Modelling the Effect of Visual Working Memory on Motion-Induced Blindness

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Abstract
We are only aware of relevant visual information, as most available visual information never enters our awareness. The visual working memory (VWM) may play a part in selecting relevant visual information for awareness.
To investigate the effect of VWM on our visual awareness, we have designed an experiment to test the influence of the content of VWM on awareness using motion-induced blindness (MIB). Information more likely to enter awareness is prone to disappear from awareness in MIB. As information matching the content of the VWM is more likely to enter awareness, our experiment is designed to investigate whether stimuli matching the content of the VWM are also more likely to disappear in MIB.
We have also made two models to predict the effect of the content of VWM on stimulus disappearance in MIB. One of these models is based on the effect of the content of VWM on breaking-continuous flash suppression (bCFS), whereas the other is based on the predicted effect of attention on the disappearance of stimuli in MIB. Using these models, we have created possible distributions of the outcomes of the experiment we designed. Based on these distributions we have also simulated trials for the experiment.
Both our models predict an increase in stimulus disappearance for stimuli matching the content of the VWM. The model based on attention assumes that the increase in stimulus disappearance for stimuli matching the content of the VWM greatly diminishes as the contrast between the stimulus and the background increases, whereas the model based on bCFS expects no such interaction between contrast and the content of the VWM.

Introduction

Visual awareness, the visual information we are conscious of, has limited capacity and can only represent a small part of the visual information available to us (Dennett, 1993). The fact that most information does not enter our awareness means that there must be a selection mechanism to allows only the relevant visual information to enter awareness. A possible part of this selection mechanism could be the visual working memory (VWM). The VWM is used to actively retain relevant information for imminent goal-directed behaviour. Using the breaking-continuous flash suppression (bCFS) paradigm, it was shown that information matching the content of the VWM is generally prioritized for visual awareness (Gayet, Paffen, & Van der Stigchel, 2013). This suggests that VWM plays a role in selecting which visual information enters awareness.

Instead of using bCFS, we will be investigating the interaction between VWM and awareness using the motion-induced blindness (MIB) paradigm. MIB is a phenomenon of visual disappearance in which a global moving pattern is superimposed on high-contrast stationary or slowly moving stimuli (generally referred to as ‘targets’). In MIB, the targets are perceived to both disappear and reappear alternately for periods of several seconds (see Fig. 1). Stimuli that are constantly on the retina and are salient seem to disappear from awareness in MIB, which makes this a very relevant phenomenon for research on the topic of awareness.

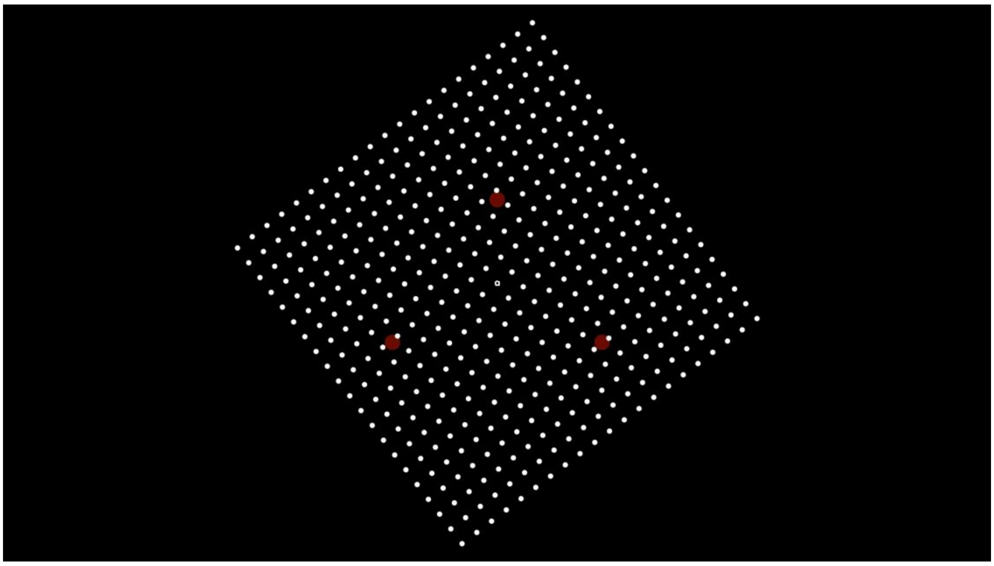

Fig. 1. An example of a snapshot of a motion-induced blindness trial. In an actual trial, the white pattern would be rotating clockwise. The red dots here are the targets and the white dot with a black centre in the middle indicates where the fixation point is. While the white pattern rotates during a MIB trial, the red dots would appear to disappear and reappear to an observer fixating on the dot in the middle of the screen.

Background on motion-induced blindness

MIB generally occurs when presented with small patterns of slowly moving or stationary stimuli (these stimuli are also called ‘targets’), with a global moving pattern (also called a ‘mask’) superimposed on it. The proportion of time in which the target is perceived to be invisible is typically used to measure the strength of MIB, but average disappearance period, initial fading time and frequency of disappearances are also used (Bonneh & Donner).

The targets will rarely or never disappear from awareness when fixated upon, but targets as close as 1 degree off fixation can already disappear from awareness and will do so more often when further away from the fixation point (Bonneh & Donner, 2011).
Objects that appear to form a group disappear together, but when close together, targets that seem to belong to different objects tend to alternately disappear (Bonneh, Cooperman & Sagi, 2001).
Although both slowly moving and stationary targets disappear, static targets seem to disappear more often (Bonneh & Donner, 2011).
Many types of masks (such as the white pattern in Figure 1) can induce the disappearance of targets, but masks that use coherent motion are usually most effective (Bonneh & Donner, 2011). As long as the target is surrounded by the mask, the target can even have an empty zone between it and the mask of a few degrees and still disappear (Bonneh et al., 2001).

It is important to note that the more contrast there is in luminance between the background and the target, the more the target is perceived to disappear (Bonneh et al., 2001; Bonneh & Donner, 2011). Increased luminance contrast between a stimulus and the background also increases the salience of that stimulus (Nothdurft, 2000). Since targets with increased luminance contrast, meaning they are more salient, are perceived to disappear more in MIB than less salient targets, MIB can be used to investigate the effect VWM has on the salience of targets. Salient stimuli are generally more likely to enter awareness than non-salient stimuli (Yantis, 2005), so by using MIB to investigate the effect of the VWM on salience we will gain insight into the effect of the VWM on awareness.

The underlying cause of the MIB phenomenon is still debated. One hypothesis is that MIB is caused by retinal stabilization. Images that are stabilized on the retina disappear in a similar way to how targets are observed to disappear in MIB (Ditchburn & Ginsborg, 1952). This perceived disappearance of stabilized images is thought to occur via adaptation, where retinal adaptation would cause fading and consequent disappearance of an image. Adaptation could also be the cause for the subjective disappearance of targets in MIB, resulting from image stabilization caused by a spontaneous reduction in microsaccades induced by the mask. This adaptation would result in fading of the target.
However, it has been found that the moving mask does not affect the microsaccades in MIB (Bonneh, Donner, Sagi, Fried, Cooperman, Heeger & Arieli 2010). While there was a reduction in microsaccades prior to the disappearance of a target and an increase in microsaccades prior to its reappearance, MIB persisted despite the presence of microsaccades (Bonneh et al. 2010). This means that, while microsaccades certainly play a role, MIB is likely not caused by retinal stabilization.

Another hypothesis is that MIB reflects spontaneous attention shifts, which dynamics are induced by the moving mask (Bonneh et al., 2001). This hypothesis is supported by fMRI responses measured in the dorsal and ventral extrastriate cortex during MIB (Donner, Sagi, Bonneh & Heeger, 2008). These fMRI responses showed that awareness of a target is linked to the strength of its representation in the ventral visual cortex, and that the spontaneous suppression of the target representation in MIB was heavily influenced by the mask representation in the dorsal visual cortex.
The mean time that a target is perceived to be invisible can be increased by withdrawing attention from the target and mask with a demanding task at the fixation point, but focusing attention on the target also increases the time of disappearance and the probability of disappearance (Schölvinck & Rees, 2009). Although it is still unclear whether MIB is actually caused by spontaneous attention shift, attention at least has a major influence on MIB.

Research question and hypothesis

As stated earlier, targets with increased luminance contrast with the background, so more salient targets, are perceived to disappear from awareness more than less salient targets in MIB (Bonneh et al., 2001; Bonneh & Donner, 2011). Since increased salience leads to an increased likelihood of entering awareness (Yantis, 2005), it is possible that targets that are more likely to enter awareness are also more likely to disappear from awareness in MIB.

If a colour is held in the visual working memory (VWM), a stimulus matching this colour enters visual awareness more quickly than stimuli whose colour does not match the colour held in the VWM (Gayet et al., 2013). While this has been tested in the bCFS paradigm, we may gain deeper insights into the role of VWM in awareness by using different paradigms

such as MIB. As such, the present study attempts to answer the question of whether targets matching the content of the VWM are more likely to disappear from awareness in MIB than targets not matching the content of the VWM.
As targets with an increased likelihood of entering visual awareness are also more likely to disappear from awareness is MIB (Bonneh et al., 2001; Bonneh & Donner, 2011; Yantis, 2005), and stimuli matching the content of the VWM are more likely to enter visual awareness (Gayet et al., 2013), we expect targets matching the content of the VWM to disappear from awareness more than targets not matching the content of the VWM. The results of this experiment could further illuminate the relation between VWM and visual awareness.

Due to current circumstances regarding COVID-19, it is impossible to safely conduct an experiment to test our hypothesis. I have added an experimental design section explaining the experiment, and my research will focus on simulating the behaviour of participants in the experiment. I will create models for the effect we expect content matching with VWM to have, and make predictions for the distribution of data that might result from our experiment as explained in the experimental design section. By making predictions and models for the effect we expect content matching of MIB targets with VWM to have, we will gain a deeper understanding of the interaction between awareness and the VWM. Using models, we can generalize our knowledge of the effect of VWM and apply this knowledge to different experiments and circumstances as well. Having models before our experiment produces results also ensures that we are truly blind to any already produced results and are thus free from bias. Once our experiment does produce results, we can assess the validity of the models and in doing so understand the ways in which the content of the VWM affects awareness (or at least understand the ways in which it does not affect awareness, in case neither of the models is correct)

Relevance to artificial intelligence

Only a small part of the available visual information enters our awareness, which means there is a selection mechanism by which we filter out all irrelevant information. Such a filter makes our processing of visual information very efficient. If we aim to make an AI system that processes visual information, it would be best if such a system processed visual information efficiently. Since we humans have an efficient selection mechanism, figuring out how this mechanism functions in humans could prove invaluable to the creation of an AI that efficiently processes visual information.

If we wish to make an AI that is conscious, which is a common goal in AI research, it would also be good to ask ourselves what such an AI should be conscious of. If we fail to implement a selection mechanism for its visual awareness, its consciousness would be filled with irrelevant visual information. We can figure out ways to implement cognitive functions, such as the selection mechanism, into systems using human cognition as a model. By understanding the role VWM plays in the selection of relevant visual information, we will be able to better implement visual selection mechanisms in AI.

Method

Design of the experiment

We plan to include 20 observers, between 18 and 25 years old, both male and female, with normal or corrected-to-normal vision. The observers will each have to go through 5 practice trials and 60 experimental trials. In a trial, the observer will be shown a colour (a variant of either red, green or blue (Fig. 2; see appendix A for an overview of these colours) for 1 second and will then, after a short interval (1s), be shown a different colour for 1 second. After another short interval (1s) the observer will be shown either a '1' or a '2' as a postcue to indicate which of these two colours is to be remembered (see Fig. 2). The other colour will be referred to as the discarded stimulus. By having the observer remember a certain colour we are ensuring that they keep this colour in their VWM.

Next, the observer will have to watch a rotating pattern with three stationary dots (targets) for 10 seconds. There are three different conditions in this experiment: One in which the colour of the remembered stimulus is used for the targets, one in which the colour of the discarded stimulus is used for the targets and one in which an unrelated colour is used for the targets. The observer will be asked to fixate on the middle of the pattern for the duration of the trial. While watching this pattern, the observer has three buttons that have to be used to indicate the visual disappearance of one (or more) of the dots. After watching the pattern for 10 seconds, the observers will be presented with two different hues of the same colour (red, green or blue) as the one they were told to remember. The observer will then have to choose which of these two corresponds to the colour they were told to remember by pressing one of two buttons. After choosing a colour, the next trial can be started by pressing the spacebar.

The experiment will measure the accumulated percentage that one or more target(s) is perceived as invisible by the observer. It will be measured for each of the different conditions (memorized, unrelated, discarded) and the effect of each condition will then be compared.

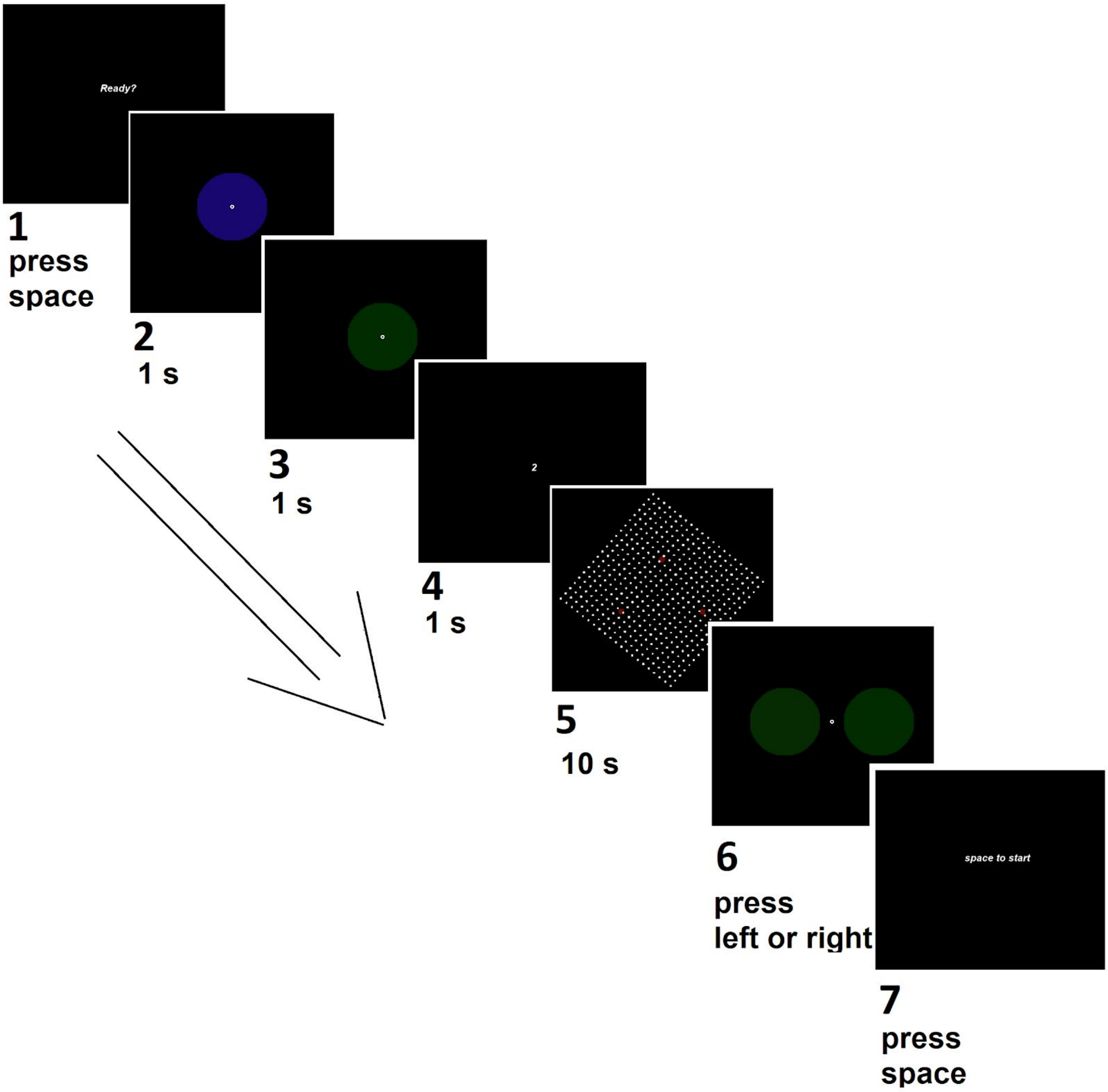

Fig. 2. Shown here is an example trial. First a screen with "Ready?" will be shown (1). After pressing the spacebar, a screen with a random variant of 5 different hues of green, red or blue will be shown for one second (2). After an interval of one second, a random variant of 5 different hues of a different colour category as the previous colour (again from either red, blue or green) will be shown for one second (3). After another interval of one second, a number (either 1 or 2) will be shown to indicate which of the previously shown colours has to be remembered (4). After another 1 second interval, the observer will have to watch a rotating pattern with 3 stationary targets for 10 seconds (5). These targets could be either the discarded, the memorized or an unrelated colour. After a last 1-second interval, the observer will be shown 2 hues of the colour they had to memorize, and by using the arrow keys indicate which of the 2 is the correct colour (6). The observer will then be asked to press space again to start a new trial (7).

Predicting the outcome of the experiment

Since a stimulus matching the content of the VWM enters visual awareness faster than a stimulus not matching the content of the VWM (Gayet et al., 2013), and it is possible that such targets are also more likely to disappear in MIB (Bonneh et al., 2001; Bonneh & Donner, 2011; Yantis, 2005), we can make predictions on the outcomes of our experiment by using models based on the effect of having a stimulus match the content of VWM in related visual phenomena. For this purpose, we have constructed two such models for the effect of VWM on MIB.

One of the models will be a complex model, which assumes that the effect of having a target match the content of the VWM will differ based on the contrast between a target and the background. The expectation that the effect of the content of the VWM differs on contrast is based on the effect of attention on related visual phenomena, which differs based on the contrast between attended stimulus and background (Reynolds & Heeger, 2009).
The other model will be a simple model, which assumes that the effect of having a target match the content of the VWM will be the same across different levels of contrast between a target and the background. This model is based on the effect of the content of VWM found in bCFS (Gayet et al., 2013).
We will then use these different models to simulate possible results from the experiment as described in the section on the design of the experiment. The data for the condition in which the targets do not match the content of the VWM is taken from Bonneh et al. (2001), so our models and predictions will be based on their findings. Naturally, the accuracy of the predictions will largely depend on how similar the experimental setups are. The most important part of these models and predictions is understanding by which mechanism content-matching with the VWM operates, and in what ways it could be similar to attention. Comparing these models to actual results gathered in the experiment as laid out in the experimental design section will prove useful in understanding the relation between awareness and the VWM.

The simple model for the expected percentages of invisibility in MIB

The first model is a simple model in which we assume that there is no specific interaction between contrast and matching the VWM content. Perceived disappearance percentage generally increases as contrast increases (Bonneh et al., 2001), and this model does not expect any changes in the rate of this increase due to the effects of VWM. We only predict, in this model, the same increase in disappearance percentage across all contrast levels due to the effects of VWM.
To calculate the effect we expect the VWM to have on MIB, we looked at the effect that matching the VWM content has on a related visual phenomenon. Gayet, Paffen, & Van der Stigchel (2013) found that, in a breaking-continuous flash suppression experiment, stimuli matching the content of VWM break through about 14% faster than similar stimuli not matching the VWM content. From this simple assumption of a 14% increase in effectiveness when having a stimulus match the content of the VWM, we have constructed a model in which the total accumulated invisibility percentage is 14% higher for targets that match the content of the VWM than targets that do not match the content of the VWM. Since the accumulated invisibility percentage changes based on the contrast, we have plotted this simple model over contrast, as seen in Figure 3. The exact model is simply:

*Effect VWM on MIB over contrast = Invisibility% without VWM for specific contrast * 1.14*

In this case, we are only multiplying the percentage of invisibility of one or more targets by 1.14, since we assume for this model that there are no other interactions between contrast and content-matching with the VWM in MIB.

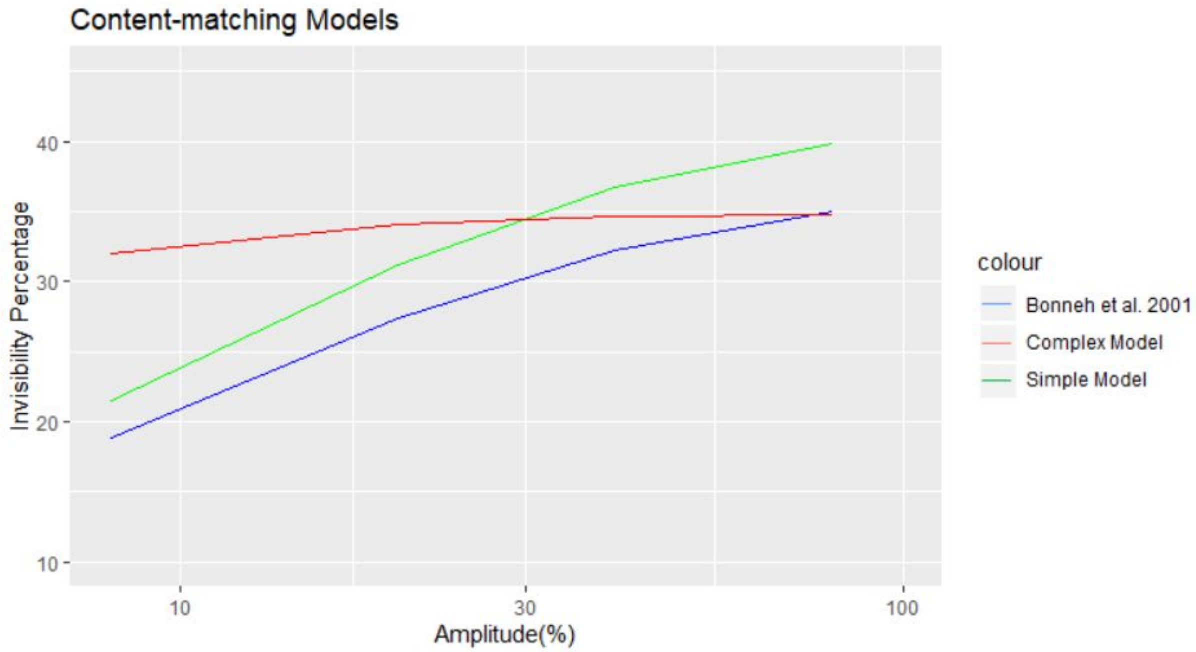

Fig. 3. The different models of the effect of content-matching with the VWM. The accumulated percentage of invisibility time for one or more targets is shown the y-axis, and on the x-axis, the target luminance contrast is shown on a logarithmic scale. The blue line indicates the results as found in Bonneh et al. (2001) for the effect of contrast on MIB. The green line indicates the simple model using a flat 14% increase in invisibility percentage. The red line indicates the complex model as described earlier, using an attentional model by Herrmann et al. (2010) based on a model by Reynolds & Heeger (2009)

The complex model for the expected percentages of invisibility in MIB

The second model is more complex. Since content-matching with the VWM has an influence on the allocation of attention (Downing, 2000), I will assume that the effect of having a target match the content of the VWM is similar to the effect of drawing attention to a target for this model. We will be able to better understand the effect of VWM on MIB if we can understand the effect of attention on MIB and related visual phenomena. After having a solid grasp on the similarities and differences between the effects of attention and the VWM, we can use our knowledge of the effect of attention on our MIB experiment to predict the effect that having the target match the content of the VWM will have.

In the breaking-continuous flash suppression task, on which content-matching has a significant effect (Gayet et al., 2013), there has also been research on visual input signalling threat (Gayet, Paffen, Belopolsky, Theeuwes & Van der Stigchel, 2016), which is visual input that draws attention (Armony & Dolan 2002). We can compare the effects of VWM and

visual input signalling threat in breaking-continuous flash suppression, and then use an attentional model to predict the effect of VWM on MIB and make our own model. The effect of threat signalling input in Gayet et al. (2016) was 1498 ms /1822 ms = 0.822, meaning that the stimulus broke through 17.8% faster when a stimulus signalled threat compared to a stimulus that did not signal threat.
The effect of content-matching in VWM measured in Gayet et al. (2013), conducted in a fairly similar way in which we will test the effect, was an increase in response time of about 14%. This means that a stimulus matching the content of the VWM broke through about 14% faster than a stimulus that did not match the content of the VWM

The effects of VWM and attention are very close in their actual values (14% vs 17.8% increase in breakthrough time) and indeed a study directly comparing the effects of salience (salient stimuli being stimuli that draw attention) and VWM on the breaking-continuous flash suppression task (Ding, Paffen, Naber & Van der Stigchel, 2019) found that there is no significant difference in breakthrough time between a non-salient stimulus congruent with the memory task and a salient-stimulus incongruent with the memory task. The effects of content-matching and attention can, therefore, be considered equal, and we will consider them equal for the purpose of generating the complex model. Keep in mind, the 'degree' in which a stimulus is salient can differ and this could influence the relation between attention and content-matching, but for this general model, we will assume the relation as stated above.

To understand the effect that attention has for different contrast levels, we can look at a normalized model of attention. Herrmann, Montaser-Kouhsari, Carrasco & Heeger (2010) made four such attentional models, predicting the effect of attention on expected responses for varying levels of contrast. The four different models by Herrmann et al. (2010) are models for different types of attention (endogenous or exogenous attention) and different attentional field and stimulus sizes (a small attention field with a large stimulus or a large attention field with a small stimulus). Endogenous attention is when attention is voluntarily directed towards a stimulus, and exogenous attention is when attention is automatically drawn towards a stimulus. As there is no voluntary decision of the observer to direct their attention to the stimuli, since keeping visual information in the VWM will automatically increase the likelihood of related stimuli to enter awareness, we will assume the type of attention to be exogenous in our MIB experiment. In the motion-induced blindness experiment, we are dealing with a large attention field and a small stimulus. The target stimuli are small dots while the attention field is most of the screen in our experimental setup. So to make the complex model, we will be using the attentional model for exogenous attention for small stimuli in a large attention field.

The attentional model for exogenous attention and a small stimulus in a large attention field from Herrmann et al. (2010) was based on a normalized model of attention for neural responses by Reynolds & Heeger 2009. The model made by Reynolds & Heeger (2009) is $\alpha c/(c+\sigma/\gamma)$, where α is the response gain, c is stimulus contrast, σ is contrast gain and γ is peak gain. To model the effects of VWM in MIB, we fit the model by Reynolds & Heeger (2009) on the data from Herrmann et al. (2010) to determine the correct constants to use for an attention experiment. We scaled the contrast gain and peak gain constants up to the MIB contrast graph. The resulting model is as follows:

*Effect VWM on MIB over contrast = Maximum Invisibility% without VWM * Contrast / (Contrast + (14.154295 / Invisibility% without VWM for specific contrast)).*

In this model 14.154295 is a constant. The model also fits well on the data for the model by Herrmann et al. (2001). The graph resulting from applying the complex model to the data by Bonneh et al (2001) can be seen in Figure 3.

Results

Expected responses for our experiment based on the models for expected invisibility percentage

In the experiment, we will be measuring the mean invisibility percentage for one or more targets and comparing the different conditions. Since we have made models for the condition where the content of the VWM matches the target colour, we can make predictions on the outcome of the experiment.

The disappearing of targets in MIB seems to follow a gamma distribution (Bonneh & Donner, 2011), similarly to other multistable perception phenomena, such as binocular rivalry (Blake & Logothetis, 2002). The gamma distribution generally uses two parameters, the shape parameter and the scale parameter. For the shape parameter, we simply need the upper possible limit of our experiment. Since our experiment ranges from 0 to 10 seconds, the shape of our distribution is has a value of 10. As we want to measure the percentage of trials corresponding to certain accumulated invisibility times, we can use the percentages of invisibility from Figure 3 for the scale parameter of the gamma distribution. Since the invisibility percentage differs based on contrast, I have made multiple graphs (Fig. 4) corresponding to the different contrasts measured in Bonneh et al. (2001).

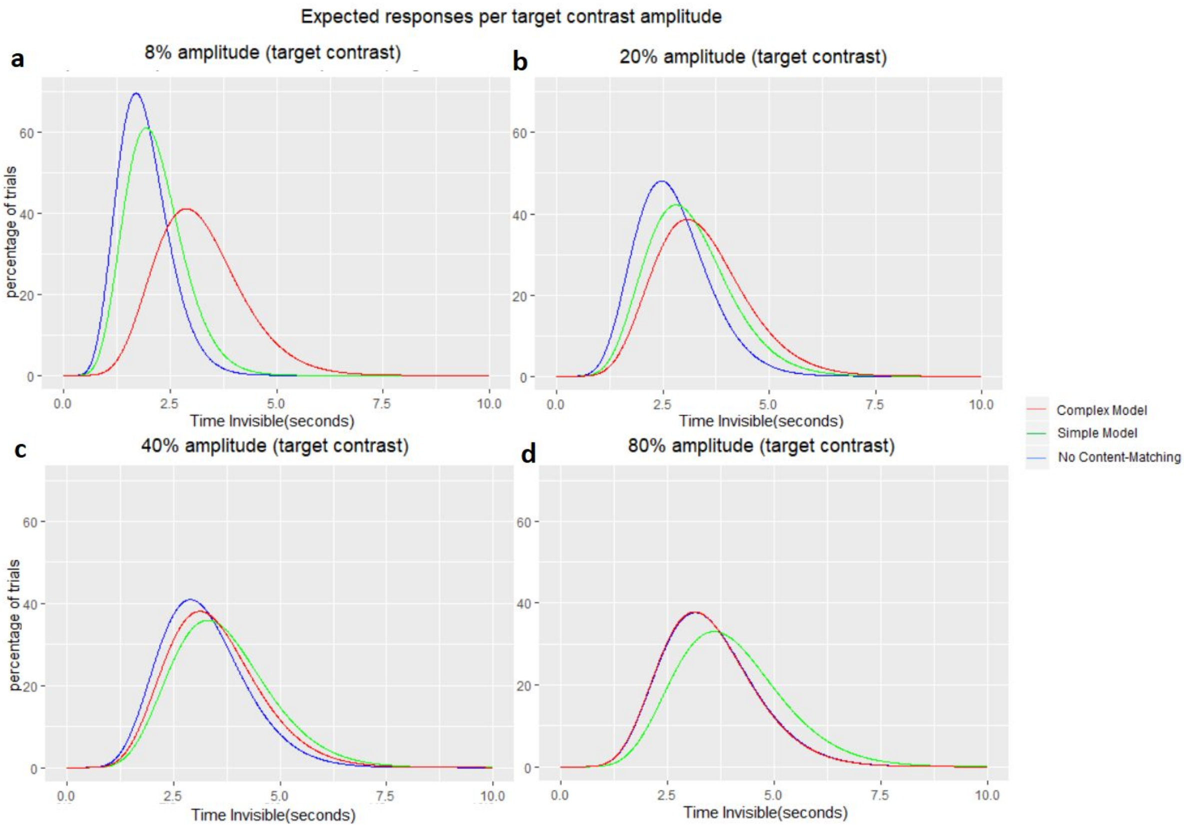

Fig. 4. We have made several predictions on the outcome of the experiment. The total time one or more targets will be perceived as invisible is displayed on the x-axis and the percentage of trials corresponding to the total time invisible is displayed on the y-axis. We have taken different values for the expected percentage of disappearance corresponding to different contrasts, as displayed in Figure 3, and constructed the expected responses for these contrasts based on the gamma distribution.

Using the gamma distribution, we can simulate data that may result from our experiment for possible observers (Fig. 5). We built 100 simulations for each condition for each contrast, totalling 1200 simulations. The simulated trials were based on the gamma distributions for their corresponding models and contrast values as laid out in Figure 4. For the ‘No content matching’ condition, we did not discriminate between ‘discarded’ and ‘unrelated’ conditions as explained in the method section, as based on the data by Gayet et al (2013) we do not expect a significant difference in results between these 2 conditions. The mean of the simulated trials for each condition is shown in Figure 5. The code for these simulations, as well as the code for the models and predictions, can be found in appendix B.

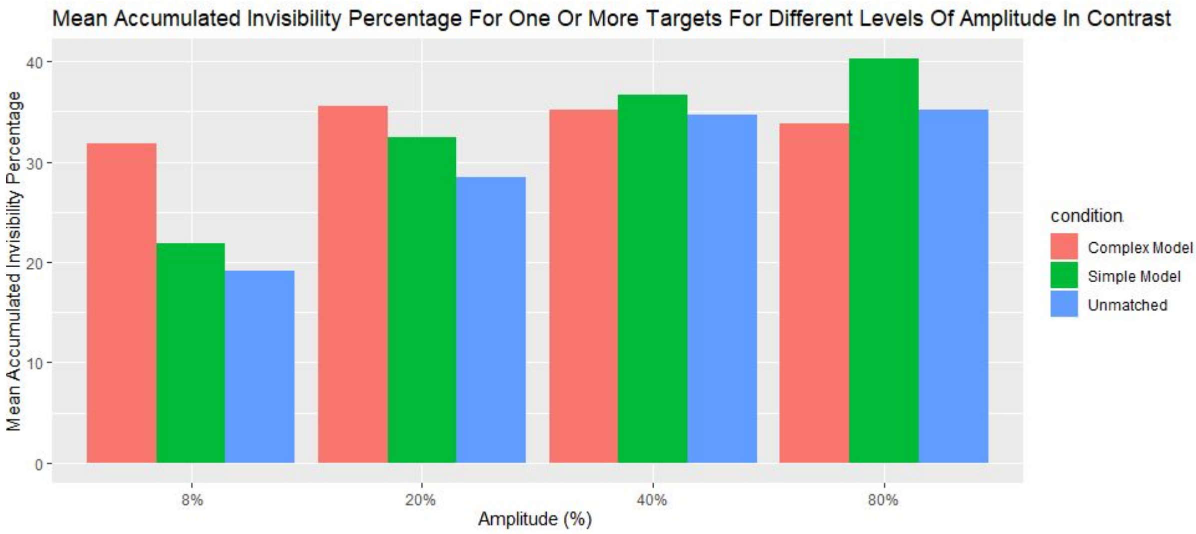

Fig. 5. Here is the average total time invisible for one or more targets for every different memorized condition in each of the different contrast conditions. The time invisible is shown on the x-axis and the contrast between the target and the background is shown on the y-axis. The three different conditions here are the unmemorized condition, the complex condition and the simple condition. The unmemorized condition here displays the results for both the discarded and the unrelated conditions as discussed in the method section since we expect these to not differ significantly. The simple model here shows simulated results we could expect for the memorized condition if the simple model is correct, and the complex model here shows the simulated results for the memorized condition if the complex model is correct.

Analysis of self-made data

To get an indication of whether my predictions could be accurate, I have conducted the experiment on myself several times and analysed the data. Since it is still unclear whether the colours used for the different conditions (mentioned in the experimental design section) are sensible, and we currently have no way of measuring the contrast and luminance of different colours, for the purposes of this analysis we have disregarded the different VWM conditions and only looked at the MIB part of the experiment. See appendix C for the code used for this analysis (made in programming language R). As seen in Figure 6, the distribution of trial results is somewhat reminiscent of the results predicted in Figure 4. Due to the small sample size of this experiment, these results are only used as an indication of the validity of the predicted results and have not been tested for significance. We have also plotted the mean invisibility percentages for each observer in Figure 7.

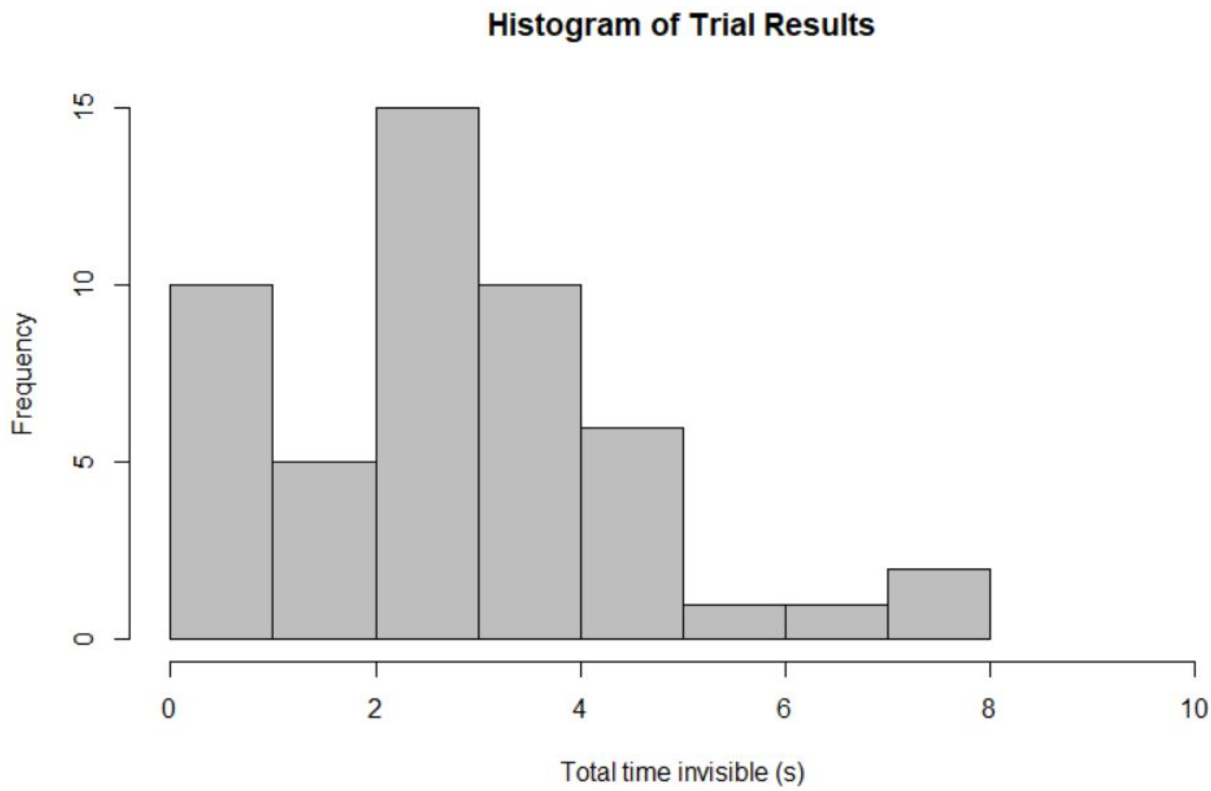

Fig. 6. I have conducted the experiment on myself several times, and the results of the 50 total trials are displayed here. The total time invisible for one or more targets is shown on the x-axis. The frequency of the total time invisible for one or more targets over 50 total trials is displayed on the y-axis. The mean for all 50 trials is 28.42 and the standard deviation is 17.8601.

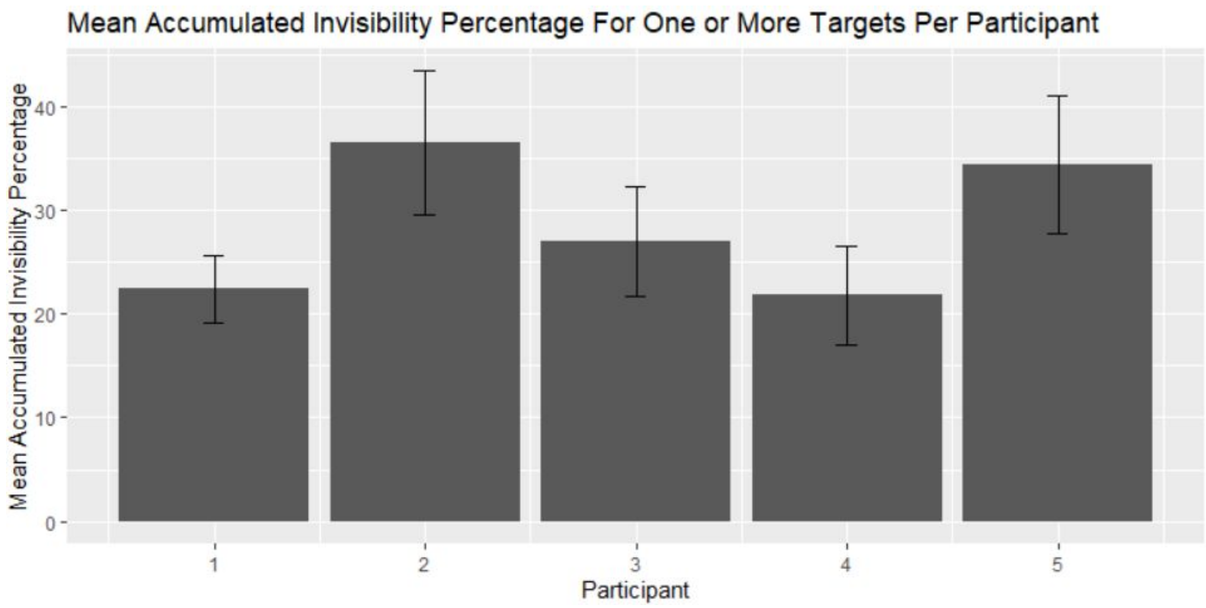

Fig. 7. A graph displaying the mean accumulated invisibility percentage for one or more targets for 5 different observers. In this case, due to circumstances, I performed the experiment on myself 5 times so keep that in mind. The observer number is displayed on the x-axis, and the mean accumulated invisibility percentage for each of the observers is shown on the y-axis. The error bars represent the standard error of the mean.

Effect of priming on MIB

We have also investigated whether there is a priming effect in the MIB experiment. Priming is a phenomenon where a change happens in the ability to produce or identify an item as a result of a specific prior encounter with the item (Schacter & Buckner, 1998). Identifying an object happens faster when the object has been seen very recently, and studies show that priming makes a stimulus more salient (Theeuwes & Van der Burg (2013). Since more salient targets disappear more than less salient targets in MIB, we can expect priming to have an effect on our MIB experiment. To test the effect priming has on MIB, we compared the different invisibility times for the different 'positions' the colour used for the target in MIB can have in the memory condition prior to the postcue (see the experimental design section). This means there are three different conditions: The colour used for the target in MIB can be on the first position before the postcue, the second position before the postcue and finally the colour used as target in MIB can be an unrelated colour to the ones shown before the postcue. we used data from 50 trials, and all data was gathered by performing the experiment on myself (this data is the same as the data used in the previous section).We split these 50 trials into the three conditions (first position, second position and unrelated colour) and calculated the mean accumulated invisibility percentage for each condition (Fig. 8). A two-tailed t-test showed a significant effect of priming for the MIB target colour being used in the second position, $t(33) = 4.33$, $p < 0.001$. No such priming effect was found for the MIB target colour being used in the first position. It should be noted that these results are only from me performing the experiment on myself, so once circumstances change and we can once again run experiments it might be worthwhile to check for priming effects in MIB. If there is a priming effect for MIB, we should equally distribute the MIB target colour positions across the different VWM conditions.

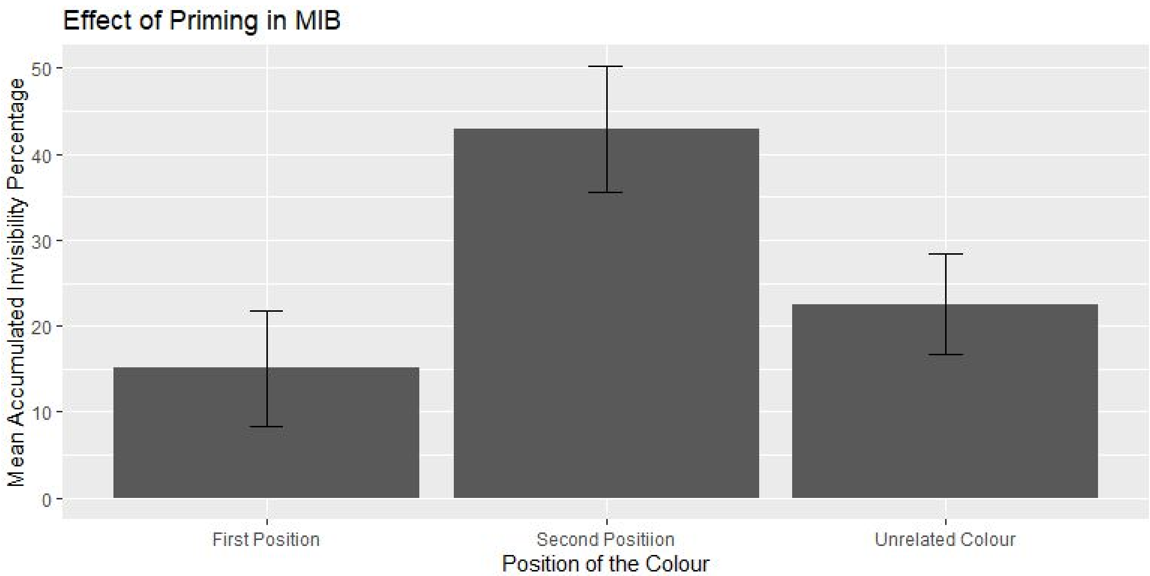

Fig. 8. A graph displaying the effects of priming in MIB. The mean accumulated invisibility percentage is displayed on the y-axis, and the different possible conditions for the colour of the target in MIB are shown on the x-axis. The error bars represent the 95% confidence interval. A two-tailed t-test indicates a significant priming effect for having the colour used for the targets in MIB be on the second position in the VWM task, $t(33) = 4.33$, $p < 0.001$. Due to circumstances, there was only one participant (me) who performed 50 trials. To be sure of these results there would need to be more research conducted on this topic.

Discussion

If information matches the content of the VWM, its access to awareness is prioritized (Gayet et al., 2013). We have investigated two possible ways in which the increased access to awareness given to information by having it match the content of the VWM could interact with the MIB phenomenon. In an attempt to further illuminate the interaction between the VWM and visual awareness, we have made models based on the two possible ways in which content matching of the VWM could interact with MIB. One of the models assumed content-matching had a similar interaction with MIB as attention would have, and the other assumed a flat increase in the mean invisibility time of one or more targets across all contrast levels. Since salient targets spend more time on average being invisible (Bonneh et al., 2001), understanding the effect of VWM on MIB gives us insight into the ways VWM affects awareness because salient stimuli enter our awareness faster (Yantis, 2005).

The simple model, as expected, predicts an increase in perceived invisibility percentage across all levels of contrast. The increase in perceived invisibility percentage is about 14%, and it remains a constant increase regardless of contrast. The complex model predicts an increase in perceived invisibility percentage which diminishes as contrast increases. For the lower contrasts, it assumes that matching a target to the content of the VWM will greatly increase its perceived invisibility time over a target that does not match the content of the VWM. For higher contrasts, however, it expects a negligible difference between the perceived invisibility time of targets that match the content of the VWM and targets that do not match the content of the VWM.

Since the experiment has not been performed yet, it is still difficult to say if one of these models will be correct. If the results of the experiments match the predictions made by the models, we will have gained a greater understanding of the mechanisms behind the interaction of VWM and visual awareness. There could be a different way in which content matching with the VWM interacts with awareness, which we have not modelled. We will then still have gained knowledge on the effects of content-matching with the VWM, if only in the sense that we would know my models to be false.

It might be worthwhile to run the experiment with different contrast values between the targets and the background. If the mechanisms behind content matching with the VWM and attention are similar, as we assumed in the complex model, the effect of content matching with the VWM will differ across contrast values so by running the experiment for varying levels of contrast we can see if the effect of content matching with the VWM indeed varies across different levels of contrast. If the results then follow a pattern similar to the predictions based on the complex model, we can assume the mechanisms behind content matching with the VWM to be similar to the mechanisms behind attention.

If the effect of having a target match the content of the VWM stays the same across contrast levels, similar to how the simple model predicts it to behave, we can assume content matching to affect awareness in a different way than attention does. It will still confirm that having stimuli match the content of the VWM increases the likelihood of such stimuli entering awareness since targets more likely to enter awareness disappear from awareness more often in MIB (Bonneh et al., 2001; Bonneh & Donner, 2011; Yantis, 2005).

The experiment might show that having a target match the content of the VWM does not increase the time it is perceived to be invisible, and it might even reduce the time a target is perceived to be invisible. If a target matching the content of the VWM does not show a significant increase in perceived invisibility time over targets not matching the content of the VWM, this could mean that having a stimulus match the content of the VWM does not affect visual awareness. Since content matching has been shown to increase the priority of information for conscious access (Gayet et al., 2013), a result in which there seems to be no effect of content matching on MIB would raise a lot of questions that would need to be answered by more follow up research.

As explained in the results section, there seems to be a significant effect of priming on MIB. Since we use the mean accumulated invisibility percentage, we can counteract the effect of priming by equally distributing the different colour positions over the different memory conditions. Since the experiment only had one participant it would be wise to also test for priming in follow up research.

It should also be kept in mind that the predictions as made in the results section (Fig. 2 & 3) are based on the data found by Bonneh et al. (2001) for the effect of contrast on MIB. If the data for targets not matching the content of the VWM yielded from our experiment differs from the data found by Bonneh et al (2001), the predictions as made in the results section will naturally also differ from the data our experiment will yield on targets matching the content of the VWM. However, we can verify the validity of the models by applying them to the data for targets not matching the content of the VWM and comparing the resulting data to the actual results for targets matching the content of the VWM yielded by our experiment.

Conclusion

We expect stimuli that match the content of the VWM to disappear more in MIB than stimuli that do not match the content of the VWM. We have made two models to predict the outcomes of a MIB experiment with memory conditions and designed an experiment to investigate the validity of these models. Results of such an experiment will greatly improve our knowledge on the effect of the VWM on awareness, and depending on the results of the suggested follow up experiment we will also have gained insight on how to model the effects of VWM in general. Understanding the role VWM plays in the selection of relevant visual information will be extremely relevant for the creation of AI systems that process visual data. For further research, I suggest conducting the MIB experiment with the VWM conditions as designed in the method section once the current situation allows for safe conduction of experiments.

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References:

Armony, J. L., & Dolan, R. J. (2002). Modulation of spatial attention by fear-conditioned stimuli: an event-related fMRI study. *Neuropsychologia*, *40*(7), 817-826.

Blake, R., & Logothetis, N. K. (2002). Visual competition. *Nature Reviews Neuroscience*, *3*(1), 13-21.

Bonneh, Y. S., Cooperman, A., & Sagi, D. (2001). Motion-induced blindness in normal observers. *Nature*, *411*(6839), 798-801.

Bonneh, Y., & Donner, T. (2011). Motion induced blindness. *Scholarpedia*, *6*(6), 3321

Bonneh, Y. S., Donner, T. H., Sagi, D., Fried, M., Cooperman, A., Heeger, D. J., & Arieli, A. (2010). Motion-induced blindness and microsaccades: cause and effect. *Journal of vision*, *10*(14), 22-22.

Dennett, D. C. (1993). *Consciousness explained*. Penguin uk.

Ding, Y., Paffen, C. L., Naber, M., & Van der Stigchel, S. (2019). Visual working memory and saliency independently influence the priority for access to visual awareness. *Journal of vision*, *19*(11), 9-9.

Ditchburn, R. W., & Ginsborg, B. L. (1952). Vision with a stabilized retinal image. *Nature*, *170*(4314), 36-37.

Donner, T. H., Sagi, D., Bonneh, Y. S., & Heeger, D. J. (2008). Opposite neural signatures of motion-induced blindness in human dorsal and ventral visual cortex. *Journal of Neuroscience*, *28*(41), 10298-10310.

Downing, P. E. (2000). Interactions between visual working memory and selective attention. *Psychological science*, *11*(6), 467-473.

Gayet, S., Paffen, C. L., Belopolsky, A. V., Theeuwes, J., & Van der Stigchel, S. (2016). Visual input signaling threat gains preferential access to awareness in a breaking continuous flash suppression paradigm. *Cognition*, *149*, 77-83.

Gayet, S., Paffen, C. L., & Van der Stigchel, S. (2013). Information matching the content of visual working memory is prioritized for conscious access. *Psychological Science*, *24*(12), 2472-2480.

Herrmann, K., Montaser-Kouhsari, L., Carrasco, M., & Heeger, D. J. (2010). When size matters: attention affects performance by contrast or response gain. *Nature neuroscience*, *13*(12), 1554.

Nothdurft, H. C. (2000). Salience from feature contrast: Variations with texture density. *Vision research*, *40*(23), 3181-3200.

Reynolds, J. H., & Heeger, D. J. (2009). The normalization model of attention. *Neuron*, *61*(2), 168-185.

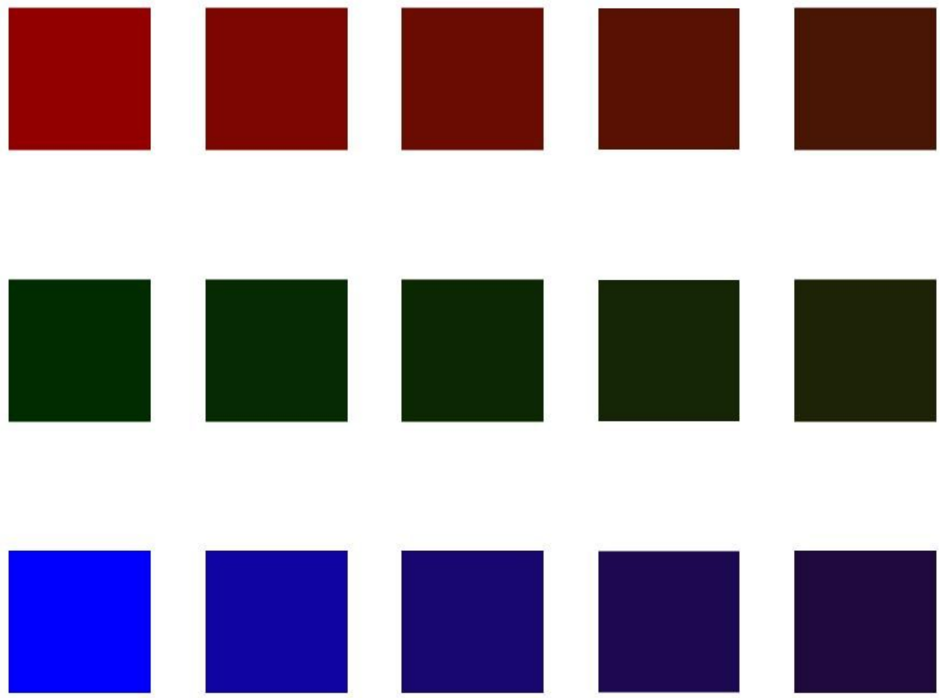
Schacter, D. L., & Buckner, R. L. (1998). Priming and the brain. *Neuron*, *20*(2), 185-195.

Theeuwes, J., & Van der Burg, E. (2013). Priming makes a stimulus more salient. *Journal of Vision*, *13*(3), 21-21

Schölvinck, M. L., & Rees, G. (2009). Attentional influences on the dynamics of motion-induced blindness. *Journal of Vision*, *9*(1), 38-38.

Yantis, S. (2005). How visual salience wins the battle for awareness. *Nature neuroscience*, *8*(8), 975-977.

Appendix A - Colours for the experiment



These are the different variants of green, red and blue that could be used in the suggested experiment as described in the design of the experiment. These colours were used in the experiment, as programmed by Zoril Olah, which I conducted on myself for the analysis of self-made data and the priming effect.

Appendix B - Code for the Models, Predictions and Simulations in R

```
### The code below in R was used in the making of the two models,
### the predictions using gamma distributions and the models and
### the simulations based on the predictions


options(show.error.locations = TRUE)
rm(list = ls())
graphics.off()

setwd ("C:/Users/RDPot/Onedrive/Documenten/KI/Scriptie/r")

library(ggplot2)

# Model for the contrast and the effects of content-matching
amplitudecontrast <- c(8,20,40,80)
contrasttable <- data.frame(amplitudecontrast = amplitudecontrast)
contrasttable $invispercent <- c(18.9,27.4,32.2,35)
contrasttable $simplemodel <- contrasttable$invispercent * 1.14
contrasttable $complexmodelv3 <- 35 * amplitudecontrast / (amplitudecontrast +
(14.154295/contrasttable$invispercent))

# recreation of attentional model by Hermann et al. 2010
xpoints <-c(0,10,20,30,40,60,80)
Hermannmodel <- data.frame(xpoints = xpoints)
Hermannmodel $redline <- c(0,0.347,1.161,1.798,2.155,2.466,2.585)
Hermannmodel $blackline <- c(0,0.218,0.855,1.492,1.953,2.425,2.6)
Hermannmodel $heegermodel2 <- 2.6 * xpoints / (xpoints + (14.154295/Hermannmodel $blackline))

# values for the three conditions, can be taken from the 'contrasttable' values and are used in several formulas
below
# instructions: To see values for different contrasts, simply change the number behind contrastvalue <- X
# 1 = 8% contrast, 2= 20%, 3 = 40%, 4=80%
# to verify, just check the contrasttable

contrastvalue <- 4
unma = contrasttable$invispercent[contrastvalue] / 100
simp = contrasttable$simplemodel[contrastvalue] /100
compl = contrasttable$complexmodelv3[contrastvalue] /100

## Prediction table
xmib <-seq(0,10,0.01)
MibTable <- data.frame(xmib=xmib)
# Scale is the % disappearance
MibTable $gammaunmatch <- (dgamma(x=xmib, shape=10, scale=unma) * 100)
MibTable $gammacomplex <- (dgamma(x=xmib, shape=10, scale=compl) * 100)
MibTable $gammasimple <- (dgamma(x=xmib, shape=10, scale=simp) * 100)

### randomtables for the simulations
MibTable $gammaunmatchrandom <-rgamma(n=xmib,shape=10,scale=unma)
MibTable $gammasimplerandom <-rgamma(n=xmib,shape=10,scale=simp)
MibTable $gammacomplexrandom <-rgamma(n=xmib,shape=10,scale=compl)

## table for the columns of randomly generated participants
```

```
unmatchavg <- c()
for (x in c(1:5)) {
  simuls = mean(sample(MibTable$gammaunmatchrandom, 40))
  unmatchavg[x] <- simuls
}
simpavg <- c()
for (x in c(1:5)) {
  simuls = mean(sample(MibTable$gammasimplerandom, 20))
  simpavg[x] <- simuls
}
complavg <- c()
for (x in c(1:5)) {
  simuls = mean(sample(MibTable$gammacomplexrandom, 20))
  complavg[x] <- simuls
}

participant <- rep(c(1:5),3)
simulations <- c(unmatchavg,simpavg,complavg)
condition <- c(rep("Unmemorized",5),rep("Simple",5),rep("Complex",5))
simgraph <- data.frame(participant,simulations,condition)

### table for randomly made participants, not devided in groups of 5 this time but for different contrastvalues.

unma8 = contrasttable$invispercent[1] / 100
simp8 = contrasttable$simplemodel[1] /100
compl8 = contrasttable$complexmodelv3[1] /100
unma20 = contrasttable$invispercent[2] / 100
simp20 = contrasttable$simplemodel[2] /100
compl20 = contrasttable$complexmodelv3[2] /100
unma40 = contrasttable$invispercent[3] / 100
simp40= contrasttable$simplemodel[3] /100
compl40 = contrasttable$complexmodelv3[3] /100
unma80 = contrasttable$invispercent[4] / 100
simp80 = contrasttable$simplemodel[4] /100
compl80 = contrasttable$complexmodelv3[4] /100

Mixtable <- data.frame(xmib=xmib)
Mixtable $gunma8  <-rgamma(n=xmib,shape=10,scale=unma8)
Mixtable $gimp8   <-rgamma(n=xmib,shape=10,scale=simp8)
Mixtable $gompl8  <-rgamma(n=xmib,shape=10,scale=compl8)
Mixtable $gunma20 <-rgamma(n=xmib,shape=10,scale=unma20)
Mixtable $gimp20  <-rgamma(n=xmib,shape=10,scale=simp20)
Mixtable $gompl20 <-rgamma(n=xmib,shape=10,scale=compl20)
Mixtable $gunma40 <-rgamma(n=xmib,shape=10,scale=unma40)
Mixtable $gimp40  <-rgamma(n=xmib,shape=10,scale=simp40)
Mixtable $gompl40 <-rgamma(n=xmib,shape=10,scale=compl40)
Mixtable $gunma80 <-rgamma(n=xmib,shape=10,scale=unma80)
Mixtable $gimp80  <-rgamma(n=xmib,shape=10,scale=simp80)
Mixtable $gompl80 <-rgamma(n=xmib,shape=10,scale=compl80)

samplors <- c(mean(sample(Mixtable$gunma8, 100)),
              mean(sample(Mixtable$gimp8, 100)),
              mean(sample(Mixtable$gompl8, 100)),
```

```
            mean(sample(Mixtable$gunma20, 100)),
            mean(sample(Mixtable$gimp20, 100)),
            mean(sample(Mixtable$gompl20, 100)),
            mean(sample(Mixtable$gunma40, 100)),
            mean(sample(Mixtable$gimp40, 100)),
            mean(sample(Mixtable$gompl40, 100)),
            mean(sample(Mixtable$gunma80, 100)),
            mean(sample(Mixtable$gimp80, 100)),
            mean(sample(Mixtable$gompl80, 100)))
condition2 <- c(rep(c("Unmatched","Simple Model","Complex Model"),4))
contrast <- c(rep("8%",3),rep("20%",3),rep("40%",3),rep("80%",3))
bigprime <- data.frame(samplors, condition2, contrast)

### Graphs


## Expected MIB result graph

Mibbasic <- ggplot(MibTable, aes(x=xmib, y=gammaunmatch, colour= "No Content-Matching")) +
  geom_line(colour= "blue") + xlab("Time Invisible(seconds)") + ylab("percentage of trials") +
  ggtitle("Expected responses for 80% amplitude (target contrast)") + ylim(0,70)
print(Mibbasic)

Mibv2 <- Mibbasic +geom_line(data=MibTable, aes(x=xmib, y=gammasimple, colour="Simple Model"),colour=
"green")
print(Mibv2)

Mibv3 <- Mibv2 +geom_line(data=MibTable, aes(x=xmib, y=gammacomplex, colour="Complex Model"), colour=
"red")
print(Mibv3)


## Contrast compared with attention Models graph

conplot <- ggplot(contrasttable, aes(x=amplitudecontrast, y=invispercent, log= "x",colour= "Bonneh et al. 2001"))
+
  geom_line(colour= "blue") + scale_x_log10(name="Amplitude(%)",limits=c(8,100)) +
  geom_line(aes(x=amplitudecontrast, y=simplemodel, colour="Simple Model"),colour = "green") +
  geom_line(aes(x=amplitudecontrast, y=complexmodelv3, colour="Complex Model"),colour = "red") +
  ylab("Invisibility Percentage") + ggtitle("Content-matching Models") +
  ylim(10,45)
 print(conplot)

 #  Below is the same code as above, but with a normal scale instead of a logarithmic one. remove the comment
signs '#' to run it
 #conplot <- ggplot(contrasttable, aes(x=amplitudecontrast, y=invispercent, colour= "Bonneh et al. 2001")) +
  # geom_line(colour= "blue") +
  # geom_line(aes(x=amplitudecontrast, y=simplemodel, colour="Simple Model"),colour = "green") +
  # geom_line(aes(x=amplitudecontrast, y=complexmodelv3, colour="Complex Model"),colour = "red")+
#   xlab("Amplitude(%)") + ylab("Invisibility Percentage") + ggtitle("Content-matching Models") +
 #  ylim(10,45) +xlim(0,100)
# print(conplot)

## Columns
```

```
# For these graphs I took the generated data from the simulations and multiplied it by 10 to get a percentage,
# I generated total time out of 10 seconds so by multiplying by 10 we get the percentage

# this graph displays 5 different participant simulations for 1 contrast value
simres <- ggplot(simgraph, aes(participant,simulations*10)) + geom_bar(stat = "identity", aes(fill = condition), position = "dodge") +
  ylab("Mean Accumulated Invisibility Percentage") + xlab("Observer") + ggtitle("Mean Accumulated Invisibility Percentage For One Or More Targets Per Observer For Different Levels Of Amplitude In Contrast")
print(simres)

#this graph displays only the averages for the conditions of 1 simulated participant
simres2 <- ggplot(bigprime, aes(contrast, samplors*10)) + geom_bar(stat = "identity", aes(fill = condition2), position = "dodge") +
  ylab("Mean Accumulated Invisibility Percentage") + xlab("Amplitude (%)") + ggtitle("Mean Accumulated Invisibility Percentage For One Or More Targets For Different Levels Of Amplitude In Contrast")
print(simres2)

## Hermann et al. attentional model in a graph
# used for visual verification of the model
herplot <- ggplot(Hermannmodel, aes(x= xpoints, y=redline, colour= "attentional influence")) +
  geom_line() + xlab("Amplitude%") + ylab("Perormance") + ggtitle("Attentional model") +
  ylim(-1,4) +xlim(0,100)
print(herplot)

herplotv2 <- herplot +geom_line(data=Hermannmodel, aes(x=xpoints, y=blackline, colour="No attentional influence"))
print(herplotv2)


herplotv3 <- herplotv2 +geom_line(data=Hermannmodel, aes(x=xpoints, y=heegermodel2, colour="No attentional influence"))
print(herplotv3)
```

Appendix C - Code for the Analysis of Data and Priming Effect in R

```
### The code below in R is intended as a script to analyse data from actual participants.
### Sadly due to circumstances the different memory conditions have not been included,
### but it does analyse data from the MIB part of the experiment. Comments are indicated by #.

options(show.error.locations = TRUE)
rm(list = ls())
graphics.off()

### Set working directory to the place where the data is saved, that way you can load the data into this script
setwd ("C:/Users/RDPot/Onedrive/Documenten/KI/Scriptie/testdata")

#libraries used for the analysis, these packages are required to execute the code.
library(ggplot2)
library(R.matlab)



## below is the function 'SummarySE', which is used for calculating confidence interval, standard error and
## standard deviation
###### SummarySE function taken from http://www.cookbook-r.com/Manipulating_data/Summarizing_data/
#######
summarySE <- function(data=NULL, measurevar, groupvars=NULL, na.rm=FALSE,
                      conf.interval=.95, .drop=TRUE) {
  library(plyr)

  length2 <- function (x, na.rm=FALSE) {
    if (na.rm) sum(!is.na(x))
    else       length(x)
  }
  datac <- ddply(data, groupvars, .drop=.drop,
                 .fun = function(xx, col) {
                   c(N    = length2(xx[[col]], na.rm=na.rm),
                     mean = mean   (xx[[col]], na.rm=na.rm),
                     sd   = sd     (xx[[col]], na.rm=na.rm)
                   )
                 },
                 measurevar
  )
  datac <- rename(datac, c("mean" = measurevar))
  datac$se <- datac$sd / sqrt(datac$N)  # Calculate standard error of the mean
  ciMult <- qt(conf.interval/2 + .5, datac$N-1)
  datac$ci <- datac$se * ciMult
  return(datac)
}
##### End of SummarySE function #####



### Section 1: Data
## To load in a participant's datafile, simply place the data in the working directory
## and add its path behind readMat

# These are the responses to the experiment
```

```
responsesettings1 <- readMat("C:/Users/RDPot/OneDrive/Documenten/KI/Scriptie/testdata//test01-results.mat")
responses1 <- responsesettings1$exp.responses
responsesettings2 <- readMat("C:/Users/RDPot/OneDrive/Documenten/KI/Scriptie/testdata//test02-results.mat")
responses2 <- responsesettings2$exp.responses
responsesettings3 <- readMat("C:/Users/RDPot/OneDrive/Documenten/KI/Scriptie/testdata//test03-results.mat")
responses3 <- responsesettings3$exp.responses
responsesettings4 <- readMat("C:/Users/RDPot/OneDrive/Documenten/KI/Scriptie/testdata//test04-results.mat")
responses4 <- responsesettings4$exp.responses
responsesettings5 <- readMat("C:/Users/RDPot/OneDrive/Documenten/KI/Scriptie/testdata//test05-results.mat")
responses5 <- responsesettings5$exp.responses

#Below is the table for checking for the effect of priming

matched1 <- c()
matched2 <- c()
unrelated <- c()
settings1 <- responsesettings1$exp.conditions
settings2 <- responsesettings2$exp.conditions
settings3 <- responsesettings3$exp.conditions
settings4 <- responsesettings4$exp.conditions
settings5 <- responsesettings5$exp.conditions
tablecounter1 <- 1
tablecounter2 <- 1
tablecounter3 <- 1
#the part of the table for the first observant
for (x in c(1:10)) {
  if (settings1[3,x] == settings1[1,x]) {
    matched1[tablecounter1] = responses1[7,x]
    tablecounter1 <- tablecounter1 + 1
  }
  else if (settings1[3,x] == settings1[2,x]) {
    matched2[tablecounter2] = responses1[7,x]
    tablecounter2 <- tablecounter2 + 1
  }
  else {
    unrelated[tablecounter3] = responses1[7,x]
    tablecounter3 <- tablecounter3 + 1
  }
}
#the part of the table for the second observant
for (x in c(1:10)) {
  if (settings2[3,x] == settings2[1,x]) {
    matched1[tablecounter1] = responses2[7,x]
    tablecounter1 <- tablecounter1 + 1
  }
  else if (settings2[3,x] == settings2[2,x]) {
    matched2[tablecounter2] = responses2[7,x]
    tablecounter2 <- tablecounter2 + 1
  }
  else {
    unrelated[tablecounter3] = responses2[7,x]
    tablecounter3 <- tablecounter3 + 1
  }
```

```
}
#the part of the table for the third observant
for (x in c(1:10)) {
  if (settings3[3,x] == settings3[1,x]) {
    matched1[tablecounter1] = responses3[7,x]
    tablecounter1 <- tablecounter1 + 1
  }
  else if (settings3[3,x] == settings3[2,x]) {
    matched2[tablecounter2] = responses3[7,x]
    tablecounter2 <- tablecounter2 + 1
  }
  else {
    unrelated[tablecounter3] = responses3[7,x]
    tablecounter3 <- tablecounter3 + 1
  }
}
#the part of the table for the fourth observant
for (x in c(1:10)) {
  if (settings4[3,x] == settings4[1,x]) {
    matched1[tablecounter1] = responses4[7,x]
    tablecounter1 <- tablecounter1 + 1
  }
  else if (settings4[3,x] == settings4[2,x]) {
    matched2[tablecounter2] = responses4[7,x]
    tablecounter2 <- tablecounter2 + 1
  }
  else {
    unrelated[tablecounter3] = responses4[7,x]
    tablecounter3 <- tablecounter3 + 1
  }
}
#the part of the table for the fifth observant
for (x in c(1:10)) {
  if (settings5[3,x] == settings5[1,x]) {
    matched1[tablecounter1] = responses5[7,x]
    tablecounter1 <- tablecounter1 + 1
  }
  else if (settings5[3,x] == settings5[2,x]) {
    matched2[tablecounter2] = responses5[7,x]
    tablecounter2 <- tablecounter2 + 1
  }
  else {
    unrelated[tablecounter3] = responses5[7,x]
    tablecounter3 <- tablecounter3 + 1
  }
}
# the mean invisibility time for all conditions
meanmatched1 <- mean(matched1)
meanmatched2 <- mean(matched2)
meanunrelated <- mean(unrelated)
# now we make a data frame for the priming effect results, so we can make a graph out of it.

colorder <- c('First Position','Second Positiion','Unrelated Colour')
resultsprime <- c(meanmatched1,meanmatched2,meanunrelated)
```

```
primingtable <- data.frame(colorder,resultsprime)

posiSE <- c(rep('1',length(matched1)),rep('2',length(matched2)),rep('3',length(unrelated)))
posisoSE <- c(matched1,matched2,unrelated)
primingSE <- data.frame(posiSE,posisoSE)
primese <- summarySE(primingSE,measurevar = "posisoSE", groupvars = "posiSE")

## We tested the data on 10 trials per participant, if there are more trials in an experiment simply
## change the numbers from 1:X and scale the invispercents accordingly

invispercents <- NA
invispercents[1:10] <- responses1[7,1:10]
invispercents[11:20] <- responses2[7,1:10]
invispercents[21:30] <- responses3[7,1:10]
invispercents[31:40] <- responses4[7,1:10]
invispercents[41:50] <- responses5[7,1:10]
meaninvispercents <- c(mean(responses1[7,1:10]),mean(responses2[7,1:10]), mean(responses3[7,1:10]),
mean(responses4[7,1:10]), mean(responses5[7,1:10]))

participantSE <- c(rep('1',10),rep('2',10),rep('3',10),rep('4',10),rep('5',10))
invispercentsSE <- data.frame(participantSE,invispercents)
invisSE <- summarySE(invispercentsSE, measurevar="invispercents", groupvars = "participantSE")




### Section 2: Graphs

## A histogram representing the actual results of all the trials
hist((invispercents/10),main="Histogram of Trial Results",xlab = "Total time invisible (s)",col="grey",xlim = c(0,10))

## A graph of the results for each participant, due to circumstances I am all 5 participants myself,
## but for purposes of this specific graph I assumed these were 5 different participants
participant <-c(1:5)
results <- data.frame(meaninvispercents,participant)
resultgraph <- ggplot(results, aes(participant,meaninvispercents)) + geom_bar(stat = "identity") +
  ylab("Mean Accumulated Invisibility Percentage") + xlab("Participant") + ggtitle("Mean Accumulated Invisibility
Percentage For One or More Targets Per Participant") +
  geom_errorbar(aes(ymin=meaninvispercents-invisSE$se,ymax=meaninvispercents+invisSE$se) , width=.1)
print(resultgraph)

# The graph for the effect of priming
priminggraph <- ggplot(primingtable, aes(colorder,resultsprime)) + geom_bar(stat = "identity", position = "dodge")
+
  ylab("Mean Accumulated Invisibility Percentage") + xlab("Position of the Colour") + ggtitle("Effect of Priming in
MIB") +
  geom_errorbar(aes(ymin=resultsprime-primese$ci,ymax=resultsprime+primese$ci, width = .1))
print(priminggraph)
```