 |
| 15 | 0.33 | 0.02 |
| 16 | 0.20 | 0.06 |
| 17 | 0.05 | 0.76 |
| 18 | 0.37 | 0.02 |
| 19 | 0.21 | 0.17 |
| 20 | 0.19 | 0.44 |

**Simple Mixture Model**

The mean best fitting parameters of the Zhang and Luck (2008) mixture model to the response accuracy data, excluding the low response accuracy group, are shown in Table X. The parameter estimates at an individual level are in Appendix X. Conditioning on recognition largely affects the precision parameter and not the memory parameter.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Table X | | | | |
| *Parameter Values for Best Fits of the Simple Mixture Model to Highly Recognized Individual Data.* | | | | |
| Recognition Rating | Low | | High | |
|  | Precision | *π* | Precision | *π* |
| All | 19.22 | 0.51 | 23.89 | 0.51 |
| Recognized | 18.24 | 0.50 | 23.79 | 0.54 |
| Highly Recognized | 18.03 | 0.50 | 19.81 | 0.56 |

*Note.*  Precision refers to the precision of the information-driven retrieval process. *π* represents proportion of responses driven by information.

**Circular Diffusion Models**

The three variants of the circular diffusion model were each fit to data at an individual level. The Bayesian Information Criterion (BIC) and Log Likelihood (LL) for the three models’ fits to each participant is shown in Table X.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Table X | |  | |  | |  | |
| Bayesian Information Criterion (BIC) and Log Likelihoods (LL) for Fits of the Models to Individual Data | | | | | | | |
| Participant | | Continuous | | Threshold | | Mixture | |
| BIC | LL | BIC | LL | BIC | LL |
| High Precision | 2 | 1072.10 | 2200.60 | 1003.11 | 2068.90 | 942.03\* | 1959.27 |
|  | 3 | 1003.21 | 2061.94 | 851.91\* | 1765.53 | 855.20 | 1784.44 |
|  | 4 | 1907.85 | 3878.09 | 1702.98 | 3475.27 | 1616.18\* | 3315.53 |
|  | 5 | 1127.15 | 2310.82 | 1014.05\* | 2090.91 | 1127.19 | 2329.75 |
|  | 6 | 771.93 | 1599.33 | 747.05\* | 1555.73 | 751.15 | 1576.26 |
|  | 7 | 766.43 | 1588.75 | 648.91\* | 1359.93 | 1529.70 | 3133.92 |
|  | 8 | 560.81 | 1178.03 | 302.98\* | 668.64 | 584.20 | 1243.61 |
|  | 9 | 1477.13 | 3010.53 | 1467.42 | 2997.37 | 1454.16\* | 2983.34 |
|  | 10 | 1023.30 | 2103.01 | 1044.56 | 2151.79 | 994.37\* | 2063.94 |
|  | 11 | 1244.35 | 2544.86 | 1103.18 | 2268.76 | 901.70\* | 1878.29 |
|  | 12 | 743.68 | 1543.59 | 493.95 | 1050.38 | 476.26\* | 1027.49 |
|  | 15 | 1300.51 | 2657.06 | 1343.38 | 2749.03 | 936.71\* | 1948.13 |
|  | 16 | 1000.38 | 2056.27 | 894.16 | 1850.00 | 888.14\* | 1850.28 |
|  | 17 | 1145.93 | 2045.93 | 1012.46\* | 2085.01 | 1039.42 | 2150.94 |
|  | 18 | 1030.68 | 2117.71 | 2049.63 | 4161.88 | 884.49\* | 1844.12 |
|  | 19 | 1782.81 | 3621.04 | 1469.25 | 3000.09 | 1391.70\* | 2857.30 |
|  | 20 | 1590.44\* | 3236.77 | 1666.55 | 3395.18 | 1685.63 | 3445.76 |
|  |  |  |  |  |  |  |  |
| Low Precision | 1 | 574.31 | 1197.40 | 635.49 | 1325.19 | 573.01\* | 1211.06 |
|  | 13 | 2079.41 | 4214.00 | 1717.02 | 3495.35 | 1558.26\* | 3190.09 |

\* Indicates lowest BIC

Both the threshold and the mixture models consistently outperformed the continuous model without guessing. This strongly suggests that participants sometimes do respond in a no-information guessing state, which is mixed with a distribution of responses driven by information which is centred on the target location. In comparing the two models which utilise a threshold, the mixture model appears to fit the data of most participants better than the pure threshold model, but this advantage is very slight and is outweighed by the penalty for complexity applied by the BIC for the two additional parameters allowing for trial-to-trial variability, as shown by the mixture model having the lowest negative log likelihood (LL) and the threshold model having the lowest BIC for most participants (Table X). This suggests that the addition of drift variability does not improve the fit of the threshold model enough to justify the additional complexity introduced into the model.

**Generalized von Mises Model**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table X  Parameter Estimates for Best Model Fits of the Generalized von Mises model without Criterion Variability | | | | | | | | | |
| Participant | *μ1* | *μ2* | *κ*1 | *κ2* | *η* | *ρ* | *a* | *Ter* | *st* |
| 1 | 3.40 | 3.38 | 0.39 | 0.61 | 1.47 | 0.20 | 2.67 | -0.34 | 0.11 |
| 2 | 2.96 | 3.04 | 3.99 | 4.31 | 0.51 | 0.06 | 4.51 | -0.32 | 0.00 |
| 3 | 3.94 | 3.96 | 2.77 | 2.95 | 1.17 | 0.16 | 3.73 | -0.35 | 0.11 |
| 4 | 4.42 | 4.50 | 3.16 | 3.57 | 1.35 | 0.02 | 4.27 | -0.17 | 0.02 |
| 5 | 3.70 | 3.85 | 3.46 | 3.81 | 1.18 | 0.09 | 4.50 | -0.30 | 0.09 |
| 6 | 1.11 | 1.66 | 10.53 | 9.26 | 1.28 | 0.02 | 1.06 | 0.22 | 0.00 |
| 7 | 3.67 | 3.67 | 3.73 | 3.81 | 0.80 | 0.07 | 2.63 | -0.33 | 0.30 |
| 8 | 3.89 | 3.93 | 4.73 | 5.69 | 0.90 | 0.03 | 3.54 | -0.10 | 0.00 |
| 9 | 1.85 | 2.03 | 0.48 | 0.10 | 0.37 | 0.31 | 1.45 | -0.16 | 0.05 |
| 10 | 3.35 | 3.44 | 5.37 | 6.40 | 1.30 | 0.02 | 4.52 | 0.00 | 0.14 |
| 11 | 0.91 | 0.96 | 6.79 | 10.50 | 1.18 | 0.04 | 1.22 | -0.06 | 0.01 |
| 12 | 3.97 | 3.81 | 3.98 | 3.85 | 0.01 | 0.08 | 4.51 | -0.35 | 0.06 |
| 13 | 1.63 | 2.13 | 1.31 | 0.40 | 1.46 | 0.02 | 1.09 | -0.16 | 0.15 |
| 15 | 3.34 | 3.76 | 1.18 | 0.57 | 1.94 | 0.13 | 1.56 | -0.14 | 0.33 |
| 16 | 2.44 | 2.45 | 3.32 | 3.87 | 0.39 | 0.10 | 3.07 | -0.22 | 0.02 |
| 17 | 2.49 | 2.60 | 0.61 | 0.87 | 0.56 | 0.07 | 3.25 | -0.35 | 0.08 |
| 18 | 3.55 | 3.60 | 3.71 | 3.55 | 0.96 | 0.10 | 4.51 | -0.22 | 0.08 |
| 19 | 3.41 | 3.41 | 1.76 | 2.12 | 0.82 | 0.09 | 2.16 | -0.31 | 0.19 |
| 20 | 0.38 | 1.35 | 5.47 | 2.22 | 0.62 | 0.17 | 1.05 | -0.14 | 0.00 |

**QQ plots will be helpful , shows joint distribution, flat RT quantiles.**

# Discussion

The first aim of this article was to conduct a version of the Harlow and Donaldson (2013) experimental paradigm and determine whether their finding that source performance was thresholded would still hold when conditioned on item recognition. Source accuracy for unrecognized items was uniform across all participants, which suggests that there was no source memory for trials in which recognition failed. Even with these trials excluded, a heavy-tailed pattern was present in most participants’ source responses. The simple mixture model, which incorporates a uniform distribution of response error on a proportion of trials, captured this heavy-tailed property of the data well.

The second aim was to apply the Smith (2016) circular diffusion model to determine if the addition of an elaborated model of the decision process would account for source accuracy and RT, specifically if the heavy tails produced by across-trial drift rate variability would fit observed data. Comparison of the continuous, threshold and hybrid variants of the circular diffusion model shows a preference for the models which allow for a mixture of a positive drift and a zero-drift process, namely the threshold and hybrid models. Across-trial drift rate variability is not sufficient to fit the tails in the distribution of response error, and in comparing the threshold and hybrid models, the addition of drift rate variability in the latter does not improve the fit of the model to data. The heavy tails instead appear to be a product of no information being available on a proportion of trials. RT data corroborates this conclusion, as no slow error pattern was observed in the joint distribution of RT and response accuracy, which would be predicted by the continuous model that relies on trial-to-trial drift rate variability. As this pattern of response is present even when recognition is successful, it can be inferred that the no-information state is not simply due to a failure to attempt source memory retrieval, as in the Hautus et al. (2008) model.

With the generalized von Mises model, we allow for non-linear scaling of source location stimuli to the representation of this information which serves as the phase angle component of drift in the evidence accumulation process. The earlier comparison of circular diffusion models suggests that a threshold underlies performance in source memory tasks. The generalized von Mises model arrives at a similar conclusion through an entirely different parameterization of across-trial variability.

Some qualifications must be made when drawing conclusions from this study. Firstly, the sequential presentation of item and source information may constitute a methodological bias towards the appearance of discrete failures as the temporal separation of the two parts increases the difficulty of binding the item to its supposedly associated source. The current modelling exercise is not able to distinguish between errors arising from such a failure and errors due to a retrieval threshold. The original motivation for presenting item and source information in this manner was to replicate the Harlow and Donaldson (2013) paradigm, in which these components were separated to prevent *unitized familiarity*, meaning that unitization of source and item might allow participants to use familiarity to complete the task, making it “more difficult to isolate a recollection threshold”. This methodology assumes a Yonelinas (1999) dual-process framework, and potentially biases results to reflect the supposed recollection threshold it was meant to isolate. There is no reason to expect that source memory in a natural environment would operate under these conditions, and a model of source memory should be able to characterize performance when source and item information is presented simultaneously. An illuminative future experiment might be to modify the experimental paradigm so that source and item are presented simultaneously in this manner, to investigate if the models presented in this article perform similarly under simultaneous presentation.

Secondly, overall performance in the source memory task was poor. Even barring the two participants whose responses did not deviate from uniformity, several participants exhibited a high rate of guessing, although their responses were not strictly uniform according to the Rayleigh test. If only a proportion of responses in the task were driven by source information, it is possible that our conclusions made on the basis of that proportion could change if overall performance was enhanced. This could be done by making the source memory task easier, perhaps with additional correlated source information or shorter study lists, to see if the present findings still hold with higher overall source accuracy.

**Implications for Models of Source Memory**

The present data corroborates the Harlow and Donaldson (2013) finding that performance on the source memory task is comprised of two components: informed responses made in an information-driven state, and guesses made in a no-information state. This corroboration comes with additional support from source response data conditioned on recognition, and a decision model that is able to account for newly collected RT data in addition to source accuracy data. Having determined that participants undertaking this task guess, it is not yet clear why these guesses arise.

SAM model, recall works by given a cue and you use to sample memories, memory strengths have to exceed a certain threshold to be output. Underlying strength is continuous. Location on circle is retrieved, with continuous strength,

**Application of the Circular Diffusion Model**

In its first application modelling performance in a continuous report memory task, the circular diffusion was successful in providing a quantitative account of both RTs and response accuracy. Continuous report tasks are more informative than two-choice alternatives because they allow insight into the precision with which a response is made, rather than categorizing responses as correct or incorrect. The circular diffusion model is able to capitalize on the additional information continuous report affords to investigate the properties of decision-making in cognitive tasks. By characterizing the decision processes when response outcomes are continuous, the circular diffusion model represents the latest development in tools with which to investigate cognitive processes underlying performance, through understanding the properties of decision-making that ultimately translate cognition into a response.

**Appendices**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table X | | | | | |
| *Parameter Values for Best Fits of the Simple Mixture Model to All Individual Data.* | | | | | |
|  | | Low Imageability | | High Imageability | |
| Participant | | Precision | *π* | Precision | *π* |
| High Accuracy |  |  |  |  |  |
|  | 2 | 25.09 | 0.63 | 17.12 | 0.71 |
|  | 3 | 10.68 | 0.39 | 10.66 | 0.51 |
|  | 4 | 31.42 | 0.45 | 46.22 | 0.50 |
|  | 5 | 20.65 | 0.45 | 18.52 | 0.61 |
|  | 6 | 15.63 | 0.20 | 13.41 | 0.17 |
|  | 7 | 12.88 | 0.59 | 8.93 | 0.63 |
|  | 8 | 40.57 | 0.80 | 43.17 | 0.89 |
|  | 9 | 0.22 | 0.77 | 0.07 | 1.00 |
|  | 10 | 53.96 | 0.81 | 51.78 | 0.85 |
|  | 11 | 8.69 | 0.32 | 13.83 | 0.38 |
|  | 12 | 37.94 | 0.64 | 44.94 | 0.64 |
|  | 15 | 0.20 | 1.00 | 82.47 | 0.03 |
|  | 16 | 16.50 | 0.51 | 11.31 | 0.58 |
|  | 17 | 0.99 | 0.11 | 4.62 | 0.10 |
|  | 18 | 10.03 | 0.66 | 25.56 | 0.58 |
|  | 19 | 13.73 | 0.17 | 3.34 | 0.33 |
|  | 20 | 27.57 | 0.13 | 10.19 | 0.22 |
|  |  |  |  |  |  |
| Low Accuracy | 1 | 10.89 | 0.04 | 250.00 | 0.02 |
|  | 13 | 64.12 | 0.02 | 249.95 | 0.01 |

*Note.*  Precision refers to the precision of the information-driven retrieval process. *π* represents proportion of responses driven by information.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table X | | | | | |
| *Parameter Values for Best Fits of the Simple Mixture Model to Recognized Individual Data.* | | | | | |
|  | | Low Imageability | | High Imageability | |
| Participant | | Precision | *π* | Precision | *π* |
| High Accuracy |  |  |  |  |  |
|  | 2 | 24.51 | 0.66 | 17.36 | 0.73 |
|  | 3 | 11.76 | 0.45 | 10.47 | 0.54 |
|  | 4 | 32.44 | 0.48 | 44.47 | 0.54 |
|  | 5 | 18.51 | 0.47 | 16.80 | 0.65 |
|  | 6 | 12.90 | 0.27 | 8.86 | 0.23 |
|  | 7 | 12.17 | 0.65 | 9.11 | 0.69 |
|  | 8 | 37.43 | 0.87 | 42.93 | 0.89 |
|  | 9 | 0.57 | 0.29 | 0.10 | 1.00 |
|  | 10 | 49.40 | 0.87 | 49.08 | 0.87 |
|  | 11 | 7.90 | 0.35 | 13.10 | 0.39 |
|  | 12 | 36.72 | 0.73 | 46.67 | 0.69 |
|  | 15 | 5.39 | 0.13 | 85.49 | 0.04 |
|  | 16 | 15.53 | 0.55 | 11.01 | 0.64 |
|  | 17 | 0.27 | 0.64 | 5.81 | 0.10 |
|  | 18 | 9.77 | 0.69 | 27.61 | 0.59 |
|  | 19 | 14.27 | 0.19 | 5.45 | 0.32 |
|  | 20 | 20.61 | 0.15 | 10.15 | 0.25 |
|  |  |  |  |  |  |
| Low Accuracy | 1 | 157.24 | 0.05 | 250.00 | 0.02 |
|  | 13 | 45.64 | 0.03 | 250.00 | 0.02 |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Table X | | | | | |
| *Parameter Values for Best Fits of the Simple Mixture Model to Highly Recognized Individual Data.* | | | | | |
|  | | Low Imageability | | High Imageability | |
| Participant | | Precision | *π* | Precision | *π* |
| High Accuracy |  |  |  |  |  |
|  | 2 | 22.47 | 0.69 | 16.61 | 0.76 |
|  | 3 | 12.11 | 0.48 | 9.97 | 0.58 |
|  | 4 | 33.96 | 0.50 | 43.79 | 0.58 |
|  | 5 | 19.47 | 0.47 | 16.12 | 0.67 |
|  | 6 | 13.73 | 0.31 | 13.30 | 0.24 |
|  | 7 | 11.58 | 0.69 | 8.90 | 0.74 |
|  | 8 | 36.73 | 0.88 | 42.74 | 0.89 |
|  | 9 | 0.69 | 0.27 | 0.14 | 1.00 |
|  | 10 | 49.03 | 0.87 | 47.47 | 0.89 |
|  | 11 | 8.27 | 0.39 | 12.60 | 0.39 |
|  | 12 | 38.12 | 0.76 | 45.42 | 0.73 |
|  | 15 | 1.45 | 0.38 | 22.78 | 0.08 |
|  | 16 | 15.53 | 0.55 | 10.80 | 0.64 |
|  | 17 | 0.90 | 0.20 | 5.27 | 0.11 |
|  | 18 | 9.95 | 0.71 | 25.90 | 0.60 |
|  | 19 | 14.27 | 0.19 | 5.45 | 0.32 |
|  | 20 | 18.29 | 0.17 | 9.52 | 0.26 |
|  |  |  |  |  |  |
| Low Accuracy | 1 | 192.59 | 0.05 | 0.22 | 1.00 |
|  | 13 | 3.69 | 0.10 | 250.00 | 0.02 |