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**Binding Processes in Episodic Memory:  
Measurement, Structure, and Moderators**

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For my family



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## Summary

Episodic memory enables people to remember personally experienced events. While these events consist of different elements, people are able to form coherent memory representations. This requires that an event's constituent elements are bound together in memory. Despite the importance of these binding processes for episodic memory, they are still only poorly understood and our abilities to measure them are limited.

In this thesis, comprising three articles, I provide a new approach for measuring binding effects and use this measure to probe properties of binding processes in episodic memory. In the first article, I introduce the new measurement approach and evaluate its suitability for measuring binding effects in comparison to previous approaches. I show that the approach has good measurement properties and is better suited for measuring binding effects than previous approaches. In the second article, I examine the structure in which event elements are bound together and whether animacy influences binding processes. I show that different binding structures are possible, such as an integrated binding structure, in which event elements are bound into a unitary representation, and a hierarchical binding structure, in which event elements are preferentially bound to particular types of elements. These may lie on a continuum of memory representations with varying degrees of integration. I further show that the presence of an animate element in an event facilitates binding, enabling more coherent memory representations with a higher degree of integration. In addition, awareness regarding commonalities of types of event elements across events may facilitate binding. In the third article, I examine whether agency influences binding processes. I show that the presence of an agentic element in an event may facilitate binding, but evidence was not conclusive and effects may have been concealed due to low memory performance. Agency may thus underlie the previously found facilitating effect of animacy on binding, since animate elements may exert their influence by providing a potential agent in an event.

One aim of my thesis is to provide a new tool for investigating binding processes in episodic memory. An additional aim is to extend our current understanding of binding structures that link together the elements of an event, as well as the factors that moderate binding processes. In doing so, I hope to advance our understanding of binding processes and enable and inform future exploration, as well as theory development and refinement, of this fundamental property underlying episodic memory.





## Articles

This cumulative thesis is based on three articles, two of which have been published and one that has been submitted for publication.

### Article I

Schreiner, M. R., & Meiser, T. (2022). Measuring binding effects in event-based episodic representations. *Behavior Research Methods*. Advance online publication. <https://doi.org/10.3758/s13428-021-01769-1>

### Article II

Schreiner, M. R., Meiser, T., & Bröder, A. (2022). The binding structure of event elements in episodic memory and the role of animacy. *Quarterly Journal of Experimental Psychology*. Advance online publication. <https://doi.org/10.1177/17470218221096148>

### Article III

Schreiner, M. R., Bröder, A., & Meiser, T. (2022). *Agency effects on the binding of event elements in episodic memory*. Manuscript submitted for publication.



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# 1 Binding Processes in Episodic Memory

In our everyday life we encounter a multitude of events, such as buying a bread at a bakery, meeting a friend in the streets, or having a meeting at work. Episodic memory refers to the capacity of remembering such experiences and has been described as a form of “mental time travel” that allows individuals to re-experience past events (Tulving, 1972, 1983, 1993). These past events are comprised of several different elements. For example, the event of buying bread at a bakery may consist of the vendor selling the bread (a person), the bought bread (an object), and the bakery (a location). In addition, there may be further sensory elements such as the smell of the bread or the noise of an oven. Yet, we do not have isolated representations of these different event elements, but are instead able to remember the entire event in a coherent manner. This necessitates that event elements, despite being represented in different neocortical regions (Alvarez & Squire, 1994; Horner et al., 2015), are bound together in memory to enable the formation of coherent memory representations. The ability to form such bindings develops from early childhood to young adulthood (Ngo et al., 2019; Reese et al., 2011; Schlichting et al., 2017), but decreases in old age (Naveh-Benjamin, 2000; Ngo & Newcombe, 2021; Old & Naveh-Benjamin, 2008). In the present thesis, I investigate a number of fundamental properties of this essential ability underlying episodic memory using statistical modeling.

## 1.1 Item- vs. Event-Based Representations

Episodic memories may vary in complexity. Some representations may only consist of a single element with specific features, for example an object with a certain color and shape such as the bread one bought at a bakery . Such *item-based representations* are static (see Hunt & Einstein, 1981). More complex episodic memories may incorporate several event elements that can potentially interact (e.g., buying bread at a bakery involves the vendor interacting with the bread). Such *event-based representations* are thus potentially dynamic (see also Rubin & Umanath, 2015). Event-based representations can be considered to be comprised of item-based representations, with storage occurring in a hierarchical manner (see Andermane et al., 2021). Event- and item-based representations may also be distinguished based on the specificity of the stored information, with item-based representations containing more specific information than event-based representations (Hunt & Einstein, 1981). Further, unlike item-based representations, event-based representations incorporate a spatiotemporal

context (e.g., Andermane et al., 2021) and allow for the construction of scenes (Robin, 2018; Rubin & Umanath, 2015). This does not necessitate that the specific features of an event’s constituent elements, which are stored as item-based representations, are exactly remembered (Rubin & Umanath, 2015). The present thesis focuses on event-based representations.

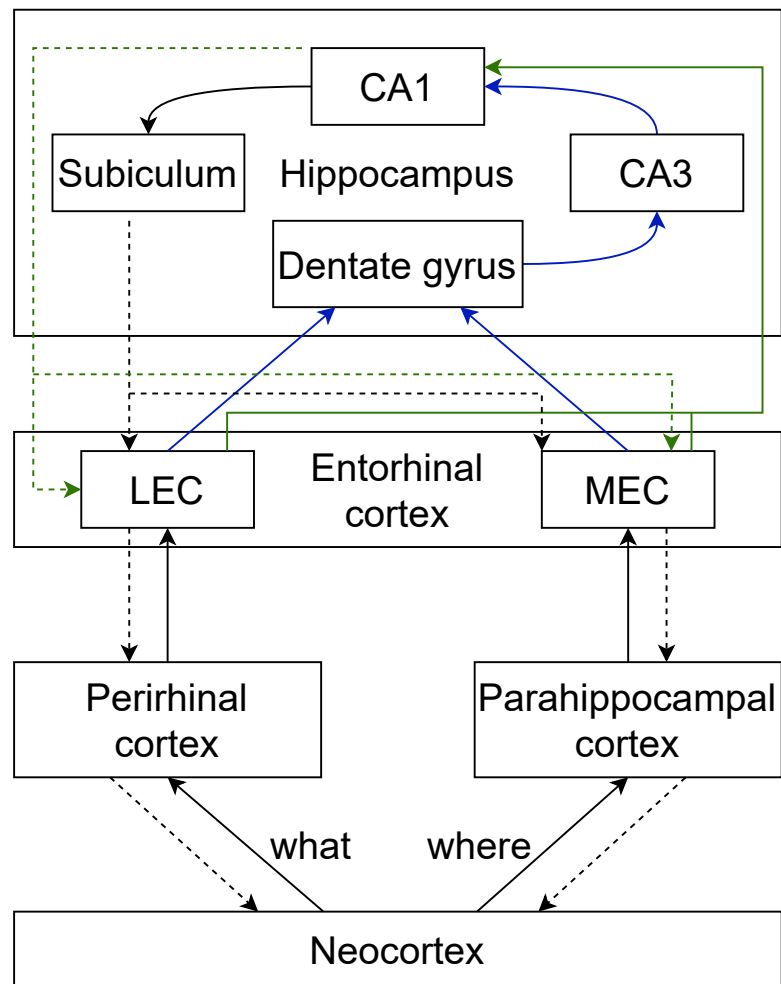
## 1.2 Neural Foundations of Binding in Episodic Memory

The conceptual distinction between item-based representations and event-based representations, which include spatiotemporal and relational information, is sustained by various neurocognitive mechanisms and brain regions. Generally, the medial temporal lobe, encompassing the perirhinal, entorhinal, and parahippocampal cortex and the hippocampus, plays a crucial role in episodic memory (Eichenbaum et al., 2007; Squire & Zola-Morgan, 1991). Specifically, the formation of event-based representations is primarily supported by the hippocampus, which is commonly seen as the structure responsible for the binding of event elements (Backus et al., 2016; N. J. Cohen & Eichenbaum, 1993; Davachi et al., 2003; Diana et al., 2010; Eichenbaum et al., 2007) and capable of combining different types of information (object, spatial, and temporal information; Sugar & Moser, 2019).

The flow of information between neocortical areas to the hippocampus is depicted in Figure 1. Information from perceptual processing areas in the neocortex is increasingly aggregated via feedforward projections to the hippocampus (Eichenbaum et al., 2007; Rolls, 2016; van Strien et al., 2009). While the processing and binding of temporal information (“when” information) may consist of a widespread brain system involving activity in the hippocampus, lateral entorhinal cortex (LEC), medial entorhinal cortex (MEC), and additional brain regions (see Eichenbaum, 2017), it has been proposed that there are two pathways for object and spatial information, respectively, which converge in the hippocampus (Eichenbaum et al., 2007; Rolls, 2016; van Strien et al., 2009). A pathway for object information (“what” pathway) involves the perirhinal cortex, which projects to the LEC. A pathway for spatial information (“where” pathway) involves the parahippocampal cortex, which projects to the MEC. Both the LEC and MEC have reciprocal connections with the hippocampus. The hippocampus itself encompasses different subregions — dentate gyrus, cornu ammonis (CA), which can be divided into further subregions (CA1-4), and subiculum (Aggleton & Brown, 1999; Saunders & Rosene, 1988). Within the hippocampus, there are two main pathways, which are strongly involved in binding in episodic memory.

**Figure 1**

*Feedforward projections from the neocortex to the hippocampus via the perirhinal, parahippocampal, and entorhinal cortex (solid lines), and backprojections from hippocampal subfields CA1 and subiculum to the neocortex (dashed lines). Blue arrows make up the trisynaptic pathway and green arrows make up the monosynaptic pathway.*



*Note.* what = object information, where = spatial information, LEC = lateral entorhinal cortex, MEC = medial entorhinal cortex, CA = cornu ammonis.

The trisynaptic pathway allows binding within events to form new episodic representations. It involves projections from the entorhinal cortex to the dentate gyrus, which is associated with pattern separation, segregating similar memories by reducing their representational overlap (Bakker et al., 2008; Neunuebel & Knierim, 2014; Rolls, 2016). Dentate gyrus projects to CA3, which is associated with relational binding (i.e., associating individual elements separated by space or time) and may act as an autoassociative network, enabling pattern completion — a whole representation being retrieved by partial activation of the representation through a recall cue (Nakazawa et al., 2002; Neunuebel & Knierim, 2014; Rolls, 2016). CA3 then projects to CA1, which is also associated with relational binding and may be particularly important for binding across temporarily divided encoding episodes (Rolls, 2016; Schlichting et al., 2014). CA1 projects back to the entorhinal cortex and, in addition, to the subiculum, which is the major output structure of the hippocampus (O’Mara et al., 2001; O’Mara, 2005; Rolls, 2016).

The monosynaptic pathway allows learning of regularities and changes across different encoding episodes and events (McClelland et al., 1995; Schapiro et al., 2017; van Strien et al., 2009). It involves direct reciprocal projections between the entorhinal cortex and CA1. Information is retrieved via backprojections from the hippocampus (CA1 and subiculum) to the neocortex (Eichenbaum et al., 2007; Rolls, 2016; van Strien et al., 2009).

In the bakery example, activation regarding the vendor and bread would travel through the “what” pathway and activation regarding the bakery would travel through the “where” pathway. The activation regarding the different types of information would converge in the hippocampus and the different event elements would be bound into a coherent memory representation via the trisynaptic pathway. The dentate gyrus would differentiate event elements in this particular event from other similar events, for example another occasion where one bought a different bread at the same bakery. CA3 and CA1 would then bind the vendor, the bread, and the bakery together, potentially including temporal information such as the time of day one went to the bakery. Then, a coherent memory representation could be retrieved through backprojections from CA1 and via the subiculum to the neocortex.

While investigating the neural mechanisms underlying binding processes in episodic memory is important for a deeper understanding of these processes, binding effects can not only be assessed with neural data, but also with behavioral data. An advantage of assessing binding effects using behavioral instead of neural data

is that such studies are much easier to conduct, less resource-intensive, and allow for larger sample sizes. In addition, some aspects of binding may not be properly examinable using neural data, but warrant investigation on a more functional level, which can be achieved by statistical modeling. In the present thesis, I use a theory-driven combination of behavioral experiments and statistical modeling to investigate binding processes in episodic memory.

### **1.3 Stochastic Dependency of the Retrieval of Event Elements**

As a consequence of successful binding, the likelihood of retrieving event elements (e.g., the bread) is increased if other event elements (e.g., the vendor or the bakery) are successfully retrieved, leading to a stochastic dependency of the retrieval of event elements (Arnold et al., 2019; Boywitt & Meiser, 2012a, 2012b; Horner et al., 2015; Horner & Burgess, 2013, 2014; Meiser & Bröder, 2002; Starns & Hicks, 2005, 2008). This stochastic dependency can be viewed as a manifestation of binding processes in episodic memory. Thus, by modeling this dependency, one can draw inferences on binding processes based on behavioral data.

In this thesis, I subsequently introduce a number of existing, contingency-based, approaches for modeling the stochastic dependency of the retrieval of event elements before introducing a newly developed approach (Schreiner & Meiser, 2022; Schreiner, Meiser, & Bröder, 2022) based on item response theory (IRT, Lord, 1980; Lord & Novick, 1968) and evaluating the different approaches regarding their suitability for measuring binding effects in episodic memory. Furthermore, I examine the structure in which different event elements are bound together, and influences of animacy and agency on the binding of event elements in episodic memory. In the first article (Schreiner & Meiser, 2022), I evaluate the different modeling approaches and show that the newly developed IRT-based approach performs best, yielding unbiased estimates, good maintenance of Type I error rates, and high power for detecting binding effects. In the second article (Schreiner, Meiser, & Bröder, 2022), I use this IRT-based approach to investigate the structure in which different event elements are bound together and to examine influences of animacy on binding processes. There, I demonstrate that binding structures may vary, with the possibility of both hierarchical binding structures, in which event elements are preferentially bound to particular types of event elements, and integrated binding structures, in which event elements

are bound into a fully integrated representation or engram (cf. Tulving, 1983). I further demonstrate that the presence of an animate element in an event facilitates binding. Finally, in the third article (Schreiner, Bröder, & Meiser, 2022), I examine influences of agency on binding processes, since agency may be a more proximate explanation for the previously found effects of animacy. There, I provide suggestive evidence that the presence of an agentic element in an event facilitates binding.



## 2 Approaches for Measuring Binding Effects

### 2.1 Contingency-Based Approaches

One class of approaches for modeling stochastic dependencies of the retrieval of event elements can be applied to data from which one can create meaningful dependency pairs, such as cued recognition (or paired associates matching) and cued recall tasks. Dependency pairs can be, for example, items (i.e., test trials in a memory test) that share a common cue or target element (see Horner & Burgess, 2013). For example, when an event consists of three elements — a person, an object, and a location, as is the case in the bakery example — the cue-target pairs, person–object and person–location, can be considered a dependency pair, since both items share a common cue (the person element). For a given dependency pair  $jj'$ , one can create a contingency table  $\mathbf{X}$  for each person  $i$  and event  $t$ , that shows whether the targets of the dependency pair were retrieved successfully (denoted by 1) or were not retrieved (denoted by 0):

$$\mathbf{X}_{it}^{jj'} = \begin{bmatrix} j = 1, j' = 1 & j = 1, j' = 0 \\ j = 0, j' = 1 & j = 0, j' = 0 \end{bmatrix} \quad (1)$$

By summing these contingency tables over events one obtains a contingency table for each person and dependency pair:

$$\mathbf{X}_i^{jj'} = \begin{bmatrix} n_{11} & n_{10} \\ n_{01} & n_{00} \end{bmatrix}, \quad (2)$$

where  $n_{11}$  denotes the frequency of the targets of both items  $j$  and  $j'$  being successfully retrieved across events,  $n_{10}$  denotes the frequency of the target of item  $j$  being successfully retrieved and that of item  $j'$  not being retrieved,  $n_{01}$  denotes the frequency of the target of item  $j$  not being retrieved and that of item  $j'$  being successfully retrieved, and  $n_{00}$  denotes the frequency of the targets of both items  $j$  and  $j'$  not being retrieved. The subsequently described contingency-based approaches for modeling stochastic dependencies of the retrieval of event elements are based on the contingency tables in Equation 2.

### 2.1.1 Approach by Horner and Burgess

In the approach by Horner and Burgess (2013), two dependency indices are calculated from the contingency tables in Equation 2. First, a data-based dependency index ( $D_{\text{HB}, i}^{\text{data}}$ ), that reflects the average proportion of items in an event whose targets were both successfully retrieved or not retrieved, is calculated by summing the leading diagonal cells of each contingency table per person and dependency pair and dividing this sum by the total number of events<sup>1</sup>  $T$ . Then, the index is obtained by averaging across the set of dependency pairs  $J$ :

$$D_{\text{HB}, i}^{\text{data}} = \frac{1}{|J|} \sum_{jj' \in J} \frac{n_{11} + n_{00}}{T} \quad (3)$$

Second, a dependency index from an “independent model” ( $D_{\text{HB}, i}^{\text{ind}}$ ) is calculated by multiplying the probability of successfully retrieving or not retrieving the items’ targets as if item responses were independent:

$$D_{\text{HB}, i}^{\text{ind}} = \frac{1}{|J|} \sum_{jj' \in J} \left( \frac{n_{11} + n_{10}}{T} \frac{n_{11} + n_{01}}{T} + \left(1 - \frac{n_{11} + n_{10}}{T}\right) \left(1 - \frac{n_{11} + n_{01}}{T}\right) \right) \quad (4)$$

The actual dependency measure ( $D_{\text{HB}, i}$ ) is then computed by subtracting the two indices:

$$D_{\text{HB}, i} = D_{\text{HB}, i}^{\text{data}} - D_{\text{HB}, i}^{\text{ind}} \quad (5)$$

This is done to avoid scaling with memory performance, since  $D_{\text{HB}, i}^{\text{data}}$  necessarily increases if many or few event elements were successfully retrieved due to strong or poor overall memory performance. The measure can take values between -1 and 1, where 0 indicates independence, positive values indicate dependency (i.e., the likelihood of retrieving an event element is larger if another event element was successfully retrieved), and negative values indicate negative dependency (i.e., the likelihood of retrieving an event element is smaller if another event elements was successfully retrieved).

### 2.1.2 Yule’s Q

Another approach for modeling stochastic dependencies of the retrieval of event elements is Yule’s Q (Yule, 1912; cf. Horner & Burgess, 2014; see also Hayman &

<sup>1</sup>An event can be broadly described as a set of elements or stimuli that are somehow related (e.g., due to spatial or temporal contiguity).

Tulving, 1989), a standardized odds ratio which is commonly used as a measure of association in memory research (e.g., Kahana, 2002; Kahana et al., 2005). Yule's  $Q$  can be calculated from the contingency tables in Equation 2 to receive person- and dependency-pair-specific indices using the following equation:

$$Q_i^{jj'} = \frac{n_{11}n_{00} - n_{10}n_{01}}{n_{11}n_{00} + n_{10}n_{01}} \quad (6)$$

By averaging across dependency pairs one can then receive person-specific indices:

$$Q_i = \frac{1}{|J|} \sum_{jj' \in J} Q_i^{jj'} \quad (7)$$

The interpretation of this measure is equivalent to the interpretation of the measure by Horner and Burgess (2013).

### 2.1.3 Adjusted Yule's $Q$

A problem of Yule's  $Q$  is that zero frequencies in the contingency table it is calculated from (e.g.,  $n_{10} = 0$ ) cause it to be bound at its extreme values (-1 or 1) or become undefined. Consider the contingency table in Table 1 from an example by Hintzman (1980) with two outcomes ( $Y_1$  and  $Y_2$ ).

**Table 1**

*Example contingency table with two outcomes  $Y_1$  and  $Y_2$  from an example by Hintzman (1980).*

	$Y_2 = 1$	$Y_2 = 0$
$Y_1 = 1$	20	0
$Y_1 = 0$	60	20

Calculating Yule's  $Q$  from Equation 6 results in a value of  $Q = 1$  (indicating a perfect positive association between the two outcomes). One can circumvent this problem by adding a constant  $c$  to each cell of the contingency tables in Equation 2 (cf. Burton et al., 2019; Horner & Burgess, 2014; see also Snodgrass & Corwin, 1988) to calculate an adjusted Yule's  $Q$  ( $Q_a$ ) using Equations 6 and 7. Adding  $c = 0.5$  to each cell of the contingency table in the example in Table 1 results in a value of  $Q_a = 0.87$ .

### 2.1.4 Simpson's Paradox

A general problem of the contingency-based approaches is that they rely on contingency tables that are aggregated across events. This makes them prone to Simpson's paradox (Hintzman, 1972, 1980; Simpson, 1951) — if  $2 \times 2$  contingency tables are collapsed into a summary one, the relationship of the two outcomes may differ from the one in the original tables. For instance, consider the example by Hintzman (1980) depicted in Table 2. Both of the original tables ( $A$  and  $B$ ) yield values of  $Q_a = 0.87$  (using  $c = 0.5$ ), indicating a positive relationship of the two outcomes. However, there is a third unobserved variable  $Z$  that is positively related to the first outcome and negatively related to the second outcome of the two contingency tables (Hintzman, 1980). The first original table corresponds to  $Z = 1$  and second original table corresponds to  $Z = 2$ . Collapsing the two contingency tables (i.e., collapsing over  $Z$ ) results in the summary table ( $A + B$ ). The summary table yields a value of  $Q_a = -0.38$ , indicating a negative relationship of the two outcomes ( $Y_1$  and  $Y_2$ ). Thus, the relationship of the two outcomes is inverted compared to the relationship in the original tables. Simpson's paradox can occur due to confounding with person differences, item differences, or person-item interactions (Hintzman, 1972, 1980; see also Burton et al., 2017). Since all of the presented contingency-based approaches yield person-specific dependency estimates, confounding with person differences is not an issue. However, the approaches may be subject to confounding with item differences and person-item interactions.

**Table 2**

*Example by Hintzman (1980) for collapsing two contingency tables into a summary one and associated  $Q_a$  values.*

A			B			A + B		
Z = 1	Y <sub>2</sub> = 1	Y <sub>2</sub> = 0	Z = 2	Y <sub>2</sub> = 1	Y <sub>2</sub> = 0	Y <sub>2</sub> = 1	Y <sub>2</sub> = 0	
Y <sub>1</sub> = 1	20	0	Y <sub>1</sub> = 1	20	60	Y <sub>1</sub> = 1	40	60
Y <sub>1</sub> = 0	60	20	Y <sub>1</sub> = 0	0	20	Y <sub>1</sub> = 0	60	40
$Q_a = 0.87$			$Q_a = 0.87$			$Q_a = -0.38$		

*Note.*  $Q_a$  were calculated by adding  $c = 0.5$  to each cell of the contingency tables.

## 2.2 An IRT-Based Approach

Schreiner, M. R., & Meiser, T. (2022). Measuring binding effects in event-based episodic representations. *Behavior Research Methods*. Advance online publication. <https://doi.org/10.3758/s13428-021-01769-1>

### 2.2.1 Parametric Variant

In the first article (Schreiner & Meiser, 2022; see also the second article, Schreiner, Meiser, & Bröder, 2022), we introduced a novel approach for measuring binding effects by modeling the stochastic dependency of the retrieval of event elements that is based on item response theory (IRT; Lord, 1980; Lord & Novick, 1968). This approach takes individual item responses rather than aggregated contingency tables as input and is consequently not prone to confounding due to Simpson’s paradox. Since IRT takes person and item differences, and person-item interactions into account, confounding with these covariates is avoided. The approach is based on the three-parameter logistic IRT model by Birnbaum (1968), because this model allows one to take guessing into account, which may frequently occur in memory tests (see e.g., Huff et al., 2011). Thus, one can model the probability of person  $i$  to give a correct response  $u$  to item  $j$  given a latent trait  $\theta$  (i.e., memory performance in the current model application), item difficulties  $\beta$ , item discrimination parameters  $\alpha$ , and item guessing parameters  $\gamma$ :

$$P(u_{ij} = 1) = \gamma_j + (1 - \gamma_j) \frac{e^{\alpha_j(\theta_i - \beta_j)}}{1 + e^{\alpha_j(\theta_i - \beta_j)}} \quad (8)$$

For the purpose of measuring binding effects, this model can usually be simplified in practical applications. In experimental investigations of binding processes, events are usually randomly generated for each participant. Thus, one may fix the item discrimination parameters to 1 (cf. the Rasch model; Rasch, 1960). If testing involves several response alternatives one may a priori fix the guessing parameters to a constant  $g$ , for example equal to the stochastic guessing probability given a fixed number of response alternatives (e.g., 0.2 for five response alternatives). Such a simplified model is described by the following equation:

$$P(u_{ij} = 1) = g + (1 - g) \frac{e^{\theta_i - \beta_j}}{1 + e^{\theta_i - \beta_j}} \quad (9)$$

The approach utilizes violations of an assumption inherent in many IRT models that follow from successful binding of event elements. The assumption of local indepen-

dence (LI) implies that item responses are independent after partialing out the latent trait (de Ayala, 2009; Lazarsfeld & Henry, 1968) and that item residual correlations are thus zero. However, given successful binding, there are additional event-specific effects that lead to a violation of the LI assumption. This leads to item residual correlations that systematically deviate from zero, such that elements of a common event are more likely to be retrieved together, or not to be retrieved together, than elements of different events. In the current approach, item residual correlations are estimated using the  $Q_3$  statistic (Yen, 1984). This statistic can be calculated for each item pair  $jj'$  (i.e., for each pairwise combination of test trials in a memory test) in four steps: (1) person and item parameters are estimated from a suitable IRT model, such as the model in Equation 9, (2) the model-implied probability for giving a correct response to each item in the item pair is derived from the model parameters, (3) the item residuals are calculated as the difference between the model-implied probability of a correct response and the observed response for each person, and (4)  $Q_3$  is calculated as the Pearson correlation of the residuals of both items across persons. Yen (1993) noted that  $Q_3$  is negatively biased given LI and suggested that a bias correction should be applied by subtracting the expected value of  $Q_3$  given LI, which is  $\frac{-1}{I-1}$ , from all  $Q_3$ . The approach then contrasts the mean residual correlations between item pairs  $kk'$  referring to the same event with the mean residual correlations between item pairs  $ll'$  referring to different events to calculate the dependency measure  $D_{Q_3}$ :

$$D_{Q_3} = \frac{1}{K} \sum_{k>k'} Q_3^{kk'} - \frac{1}{L} \sum_{l>l'} Q_3^{ll'}, \quad (10)$$

where  $K$  is the number of item pairs belonging to the same event and  $L$  is the number of item pairs belonging to different events. Given binding of event elements and a resulting stochastic dependency of the retrieval of event elements, within-event item residual correlations deviate from zero, whereas between-event item residual correlations are close to zero. Quantifying the dependency measure relative to the mean between-event item residual correlations allows for corrections of spurious item residual correlations that may be present in the data or be induced due to model misspecification, since these would affect both within- and between-event item residual correlations. The interpretation of the measure is equivalent to the one of the contingency-based measures, with zero indicating independence, positive values indicating positive dependency, and negative values indicating negative dependency.

Due to the sampling distribution of  $Q_3$  being unknown (Chen & Thissen, 1997),

the sampling distribution of  $D_{Q_3}$  is also unknown. In addition, the approach returns an overall measure of dependency for a given experimental condition or group. Thus, classical testing approaches (e.g.,  $t$ -tests) are not applicable. For testing whether dependency or differences in dependency significantly differ from zero one can instead use a bootstrap approach. We use parametric bootstrapping, thus using the parameters estimated from the IRT model to generate data under the assumption that the data-generating model is true. When sampling from a unidimensional IRT model such as the one in Equation 9, this implies that the LI assumption holds and there is thus no dependency. By calculating the dependency measure or differences in dependency measures for each bootstrap sample one can generate distributions of the respective indices under the null hypothesis, from which  $p$  values for the observed indices can be derived. For testing for differences in dependency, the null hypothesis is that dependency in the compared conditions or groups is equal, but not necessarily zero. Thus, for this kind of test, one needs to generate data from a model that allows for dependencies in item responses. This can be achieved by sampling from a bifactor IRT model (see Gibbons & Hedeker, 1992; Wainer & Wang, 2000), which extends the model in Equation 8 by including additional, event-specific, latent traits  $\lambda$ , thus making the model multidimensional:

$$P(u_{ij} = 1) = \gamma_j + (1 - \gamma_j) \frac{e^{\alpha_j(\theta_i - \beta_j) - \alpha_{t(j)}\lambda_{it(j)}}}{1 + e^{\alpha_j(\theta_i - \beta_j) - \alpha_{t(j)}\lambda_{it(j)}}}, \quad (11)$$

where  $\lambda$  is the event-specific latent trait of person  $i$  for event  $t(j)$  to which item  $j$  belongs. In accordance with the simplifications made to the model in Equation 9, this model can also be simplified:

$$P(u_{ij} = 1) = g + (1 - g) \frac{e^{\theta_i - \beta_j - \lambda_{it(j)}}}{1 + e^{\theta_i - \beta_j - \lambda_{it(j)}}} \quad (12)$$

All latent traits in this model are mutually independent, and thus there is no conditional dependency in item responses referring to different events. The event-specific latent traits induce stochastic dependencies of item responses referring to the same event via their variance, with higher variances indicating higher dependencies (i.e., stronger event-specific effects). For informing the parametric bootstrap, one also needs to fit this model to the empirical data. Since experiments usually include several events, the model may quickly become highly dimensional, because an additional event-specific trait is required for each event. This is especially problematic considering the relatively small sample sizes typical of experiments compared to, for example,

large-scale educational assessments. To mitigate this problem, it is advisable to reduce the number of parameters to be estimated by setting equality constraints on event-specific trait variances within experimental conditions or groups, also considering that events are usually randomly generated for each participant.

### 2.2.2 Nonparametric Variant

While the previously described IRT-based approach is parametric, Debelak and Koller (2020) proposed a nonparametric estimation procedure for  $Q_3$ , with which a nonparametric variant of the dependency measure ( $D_{Q_3}^{\text{np}}$ ) can be calculated. The estimation procedure builds on the nonparametric testing framework by Ponocny (2001) and on a property of the Rasch model (Rasch, 1960) that marginal person and item sums are sufficient statistics for person and item parameters. Thus, the procedure involves the generation of bootstrap samples of artificial response matrices with the same marginal sums as the observed response matrix, using a Markov-Chain Monte-Carlo algorithm by Verhelst (2008). Then, the probability for a person giving a correct response to an item is calculated by averaging the respective responses in the generated artificial response matrices ( $u_{ij}$ ) across bootstrap samples. Subsequently, nonparametric  $Q_3$  statistics and  $D_{Q_3}^{\text{np}}$  are calculated like their parametric counterparts (see Equation 10). In addition, one can calculate  $D_{Q_3}^{\text{np}}$  for each bootstrap sample to derive  $p$  values for  $D_{Q_3}^{\text{np}}$  and differences in  $D_{Q_3}^{\text{np}}$ .

## 2.3 Evaluation of Measurement Approaches

Given the availability of several approaches for measuring binding effects in episodic memory, the question remains which of these approaches are best suited for this task. While I already discussed some advantages of the IRT-based approach compared to the contingency-based approaches, such as the susceptibility to Simpson's paradox of the latter, in the first article (Schreiner & Meiser, 2022), we further evaluated the different approaches in terms of three important measurement properties (cf. J. Cohen, 1988): (1) bias of the estimates yielded by the different approaches, (2) Type I error rates, and (3) power. This was done for both tests against independence of individual estimates and tests for differences between experimental conditions. In addition, we investigated how susceptible the measurement properties of the different approaches are to variations in overall memory performance of the sample. Ideally, dependency measures should not be susceptible to memory performance to allow for



dissociating dependency of the retrieval of event elements due to binding effects from higher memory performance.

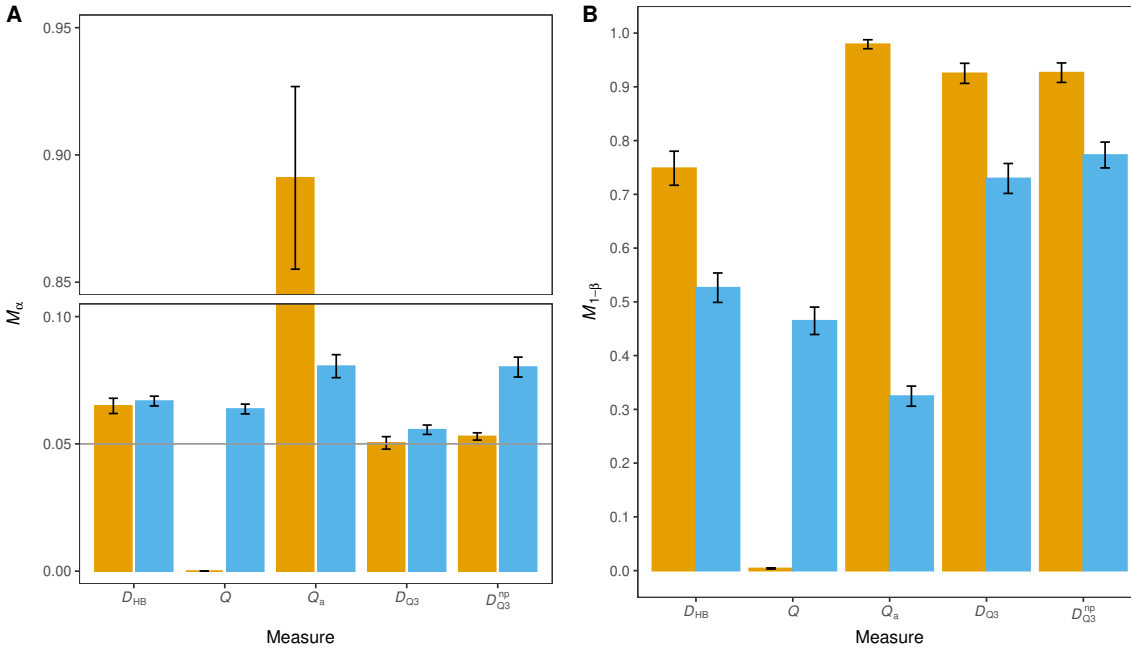
For the evaluation, we conducted a Monte Carlo simulation in which we simulated an experimental within-subjects design with two experimental conditions, a total of  $T = 30$  events (15 per condition), and five response options in the memory test (resulting in a stochastic guessing probability of  $g = 0.2$ ). We simulated six test trials per event, which corresponds to testing each association in an event consisting of three elements in both directions (e.g., testing vendor–bread, bread–vendor, vendor–bakery, bakery–vendor, bread–bakery, and bakery–bread). Item responses were drawn from a bifactor IRT model (Gibbons & Hedeker, 1992; Wainer & Wang, 2000, see Equation 11), which allowed us to induce dependencies between item responses by adding event-specific latent traits ( $\lambda$ ). We varied the sample size ( $N = \{25, 50, 75, 100\}$ ), the dependency of the retrieval of event elements by varying the variances of the event-specific latent traits ( $\text{Dep.} = \{0, 0.5, 1\}$ )<sup>2</sup>, differences in dependency between experimental conditions by increasing event-specific trait variances in the second condition relative to the first condition ( $\text{Dep.}_{\text{diff}} = \{0, 0.5, 1\}$ ), and the overall level of memory performance in the sample by changing the mean of the general latent trait  $\theta$  ( $P = \{-2, 0, 2\}$ , resulting in a proportion of 40%-42%, 59%-60%, and 75%-80% correct responses, respectively). This resulted in 108 simulation conditions, for each of which we conducted 1,000 replications. For the contingency-based approaches ( $D_{\text{HB}}$ ,  $Q$ , and  $Q_a$ ), we conducted one-sample  $t$ -tests against zero for testing against independence and paired  $t$ -tests for testing for differences between conditions. For the IRT-based approaches we used bootstrapping (parametric for  $D_{Q_3}$ , nonparametric for  $D_{Q_3}^{\text{np}}$ ) for determining statistical significance, using 1,000 bootstrap samples, respectively (cf. Davison & Hinkley, 1997). All tests were one-tailed, since no negative dependencies can be induced using the bifactor model.

Figure 2 shows average Type I error rates and power of the different measures across simulation conditions. More detailed results are presented in the first article (Schreiner & Meiser, 2022). The simulation revealed that  $Q$  is negatively biased, whereas  $Q_a$  is positively biased. For both measures the bias increases with increasing memory performance. For  $Q_a$  this results in severely inflated Type I error rates that further increase with increasing memory performance. For  $Q$  this results in virtually no sensitivity to dependency when testing against independence (i.e., very low power).

<sup>2</sup>Note that for event-specific trait variances of zero the bifactor model reduces to a unidimensional model with the LI assumption (i.e., independence of item responses given the general latent trait).

**Figure 2**

Average Type I error rates (A) and power (B) of the different measures across simulation conditions when testing against independence and when testing for differences between conditions in the simulation study by Schreiner and Meiser (2022).



*Note.* For Type I error rates (A), the horizontal grey line indicates the nominal significance level. For tests against independence, values are also averaged across the simulated experimental conditions. Error bars represent  $\pm SEM$ .

However, estimates of dependency differences between conditions are unbiased, but  $Q_a$  tends to yield slightly increased Type I error rates when testing for dependency differences. In terms of power, both  $Q$  and  $Q_a$  are inferior to the other approaches.  $D_{HB}$ ,  $D_{Q3}$ , and  $D_{Q3}^{np}$  are unbiased and not susceptible to memory performance given independence of item responses. All three measures show acceptable to good maintenance of the nominal significance level. Given dependency, the measures are affected by memory performance ( $D_{HB}$  less so than the IRT-based approaches), but this kind of susceptibility is less concerning, since it only occurs if there is a true effect, and thus only affects power, but not Type I error rates. The IRT-based approaches however yield higher power for detecting dependency than does  $D_{HB}$  and power is affected by memory performance to a similar degree for all three measures. When considering

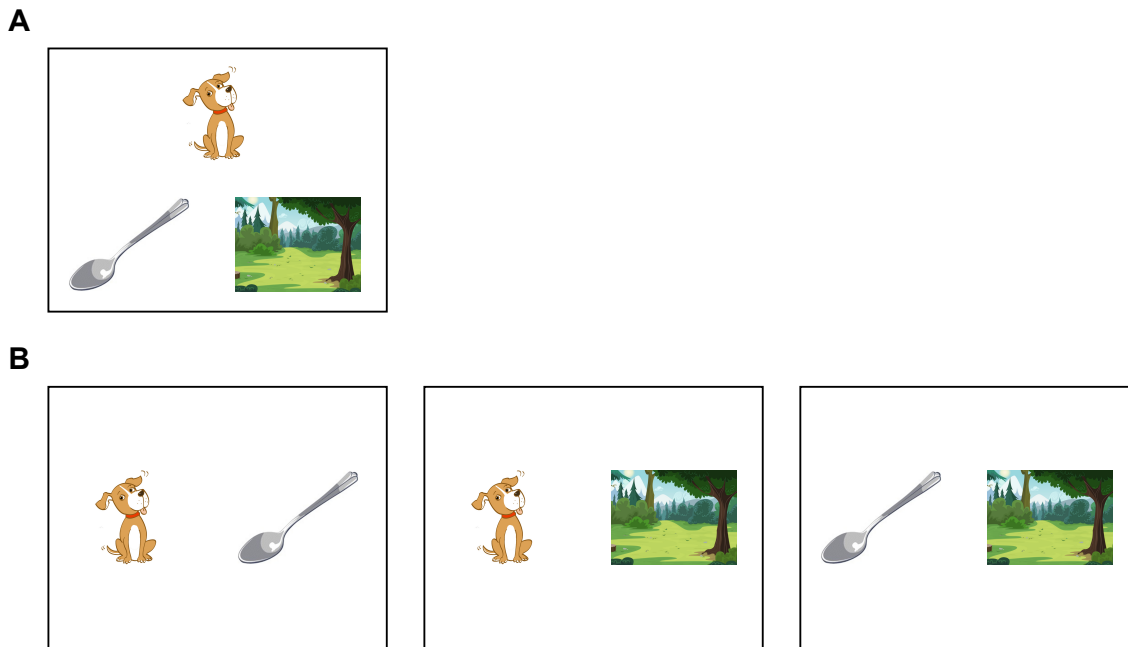
dependency differences and testing for differences between conditions, these results were largely mirrored. However,  $D_{Q_3}^{\text{pp}}$  yields increasing Type I error rates as dependency in the data increases. This is not the case for the other measures. In addition, given true differences in dependency between conditions, estimates of dependency differences from all measures shift closer to zero as dependency in the data increases, resulting in decreasing power with increasing dependency in the data.

As a complement to the simulation study, we reanalyzed an empirical dataset by James et al. (2020) using the different approaches to compare resulting inferences drawn from empirical data (using two-tailed testing). In their first experiment ( $N = 45$ ), James et al. (2020) presented participants with 30 events, each consisting of 3 elements (an animal, an object, and a location) that were shown as cartoon illustrations and additionally named via audio recordings projected through headphones. Using a cued recognition test, there were six test trials per event (i.e., each association was tested in both directions). The experiment encompassed two within-subjects conditions: In a simultaneous encoding condition, all event elements were shown simultaneously, during a single learning trial (cf. Horner & Burgess, 2013). In a separated encoding condition (cf. Horner et al., 2015; Horner & Burgess, 2014), event elements were shown sequentially pairwise, across three temporarily divided learning trials (see Figure 3).

Two previous studies found a significant positive dependency of the retrieval of event elements in both the simultaneous and separated encoding condition that did not significantly differ between the conditions (Bisby et al., 2018; Horner & Burgess, 2014), suggesting binding effects of similar magnitude in both conditions. However, James et al. (2020) found a significant dependency only in the simultaneous encoding condition, but not in the separated encoding condition, with a significant difference between the conditions, suggesting binding effects were only present in the simultaneous encoding condition. All three studies employed the approach by Horner and Burgess (2013). Using the IRT-based approaches, both the parametric and nonparametric variant yielded a significant dependency in both conditions, but the dependency in the simultaneous encoding condition was significantly larger. These results are thus more consistent with the results by Bisby et al. (2018) and Horner and Burgess (2014) than are the results by James et al. (2020). The significant dependency in the separated encoding condition may be explained by the higher power for detecting dependencies of the IRT-based approaches compared to the approach by Horner and Burgess (2013).  $Q$  and  $Q_a$  yielded diverging results, with  $Q$  yielding no

**Figure 3**

*Exemplary learning trials of a simultaneous encoding condition (A) and a separated encoding condition (B) for an event encompassing the elements dog, spoon, and forest.*



*Note.* Pictures were taken from James et al. (2020), available at <https://osf.io/vqzh8/>. Learning trials in a separated encoding condition usually do not directly follow each other but are presented interleaved with learning trials from other events. This was also the case in James et al. (2020).

significant dependency in the simultaneous encoding condition and a significant negative dependency in the separated encoding condition, with a significant difference between the conditions, and  $Q_a$  yielding a significant dependency in both conditions, with no significant difference between the conditions. These divergent findings may be explained by the measures being biased.

In sum, the parametric IRT-based approach ( $D_{Q_3}$ ) seems best suited for measuring the stochastic dependency of the retrieval of event elements as an indicator of binding effects, yielding unbiased estimates of dependency and dependency differences, good maintenance of Type I error rates, high power, and empirical inferences in accordance with previous findings. The nonparametric variant ( $D_{Q_3}^{np}$ ) also generally performs well, but is prone to increased Type I error rates when testing for differences in dependency.  $Q$  and  $Q_a$  on the other hand seem unsuited for measuring binding effects, given their bias and associated problematic Type I error rates and power, and

the strongly diverging empirical inferences drawn when using these measures. The approach by Horner and Burgess (2013) ( $D_{\text{HB}}$ ) also seems to yield a suitable measure, albeit performing worse than  $D_{\text{Q}_3}$ . However, it may be particularly useful when person-specific estimates are required, for example when one wants to investigate the influence of continuous covariates such as age on the binding of event elements. Person-specific estimates are not yet provided by  $D_{\text{Q}_3}$ .

Besides the discussed advantages of the IRT-based approach and its insusceptibility to Simpson's paradox, the approach provides some additional advantages over the contingency-based approaches. While the latter are in essence descriptive, the IRT-based approach utilizes established and plausible modeling of meaningful psychological variables (e.g., memory performance as a latent trait and event-specific effects defined in terms of item residual correlations and as additional latent traits in bifactor models). Resulting person and item parameters can also be used for additional analyses and goals, for example for investigating participants' memory performance or the compilation of study materials if one wants to use the same events across participants, to ensure comparable difficulty of different events. The IRT-based approach, resting on individual item responses, can further be applied to a greater variety of test formats, such as free recall, in which the lack of cue-target pairs would render dependency pairs used in the contingency-based approaches arbitrary. Finally, the IRT-based approach can be extended to polytomous item responses, for example by using the rating scale (Andrich, 1978) or partial credit model (Masters, 1982) and then calculating item residual correlations from these models. A potential application with polytomous item responses may be the investigation of dependencies in confidence judgments in memory tasks.



## 3 Binding Structures

In Chapter 2, I identified suitable approaches, particularly an approach based on IRT, for measuring binding effects. In the following chapters, I will use this measure ( $D_{Q_3}$ ) to investigate substantive research questions regarding the binding of event elements in episodic memory. An important question is the structure in which different event elements are bound together, since this is a fundamental aspect of information storage and retrieval in episodic memory. There exist different competing accounts of how bound event elements are structured.

### 3.1 Integrated Binding Accounts

Integrated binding accounts suggest that event elements are bound into a unitary representation, which can be accessed in a holistic manner. Tulving (1983) suggested that information regarding different event elements is stored in event engrams, which are discrete bound event representations. The hippocampus may act as a convergence zone that binds event elements into discrete engrams that can be retrieved by partial activation of event elements via pattern completion (Damasio, 1989; Marr, 1971; Moll & Miikkulainen, 1997). Furthermore, the integrative encoding hypothesis suggests that the hippocampus integrates newly encountered associations into existing overlapping ones, which ultimately leads to integrated representations containing all event elements (Shohamy & Wagner, 2008; Zeithamova et al., 2012). As a consequence of integrated binding structures, one can assume that there are no longer individual associations between individual event elements. Instead, event elements are fully integrated into a superordinate memory structure that can only be accessed holistically. Therefore, asymmetries in binding strength are not possible.

### 3.2 Pairwise and Hierarchical Binding Accounts

Other accounts suggest that event elements may be bound together in a network of pairwise associations that potentially allows for asymmetries in binding strength. Relational memory theory suggests that the hippocampus flexibly binds elements into a network-like structure depending on task demands (N. J. Cohen & Eichenbaum, 1993; Eichenbaum, 1999; see also Eichenbaum & Cohen, 1988, 2001). With ensemble encoding, associations may be stored as overlapping neural ensembles, but these ensembles may remain distinct rather than forming a unitary representation

(Cai et al., 2016). The theory of event coding (TEC) suggests that feature codes, being codes of stimuli, are perceptually activated and bound into event files (Hommel, 1998, 2009; see also the recently proposed binding and retrieval in action control [BRAC] framework; Frings et al., 2020). Event files consist of multiple local interconnections of feature codes (Hommel, 1998, 2004) and connections may be sparse, since not all possible connections are necessarily formed (Moeller et al., 2019). Feature codes may also contribute to the event file with varying degrees (Hommel et al., 2001). Thus, binding asymmetries are possible in the TEC. The Span-Cospan model of episodic memory (Healy & Caudell, 2019) suggests that event elements are bound into higher-order representations of event segments, which may be bound into further higher-order representations, up to a representation encompassing the entire event. However, holistic access to individual event segments is maintained. Representations and connections can vary in strength, and thus the model also allows for asymmetries in binding strength. These accounts suggest that event elements may be bound into a hierarchical binding structure, in which some elements are preferentially bound to other elements. Such structures may be enabled by systematic variations in binding strength (including binding strengths of zero, i.e. no direct bindings being formed between some event elements).

### 3.3 Testing an Integrated Against a Hierarchical Binding Account

Schreiner, M. R., Meiser, T., & Bröder, A. (2022). The binding structure of event elements in episodic memory and the role of animacy. *Quarterly Journal of Experimental Psychology*. Advance online publication. <https://doi.org/10.1177/17470218221096148>

In the second article (Schreiner, Meiser, & Bröder, 2022), we empirically tested an integrated against a hierarchical binding structure using an experimental paradigm suitable to distinguish between these different binding structures in three experiments. Participants were presented several events consisting of three elements presented as nouns and were instructed to imagine these elements as part of a scene and interacting in a meaningful manner. In Experiment 1, all events consisted of an animal, an object, and a location (animacy condition). Experiments 2 and 3 additionally included a non-animacy condition in which events consisted of two types of objects (means of transportation and tools) and a location. Animacy condition was a within-



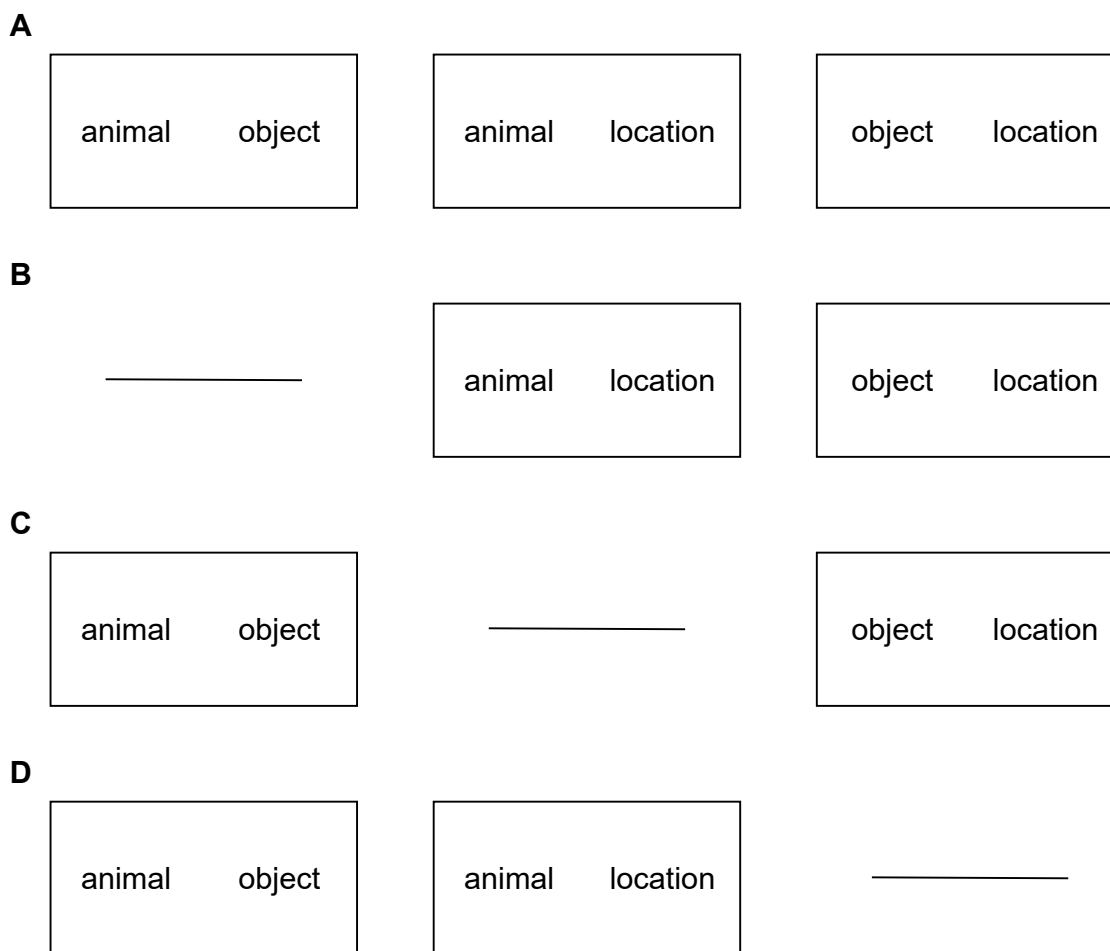
subjects factor in Experiment 2 and a between-subjects factor in Experiment 3. We manipulated animacy because we suspected it to facilitate the formation of hierarchical binding structures, but the rationale behind different animacy conditions is primarily discussed in Chapter 4. We employed the separated encoding paradigm (Horner et al., 2015; Horner & Burgess, 2014), in which event elements are presented sequentially pairwise. In addition to a closed-loop (CL) condition (coherent encoding episodes), in which all possible pairwise associations are presented (see Figure 4A, see also Figure 3B), we additionally included three open-loop (OL) conditions, in which we excluded one of the possible pairwise associations from presentation, respectively (non-coherent encoding episodes, see Figure 4B-D). In a subsequent test phase, participants were presented with an event element as a cue and had to select the associated target element that belonged to the same event as the cue from six response alternatives.

While we included the closed-loop condition to replicate previous findings showing that event elements can be bound across several temporarily divided encoding episodes (Bisby et al., 2018; Horner et al., 2015; Horner & Burgess, 2014; Joensen et al., 2020), integrated and hierarchical binding structures make different predictions regarding the pattern of stochastic dependencies of the retrieval of event elements across the different open-loop conditions. Because an integrated binding structure consists of a unitary event representation that can only be accessed holistically, dependency should not vary across the open-loop conditions, since all associations, including the one not presented, are fully integrated and should be readily retrieved with all the other associations (or integration may fail for non-coherent encoding episodes; cf. Horner et al., 2015; Horner & Burgess, 2014). However, in a hierarchical binding structure there are systematic variations in binding strength. Thus, associations between more strongly bound event elements should more strongly contribute to a stochastic dependency of the retrieval of event elements than associations between less strongly bound event elements. Excluding associations from presentation that would more strongly contribute to dependency should therefore diminish dependency compared to excluding associations that would less strongly contribute to dependency, and thus dependency should vary across the different open-loop conditions.

The dependency results for the three experiments are shown in Figure 5. While we replicated a significant positive dependency in two out of the three experiments (in Experiments 1 and 3), suggesting that event elements can indeed be bound across several temporarily divided encoding episodes, at least if encoding episodes are coher-

**Figure 4**

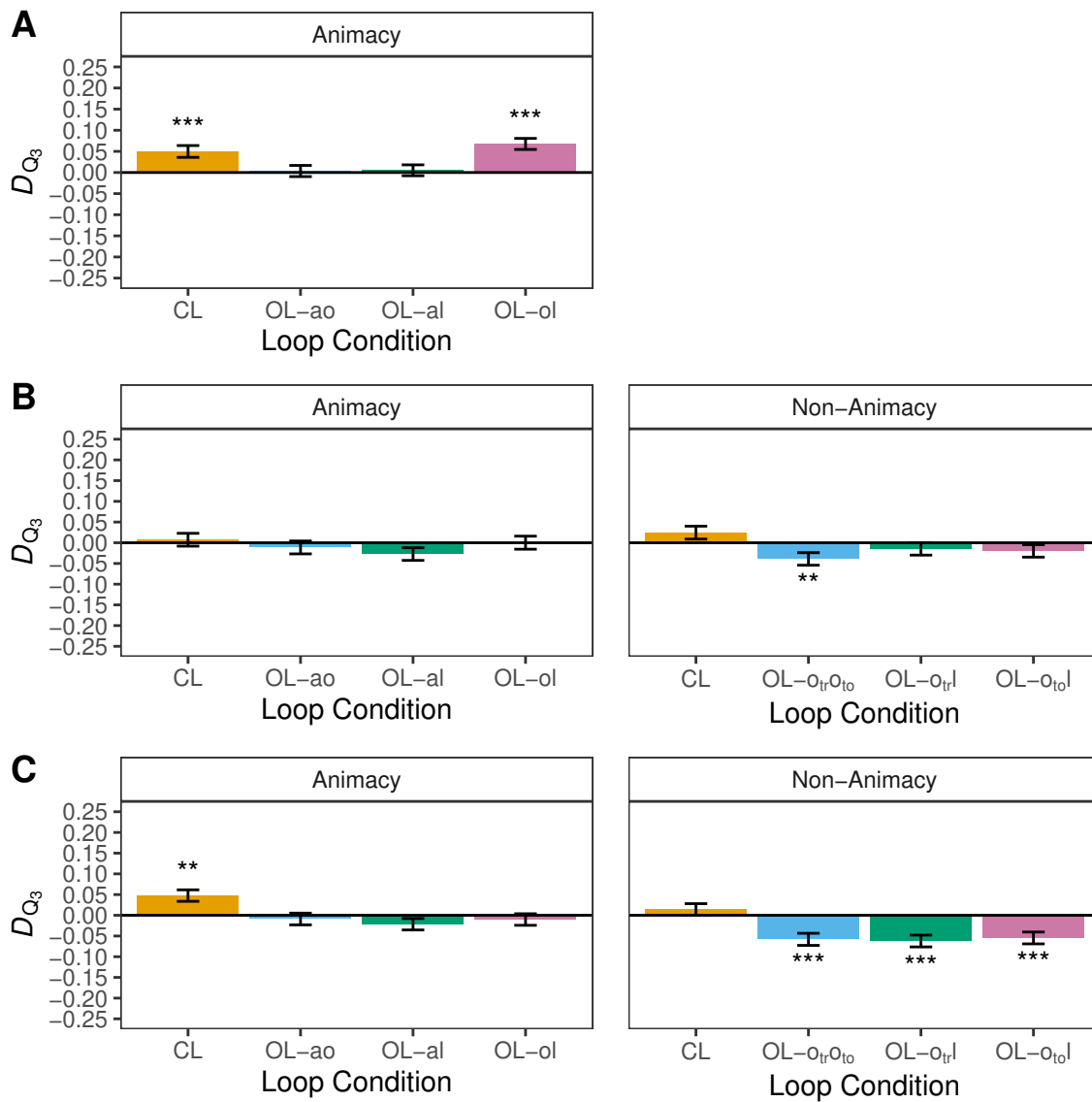
*Learning trials for the closed-loop condition (A) and for different open-loop conditions (B-D) for an event consisting of an animal, an object, and a location in the separated encoding paradigm.*



*Note.* Horizontal lines indicate that the respective learning trial did not occur in the respective condition. Learning trials for an event did not directly follow each other but were presented interleaved with learning trials from other events.

Figure 5

Dependency of the retrieval of event elements by animacy and loop condition for Experiment 1 (A), Experiment 2 (B), and Experiment 3 (C) of Schreiner, Meiser, and Bröder (2022).



Note. \*\* $p < .01$ , \*\*\* $p < .001$ . CL = closed-loop, OL-ao = open-loop with association animal – object excluded, OL-al = open-loop with association animal – location excluded, OL-ol = open-loop with association object – location excluded, OL-o<sub>tr</sub>o<sub>t<sub>o</sub></sub> = open-loop with association means of transportation – tool excluded, OL-o<sub>tr</sub>l = open-loop with association means of transportation – location excluded, OL-o<sub>t<sub>o</sub></sub>l = open-loop with association tool – location excluded. Error bars represent  $\pm SE$ .

ent, results regarding the binding structure were mixed. In Experiment 1 there was a significant positive dependency in the open-loop condition in which the association object – location was excluded that did not significantly differ from the dependency in the closed-loop condition and was significantly larger than the dependency in the other open-loop conditions in which the animal – object or animal – location association was excluded. This result pattern suggests that event elements are bound in a hierarchical manner (cf. Cai et al., 2016; N. J. Cohen & Eichenbaum, 1993; Eichenbaum, 1999; Healy & Caudell, 2019; Hommel et al., 2001), with event elements being preferentially bound to the animal element. In the animacy condition of Experiment 3 however, we did not find a significant dependency in any of the open-loop conditions. This finding is more consistent with an integrated binding structure (Damasio, 1989; cf. Horner et al., 2015; Horner & Burgess, 2014; Joensen et al., 2020; Marr, 1971; Moll & Miikkulainen, 1997; Shohamy & Wagner, 2008; Tulving, 1983; Zeithamova et al., 2012), with integration failing for non-coherent encoding episodes (cf. Horner et al., 2015; Horner & Burgess, 2014).

Experiment 2 was not particularly informative regarding a distinction between an integrated and a hierarchical binding structure, since we did not find a significant dependency in almost all conditions, not even in the closed-loop conditions. This suggests that in this experiment participants may have formed independent pairwise representations of event elements that were not integrated into a superordinate memory representation. This may have been the case because, in Experiment 2, events could vary in the composition of their elements, since they consisted of an animal, an object, and a location in the animacy condition, and two types of objects, and a location in the non-animacy condition. Since animacy condition was manipulated within-subjects, participants may have been less aware of the underlying event structure compared to the other experiments, which may have interfered with the formation of abstract representations of event structures. These may, however, be beneficial for binding (Morton et al., 2020; see also Kumaran, 2013; Kumaran & Ludwig, 2013).

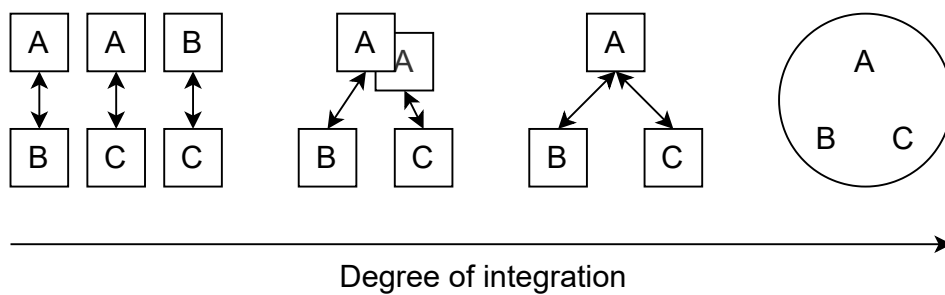
Interestingly, we found significant negative dependencies in the open-loop conditions of the non-animacy condition in Experiment 3 (and also in one condition in Experiment 2). This may suggest that pairs of event elements were encoded as distinct overlapping events and representations were then driven apart by pattern separation processes in the hippocampus (see Zotow et al., 2020). An alternative explanation may be that the selective retrieval of one event element may have inhibited the re-

trieval of other event elements at the time of testing (cf. Horner & Burgess, 2013) and negative dependencies may thus be due to retrieval-induced forgetting (Anderson et al., 1994).

In sum, the results of the three experiments yielded unclear evidence for specific binding structures. This may suggest that different types of binding structures can be formed (and may even exist in parallel). For example, it is conceivable that there may exist a continuum of increasingly integrated memory representations, as depicted in Figure 6. Weakly integrated representations may be represented by independent pairwise bindings and may have occurred in Experiment 2. (Initially) overlapping pairwise representations may be slightly more integrated and may have occurred in the non-animacy condition of Experiment 3. Further up the continuum may then be hierarchical binding structures, as suggested by the results of Experiment 1, and ultimately fully integrated binding structures, as suggested by the results in the animacy condition of Experiment 3. While more integrated representations may intuitively be beneficial, they may also come with costs and may lead to seemingly paradoxical effects. For example, while initially overlapping pairwise representations may be considered higher up the integration continuum than independent pairwise representations, they may lead to negative dependencies due to pattern separation processes driving representations apart. This however, is an adaptive property of the hippocampus that reduces interference between similar representations in memory (Guzowski et al., 2004; Neunuebel & Knierim, 2014; Yassa & Stark, 2011). Also, while integrated representations may require less storage space than hierarchical representations, because all event elements are bound into a unitary representation, individual associations are no longer accessible in integrated representations. Thus, if a memory trace is too weak or fades over time, accessibility to the whole representation may be lost (see e.g., Joensen et al., 2020), whereas for hierarchical representations some associations may still be accessible and help in inferring the remaining associations. The degree of integration a memory representation achieves may be influenced by several moderators.

**Figure 6**

*Schematic depiction of representations for an event consisting of three event elements (A, B, and C) along an integration continuum. From left to right, the depicted representations are independent pairwise, (initially) overlapping pairwise, hierarchical, and integrated representations.*



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## 4 Moderators of Binding Processes

In Chapter 3, I presented and discussed evidence suggesting that the structure in which event elements are bound together may vary, such that different binding structures with different degrees of integration are possible. From that the question follows what causes some events to achieve higher degrees of integration than others. In this chapter, I will thus investigate moderators of the binding of event elements.

So far, such moderators have only been scarcely investigated. James et al. (2020) found that, when presenting event elements as words, the addition of spoken words to the presentation of written words (i.e., multimodal instead of unimodal presentation) disrupted binding. Also, the use of picture stimuli disrupted binding compared to written stimuli, suggesting an effect of the modality of the presentation of event elements. Further, there is some evidence that knowledge or awareness regarding the structure of an event, such as the number and types of elements making up an event, facilitates binding (Kumaran, 2013; Kumaran & Ludwig, 2013; Morton et al., 2020). Our findings in Schreiner, Meiser, and Bröder (2022), in which we found no binding effects in an experiment in which events could consist of different sets of element types (varying event composition) compared to experiments in which they always consisted of the same set of element types (fixed event composition) corroborates this evidence. Awareness regarding the structure of an event may enable people to map representations on a latent geometric space, facilitating integration and enabling vector-based retrieval and inference (Morton et al., 2020).

### 4.1 Animacy

The presence of an animate element in an event may be another moderator facilitating the formation of coherent memory representations. Animate entities are living things that are capable of independent movement and able to change direction without warning (Bonin et al., 2015). Animacy is an important factor influencing human cognition (Nairne et al., 2013, 2017) that may be explained by selective pressure shaping our ancestors' memory system (Nairne et al., 2007, 2008). In this context, animacy may be an important survival-related factor. For example, animate entities may be potential prey, predators, or sexual partners (Bonin et al., 2015; Nairne et al., 2017). Regarding memory performance, an animacy effect has been commonly found, such that words with an animate referent are remembered better than words with an inanimate referent (e.g., Li et al., 2016; Nairne et al., 2013; VanArsdall et al., 2015).

This effect has been robustly found across a variety of test formats, including free recall (Bonin et al., 2015; Leding, 2019; Li et al., 2016; Madan, 2021; Nairne et al., 2013; Popp & Serra, 2016), recognition (Bonin et al., 2014; Leding, 2020; VanArsdall et al., 2013), and judgments of learning (DeYoung & Serra, 2021; Li et al., 2016). In cued recall tests, evidence for an animacy effect has been mixed, with some studies finding an effect (DeYoung & Serra, 2021; Laurino & Kaczer, 2019; VanArsdall et al., 2015) and some studies even finding an opposite effect (Kazanas et al., 2020; Popp & Serra, 2016). These inconsistent findings may be explained by variability in within-pair similarity of the word pairs learned in cued recall tasks (Serra & DeYoung, 2022).

Beyond enhancing memory performance, in the second article (Schreiner, Meiser, & Bröder, 2022), we found evidence that animacy also facilitates the binding of event elements in episodic memory. In Experiment 1, in which events consisted of an animal, an object, and a location, we found a significant positive dependency of the retrieval of event elements when all possible pairwise associations between event elements were presented (closed-loop condition) and when an association not involving the animate element was excluded from presentation (one of the open-loop conditions), whereas we did not find dependencies when an association involving the animate element was excluded (see Figure 5A). This suggests a hierarchical binding structure, in which the inanimate event elements (object and location) are preferentially bound to the animate element (the animal).

In the subsequent experiments we manipulated animacy by constructing events that either included an animate element (as was the case in Experiment 1, animacy condition) or did not include an animate element (non-animacy condition). In the non-animacy condition, event elements consisted of two types of objects (a means of transportation and a tool) and a location. While manipulating animacy within-subjects yielded uninformative results, likely due to resulting varying event compositions and reduced awareness regarding the underlying event structure (cf. Kumaran, 2013; Kumaran & Ludwig, 2013; Morton et al., 2020, see Chapter 3), manipulating animacy between-subjects yielded strongly diverging result patterns between the animacy and non-animacy condition (see Figure 5C). While the result pattern in the animacy condition suggests an integrated binding structure (there was a significant positive dependency in the closed-loop condition, but no significant dependencies in the open-loop conditions), there were negative dependencies in the open-loop conditions of the non-animacy condition, potentially suggesting that overlapping pairwise



representations were formed (cf. Zotow et al., 2020) and no significant dependency in the closed-loop condition. These results suggest that representations with a higher degree of integration have been achieved in the animacy compared to the non-animacy condition.

In sum, the results suggest that the presence of an animate element in an event enables higher degrees of integration, and thus facilitates the formation of more coherent memory representations. The presence of an animate element may either provide a critical element in hierarchical binding structures, to which other event elements are preferentially bound (cf. Experiment 1), or facilitate the full integration of event elements into an integrated binding structure (cf. Experiment 3). In a supplemental analysis we found that facilitating effects of animacy only occurred for events for which an association involving the animate element was presented first. Animate elements may thus exert their influence by providing a potential agent in an event.

## 4.2 Agency

Schreiner, M. R., Bröder, A., & Meiser, T. (2022). *Agency effects on the binding of event elements in episodic memory*. Manuscript submitted for publication.

The facilitating effects of animacy on the binding of event elements in episodic memory may be due to animate elements providing a potential agent in an event, and thus effects may actually be driven by *agency*. Agency can be defined as “acting or having the capacity to act autonomously in a given environment” (Suitner & Maass, 2016, p. 248; see also Hitlin & Elder, 2007). While this definition certainly applies to animate entities, agency may also extend to inanimate entities (Johnson & Barrett, 2003; Lowder & Gordon, 2015). In that sense, agency can be considered to be a property of animate entities, but animacy may only be one of several factors contributing to agency. For example, the active performance of an action may be another factor contributing to an entity’s perceived agency (e.g., a hunting fox may be ascribed more agency than a fox laying passively on the ground or a rabbit being hunted). Agency may thus be a more proximate explanation for the facilitating effects of animacy on the binding of event elements.

In the third article (Schreiner, Bröder, & Meiser, 2022), we tested whether agency, beyond animacy, facilitates the binding of event elements in five experiments. Participants were presented several events consisting of three event elements. Event elements were either three types of objects (a means of transportation, a tool, and a

food item, Experiments 1 and 2) or three types of animals (a mammal, a bird, and an insect, Experiments 3-5) to avoid confounding with animacy and were presented as nouns. In Experiments 1-3 we employed the separated encoding paradigm (Horner et al., 2015; Horner & Burgess, 2014), which we also used in Schreiner, Meiser, and Bröder (2022), but this time we only included the closed-loop condition, in which all possible pairwise associations are presented<sup>3</sup>. In Experiments 4 and 5 we employed the simultaneous encoding paradigm (Horner & Burgess, 2013), in which all event elements are presented in a single learning trial. While the separated encoding paradigm provides a stricter test of binding, because event elements need to be bound across temporarily divided encoding episodes and binding effects are thus less likely confounded with covariations in perceptual variables, binding effects in the simultaneous encoding paradigm tend to be more robust (see James et al., 2020) and the simultaneous presentation of event elements is closer to how events are naturally experienced. Thus, in Experiments 1-3 there were two event elements per learning trial and three learning trials per event, and in Experiments 4 and 5 there were three event elements per learning trial and only one learning trial per event.

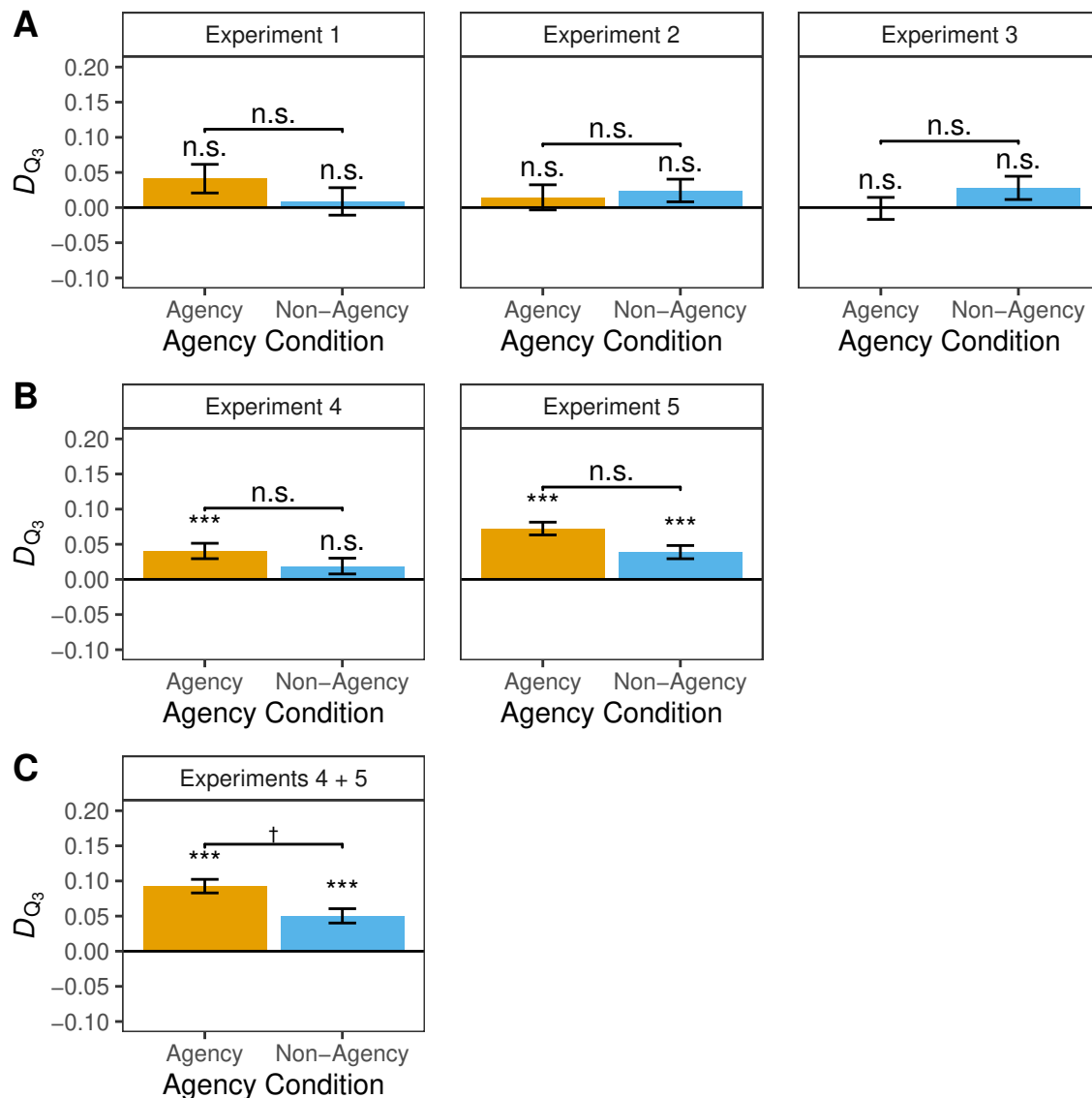
Event elements were presented embedded in sentences and we used a linguistic agency manipulation. In sentences with interpersonal action verbs (e.g., *hit*) the agent tends to be the grammatical subject, whereas the patient of the action tends to be the grammatical object (Kasof & Lee, 1993). In addition, the grammatical subject is perceived as more agent-like than the grammatical object (Kako, 2006) and the agent is given greater causal weight than the patient (Brown & Fish, 1983; Kassin & Lowe, 1979). We thus constructed sentences such that, in the agency condition, one of the event elements (the agent) served as the grammatical subject in a transitive active sentence (e.g., *The dog grabs the eagle.*), whereas the non-agentic element(s) served as the grammatical object(s). In the non-agency condition, we used passive sentences (e.g., *The dog and the eagle are being grabbed.*), in which the grammatical subject is not an agent (Kako, 2006). Such passive sentences were also used for sentences in the agency condition that did not include the agent element (this could only occur in the separated encoding paradigm). In a subsequent test phase, participants were presented with an event element as a cue and had to select the associated target element that belonged to the same event as the cue from six response alternatives, like in Schreiner, Meiser, and Bröder (2022).

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<sup>3</sup>Experiment 2 also encompassed additional open-loop conditions to examine the binding structure of event elements, but yielded uninformative results concerning this question.

Figure 7

Dependency of the retrieval of event elements by agency condition for experiments employing the separated encoding paradigm (A), for experiments employing the simultaneous encoding paradigm (B) and for the aggregate analysis of Experiments 4 and 5 including only participants with above-median performance (C) of Schreiner, Bröder, and Meiser (2022).



Note. \*\*\* $p < .001$  (two-tailed), † $p < .05$  (one-tailed), n.s. = non-significant. Error bars represent  $\pm SE$ . For Experiment 2 only data for the closed-loop conditions are shown.

The dependency results for the five experiments are shown in Figure 7. In experiments in which we employed the separated encoding paradigm (Experiments 1-3) we did not find any significant dependency of the retrieval of event elements in the agency and non-agency conditions (see Figure 7A), and thus no evidence for binding effects. This is at odds with results of previous studies, which found that binding effects also occur for (coherent) temporarily divided encoding episodes (Bisby et al., 2018; Horner et al., 2015; Horner & Burgess, 2014; Joensen et al., 2020; Schreiner, Meiser, & Bröder, 2022). The main difference between our experiments in Schreiner, Bröder, and Meiser (2022) and these previous studies is that we presented event elements embedded in sentences instead of presenting them as individual words or pictures. Presenting individual stimuli may allow participants to freely associate them, which may be further encouraged by the imagery instruction participants typically receive in these experiments. This may facilitate the binding of event elements compared to the more prestructured presentation of event elements embedded in sentences, which may inhibit participants' ability to freely associate them. Since our linguistic agency manipulation relied on the presentation of event elements embedded in sentences, it may not have worked well in combination with the separated encoding paradigm.

In experiments in which we employed the simultaneous encoding paradigm (Experiments 4 and 5), we found significant positive dependencies of the retrieval of event elements (see Figure 7B), and thus evidence for binding effects. In Experiment 4 this was only the case in the agency condition. In Experiment 5, which had a larger sample size and a slightly longer presentation duration, this was the case in both the agency and non-agency condition. However, while the result pattern pointed in the expected direction (a higher dependency in the agency than in the non-agency condition), the difference in dependency between the two conditions was non-significant in both experiments.

It is noteworthy that memory performance in all experiments was quite poor. In Experiments 4 and 5, the average proportion of correct responses in the agency condition was 24%-26% and 23% in the non-agency condition. This is much lower than the memory performance in previous studies. For example, in our experiments in Schreiner, Meiser, and Bröder (2022) the average proportion of correct responses ranged from 38%-49% and in the experiments by Horner and Burgess (2013) it ranged from 57%-71%. As we showed in Schreiner and Meiser (2022), lower levels of memory performance are associated with lower power for detecting binding effects and differences in binding effects between conditions. It may thus have been the case that

the low memory performance in the experiments prevented the reliable detection of a difference in dependency between the agency and non-agency condition.

Consequently, we performed a supplemental analysis in which we only included participants with above-median memory performance in their respective condition in Experiments 4 and 5 and aggregated the data from the two experiments to account for the reduced sample size. With this analysis, we found significant positive dependencies in both the agency and non-agency condition and, importantly, the difference in dependency between the conditions was also significant (see Figure 7C). The dependency was higher in the agency than in the non-agency condition. This finding corroborates the descriptive result patterns of Experiments 4 and 5 and suggests a facilitating effect of agency on the binding of event elements that may have been concealed due to low memory performance in the experiments.

In sum, the results of the experiments hinted at a facilitating effect of agency on the binding of event elements. While the results from the experiments with sequential pairwise event presentation were inconclusive, this may have been due to this presentation format being not particularly well suited for investigating the research question in combination with the linguistic agency manipulation used. Since event elements were embedded in sentences, this may have inhibited participants' ability to freely associate them. The results from the experiments with simultaneous event presentation yielded evidence for binding effects, but only descriptive evidence for a facilitating effect of agency. More concrete evidence only emerged in a supplemental analysis with aggregated data and only including participants with above-median memory performance. Thus, while the results are not very clear, they hint at a facilitating effect of agency and this effect may have been concealed due to low memory performance in the experiments. Therefore, agency may indeed be a more proximate explanation for the facilitating effects of animacy on the binding of event elements in Schreiner, Meiser, and Bröder (2022) and the presence of an agentic element in an event may facilitate the formation of more coherent memory representations.



## 5 Conclusion

The ability to bind together different elements of an event into a coherent memory representation is a fundamental property underlying episodic memory. Yet, little is known about how these binding processes work or how to properly measure them. In this thesis, I introduced and evaluated a novel approach for measuring binding processes in episodic memory using behavioral data. I then used this approach to examine the structure in which different event elements are bound together and moderators of binding processes.

Given that an event's constituent elements are successfully bound together, there should be a stochastic dependency of the retrieval of event elements (Arnold et al., 2019; Boywitt & Meiser, 2012a, 2012b; Horner et al., 2015; Horner & Burgess, 2013, 2014; Meiser & Bröder, 2002; Starns & Hicks, 2005, 2008). By modeling this dependency one can derive measures of binding effects. However, earlier modeling approaches (see Burton et al., 2019; Horner & Burgess, 2013, 2014; Yule, 1912) are contingency-based and come with a number of limitations, such as susceptibility to Simpson's paradox (Hintzman, 1972, 1980; Simpson, 1951). In the first article (Schreiner & Meiser, 2022; see also Schreiner, Meiser, & Bröder, 2022), we introduced a novel approach based on item response theory (Lord, 1980; Lord & Novick, 1968) that overcomes some limitations of previous approaches. For example, because the approach takes individual item responses instead of aggregate contingency tables as input, it is not susceptible to Simpson's paradox. In an evaluation, the approach yielded unbiased estimates, good maintenance of Type I error rates and high power for detecting binding effects, outperforming the contingency-based approaches. While dependency estimates scaled with memory performance, this only affected power but not Type I error rates. One drawback of the approach is that, while it takes person differences into account, it provides an overall measure of dependency, whereas the contingency-based approaches provide person-specific dependency estimates. In the subsequent articles we used this IRT-based approach to examine important properties of binding in episodic memory.

In the second article (Schreiner, Meiser, & Bröder, 2022), we investigated the structure in which different event elements are bound together. There are competing accounts of binding structures in the literature. One class of accounts suggests an integrated binding structure, in which all event elements are bound into one unitary representation or engram (Damasio, 1989; Marr, 1971; Moll & Miikkulainen, 1997;

Shohamy & Wagner, 2008; Tulving, 1983; Zeithamova et al., 2012). Another class of accounts suggest a system of pairwise bindings in which asymmetries in binding strength are possible, making possible a hierarchical binding structure, in which event elements are preferentially bound to particular types of elements (Cai et al., 2016; N. J. Cohen & Eichenbaum, 1993; Eichenbaum, 1999; Healy & Caudell, 2019; Hommel et al., 2001). We extended the separated encoding paradigm (Horner et al., 2015; Horner & Burgess, 2014), in which event elements are presented sequentially pairwise across several temporarily divided encoding episodes (either all possible associations are shown [coherent encoding episodes] or one association is excluded from presentation [non-coherent encoding episodes]), with several non-coherent encoding conditions, in which we consistently excluded one of the possible associations from presentation. In doing so, we replicated previous findings demonstrating that binding across temporarily divided encoding episodes is possible (Bisby et al., 2018; Horner et al., 2015; Horner & Burgess, 2014; Joensen et al., 2020). We further found evidence for different binding structures, including both integrated, hierarchical, and, potentially, overlapping pairwise representations. This suggests that different binding structures can be possibly formed and implies the need for an overarching account bridging the accounts in favor of integrated binding structures and those in favor of a system of pairwise bindings. For example, memory representations may lie on a continuum with varying degrees of integration. Different testing demands or contexts may elicit different structures, such that how events are represented may not be fixed, but vary dynamically based on the specific demands or contexts at play. This would be consistent with relational memory theory (N. J. Cohen & Eichenbaum, 1993; Eichenbaum, 1999). Thus, several moderators may influence the degree of integration and therefore the binding structure of a memory representation.

Also in the second article (Schreiner, Meiser, & Bröder, 2022), we investigated the influence of animacy on the binding of event elements. Animacy has previously only been investigated in relation to memory performance, but not regarding the coherence of memory representations. Regarding memory performance, an animacy effect has been robustly found, such that words describing an animate entity are remembered better than words describing an inanimate entity (e.g., Li et al., 2016; Nairne et al., 2013; VanArsdall et al., 2015). Extending these findings, we found evidence that the presence of an animate element in an event also facilitates binding, leading to more coherent memory representations than if an event is only comprised of inanimate elements.



In the third article (Schreiner, Bröder, & Meiser, 2022), we investigated the influence of agency on the binding of event elements. While robust effects were not seen, the pattern of results hinted at a facilitating effect of the presence of an agentic element in an event on binding. Agency effects may thus underlie the previously found facilitating effects of animacy. These may have occurred because the presence of an animate element in an event provides a potential agent. However, animacy may only be one of several factors contributing to agency (see e.g., Johnson & Barrett, 2003; Lowder & Gordon, 2015). In addition, our results suggest that the opportunity to freely associate event elements may facilitate binding. We only found binding effects when event elements were presented simultaneously, but not when they were presented sequentially pairwise, although binding effects have been found under such circumstances in previous studies (Bisby et al., 2018; Horner et al., 2015; Horner & Burgess, 2014; Joensen et al., 2020; Schreiner, Meiser, & Bröder, 2022). However, in Schreiner, Bröder, and Meiser (2022) we presented event elements embedded in sentences instead of presenting them as individual stimuli. This presentation format may have made the described scenes more prestructured and inhibited participants' ability to freely associate event elements. This also corroborates evidence suggesting that additional processes may be required when binding event elements across temporarily divided encoding episodes compared to binding within a single encoding episode (see James et al., 2020).

Our findings on moderators of binding processes in episodic memory add to a limited number of previous findings. These suggest that multimodal compared to unimodal presentation of stimuli disrupts binding and that written stimuli facilitate binding compared to picture stimuli (James et al., 2020). The latter finding may also be consistent with our findings suggesting that free association facilitates binding (Schreiner, Bröder, & Meiser, 2022), since written stimuli may be more freely associated than picture stimuli. Further, awareness regarding the structure of an event, such as the number and types of its constituent elements, may facilitate binding (Kumaran, 2013; Kumaran & Ludwig, 2013; Morton et al., 2020). This is also corroborated by our findings in Schreiner, Bröder, and Meiser (2022). There, we only found binding effects with fixed event compositions, in which all events comprised the same set of element types, but not with varying event compositions, in which events could comprise different sets of element types. Participants' awareness regarding the underlying event structure may have been reduced in the case of varying compared to fixed event compositions.

To conclude, the present thesis provides a novel measure for investigating binding processes in episodic memory and insights into some properties of these binding processes. I demonstrated that the novel measure is well-suited to probe binding effects. Moreover, I provided evidence that event elements may be bound into different types of event structures with different degrees of integration and that the degree of integration a memory representation achieves may be influenced by moderators such as animacy or agency. Thereby, I provide researchers with a new tool to investigate binding processes in episodic memory and extend a relatively limited body of empirical evidence regarding these binding processes. The somewhat nuanced findings highlight the complexity of the system underlying binding processes in episodic memory and call for the development and refinement of theories and models to better understand this fundamental property of our memory system.

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*"I can't carry it for you, but I can carry you!"*

from *The Return of the King*

by J. R. R. Tolkien

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## B Statement of Originality

1. I hereby declare that the presented doctoral dissertation with the title *Binding Processes in Episodic Memory: Measurement, Structure, and Moderators* is my own work.
2. I did not seek unauthorized assistance of a third party and I have employed no other sources or means except the ones listed. I clearly marked any quotations derived from the works of others.
3. I did not yet present this doctoral dissertation or parts of it at any other higher education institution in Germany or abroad.
4. I hereby confirm the accuracy of the declaration above.
5. I am aware of the significance of this declaration and the legal consequences in case of untrue or incomplete statements.

I affirm in lieu of oath that the statements above are to the best of my knowledge true and complete.

Signature:

Date:



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## C Co-Authors' Statements

### Co-Author: Thorsten Meiser

With this statement, I confirm that the following articles included in the present thesis were primarily conceived and written by Marcel R. Schreiner.

Schreiner, M. R., & Meiser, T. (2022). Measuring binding effects in event-based episodic representations. *Behavior Research Methods*. Advance online publication. <https://doi.org/10.3758/s13428-021-01769-1>

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Marcel R. Schreiner designed and conducted all experiments reported in Schreiner, Meiser, and Bröder (2022) and Schreiner, Bröder, and Meiser (2022) as well as the simulation reported in Schreiner and Meiser (2022). He analyzed all data in all three manuscripts and wrote most of the articles, including first drafts and revisions of the manuscripts. I contributed to the development and refinement of the research questions, study design, and statistical analyses. Furthermore, I revised the manuscripts.

Prof. Dr. Thorsten Meiser  
Mannheim, October 2022

**Co-Author: Arndt Bröder**

With this statement, I confirm that the following articles included in the present thesis were primarily conceived and written by Marcel R. Schreiner.

Schreiner, M. R., Meiser, T., & Bröder, A. (2022). The binding structure of event elements in episodic memory and the role of animacy. *Quarterly Journal of Experimental Psychology*. Advance online publication. <https://doi.org/10.1177/17470218221096148>

Schreiner, M. R., Bröder, A., & Meiser, T. (2022). *Agency effects on the binding of event elements in episodic memory*. Manuscript submitted for publication.

Marcel R. Schreiner designed and conducted all experiments reported in Schreiner, Meiser, and Bröder (2022) and Schreiner, Bröder, and Meiser (2022). He analyzed all data in both manuscripts and wrote most of the articles, including first drafts and revisions of the manuscripts. I contributed to the development and refinement of the research questions and study design. Furthermore, I revised the manuscripts.

Prof. Dr. Arndt Bröder  
Mannheim, October 2022

## D Copies of Articles

