Evaluating a conceptual network model using state changes in a computerized change blindness task

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PSB3E-BT15: Bachelor Thesis

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Month 02, 2022

Abstract

A continuation of the 2021 research thesis is conducted, investigating the premises of the conceptual network model (De Vries, 2004) on binding and the critical threshold of cell assemblies, using a computerized change blindness task. The previous study found support for the hypothesis that shared identity and distance interact to increase accuracy, only for exemplar changes, and not state changes. In this experiment, objects which undergo state changes were used. The object stimuli were taken from the same collection as the previous research, however not using any objects which undergo a change in color or shape. The stimuli were then sorted into two sets of 6 categories each, with four objects per category, and two pictures of the same object, in two different states. Due to participants of the previous experiment finding the task difficult, it was simplified by always having a change occur, and introducing a confidence rating to evaluate if this is impactful, as well as investigating how accuracy and confidence are related. The hypothesis predicts that shared identity and distance will interact to produce the highest accuracy, and that accuracy and confidence will have a positive relationship. A 2x2 RM ANOVA and two 2x1 RM AVOVAs were conducted using independent variables shared identity and distance, for each of the two dependent variables: Change detection accuracy, and participant's confidence scores. The results show support for both of these hypotheses. This provides support for the proposed conceptual network model (De Vries, 2004).

Keywords: Change blindness, Binding, Critical Threshold, Cell-assembly.

Change blindness

This is a follow-up study of an experiment conducted by bachelor thesis the previous year (Braam, 2021; Drake, 2021, Dzhurkov, 2021; Koot, 2021; Wazny, 2021), of which this paper is a direct continuation. This paper uses the conceptual network model proposed by De Vries (2004) to investigate the change blindness phenomenon, which is “when retinally localizable information signaling a change is masked by an eye movement or a flashed blank screen, causing observers to have difficulty detecting changes to the visual details of a scene” (Simonds & Levin, 1998). To illustrate the effect in a real-world setting, imagine you are going shopping. You park your car and walk into the shop only to realize that you had forgotten your bag. Upon returning to your parking space, would you be able to tell if one of the six cars surrounding your car has left its spot and been replaced by a different car? Most likely not, in order to remember every detail of our environment and interactions, we would need an exponential amount of neural structure to create permanent connections between objects and locations. Research suggests that people are not sensitive to detect such changes in the real world (Simonds & Levins, 1998). To imagine if this was the case, we can draw insights from the rare cases of hyperthymesia or highly superior autobiographical memory (HSAM), which is a rare disorder in which patients suffer from an inability to forget or considering a more common disorder, PTSD - of which the sudden onset of traumatic memories is a core diagnostic feature - it is possible to understand the daily implications of the inability to forget. Viewing our memory through the metaphor of a computer, it's simple to understand why storing immensely large quantities of information may be a hindrance. The more information is stored in the memory, the more information needs to be sorted through every time we need to access a piece of information. In order to interact and function within an environment, it is required to have knowledge about what objects are in it, and the corresponding location of each of those objects. For example, you might know something was taking up a particular spot in your environment, without knowing what that object was. Or the opposite, knowing that an object was in our general vicinity, but not quite remembering where it was. Without making this connection, it is not possible to determine if an object has changed its location whilst outside of one's attention or visual field. Without this concept of object and location being connected, change blindness would be constantly in effect, making it impossible to detect changes that occur in the environment.

Binding

Change blindness occurs when the connection between the neural representations of objects and locations does not form or activate. Binding is the link that connects neural representations of an object's identity to the location that said object occupies in the environment (De Vries, 2004). This process of binding will be discussed through the functional and structural levels of description. The functional level of description is a top-down process in which the processes and mechanisms of the system are understood in terms of their function, whilst the structural level of description is a bottom-up process in which parts of the system are reduced down to the smallest properties of the parts, which is the individual neurons (Dalenhort & De Vries,1998). There is support for the argument of maps (Cooper, 2005), which implies that characteristics of objects such as location, orientation, color, and movement are held in separate areas (Treisman & Gelade, 1980). At the functional level, binding is explained as a cognitive process in which the representation of an object is connected to a spatial map that represents the location in the environment. At the structural level, the process of binding is explained in terms of the neural structures that make up the brain, with the groups of neurons that represent the object and the location connecting. However, explaining this connection on the structural level results in what is known as the variable binding problem (Feldman, 2012). Namely the question, how do the two abstract representations of object and location form this connection in terms of physiological structure? The two ways this can be explained is that there must be an immensely large amount of pre-existing physical connections between all possible objects and all possible locations, waiting to be activated. This however would require vast amounts of neural structure and computational power making it highly inefficient and very unlikely as a plausible explanation, as well as the previously mentioned drawbacks. Therefore, a model in which these connections do not occur permanently through physical neural connections is much more likely. A temporary connection between the two neural structures that represent the object and location that occur as a result of being activated simultaneously is in line with the current explanation of this phenomenon. However, this then brings to light the question of how binding of object and location can occur when multiple stimuli are presented simultaneously. To address this question, the conceptual network was proposed by De Vries (2004). This conceptual network is based on principles of neural connectivity. This model is built on the Tanzi-Hebb rule of learning which is often summarized as “neurons that fire together, wire together” (Hebb, 1949; Tanzi, 1893). This states that a neuron receives excitation from another, resulting in structural changes that make the connection between the two stronger, as well as an increase in synaptic efficiency, decreasing the resistance of excitation (Cooper, 2005). This causes the formation of neuronal groupings with permanent connections known as cell assemblies, at the structural level and memory traces at the functional level. They are groupings of neurons that together, represent a variety of characteristics that together make up a specific object identity. In this experiment, these object identities are that of the objects which are presented in the matrix.

Conceptual network model

How do elements in the proposed conceptual network influence accuracy of detecting a change in objects using a change blindness task? The change detection accuracy is the mean percentage of trials in which the participant is able to correctly identify the location of the change that occurred. In future writing, this dependent variable will be referred to as accuracy.

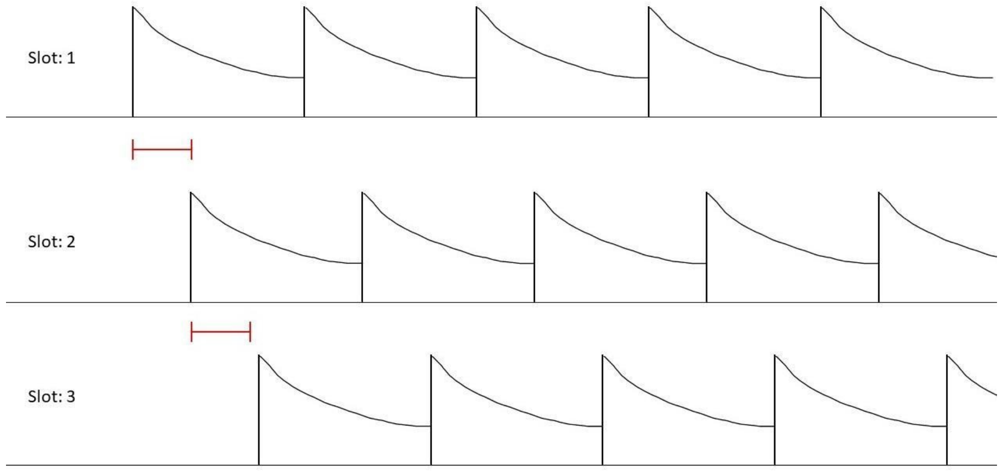
One issue that stems from the binding explanation is that "there is a fundamental problem of how the correct bindings come into existence for several simultaneously presented objects" De Vries (2004). The explanation given for this is that the binding occurs serially through the function of a scanning mechanism. As a consequence of this mechanism, only one memory trace of an object and location on the spatial map is processed at a time. Once the link has formed and the binding has occurred, the scanning mechanism is activated again, which leads to the next pair being processed, resulting in the binding process occurring in a serial manner. One possible explanation for how the mechanism pairs the correct elements from different maps is that the binding is context-dependent (De Vries, 2004). Therefore, in order for both the object and spatial map to become active simultaneously, they must be a part of the same context. Due to the maps being active simultaneously in the same context, the spike trains begin to resonate, which forms the binding between them (De Vries, 2004).

Slot-Based Capacity System

This mechanism of serial binding explains how multiple objects are presented in unison and bind to the spatial map which stores their location in the environment. Is there, however, a limit to the number of objects that can be stored in the working memory? Luck and Vogel (2013) discuss exactly this, presenting two models of how stimuli are stored in the working memory. Two models are presented in the paper: The resource-based model, and the slot-based model. The authors argue that the research literature supports the slot-based model of working memory, which states that there is a maximum number of "slots", which can be active in the working memory at the same time. The explanation for this is that information in the working memory passively decays. Therefore, the repeated firing of these slots is required for the information to remain in the working memory and be accessible. However, only one slot can be fired at one time, meaning that the only way multiple slots can be active in the working memory at one time is by them firing in a serial manner, as seen in Figure 1.

Figure 1

Sequential firing of cell-assemblies



Note. The red line indicated the time in between two cell-assemblies' firings.

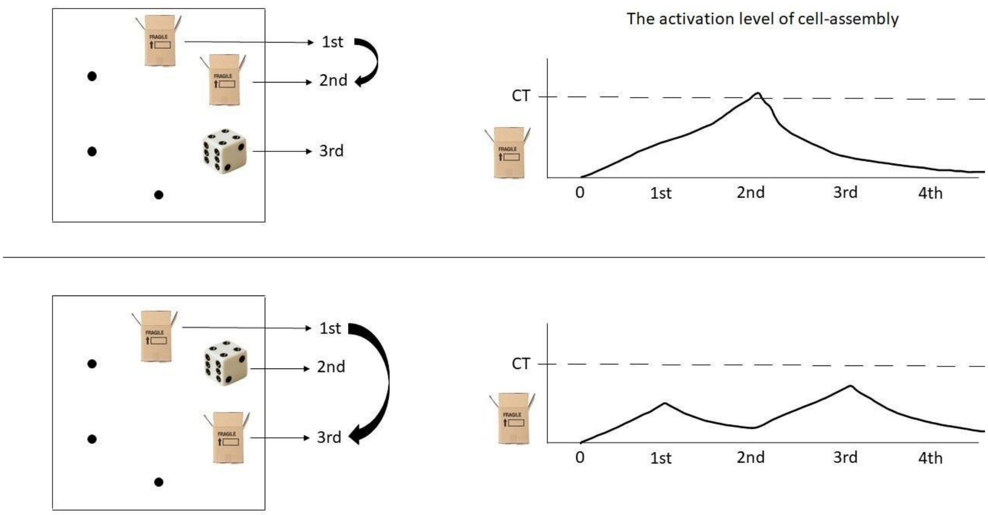
They use k to symbolize this maximum, which on average is four slots. These slots are groupings of individual neurons; therefore, they are the same as the cell assemblies discussed in the conceptual network. This is the reason why the matrix used in this paper's computerized task, contains six different locations with an object each. As if it did not contain more objects than k, participants would be able to remember each object and not experience change blindness. (Lamme, 2003).

Critical threshold

When multiple objects sharing the same identity are presented, the involved memory trace will make multiple bindings, one to each location. As this binding occurs, the cell assembly reaches closer to the critical threshold. Once a sufficient number of neurons have become active, the excitation level of the assembly rises autonomously to its maximum. When the activation level exceeds the critical threshold the corresponding location or identity is assumed to be in short-term memory (Dalenoort, 1985). This activation decreases with time, meaning the longer the time in between the binding of an identity to multiple locations on the spatial map, the less activated the memory trace will be. Therefore, forming multiple bindings in quick succession increases the activation of a cell assembly which results in a higher likelihood that it will reach its critical threshold. The relationship between this critical threshold and the concept of change blindness is that change blindness occurs when the excitation of the cell assembly is not enough to pass its critical threshold. This process is visualized in Figure 2.

Figure 2

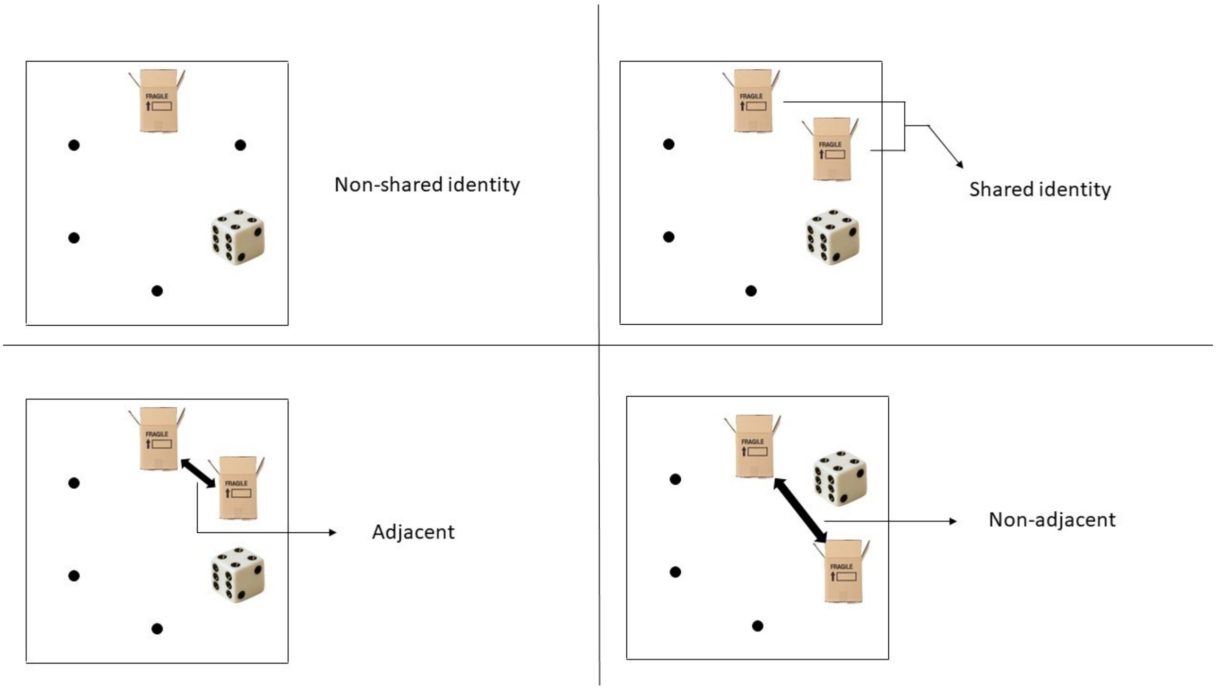
Location in the matrix and reaching of critical threshold



Based on this principle of the conceptual network (De Vries, 2004), the 2021 research thesis hypothesized that: (1) If there is another object sharing its identity with the target object in the matrix, the accuracy of the target will be higher than if the target identity is unique in the matrix. In the following writing, this will be referred to as the identity hypothesis. (2) If this object with a shared identity is next to the target object, the accuracy will be higher than if the shared identity object is one location apart from the target object. This will be referred to as the interaction hypothesis. Main effects were expected for the factors: Shared identity and Distance, and an interaction effect was expected between the two factors, meaning when two objects share an identity, the increase in accuracy will be stronger when they are next to each other, rather than spaced one object apart.

Figure 3

Independent variables: Shared identity & Distance explained in matrix example



Past thesis

The 2021 research thesis (Braam, 2021; Drake, 2021, Dzhurkov, 2021; Koot, 2021; Wazny, 2021) was carried out to investigate how changes in object's states and exemplars influence the accuracy in a computerized change blindness task. A change in the state of an object involved it going from open to closed, empty to full, whole to halved, or vice versa. A change in exemplars involved the object being replaced by another object that shared the same object identity, whilst still being a different object. Such as a key being exchanged for another type of key. Due to the brief time length in which the frames were presented, a cue was used to direct the attention of the participant to the relevant area in which the change may take place. The type of cue used for this purpose had two levels to investigate their effect on change detection accuracy. The simple cue was a red line pointing from the middle of the screen to the objects that were being cued. The purpose of this cue is to protect the participant from experiencing CB, through the role of attention (Lamme, 2003). The cue decreases the number of objects that have to be stored in the working memory from six to 3, however, this is not the only way it prevents CB. Even after the pre-change display has disappeared, a neural structure representing it is present, and through attention, individual stimuli can be selected and brought into conscious awareness through the working memory (Lamme, 2003. The identity cue was a picture of the object being cued, appearing in the middle of the screen.

Experiments carried out by the 2021 thesis experiment (Braam, 2021; Drake, 2021, Dzhurkov, 2021; Koot, 2021; Wazny, 2021) did not result in agreed support. All found support for hypothesis 1: accuracy will increase when the target object shares its identity with another object in the matrix. Only the experiments using exemplar changes found support for hypothesis 2: That accuracy will be higher when the shared identity object was adjacent to the target. The experiments that found support for this differed from the rest, as their stimuli pairs were made up of changes in exemplars with a shared identity, rather than state changes as in the other three experiments. This creates the question of why changes in the states of objects did not produce the expected results. One confounding variable of the part experiment is the color change that occurs between two pictures of the same object identity. As illustrated through sample arrays in the paper by Luck & Vogel (2013), a typical change blindness task commonly used squares of different colors as stimuli, using a similar trial structure as used here. Therefore, since participants are able to notice changes in the color of the stimuli, when there is a noticeable difference in an object's pair of pictures in terms of color, this can result in much higher accuracy for this object, compared to one in which the color remains the same. To illustrate this effect, in figure 4 below, the object with the highest accuracy and the two objects with the lowest accuracy is shown.

Figure 4

Example stimuli from the 2021 thesis, showing the highest accuracy object (left), and two of the lowest accuracy objects (middle, right).

Current research

As the expected interaction effect only occurred in the experiments where there was a change in exemplars, this experiment will use changes in state to further investigate its role in change blindness. Due to participants describing the experiment as being difficult, the task has been simplified by removing the possibility of no change occurring, thereby reducing the number of possible answers from three to two. In order to know if this change is effective, a confidence response is given for each trial. This may also provide insight into the relationship between the confidence and accuracy of participants' responses. Two aspects of the stimuli used were identified as potential confounding variables, namely the role of color and shape, making some object changes much easier to identify on the basis of those than the change in state or exemplars. In order to control for this, the objects to which this applies to have been removed to the fullest extent possible with the select stimuli available. And are we able to correctly identify the location of the change without knowing what it is that has changed in the object at that location? Drawing from the conceptual network model, are three hypotheses. The first predicts that when the matrix contains an object that shares its identity with the target object, the accuracy of detecting a state change will be higher than if the target object does not share its identity with another object in the matrix. The second hypothesis predicts that when the object sharing its identity with the target object is adjacent to the target object, the accuracy will be higher than when it is not adjacent. Third, when the matrix contains two objects that share their identity with each other but not the target, the accuracy will not be different from when every object in the matrix is unique. As this process appears to be conscious, the fourth hypothesis predicts that the relationship between participants' ability to accurately detect where the change has occurred, will have a positive relationship with their self-reported confidence that their response contained the correct location of the change. This will help us understand the degree to which change detection is a conscious process. Are we able to correctly report that a change has occurred without being consciously aware of the change?

This experiment is number one of six experiments that will be performed in parallel as a part of the bachelor thesis research project. It makes use of the same computerized task as the other five experiments being performed alongside it, as well as that of the 2021 thesis experiment. To control for the possible effect of the objects themselves, experiments one (Griffiths, 2022), three (Piletti, 2022), and five (Houter, 2022) will use object set two, whilst experiments two (Garcia Martin, 2022), four (Van den Brink), and six (De Vries,2022) will use object set two. Between the experiments, there will be differences in the duration of the pre-change screen, pre-cue screen, cue-screen, and post-cue screen to evaluate the effect of said screen durations. The type of cue used will also vary between the experiments, with experiments one and two using a simple cue (red line), and the rest making use of an identity cue (picture of object being cued).

Method

Participants

A total of 42 participants took part in the experiment. Two participants were recruited using volunteer sampling and received no compensation. 40 were recruited using a participant pool that consists of first-year students from the Department of Behavioral and Social Sciences at the University of Groningen. In order to fulfill their first-year requirements, the first years must take part in a set minimum amount of psychology research experiments conducted by the university (SONA program). The sample was made up of 9 males and 33 females (mean age = 20.05, SD = 2.095.). 3 participants were excluded from the experiment due to not completing the experiment, having a mean accuracy > 5%, or repeatedly clicking on the cue location as their response. The ethical committee of the Faculty of Behavioral and Social Sciences at the University of Groningen has approved the experiment. There are no risks to the participants as a result of participating in this study.

Stimuli

The pictures of objects used in this experiment come from the Konkle Labs online database (Brady et al., 2008). Which contains a collection of pictures of 200 objects, each object having a pair of pictures, in which the object is shown in one of two states. Examples of these can be seen in Figure 5.

Figure 5

Stimuli in two different states

The majority of the state changes fall within these descriptions, open and closed, full versus empty, whole versus halved, and change in orientation. For this experiment, only state change pairs were used, as this experiment is investigating whether the effects of shared identity and distance can be demonstrated for this type of object change. This is done as the past thesis only found evidence for the main and interaction effect of these variables for changes in exemplars, and did not find significant effects when using these state changes. The objects previously used in the past experiment (Braam, 2021; Drake, 2021, Dzhurkov, 2021; Koot, 2021; Wazny, 2021) were evaluated using their respective change detection accuracy. Any object with an accuracy similar to guessing chance was removed. To control the effect of the shape and color on change detection accuracy, objects which had a noticeable change in color or shape within the pair were removed from the selection. As accurately detecting a change could then be attributed to noticing a change in color or shape, and not a change in the state of the object. To control for the possible effect of the individual stimuli used (changes in certain types of objects being easier to detect), two sets of object categories were needed. This way, this experiment and two of the experiments being conducted in parallel (Martin Garcia, 2022; V. Piletti, 2022) use Set 1, whilst the other experiments use Set 2 (J. Houter, 2022; I. van den Brink,2022). Differences in findings between the two sets could therefore be attributed to the stimuli used. A visualization of the matrix used in this experiment can be found in figure 6. As the matrix used in the task contains six different positions, and each object in each position must contain an object that does not share its identity with any other objects in the matrix, 6 different categories of objects are required.

Figure 6

Example matrix of an array of objects displayed in the pre-change stage

Two sets of six unique categories mean that 12 categories are needed. The 12 distinct and non-overlapping categories that were created and divided into two sets are as follows. Set 1: storage, household appliances, electronics, entertainment, drinks, baking. Set 2: fruit, antiques, kitchen, tools, animal, clothing. The objects were then divided so that there were 4 objects in each category. The 12 categories were separated into two sets to act as a control for the possible confounding effect of the objects used when comparing experiment findings, as some pairs may be easier than others to notice a change. This experiment was conducted using the objects and categories of Set 1.

Design

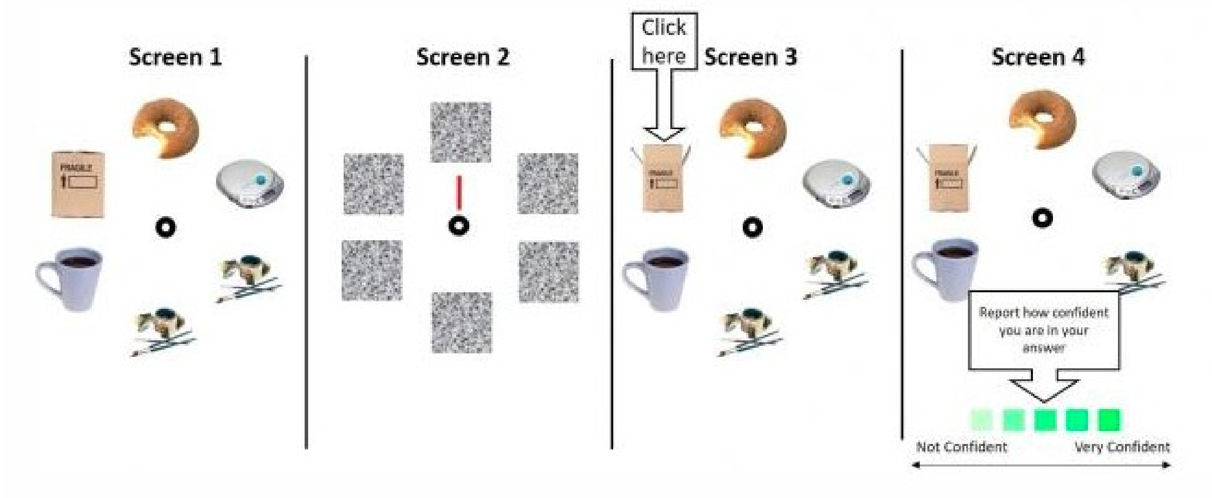
The experiment used a 2x2 within-subject design. The first independent variable is shared identity which has two levels. All objects in the matrix are unique (one from each category), or two objects in the matrix share their identity with each other (the same object in the same or different state as the other). The second independent variable is distance, which also has two levels. Either the two objects sharing identity are directly parallel to each other (no object is in between them), or the two objects are not parallel to each other (separated by a different unique object in between). The first dependent variable is the mean accuracy of change detection. The second dependent variable is the confidence level of the participant's response, which is a Likert scale of 5 levels, ranging from very low confidence to very high confidence.

Procedure

Due to the current state of the COVID-19 pandemic, the participants completed the experiment in their own homes using a laptop or a desktop computer. Before beginning the computerized task, the participants read the information regarding the study in the program Qualtrics (Qualtrics, Provo, UT). First, they are informed about the materials required, which is a laptop or desktop along with a mouse. The participants were provided with an overview of the study, including its purpose, informed consent, participation compensation, recording of personal information, task instructions, and contact information. Detailed instructions for the task can be found in Appendix 1. Once fully informed, the participants were asked to give their informed consent and were then allowed to take part in the study.

Figure 7

Task instructions participants were given before participating

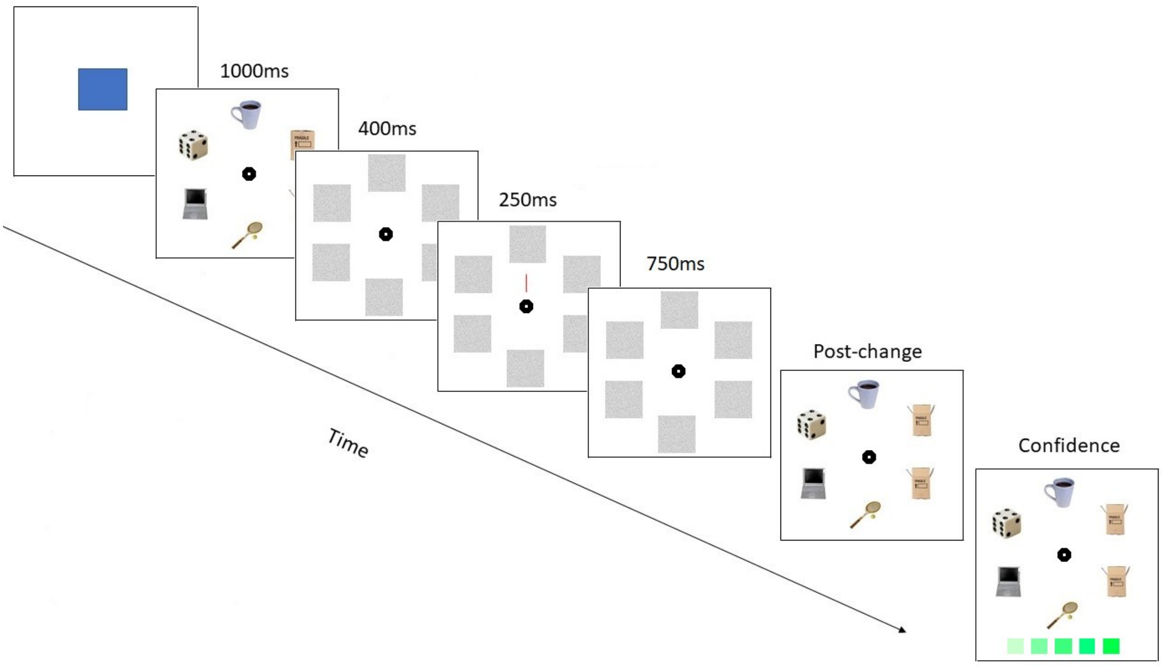


The task was performed in OZWeb (Mathôt, & March, in press) where the participants first completed two practice blocks of 8 trials, where they received feedback in the form of the black center circle of the matrix turning a green color, indicating that they responded correctly or red color to indicate if they did not respond correctly to each trial. Once the practice trials were complete, they continued with the experimental trials of four blocks. Each block consists of 24 trials meaning that the experiment consists of 96 trials. The practice and experimental trials are identical, other than the participants only receiving feedback for the practice trials, and not the experimental trials. Each trial began with a blue square in the middle of the screen which lasted until pressed. Once pressed with their mouse cursor, participants were presented with the pre-change display, a matrix of 6 positions arranged in a circle around the center of the screen, which lasted for 1000ms. Each position had an object from each category, except for when two positions had objects from a shared category (Shared identity) which made up 50 percent of the trials. Then the pre-cue mask screen was presented for 400ms, in which the screen consisted of the same matrix, but the objects were replaced by 6 identical grey static squares. This was done to hinder the ability to detect a change in state, by noticing a movement, which is possible when no mask is present, by inhibiting the visual working memory. The cue screen was then presented for 250ms in which there was a red line pointing from the middle of the screen toward the location of the cued object, of which the target object would be to either the left or right. The post-cue mask screen, which is identical to the pre-cue mark screen, was then presented for 750ms. Then the post-change display screen containing the changed object was presented until a response was given, as seen in Figure 7. Once the response was given, 5 small green squares of varying brightness were presented. The participants then rated how confident they are in their response about the location of the change. The most left green square (The brightest) represented having low confidence, and the most right (The darkest) represented having the highest confidence.

In order to satisfy the independence assumptions of statistical analyses and to prevent order effects, the 24 trials of each condition (94 trials in total) were randomly distributed across the entire experiment, and not within each block. Two of the positions in the matrix always objects that shared identity, which positions contained these objects, as well as the target object, were randomized over the entire experiment, meaning each position equally contained the target object ⅙ of the trials.

Figure 8

Screen progression through a trial



Statistical analysis

The data output from the experimental task was first stored on the OSWebs server and was then transformed into an excel file. To prepare the data for analysis the aggregation and restructuring procedure detailed by (Add citation) was used. The raw output was restructured to show for each participant, the mean change detection accuracy and mean response confidence score of each experimental condition. The analysis was done in two parts. To investigate the main effect, and interaction effect of shared identity and distance on the change detection accuracy, one repeated measures ANOVA and two one-way ANOVAs were performed. To investigate the effect of said conditions on the participant's mean response confidence, one repeated measures ANOVA and two one-way ANOVAs were performed.

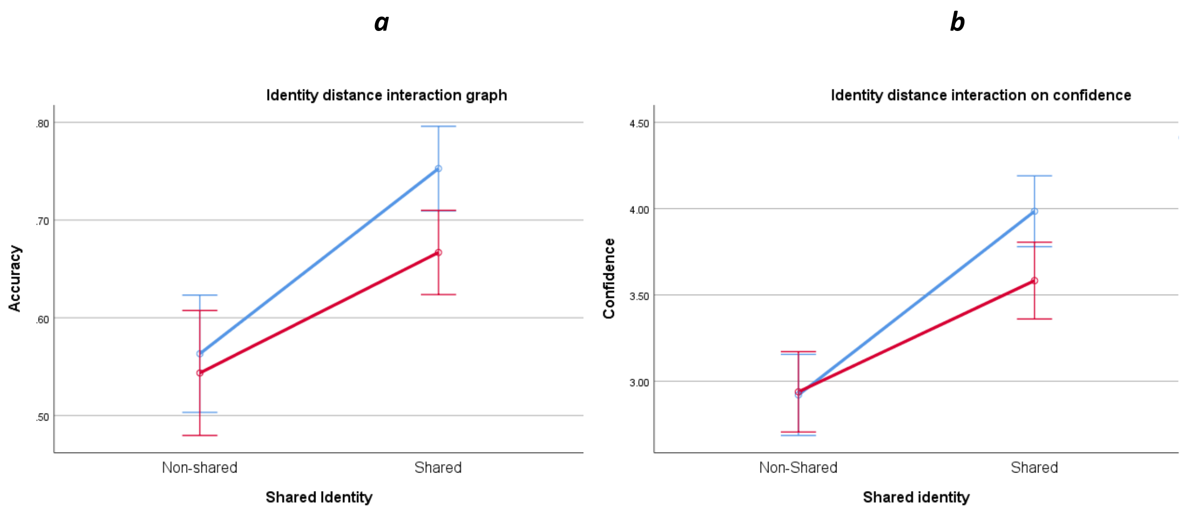
Results

For the analysis of data to be possible, the assumptions of the tests used must be met. Repeated measures ANOVA make the following assumptions: Independence, normality, and sphericity. The assumption of independence was met as the conditions were equally distributed and randomized across each participant's experiment. Normality was assessed with a Shapiro-Wilk test for each condition: results are found in Appendix B: Table 1. Out of the four conditions, only condition not-shared, and adjacent was found to not meet the assumption of normality. However, repeated measures ANOVA is robust against violation of normality. The assumption of sphericity is not relevant as each independent variable has only two levels.

A 2 (shared identity) x 2 (Distance) repeated-measures ANOVA was performed using accuracy as the dependent variable. The within-subject effect showed a significant interaction effect of shared identity * distance on accuracy $F(1, 39) = 4.695$, $p = .037$, $\eta\ 2 = .110$. There was also a significant effect of shared identity on accuracy $F(1,39) = 36.741$, $p < .001$, $\eta\ 2 = .492$, as well as a significant effect of distance on accuracy $F(1, 39) = 15.137$, $p < .001$, $\eta\ 2 = .285$, as illustrated in Figure 9a. The results show that shared identity $M = 0.553$, $SE = .029$, 95% CI (.495-.612) had higher accuracy than non-shared $M = .710$, $SE = 0.02$, 95% CI (0.670-.750). The results also show that accuracy is higher for adjacent $M = .658$, $SD = .021$, CI (.614-.701) than non-adjacent $M = .605$, $SD = .023$, CI (.559-.651). Two 2 x 1 ANOVAs were conducted. The first looked at the shared conditions using distance (adjacent vs not-adjacent) as its independent variable and accuracy as its dependent variable. It showed that there was a significant difference in accuracy ($F(1,39) = .24.860$, $p < .001$) between the adjacent ($M = .753$, 95% CI = .709, .797) and not-adjacent ($M = .667$, 95% CI = .623, .710) conditions, for non-shared trials. The second looked at the non-shared conditions using distance (adjacent vs not-adjacent) as its independent variable and accuracy as its dependent variable. It showed that there was not a significant difference in accuracy ($F(1,39) = .719$, $p = .402$) between the adjacent ($M = .563$, 95% CI = .502, .624) and not-adjacent ($M = .544$, 95% CI = .479, .608) conditions, for non-shared trials. These results support Hypothesis 1: That shared identity with another object will result in higher accuracy. They also support Hypothesis 2: That shared identity and distance interact resulting in even higher accuracy. There is also support for Hypothesis 3: That the distance between two shared identities, that are not the target, will not influence the accuracy.

Figure 9

*Interaction effect (Shared identity * Distance) on (a) accuracy and (b) confidence, with blue = Adjacent, red = Non-adjacent*



Note: The error bars represent the 95% confidence interval.

These results are corroborated by figure 6a, which shows that for non-shared identity, the conditions of adjacent (Blue Line) and non-adjacent (Redline) are not significantly different, as shown by the overlap of their overlapping error bars.

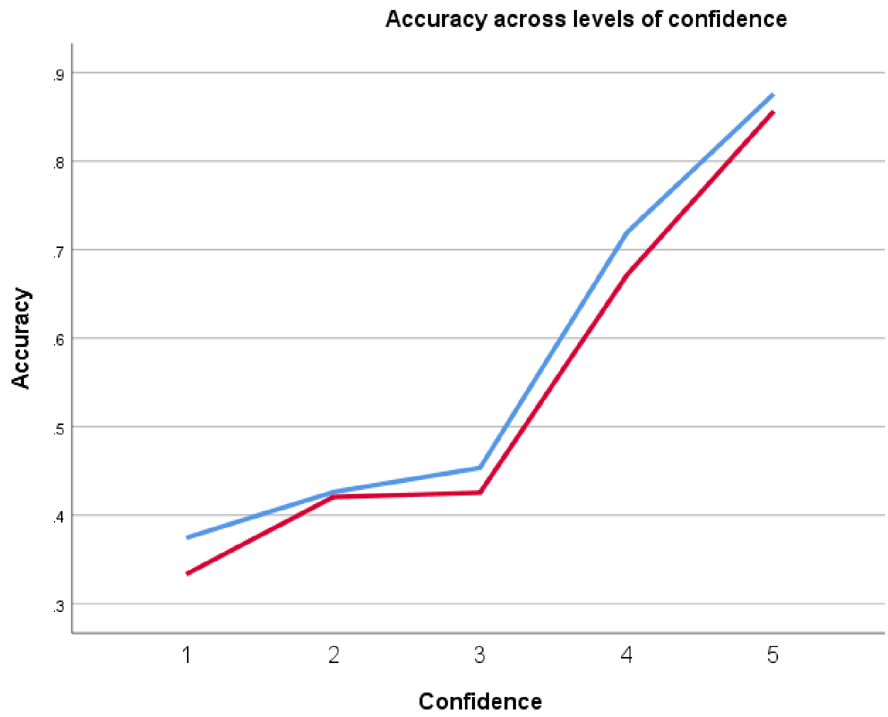
Confidence

To investigate the relationship between shared identity and distances' effect on the confidence of the participant's responses, a 2 x 2 RM ANOVA and two 2 x 1 RM ANOVA were conducted. The assumption of independence, normality, and sphericity apply to the tests used. Independent samples are assured through the randomization procedure as before. To test for normality, a Shapiro Wilk test was used, Appendix B: Table 4. The data for conditions shared, adjacent and shared, and non-adjacent were found to not be normally distributed. However, RM ANOVA is robust against this assumption being violated. sphericity does not apply as there are only two levels to the independent variables.

A 2 (shared identity) x 2 (Distance) repeated-measures ANOVA was performed using confidence as the dependent variable. The within-subject effect showed a significant interaction effect of shared identity * distance for confidence $F(1, 39) = 43.719$, $p < .001$, $\eta^2 = .529$. There was also a significant main effect of shared identity on confidence $F(1,39) = 91.629$, $p < .001$, $\eta^2 = .701$, as well as a significant main effect of distance on confidence $F(1, 39) = 18.979$, $p < .001$, $\eta^2 = .327$, as illustrated in figure 9b. The results show that shared identity $M = 3.784$, $SE = .103$, 95% CI (3.575, 3.993) had higher confidence than non-shared $M = 2.929$, $SE = .114$, 95% CI (2.699, 3.160). The adjacent $M = 3.453$, $SD = .098$, CI (3.255, 3.651) and non-adjacent $M = 3.260$, $SD = .105$, CI (3.047, 3.473), conditions were not shown to be significantly different. Two 2 x 1 repeated measure ANOVAs were conducted. The first looked at the shared conditions using distance (adjacent vs not-adjacent) as its independent variable and confidence as its dependent variable. It showed that there was a significant difference in confidence ($F(1,39) =50.963$, $p <.001$)) between the adjacent ($M = 3.985$, 95% CI = 3.777, 4.193) and not-adjacent (M = 3.583, 95% CI = 3.358, 3.808) conditions, for shared trials. The second ANOVA looked at the non-shared conditions using distance (adjacent vs not-adjacent) as its independent variable and confidence as its dependent variable. It showed that there was not a significant difference in confidence ($F(1,39) = .114$, $p = .737$) between the adjacent (M = .2.921, 95% CI = 2.683, 3.158) and not-adjacent (M = 2.938, 95% CI = 2.703, 3.174) conditions , for non-shared trials. This mirrors the results found for the dependent variable accuracy, showing support for hypothesis 4: That there is a positive relationship between the accuracy of the participant's responses and their confidence in those responses, as the conditions that result in higher accuracy also result in higher confidence. This shows supports the hypothesis that accuracy and confidence have a positive relationship. However, note that the means of dist = adjacent and non-adjacent only barely fall within each other's confidence intervals, meaning if the power of the test was higher (more participants), this might have yielded significant differences between the conditions of distance.

Figure 10

Accuracy across levels of confidence: Shared identity (Blue) and Non-shared identity (Red)



Note: Here the positive relationship between the two dependent variables can be seen. Overall, the conditions with a shared identity resulted in slightly higher confidence than non-shared conditions.

Discission

The aim of this study was to investigate how the factors of shared identity and distance described in the conceptual network (De Vries, 2004) influence the accuracy of detecting changes in an object which undergo a state change, using a computerized change blindness task. The first hypothesis, that presence of objects sharing identity with the target will increase accuracy, is based on the premise of the conceptual model (De Vries, 2004) that each of the multiple serial bindings between an object identity (in the form of a cell assembly) and different locations on a spatial map will increase the activation of said cell-assembly. The result of which is that the cell assemblies' excitation level is more likely to reach the critical threshold, resulting in conscious awareness and the object being in the working memory. This hypothesis is supported by the results of the RM ANOVA, reporting a significant main effect for the presence of a shared identity object increasing the accuracy of the task. The second hypothesis predicts that there will be an interaction effect between the presence of a shared identity and the distance between the two objects. This is based on the premise that there is a decay in the activation of cell assemblies over time. Therefore, the longer the duration in between binding, the lower the highest point of activation will be, and, the less likely it is that the cell assembly will reach its critical threshold. As the memory traces of the objects in the display are assumed to become bound to the spatial map in a serial manner, the physical distance between them will (how many objects must be processed in between processing those with shared identity) determine the duration between activation. A significant interaction effect was observed, showing support for the hypothesis. The implication of this finding is that the state in which an object is presented is a part of the object's identity as a whole, as well as being something that can be used to distinguish two separate, identical objects. In the same way that it is possible to distinguish between different exemplars of the same item, such as two different cars, it's possible to distinguish between the same objects, based on their state, such as open or closed. The participants described that they perceived themselves performing better on the trials in which there were two shared objects in the matrix, even when neither was the target object. However, support for this hypothesis was not found, meaning that the presence of objects with a shared identity that was not the target, did not increase the accuracy of detecting a change in the target object. It was expected that the relationship of participants' accuracy on the task, should be positively correlated with the confidence those participants have that their response is correct. This hypothesis predicts that the memorizing, and detecting of changes in objects is a conscious process. meaning it's not a task that can be performed without actively allocating one's attention to the task. The results of three RM ANOVAs found support for this hypothesis. Showing that the conditions that resulted in increased accuracy also resulted in increased confidence in their responses. This heavily implies change detection in this type of task is a conscious process.

Other Experimental Findings

Presence of an object with a shared identity was found to increase accuracy, which is in agreement with previous works (De Vries, 2004; Braam, 2021; Drake, 2021, Dzhurkov, 2021; Koot, 2021; Wazny, 2021), as well as the studies done in parallel, as a part of this thesis project (Martin, 2022; Piletti, 2022; van den Brink, 2022; Houter, 2022). This shows that the shared identity effect is not dependent on the type of cue used, or the different durations of presentation time of any of the different screens from pre-change to post-change. The results support the expected interaction effect of shared identity and distance on the accuracy, this is a result that was only found in the past thesis studies which made use of stimuli involving exemplars (Source). This is the first significant result, in which state changes were used, that supports this hypothesis. Experiment 2 (Martin, 2022), making use of the same task and simple cue, but differing in the duration of presentation of the different screens, also found this significant interaction. This experiment made use of Set 2 of the stimuli, therefor any found or not found effects are unlikely caused by the stimuli used. However, experiments (Piletti, 2022), (van den Brink, 2022), (Houter, 2022) did not find this interaction effect. These experiments all made use of an identity cue, either presented for a set duration (250ms) or until the participant provided their response. This suggests that the type of cue used has an influence on the interaction between the two independent variables on participants' performance in change blindness tasks. A possible explanation for this entails the fact that the identity cue could have an effect on the way participants explore their representation of the matrix after the pre-change screen has disappeared. When the identity cue is presented, the participants give attention to their representation of the matrix in their memory, and first, try to identify where the object being cued was located, and then bring the two objects parallel to it into conscious awareness through the working memory. In the simple cue experiments, only 3 objects are activated since the cue directly tells them the locations of the objects needed for the trial. However, in the identity cue experiments, the participants give attention to all objects, first to identify where the cued object was, and then narrow down the attention to the two objects adjacent to the cued object. Some participants stated that they perceived themselves performing with higher accuracy when the two objects sharing identity were not the target. However, the model predicts that this would not be the case, hypothesis 3 was formulated that this would not be the case. The results showed support for this hypothesis. This is also corroborated by experiments of (Martin, 2022), (Piletti, 2022), and (van den Brink, 2022). However, the experiment by (Houter, 2022) did find that distance between objects which share identity with each other, but not the target object, increases the accuracy of the target. As predicted, the results showed that there was a positive relationship between the accuracy of participants and their confidence in their responses. This was also found in the other experiments run in parallel.

Limitations and Future Directions

Overall, this study has found support for the conceptual network model (De Vries, 2004). One limitation of the current study is that it took place during the COVID-19 pandemic, resulting in the participants having to perform the task at home. Because of this, aspects such as screen size, being confused about the task, or being distracted could not be controlled. The collection of object pictures, from which the stimuli were taken, was not large enough to only select very specific types of objects. Neither did it afford the opportunity to only select objects which were similar in the degree to which the changes were noticeable, between the two states. This was a limitation and a possible future exploration area, investigating how changes in different states are noticed. For example, is it easier to notice the change from open to closed, than from full to empty? Follow-up studies should investigate what types of conditions are required for the expected interaction effect to be present. They should also investigate how different aspects of object identities are stored and influence change blindness detection. How do people's expectations and preconceived notions about object characteristics influence their ability to detect change? An example of an object not being congruent with people's expectations would be fruit that has been grown inside of a mold, such as square or heart-shaped watermelons, or even buddha shaped pears. How are these characteristics stored or represented in cognition and neural structure? Does each characteristic of an object have its own neural structure that all needs to be activated simultaneously? For example, if a person views an apple, does it result in the firing of cell assemblies individually representing its characteristics (Green, round, edible, fruit, etc). Or are object identities stored in a single cell assembly, which contains the most common prototypical characteristics of said object. And if so, what does this mean for object recognition of such as object as a buddha-shaped pear? Will the person recognize it as a pear, a figure, or both?

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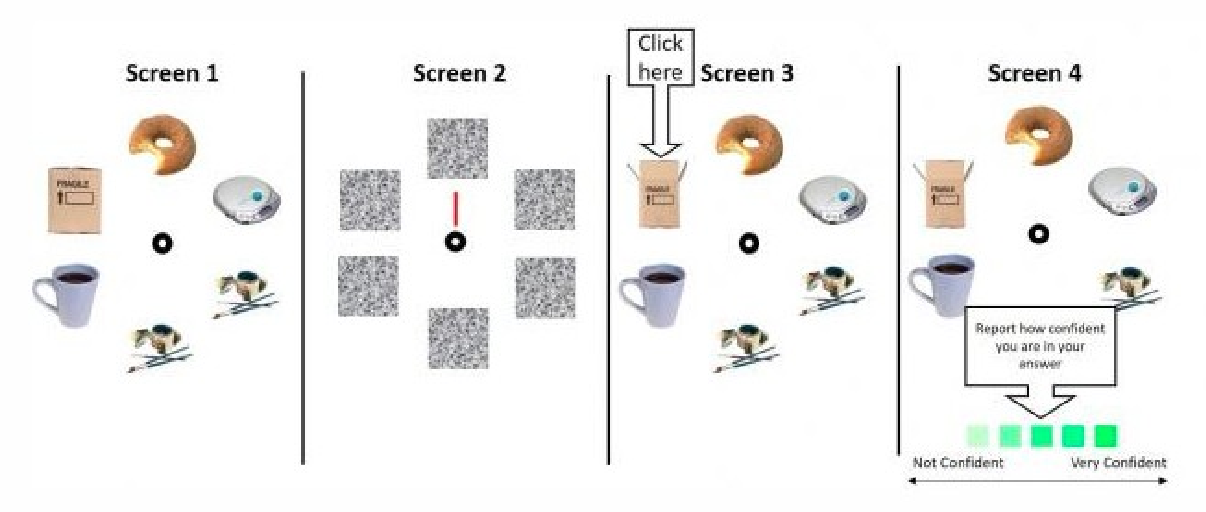
Appendix A

Instructions for experiment

The instructions given to the participants are as follows: The experiment contains several trials. Each trial consists of 4 screens that are displayed one after another. Your task is to remember the objects in Screen 1 because after they have been masked by Screen 2, you have to decide in Screen 3 which of the previously displayed objects has changed. Since Screen 1 is presented only briefly, Screen 2 contains a cue to help you. The cue will be a red line that is pointing from the center of the screen towards one of the 6 objects on the screen. The object that is being pointed at is the cued object. In each trial, a single object, either to the left or to the right of the cue, will change. Below you will see an example of the trial where the object next to the cue has undergone a change. You must click on the object that has changed.



Afterward, you need to rate how confident you are that you saw the change, just as in the previous example. Please choose the square that best represents how confident you are in your answer. If you did not notice a change and are guessing, please select the response that represents having the least confidence. The speed at which you respond will not be measured, as this is not a reaction time task. However, it is a memory task, meaning taking excessively long will increase the risk of forgetting the correct response. Please complete the task at the speed which you are most able to notice, and report the correct object.

Appendix B: Result section tables

Accuracy

Table 1.

Shapiro-Wilk Test on accuracy

	W	df	Sig.
Not shared, distance 0	.152	39	.019
Not shared, distance 1	.094	39	.336
Shared, distance 0	.114	39	.512
Shared, distance 1	.109	39	.530

Table 2.

Descriptive statistics: Accuracy

	Mean	Lower Bound	Upper Bound
Not shared, distance 0	.563	.502	.624
Not shared, distance 1	.544	.479	.608
Shared, distance 0	.753	.709	.797
Shared, distance 1	.667	.623	.710

Table 3.

2 (Shared) x 2 (Distance) RM ANOVA on DV: Accuracy

	df	F	Sig.	Partial Eta Squared	Observed Power[a]
shared	1	36.741	.00*	.492	1.000
Error(shared)	38				
distance	1	15.137	.00*	.285	.966
Error(distance)	38				
shared * distance	1	4.695	.037	.110	.560
Error(shared*distance)	38				

Note. *p<.001

Confidence

Table 4.

Shapiro-Wilk Test on confidence

	W	df	Sig.
Not shared, distance 0	.087	39	.343
Not shared, distance 1	.075	39	.658
Shared, distance 0	.119	39	.011
Shared, distance 1	.109	39	.011

Table 5.

Descriptive statistics: Confidence

	Mean	Lower Bound	Upper Bound
Not shared, distance 0	2.921	2.683	3.158
Not shared, distance 1	2.938	2.703	3.174
Shared, distance 0	3.985	3.777	4.193
Shared, distance 1	3.583	3.358	3.808

Table 6.

2 (Shared) x 2 (Distance) RM ANOVA on DV: Confidence

	df	F	Sig.	Partial Eta Squared	Observed Power[a]
shared	1	91.629	.00*	.701	1.000
Error(shared)	38				
distance	1	18.979	.00*	.327	.989
Error(distance)	38				
shared * distance	1	43.719	.00*	.529	1.000
Error(shared*distance)	38				

Note. *p<.001

Appendix C

Stimuli