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The change probability effect: Incidental learning, adaptability, and shared visual working memory resources

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A B S T R A C T

Statistical properties in the visual environment can be used to improve performance on visual working memory (VWM) tasks. The current study examined the ability to incidentally learn that a change is more likely to occur to a particular feature dimension (shape, color, or location) and use this information to improve change detection performance for that dimension (the change probability effect). Participants completed a change detection task in which one change type was more probable than others. Change probability effects were found for color and shape changes, but not location changes, and intentional strategies did not improve the effect. Furthermore, the change probability effect developed and adapted to new probability information quickly. Finally, in some conditions, an improvement in change detection performance for a probable change led to an impairment in change detection for improbable changes.

1. Introduction

Although it is well established that there is a limit to the amount of information that can be represented in visual working memory (VWM; Alvarez & Cavanagh, 2004; Eng, Chen, & Jiang, 2005; Irwin, 1992; Irwin & Andrews, 1996; Levin, Simons, Angelone, & Chabris, 2002; Mitroff, Simons, & Levin, 2004; O'Regan, 1992; Rensink, 2000; Simons, 1996; Simons & Levin, 1997; for review see Simons and Rensink, 2005), it may be possible to improve performance on VWM tasks when resources can be focused on the most task-relevant features of an object (Droll & Hayhoe, 2007; Droll, Hayhoe, Triesch, & Sullivan, 2005; Triesch, Ballard, Hayhoe, & Sullivan, 2003). For example, if an air traffic controller is monitoring several planes for changes in color or shape, performance may be improved for higher probability changes (change probability effect) by allocating recourses preferentially toward the feature dimension[1] with the higher change probability. Furthermore, the air traffic controller may be able to incidentally learn and use the probability information to improve change detection performance without the use of intentional strategies (Beck, Angelone, Levin, Peterson, & Varakin, 2008; Chun & Jiang, 1998, 2003). The current study further characterizes the change probability effect by examining whether it develops and adapts similarly for different feature dimensions and the extent to which improving VWM performance for probable changes impairs performance for improbable changes.

1.1. Incidental learning of probability information

Research suggests that probability information can be incidentally learned and then used to identify repeated object triplets (Fiser & Aslin, 2002, 2005; Turk-Browne, Isola, Scholl, & Treat, 2008; Turk-Browne, Junge, & Scholl, 2005; Turk-Browne,

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[1] The terms *dimension* and *feature* will be used as outlined by Treisman and Gelade (1980); dimension refers to all separable parts of the visual scene (color, shape, size, etc.), and feature refers to a value of that dimension (green, square, large, etc.).

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Scholl, Chun, & Johnson, 2009), to locate a target more efficiently (Brady & Chun, 2007; Chun & Jiang, 1998, 2003; Jiang & Chun, 2001; Peterson & Kramer, 2001; Pollmann & Manginelli, 2009; Reder, Weber, Shang, & Vanyukov, 2003; Shinoda, Hayhoe, & Shrivastava, 2001), and to improve change detection performance (Beck, Angelone, & Levin, 2004; Beck, Peterson, & Angelone, 2007; Beck et al., 2008; Logie, Brockmole, & Vandenbroucke, 2009; Olson, Jiang, & Moore, 2005; Umemoto, Scolari, Vogel, & Awh, 2010). The goal of the current study is to determine what types of probability information can be learned in a change detection task.

Location probability information can be learned during a laboratory change detection task and used to improve performance. (Beck et al., 2008; Olson et al., 2005; Umemoto et al., 2010). Olson et al. (2005) found that participants could detect the location of a missing square better in repeated trials, but only if the square that disappeared was always in the same location. Beck et al. (2008) found that participants detected more shape changes when the change always occurred to an object in the same general location (e.g., the right column in a four column display), even when they were not explicitly told that location would be predictive of the change. Similarly, Umemoto et al. (2010) found that participants were more accurate at detecting color changes if the changes occurred in a quadrant where changes were more likely to occur. These studies suggest that location probability information can be learned and used to improve change detection performance by biasing storage to the objects in the probable change locations and thereby reducing the overall load on VWM.

Beck et al. (2008) also included an experiment in which color, rather than location, was predictive of the change. That is, a particular colored object always changed shape. If participants could learn that, for example, a red object would always be the object that changed, this should improve performance because they would only need to remember the red items. However, shape change detection performance was not improved if the object that changed shape was always the same color. Why were participants able to learn and use location, but not color, probability information?

One possibility is that only statistical information about location can be incidentally learned during a change detection task and subsequently used to improve change detection performance, perhaps because of a special role of location in processing visual information (Hollingworth, 2007; Pisella, Berberovic, & Mattingley, 2004; Treisman & Gelade, 1980; Tsal & Lavie, 1988). Location may be attended automatically (Tsal & Lavie, 1988), attention to location is crucial for feature integration (Treisman & Gelade, 1980), configuration changes tend to be more easily noticed than feature changes (Simons, 1996), and changes to an object are more likely to be noticed if the object does not change location (Hollingworth, 2007). Therefore, location probabilities, but not color probabilities, may influence whether a change is detected because of the specialized role of location in visual processing. This would suggest that only location probability information can be learned and used to improve change detection performance.

A second possibility is that participants in Beck et al.'s (2008) study did not incidentally learn and use color probability information because color was not relevant to the change detection task (participants were instructed to detect a shape change). Because attention is required for learning probability information (Baker, Olson, & Behrman, 2004; Jiang & Chun, 2001; Turk-Browne et al., 2005) and task irrelevant features may not be attended (Droll & Hayhoe, 2007; Droll et al., 2005; Triesch et al., 2003), probability information about task-irrelevant features is unlikely to be learned.

When a block-sorting task required attention to one dimension (e.g., sorting blocks by shape), changes to another dimension (e.g., size) of the object were noticed less frequently than changes to the task-relevant dimension (Droll & Hayhoe, 2007). Furthermore, Turk-Browne et al. (2005) found that when a cover task required detecting shape repetitions in one color but not another, statistical learning for repeated shape triplets occurred only for shape triplets occurring in the attended color. The authors concluded that attention is necessary for statistical learning to occur. Together these studies suggest that incidental learning of probability information may not occur for a feature dimension that is not directly relevant to the task. However, location probability information may be learned because location is still relevant to detecting a change: location may be automatically attended (Tsal & Lavie, 1988), and feature maps can be created without attention (Treisman & Gelade, 1980). While participants may choose, based on task relevance, to not consolidate feature dimensions such as color, shape, and orientation into memory (Woodman & Vogel, 2008), location may be automatically consolidated. Thus, attention may not be required to learn location probabilities like it is to learn feature probabilities.

While previous studies have examined whether probability information could be learned and used to determine which objects should be stored in VWM (Beck et al., 2008; Olson et al., 2005; Umemoto et al., 2010), the current study examined whether probability information could be learned and used to determine which features (e.g., color or shape) should be stored in VWM. Previous research suggests that probability information can effect which features of an object are stored in VWM. Beck et al. (2004) found that participants were more accurate at detecting feature changes that were more likely to occur in real-world situations. For example, participants more readily detected a lamp changing from onto off (a probable change) than a green lamp changing into a blue lamp (an improbable change). Unlike Beck et al. (2008) and Umemoto et al. (2010), in Beck et al. (2004), probability information was found in the change type, not in a particular set of objects. That is, one change type (on or off) was more likely to occur than another (green to blue) within the same object. This suggests that probability about the change type can be learned and used to detect changes.

In the current study, we examined the ability to learn and use change probability information – for location, shape, and color – when the probability information occurs within the changing feature dimension. Participants completed a set of weighted probability trials in which any feature dimension could change, but one type of change (e.g., color change) was more likely to occur than others. All feature dimensions were relevant to the task because any change type could occur on any given trial; however, the probability information made one dimension (the most probable change type) more task-relevant than the others. If probability information presented in a task-relevant dimension can be learned and used to improve performance on a VWM task, then change detection performance should be higher for a change type when it is most probable, compared to when all change types are equally probable (the change probability effect).

Given that which feature is the most task relevant may change unexpectedly and frequently, a system that could adapt quickly to new probability information would be advantageous. Therefore, the current experiments also examined the development and adaptability of the change probability effect. The ability to learn and use probability information may only require limited exposure to the probability information (Brady, Konkle, & Alvarez, 2009; Chun & Jiang, 1998; Pollmann & Manginelli, 2009; Turk-Browne et al., 2009). For example, Chun and Jiang (1998) found that visual search performance was faster in repeated search displays (contextual cueing) after only five repetitions of the search arrays. Brady et al. (2009) found that participants could remember more colors from an array if color pairs were repeated across trials; this improvement was found within the second block of 60 trials. This suggests that probability information can be learned with limited exposure to the information.

When probability information in the visual world changes, the allocation of VWM resources may quickly adapt in response to the new probability information. In order to examine how quickly probability information can be learned and used to improve performance, the change probability effect was examined across the weighted probability trials. In addition, following the weighted probability trials, participants completed a set of equal probability trials, during which all change types occurred equally often, to determine if the learned probability information from the weighted probability trials would continue to bias performance toward the probable change dimension or if VWM performance would reflect the more recent probability information.

1.2. Biased allocation of VWM resources

Evidence that probability information can be learned and used to improve performance in a VWM task would suggest that more VWM resources are allocated to the probable change feature than to improbable change features. Specifically, a performance tradeoff between dimensions may occur when one dimension is more task-relevant than others (Bonnel & Prinzmetal, 1998; Johnson, Hollingworth, & Luck, 2008; Wheeler & Treisman, 2002). Previous research indicates that statistical learning during change detection may occur if participants can use probability information to bias VWM toward a specific subset of objects (Beck et al., 2008; Umemoto et al., 2010). Therefore, a performance tradeoff between dimensions when one becomes more task-relevant is likely the result of preferential storage in VWM of the probable feature dimension. The ability to preferentially store features from task-relevant dimensions will be considered from the perspective from three hypotheses: independent stores, object slot, and flexible resource.

According to the independent stores hypothesis, features from different dimensions are stored separately in VWM (Bays, Wu, & Husain, 2011; Delvenne & Bruyer, 2004; Wheeler & Treisman, 2002). While features from the same dimension share capacity, features from different dimensions do not (Wheeler & Treisman, 2002). Therefore, an increase in performance for the probable change should not co-occur with a decrease in performance for improbable changes.

The object slot hypothesis proposes that the structure of VWM is a set number (about 3–4) of object-based slots (Awh, Barton, & Vogel, 2007; Gajewski & Brockmole, 2006; Luck & Vogel, 1997; Serences, Ester, Vogel, & Awh, 2009; Vogel, Woodman, & Luck, 2001; Zhang & Luck, 2008). There is no cost to capacity for storing an object composed of multiple features (Luck & Vogel, 1997). Therefore, there would be no capacity benefit to selectively store only task-relevant features of an object (although selective encoding of single features may allow information to be consolidated more quickly; Woodman & Vogel, 2008). This would suggest that a storage tradeoff between a more and less probable dimensions is unlikely. However, a performance tradeoff because of preferential comparison of the dimension that is more likely to change cannot be excluded (Awh et al., 2007; Hollingworth, 2003).

The flexible resource hypothesis suggests that VWM is not set by a fixed number of slots, but rather by a pool of resources. (Alvarez & Cavanagh, 2004; Bays & Husain, 2008; Eng et al., 2005; Fougnie, Asplund, & Marois, 2010; Olson & Jiang, 2002; Song & Jiang, 2006; Wilken & Ma, 2004; but see Cowan & Rouder, 2009). Unlike the object slot hypothesis, the flexible resource hypothesis suggests that objects stored within VWM compete for the same resource. If the total amount of load carried by each object can be reduced by preferentially storing the task-relevant features of an object, then more objects may be stored in VWM. This would suggest that a performance tradeoff would be expected between more and less probable feature dimensions.

1.3. The current study

In the current study, participants completed a change detection task consisting of a weighted probability phase and an equal probability phase. During the weighted probability phase of the experiment, one change type (location, shape, or color) was more likely to occur than the others. After the weighted probability trials, participants completed equal probability trials in which each change type was equally likely to occur. We examined the following hypotheses:

(1) *Incidental Learning and the Change Probability Effect Hypothesis*: Participants can incidentally learn that one change type is more likely to occur and then use this information to improve change detection performance. This will be evidenced by higher change detection performance for a change type when it is most likely to occur than when all change types

are equally likely. In Experiment 1 participants were not informed about the change probability information and therefore had to learn it incidentally. In Experiment 2, participants were told which type of change is most likely to occur to examine whether intentional strategies affected the change probability effect.

(2) *Development and Adaptability Hypothesis*: Probability information can be learned and adjusted quickly. Performance during the weighted probability trials was separated into three consecutive blocks in order to examine how the effect developed. Following the weighted probability trials, participants completed a phase of equal probability trials. This equal probability block was used to assess whether change detection would continue to be biased toward a particular feature dimension, even after that change type was no longer most likely.
   a. The ability to learn and use probability information quickly will be evidenced by the presence of the change probability effect as early as the first block of weighted probability trials.
   b. The adaptability of the change probability effect will be evidenced by a decrease in the effect from the final block of the weighted probability trials to the equal probability trials.

(3) *Shared Resources Hypothesis*: Improving change detection performance for the probable change will result in a decline in performance for the improbable changes, suggesting that VWM resources are shared across feature dimensions. For example, color change detection performance should be lower if shape changes are most likely than if all types of changes are equally likely.

2. Experiment 1

2.1. Method

2.1.1. Participants

One hundred and thirty-five undergraduate students with normal or corrected to normal vision participated in this experiment for credit in their psychology courses (109 female, 26 male; average age 20.9 years). Thirty-four participants were randomly assigned to the control condition, 32 to the location condition, 35 to the color condition, and 34 to the shape condition.

2.1.2. Materials

This experiment was completed using Superlab 4 to present the stimuli and record the data on iMac computers (20 inch screen). Each object was approximately 2.5 cm, presented on a white screen, subtending 2.4° visual angle, from a viewing distance of approximately 47 cm.

Four novel shapes (see Fig. 1) and four colors (red, RGB: 225, 0, 0; blue: 0, 16, 255; yellow, 255, 231, 0; and green, 0, 140, 66) were used to create a set of 16 objects. These objects were used to create 516 object arrays: 129 pre-change arrays, and three sets of 129 post-change arrays. Thus, for each pre-change array, there were three corresponding post-change arrays, one for each of the following change types: (1) color change, (2) shape change, and (3) location change. Each array contained six objects placed in one of 12 locations in a 4×3 grid. The objects and their locations were chosen randomly for each array, with the constraints that one object appeared in each column, each shape appeared at least once, and at least three colors appeared in the pre-change array. The post-change arrays followed similar constraints. If a location change occurred and the object chosen to change location was the only object in that column, the object changed to a new location within the column, so that at least one object remained in each column in the post-change array. In addition, at least three colors and shapes were required to appear on the post-change arrays. Because there were four shapes present on any pre-change array, if a shape change occurred, it could occur to any object. Also, there were only eight pre-change arrays in which only three colors were present; in each of these arrays, there were two objects of each color. Therefore, when a color change occurred, it could also occur to any object to maintain the restraint that at least three colors were required to be present.

2.1.3. Procedure

Participants completed 129 change detection trials: 99 weighted probability trials and 30 equal probability trials. On each trial, participants viewed a pre-change array for 2000 ms, followed by an 800 ms ISI, then a post-change array until response. In the post-change array, one object changed location, shape, or color (all trials were change trials). Participants responded by clicking on the changed object with the mouse (see Fig. 1). Responses were recorded as correct if participants clicked on the object that changed (chance performance = 0.17). After the participants responded, the post-change array disappeared and they were prompted to press a key on the keyboard to begin the next trial. The frequency of each change type (location, shape, or color) differed by weighted-probability condition.

Participants were randomly assigned to one of four probability conditions: control, color, shape, and location. These conditions differed by the number of color, shape, and location trials that occurred during the weighted probability phase of the experiment. In the control condition, there were 33 color change trials, 33 shape change trials, and 33 location change trials. In the color condition, there were 75 color change, 12 location change, and 12 shape change trials. In the shape condition, there were 75 shape change, 12 color change, and 12 location change trials. In the location condition, there were 75 location

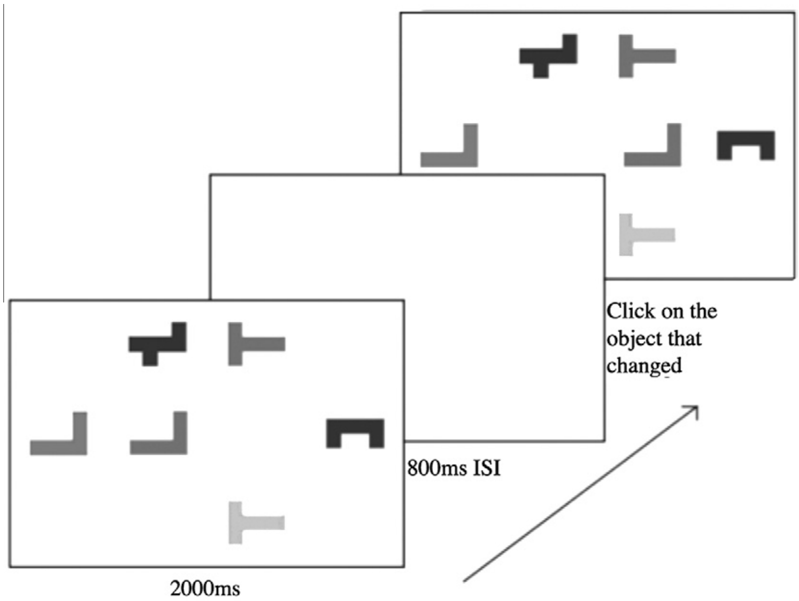

Fig. 1. The procedure for the change detection task. This is an example of a location change trial.

change trials (75 "probable" trials), 12 color change trials, and 12 shape change trials (24 "improbable" trials). Following the weighted probability trials, all participants completed the same 30 equal probability trials (10 of each change type). The equal probability trials immediately followed the weighted probability trials and participants were not alerted to the transition.

2.1.3.1. Awareness questionnaire. Following the change detection task, participants completed a questionnaire to determine whether they were aware of the change probability information. First, participants were asked to list any strategies they used to detect the changes (question 1). Next, they were asked to indicate whether some types of changes were more likely to occur than others, or whether they were all equally likely to occur (question 2). Participants were then asked to estimate the percentage of trials for which each type of change occurred (question 3). Finally, participants were asked whether some types of changes were more likely to occur at one part of the experiment, but not another (question 4). The purpose of question 4 was to assess awareness of the transition between the weighted-probability and equal-probability trials. Each question was presented on the computer screen one at a time and the participants used the keyboard to enter their responses.

2.2. Results

2.2.1. Overall performance

A 4 (condition) $\times$ 3 (change type) repeated measures ANOVA of proportion correct on the weighted-probability trials was conducted. This revealed a main effect of change type $F(2,262) = 230.57$, $p < .001$, $\eta_p^2 = .64$, and a change type by condition interaction, $F(6,262) = 19.38$, $p < .001$, $\eta_p^2 = .31$. No main effect of condition was found, $F(3,131) = 2.0$, $p > .05$, $\eta_p^2 = .04$. Overall, location performance ($M = .75$, $SD = .15$) was higher than color performance ($M = .60$, $SD = .19$), $t(134) = 8.48$, $p < .01$, which was higher than shape performance ($M = .41$, $SD = .17$), $t(134) = 8.41$, $p < .01$.

2.2.2. Change probability effect

If probability information can improve change detection, change detection performance for probable changes during the weighted probability trials should be higher than performance for the same change type in the control condition (see Fig. 2). To test this, one-way ANOVAs were conducted for each change type (location, color, and shape) with condition as the between subject factor. All three ANOVAs were significant: color, $F(3,131) = 8.5$, $p < .01$, $\eta_p^2 = .16$; shape, $F(3,131) = 20.93$, $p < .01$, $\eta_p^2 = .32$; and location, $F(3,131) = 3.12$, $p < .05$, $\eta_p^2 = .06$. Planned comparisons revealed that color performance was significantly higher in the color condition than in the control condition, $t(67) = -3.68$, $p < .01$, and shape performance was significantly higher in the shape condition than in the control condition, $t(66) = -4.40$, $p < .01$. However, location performance was not higher in the location condition than the control condition, $t(64) = -.69$, $p > .05$. Therefore, for both shape and color changes, performance was higher when each of those change types were most likely than when all change types were equally likely.

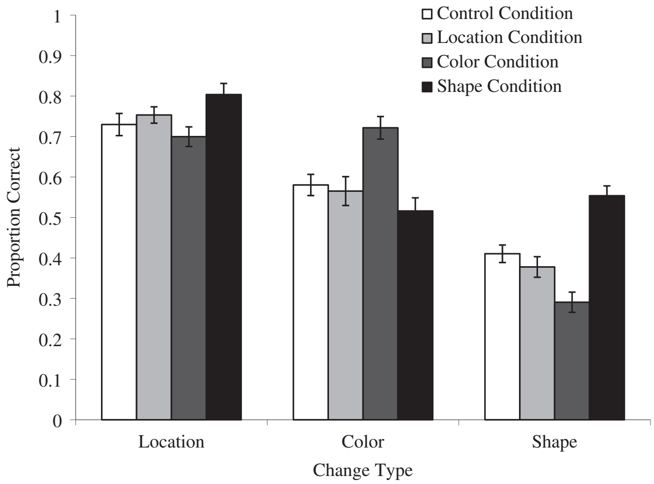

Fig. 2. Proportion correct from the weighted probability trials in Experiment 1.

2.2.3. Development and adaptability of the change probability effect

To measure the development of the change probability effect in the color, shape, and location conditions, the probable change trials in the weighted probability phase were grouped into three consecutive blocks. The first 25 probable trials presented were grouped into Block 1, the second 25 probable trials were grouped into Block 2 and the final 25 probable trials were grouped into Block 3. The 24 improbable trials were not included in the analyses. In the control condition, trials for each change type were grouped into three consecutive blocks of eleven trials (i.e., the first 11 color change trials were grouped into Color Block 1, etc.). For each change type, to measure the development of the change probability effect, performance in the weighted probability condition was compared to the control condition with block as a within subjects factor (see Fig. 3). To measure the adaptability of the change probability effect, performance between the weighed probability condition and the control condition was compared in the final block of the weighted probability trials (Block 3) and in the equal probability trials (Block 4).

2.2.3.1. Development of the change probability effect. Three separate ANOVAs were conducted: one each for color, shape, and location changes. To measure the development of the color change probability effect, a 3 $\times$ 2 repeated measures ANOVA was conducted with block (1–3) as the within subjects factor and condition (color and control) as the between subjects factor. Mauchly's test of sphericity was significant, so a Greenhouse-Geisser correction was used. This ANVOA revealed a main effect of condition, $F(1,67) = 10.03$, $p < .01$, $\eta_p^2 = .13$, but no main effect of block $F(1.75,117.32) = .79$, $p > .05$, $\eta_p^2 = .01$. There was no interaction between condition and block, $F(1.75,117.32) = .80$, $p > .05$, $\eta_p^2 = .041$ Planned comparisons revealed that color performance was significantly higher in the color condition than in the control condition for all three weighted probability blocks: Block 1, $t(67) = -2.73$, $p < .01$; Block 2, $t(67) = -2.05$, $p < .05$; and Block 3, $t(67) = -3.42$, $p < .01$.

The ANOVA for shape changes revealed a main effect of condition, $F(1,66) = 19.77$, $p < .01$, $\eta_p^2 = .23$, a main effect of block, $F(2,132) = 3.54$, $p < .05$, $\eta_p^2 = .05$, but no interaction, $F(2,132) = .76$, $p > .05$, $\eta_p^2 = .01$. Planned comparisons revealed that performance was higher in the shape condition for all three weighted probability blocks: Block 1, $t(66) = -2.50$, $p < .05$; Block 2, $t(66) = -3.73$, $p < .01$; and Block 3, $t(66) = -1.64$, $p < .01$.

The ANOVA for location changes (Mauchly's test of sphericity was significant, so a Greenhouse-Geisser correction was used) revealed no main effect of block, $F(1.83,116.91) = .32$, $p > .05$ $\eta_p^2 = .01$, no main effect of condition, $F(1,64) = .62$, $p > .05$, $\eta_p^2 = .01$, and no interaction, $F(1.90) = .40$, $p > .05$ $\eta_p^2 = .01$. Planned comparisons revealed no difference in performance between location and control conditions across all blocks: Block 1, $t(64) = -1.00$, $p > .05$; Block 2, $t(64) = -.13$, $p > .05$; Block 3, $t(64) = -.81$, $p > .05$.

2.2.3.2. Adaptability of the change probability effect. To measure the adaptability of the color change probability effect a 2 $\times$ 2 repeated measures ANOVA was conducted with block (3 and 4) as the within subjects factor and condition (color and control) as the between subjects factor. The ANVOA revealed a main effect of condition, $F(1,67) = 5.71$, $p < .05$, $\eta_p^2 = .1$, but no main effect of block $F(1,67) = .02$, $p > .05$, $\eta_p^2 = .00$. There was also an interaction between condition and block, $F(1,67) = 5.38$, $p < .05$, $\eta_p^2 = .07$. There was no difference in performance in Block 4 (equal probability block) $t(67) = -.57$, $p > .05$ between the control and color conditions.

The shape ANOVA revealed a main effect of condition, $F(1,66) = 11.01$, $p < .01$, $\eta_p^2 = .14$, but no main effect of block, $F(1,66) = .44$, $p > .05$, $\eta_p^2 = .01$, and marginal interaction, $F(1,66) = 3.19$, $p = .08$, $\eta_p^2 = .08$. Planned comparisons revealed that there was no difference between the control and shape conditions in Block 4: $t(66) = -1.64$, $p > .05$.

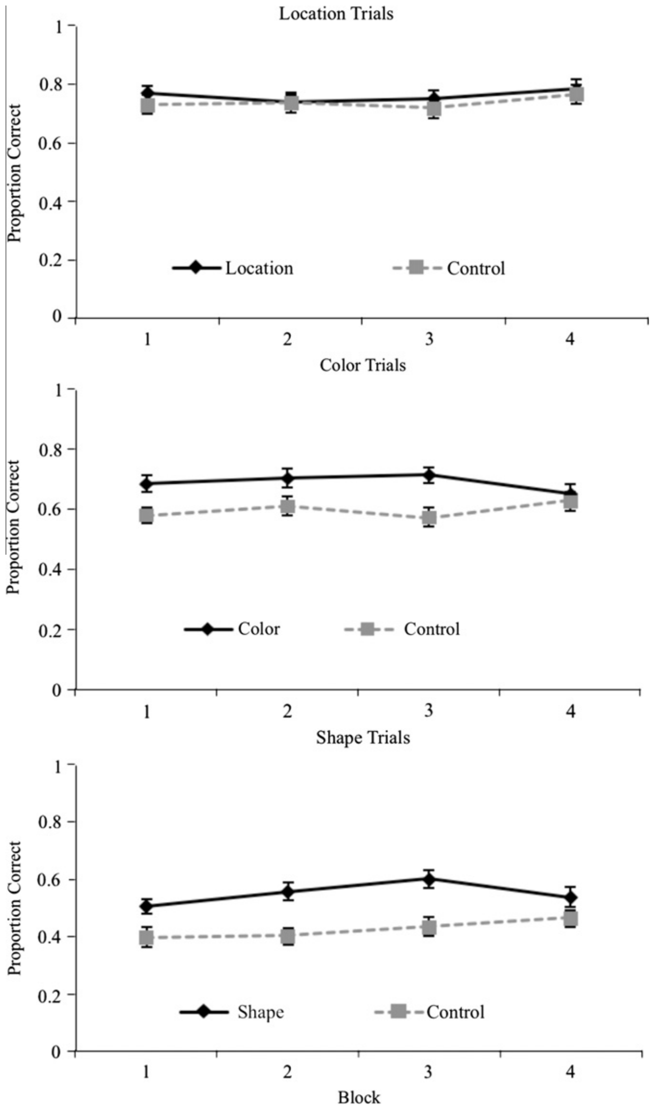

Fig. 3. Proportion correct across blocks of weighted (Blocks 1–3) and the equal probability block (Block 4) in Experiment 1. Each graph represents performance for a particular change type (location, color, or shape). Each dark solid line represents a weighted probability condition, while the gray dashed line represents performance in the control condition for in each graph.

Finally, the location ANOVA revealed no effect of condition, $F(1,64) = .5$, $p > .05$, $\eta_p^2 = .01$, a marginal effect of block, $F(1,64) = 3.38$, $p = .07$ (performance was higher in Block 4 than Block 3), but no interaction, $F(1,64) = .14$, $p > .05$, $\eta_p^2 = .00$. There was no difference between the control and shape conditions in Block 4 $t(64) = -.40$, $p > .05$.

2.2.4. Shared resources

To examine the role of shared resources between feature dimensions, performance for each change type in the control condition was compared to the conditions in which it was improbable (see Fig. 2). If allocating resources to the probable change feature takes resources away from the improbable change dimensions, when a change is improbable, performance should be lower than when all changes are equally likely. Planned comparisons revealed that color change detection performance in the control condition was not different from color change detection performance in the shape, $t(66) = 1.54$, $p > .05$, or location, $t(64) = .35$, $p > .05$, conditions. Shape performance was lower in the color condition than the control condition, $t(67) = 3.62$, $p < .01$, although there was no difference in shape change detection performance between the location and control conditions, $t(64) = .98$, $p > .05$. There was no difference in location change detection performance between the color and control conditions, $t(67) = .82$, $p > .05$, although location change detection performance was marginally higher in the shape condition relative to the control condition, $t(64) = -1.91$, $p = .06$.

2.2.5. Awareness questionnaire

To determine whether explicit awareness is required for the change probability effect, responses from the questionnaire were used to determine which participants had explicit awareness of probability information. None of the participants spontaneously mentioned noticing or using probability information to improve performance (question 1); however, responses to question 3 and 4 revealed that 43% ($n = 58$; 29 in the color condition, 13 in the shape condition, 16 in the location condition,) of participants indicated some level of explicit awareness. These participants were removed from analysis and one way ANOVAs for each change type (color, shape, and location), with condition as the between subjects factor were conducted with only the data from the unaware participants (all participants in the control condition were considered to be unaware).

The color ANOVA was marginally significant, $F(3,73) = 2.55$, $p = .06$, $\eta_p^2 = .10$; this was likely due to insufficient power (only 6 participants were included in this analyses). The shape ANOVA $F(3,73) = 8.53$, $p < .01$ and the location ANOVA, $F(3,73) = 4.27$, $p = .01$ $\eta_p^2 = .15$, were both significant. Planned comparisons revealed a similar pattern of results as was found when all participants were included in the analyses. Color performance in the color condition ($M = .70$, $SD = .20$) was marginally higher than color performance in the control ($M = .58$, $SD = .16$), $t(38) = -1.81$, $p = .08$. In addition, shape performance in the shape condition ($M = .55$, $SD = .13$) was higher than shape performance in the control ($M = .41$, $SD = .13$), $t(53) = -4.02$, $p < .01$. Location performance was not higher in the location condition ($M = .75$, $SD = 12$) than in the control condition ($M = .73$, $SD = 16$), $t(48) = -.44$, $p > .05$. Therefore, excluding participants who became explicitly aware of the probability information did not eliminate the change probability effect.

2.3. Discussion

The results from Experiment 1 indicate that incidental learning can lead to a change probability effect for color and shape changes. Color performance increased when color changes were most likely and shape performance increased when shape changes were most likely. However, location probability information did not increase location change detection performance. This may have been because of a ceiling effect, and/or because location is always encoded (making it insensitive to probability). However, the tradeoff in performance between shape and color demonstrates that the ability to detect both shape and color changes can be improved by increasing the probability of change.

The results also indicated that the change probability effect developed and adapted quickly (Brady et al., 2009; Chun & Jiang, 1998; Turk-Browne et al., 2009). For both color and shape, the change probability effect was found in the first block of weighted probability trials and this effect was eliminated by the equal probability phase of the experiment. This quick learning and adaptability would be a useful ability for VWM, as task demands may change frequently and without warning.

Finally, evidence from improbable changes suggests that some VWM resources may be shared between feature dimensions; when color changes were most likely, the ability to detect shape changes was impaired compared to when all types of changes were equally likely. This suggests that shape shares some VWM resources with color, and that shifting resources toward color impairs the ability to detect shape changes. However, this tradeoff was not perfect: color change detection performance was not reduced in the shape condition relative to the control condition. This may be because shape changes were generally more difficult to detect than color changes (see Fig. 2); changes that are most difficult to detect may be most vulnerable to disruption when VWM resources are shifted.

Although many participants (43%) became aware of the probability information during the course of the experiment, excluding these participants did not alter the results. This suggests that the change probability effect can occur through incidental learning of the change probability information, with or without explicit awareness of the probability information. However, it is possible that incidental learning impairs the effect and it would be stronger with intentional learning. Intentional strategies may result in the direction of more VWM resources toward the relevant feature dimension and, therefore, improve the change probability effect.

3. Experiment 2

Experiment 2 examined the role of intentional strategies in using probability information to improve change detection performance. Although participants are not necessarily aware of the potential benefit of intentional strategies, intentional memory strategies can improve memory performance relative to incidental memory performance (Beck, Levin, & Angelone, 2007). However, performance on incidental memory tasks can be quite good, suggesting that intentional strategies are not always necessary (Castelhano & Henderson, 2005). In Experiment 2, we test the possibility that optimal VWM performance may result from intentional direction of resources toward the feature dimension most likely to change. In addition, a verbal load was also added in Experiment 2 to ensure that participants did not use verbal strategies to enhance performance for the relevant feature dimension.

3.1. Methods

3.1.1. Participants

One hundred and thirty-eight undergraduate students with normal or corrected to normal vision (104 female, 34 male; average age 20 years) participated in this experiment for credit in their psychology courses. Thirty-four participants were randomly assigned to the control condition, 34 to the location condition, 35 to the color condition, and 35 to the shape condition.

3.1.2. Procedure

The procedure for Experiment 2 was identical to Experiment 1, except for the following changes. Participants in the location, shape, and color conditions were told which type of change was most likely to occur. For example, prior to the start of the experiment, participants in the color condition were told, "In this experiment, color changes are most likely to occur. You will find that detecting changes will be easier if you focus on the color of the objects". Participants in the control condition were instructed that all types of changes were equally likely to occur. In addition, a verbal load was added. Participants were asked to repeat a string of four letters throughout the entire experiment. The experimenter was seated in the room with the participant to ensure completion of the verbal load. If the participants stopped repeating the letters, they were prompted to recite the letters by the experimenter.

3.2. Results

3.2.1. Overall performance

A 4 (condition; between subjects) $\times$ 3 (change type; within subjects) ANOVA of proportion correct on the weighted-probability trials revealed a main effect of change type, $F(2,140) = 88.29$, $p < .01$, $\eta_p^2 = .56$ and a condition $\times$ change type interaction, $F(6,140) = 7.48$, $p < .01$, $\eta_p^2 = .24$, but no main effect of condition, $F(3,70) = 1.46$, $p > .05$, $\eta_p^2 = .06$. Planned comparisons of change type revealed that location performance ($M = .67$, $SD = .17$) was significantly higher than color performance ($M = .53$, $SD = .19$), $t(73) = 5.61$, $p < .01$ and color performance was higher than shape performance ($M = .34$, $SD = .15$), $t(73) = 5.58$, $p < .01$.

3.2.2. Change probability effect

As in Experiment 1, one-way ANOVAs were conducted for each change type (color, shape, and location) with condition as the between subjects factor (see Fig. 4). Both the color change, $F(3,134) = 9.09$, $p < .01$, $\eta_p^2 = .17$, and the shape change, $F(3,134) = 16.22$, $p < .01$, $\eta_p^2 = .27$ ANOVAs were significant. However, the location change ANOVA was not significant, $F(3,134) = 1.04$, $p > .05$, $\eta_p^2 = .02$. As in Experiment 1, planned comparisons revealed that color change performance was higher in the color condition than in the control condition, $t(67) = -2.63$, $p < .05$, and shape performance was higher in the shape condition than in the control condition, $t(67) = -4.09$, $p < .01$. However, no difference in location performance between the location and control conditions, $t(66) = -.97$, $p > .05$.

In order to examine the size of the change probability effect in Experiment 1 versus Experiment 2, a 3 (change type) $\times$ 4 (condition) $\times$ 2 (experiment) ANOVA was conducted for performance on the weighted probability trials with change type as a within subjects factor and condition and experiment as between subject factors. Mauchly's sphericity test was significant, so a Greenhouse-Geisser correction was used. The ANOVA revealed main effects of condition, $F(3,265) = 3.70$, $p < .05$, $\eta_p^2 = .04$; change type, $F(1.92,509.18) = 438.71$ $p < .01$, $\eta_p^2 = .62$, and experiment, $F(1,265) = 27.70$, $p < .01$, $\eta_p^2 = .10$. Overall, performance in Experiment 1 ($M = .58$, $SD = .22$) was higher than performance in Experiment 2 ($M = .52$, $SD = .22$), $p < .01$. However, none of the interactions with the experiment factor were significant, supporting the conclusion that the pattern of results was consistent across experiments.

To confirm that the size of the change probability effect for each change type was similar across experiments, additional ANOVAs were run for each change type with condition (probability or control) and experiment (1 or 2) as between subjects

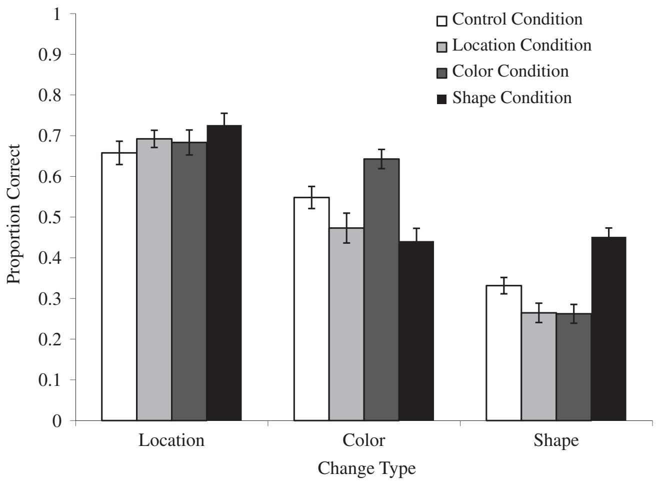

Fig. 4. Proportion correct from the weighted probability trials in Experiment 2.

factors. If the color change probability effect is greater with intentional instructions, for example, condition should interact with experiment in the color ANOVA. For all change types, there was no interaction between condition and experiment, color, $F(1,138) = .79$, $p > .05$, $\eta_p^2 = .01$, shape $F(1,137) = .28$, $p > .05$, $\eta_p^2 = .00$, and location, $F(1,134) = .05$, $p > .05$, $\eta_p^2 = .00$. However, all change types did demonstrate a main effect of experiment (performance in Experiment 1 was greater than Experiment 2 for all change types): color, $F(1,138) = 4.45$, $p < .05$ ns, $\eta_p^2 = .03$, shape $F(1,137) = 16.98$, $p < .01$, $\eta_p^2 = .11$, and location, $F(1,134) = 7.18$, $p < .01$ $\eta_p^2 = .05$. In addition, only the color and shape ANOVAs revealed a main effect of condition, color, $F(1,138) = 20.14$, $p < .01$ $\eta_p^2 = .13$ shape, $F(1,137) = 36.05$, $p < .01$ $\eta_p^2 = .21$, location, $F(1,134) = 1.37$, $p > .05$, $\eta_p^2 = .01$.

3.2.3. Development of the change probability effect

The development of the change probability effect was analyzed as in Experiment 1 (see Fig. 5). To measure the development of the color change probability effect, a repeated measures ANOVA was conducted with block (1–3) as the within subjects factor and condition (color or control) as the between subjects factor. A main effect of condition was found, $F(1,67) = 6.92$, $p < .05$, $\eta_p^2 = .09$; however, the main effect of block was not significant, $F(2,134) = .13$, $p > .05$, $\eta_p^2 = .00$, nor was the interaction, $F(2,134) = 1.12$, $p > .05$, $\eta_p^2 = .02$. Planned comparisons revealed that performance was greater in the color condition in Block 1, $t(67) = -2.47$, $p < .05$ and Block 3, $t(67) = -2.71$, $p < .01$; however, there was no difference in Block 2, $t(67) = -1.34$, $p > .05$.

The ANOVA for shape changes revealed a main effect of condition, $F(1,67) = 16.89$, $p < .01$, $\eta_p^2 = .20$, no main effect of block, $F(2,134) = .66$, $p > .05$, $\eta_p^2 = .05$ and no interaction, $F(2,134) = .60$, $p > .05$ $\eta_p^2 = .01$. Planned comparisons revealed that

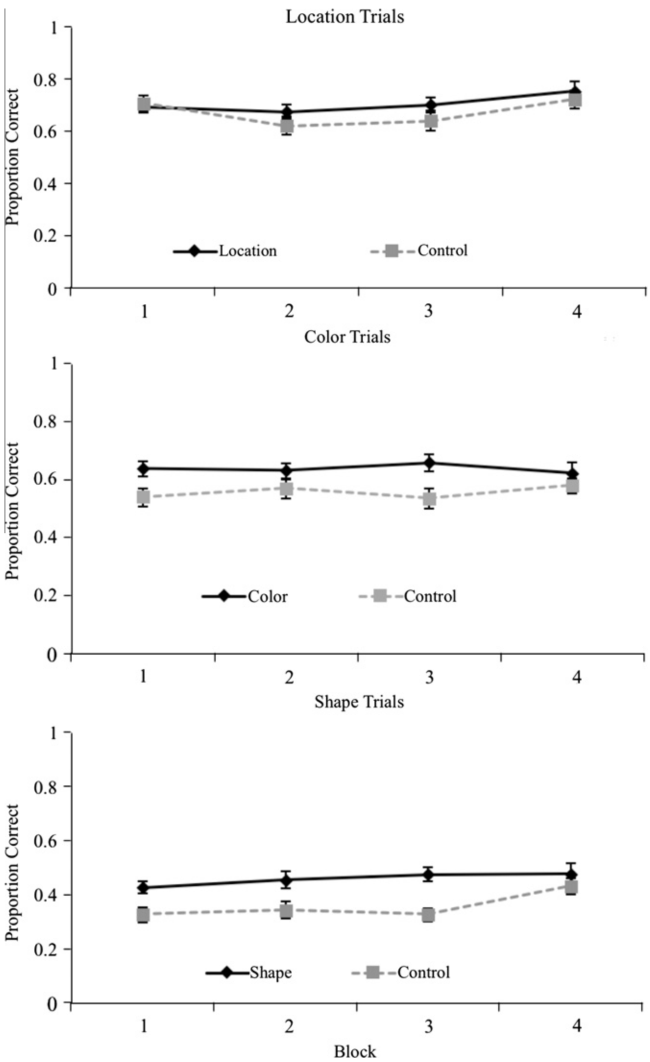

Fig. 5. Proportion correct across blocks of weighted (Blocks 1–3) and equal probability block (Block 4) in Experiment 2. Each graph represents performance for a particular change type (location, color, or shape). Each dark solid line represents a weighted probability condition, while the gray dashed line represents performance in the control condition in each graph.

performance was higher in the shape condition than the control condition across all three blocks of the weighted probability trials: Block 1, $t(67) = -2.86$, $p < .01$; Block 2, $t(67) = -2.45$, $p < .01$; and Block 3, $t(67) = -4.23$, $p < .01$.

The ANOVA for location changes revealed a marginal effect of block, $F(2,132) = 2.96$, $p = .06$, $\eta_p^2 = .04$, but no main effect of condition, $F(1,66) = .95$, $p > .05$, $\eta_p^2 = .01$, and no interaction, $F(2,132) = 1.79$, $p > .05$, $\eta_p^2 = .03$. In addition, planned comparisons revealed that there was no difference between the location and control conditions at any block: Block 1, $t(66) = .31$, $p > .05$; Block 2, $t(66) = -1.2$, $p > .05$; Block 3, $t(66) = -1.36$, $p > .05$.

3.2.4. Adaptability of the change probability effect

To measure the adaptability of the color change probability effect, a 2×2 ANOVA with Block (3 and 4) as a within subjects factor and condition (color and control) as a between subjects factor was conducted. There was a no effect of block, $F(1,67) = .03$, $p > .05$, $\eta_p^2 = .00$, a main effect of condition, $F(1,67) = 4.96$, $p < .05$, $\eta_p^2 = .07$, but no interaction, $F(1,67) = 2.40$, $p > .05$, $\eta_p^2 = .04$. However, there was no difference between the color and control conditions in Block 4 (equal probability block), $t(67) = -.95$, $p > .05$.

The shape ANOVA revealed a main effect of block, $F(1,67) = 5.69$, $p < .05$, $\eta_p^2 = .08$ (overall, performance was higher in Block 4 than Block 3), a main effect of condition, $F(1,67) = 7.25$, $p < .01$, $\eta_p^2 = .10$, and a significant interaction, $F(1,67) = 5.32$, $p < .05$, $\eta_p^2 = .07$. Performance was not significantly different between the control and shape condition in Block 4: $t(67) = -.97$, $p > .05$.

The location ANOVA revealed a main effect of block (performance was higher in Block 4 than Block 3), $F(1,66) = 8.30$, $p < .01$, $\eta_p^2 = .11$, but no effect of condition, $F(1,66) = 1.29$, $p > .05$, $\eta_p^2 = .02$, and no interaction, $F(1,66) = .40$, $p > .05$, $\eta_p^2 = .01$. Planned comparisons revealed that there was no difference between the control and location conditions in Block 4, $t(66) = -.73$, $p > .05$.

3.2.5. Shared resources

To investigate whether VWM resources are shared between feature dimensions, for each change type, improbable change performance was compared to performance in the control condition (see Fig. 4) as in Experiment 1. Planned comparisons for color change detection performance showed a marginal decrease in the location condition relative to the control condition, $t(66) = 1.65$, $p = .10$, and a significant reduction in the shape condition relative to the control condition, $t(67) = 2.60$, $p < .05$. Shape change detection performance was significantly reduced in both the location, $t(66) = 2.15$, $p < .05$, and color, $t(67) = 2.26$, $p < .05$, conditions relative to the control condition. For location change detection performance, there was no difference between the color and control conditions, $t(67) = -.61$, $p > .05$, although there was a marginal improvement in the shape condition relative to the control, $t(67) = -1.69$, $p = .10$.

3.3. Discussion

The results of Experiment 2 are consistent with those of Experiment 1: when shape changes were most likely, shape change detection improved; when color changes were most likely, color change detection improved. In addition, location changes were detected most easily but, as in Experiment 1, there was no change probability effect for location changes. This suggests that the change probability effect occurs to the same extent with intentional or incidental learning.

The size of the change probability effect is also similar across experiments. When the results of Experiments 1 and 2 were compared, there were no interactions with experiment. This was true for each change type. In addition, the difference in performance between the probability condition and the control condition was similar for both color and shape in both Experiments. That is, color performance was 14% higher in the color condition than the control in Experiment 1 (in Block 3, where the change probability effect should be strongest) and 12% higher in Experiment 2. For shape, the difference was 17% in Experiment 1 and 15% in Experiment 2.

The development and adaptability of the change probability effect also remained similar with intentional instructions. The same pattern of results across weighted probability blocks was found in Experiment 1 as in Experiment 2 (with the exception that there was no difference between the color and control conditions in Block 2 for color changes).

The introduction of explicit instructions did appear to strengthen the shared resources effect. In Experiment 2, color performance was reduced when shape changes were most likely and shape performance was reduced when color changes were most likely. In Experiment 1, only the latter was true. In the Discussion of Experiment 1, it was hypothesized that it is easier to bias VWM away from more difficult to detect changes. Explicit instructions may help bias VWM resources away from changes that are more easily detected.

Overall performance was higher in Experiment 1 than Experiment 2, although this may have been the result of the additional memory load of repeating digit strings (Morey & Cowan, 2004). However, the results from Experiment 1 were replicated after the addition of a verbal load, which suggests that the change probability effects were not the result of verbal rehearsal. These results support the hypothesis that participants can use probability information to improve performance for color and shape changes, with or without intentional learning.

4. General discussion

The results from Experiments 1 and 2 demonstrate that probability information can improve change detection performance for color and shape changes. The change probability effect occurred when incidental learning was required, and it was not improved by intentional learning. In addition, the change probability effect developed and adapted quickly. The effect was evident within the first block of trials and adjusted quickly to reflect the new probability information in the equal probability trials. Finally, in some instances, the change probability effect occurred at a cost to the improbable change feature dimensions. These results suggest that participants can quickly learn that a particular feature dimension (either shape or color) is likely to change and improve performance and become better at detecting changes to that dimension, likely by biasing VWM resources (this prioritization of task-relevant dimensions may have been influenced by attentional enhancement of task-relevant dimensions and inhibition of task-irrelevant dimensions).

4.1. Change probability effect

In both experiments, participants were able to more accurately detect color and shape changes when those changes were most likely to occur. This suggests that it is possible to learn probability information about color and shape, but that attention to those dimensions may be required for statistical learning (Baker et al., 2004; Jiang & Chun, 2001; Turk-Browne et al., 2005). In Beck et al. (2008), probability information was provided in a non-changing feature dimension, which was likely not attended because it was not task relevant (Droll & Hayhoe, 2007; Droll et al., 2005; Triesch et al., 2003). Furthermore, participants knew that only shape changes occurred, which likely biased attention away from color from the start of the experiment, preventing them from learning the color probability information. Together, this suggests that participants can learn and use color and shape probability information to improve change detection performance, but only if the dimension is task-relevant.

4.2. Location change probability effect

In the current experiments, location probability information did not improve location change detection performance, even though past research has shown that location probability information can be used to detect a target or changes in other feature dimensions (Beck et al., 2008; Chun & Jiang, 1998; Olson et al., 2005; Umemoto et al., 2010). However, it should be noted that in previous research in which participants were able to use location probability to more accurately detect a change (Beck et al., 2008; Umemoto et al., 2010), this probability information could be used to reduce the total number of objects stored in VWM. For example, if a change is very likely to occur in the right column of a grid, then the participants only need to remember the objects in that column to complete the task. This was not the case in the current set of experiments. Rather, the probability information limited the number of features of each object that needed to be stored in VWM. Therefore, the lack of a probability effect for location in the current study is not necessarily in conflict with previous research and may indicate that location information can be used to bias the number of objects stored in VWM, but not the number of features stored in VWM.

There are several possible reasons why a change probability effect was not found for location. First location change detection performance was high, possibly indicating that ceiling effects prevented location performance from improving. Location changes may have been more discriminable than shape and color changes, as there were 12 locations but only four shapes and colors. Location may also be processed in a way that is unique from features of an object such as color and shape (Tsal & Lavie, 1988); while participants may choose to selectively ignore features such as color and shape (Woodman & Vogel, 2008), this may not be possible for location. In addition, in the current experiments, participants were required to click on an object to report a change. This may have made location task-relevant, even in the color and shape conditions. Because location was always task-relevant, performance was not improved by probability information. In order to determine whether location probability information can be used to improve location change detection, the factors of task-relevance and ceiling effects would need to be reduced.

4.3. Development and adaptability

Participants were able to use probability information very quickly: change probability effects for color and shape appeared within the first block of weighted probability trials. This supports research showing that participants are able to learn probable feature information very quickly and use it to locate targets or find changes (Brady et al., 2009; Chun & Jiang, 1998; Turk-Browne et al., 2009). In addition, the change probability effect was eliminated when the probability information was no longer present. Quick changes in the allocation of resources would be useful in an environment in which task demands are constantly changing. For example, the air traffic controller may first choose to remember the color of each plane, but if conditions changed and shape changes became more likely, she would have to quickly change to remembering shape.

4.4. VWM resources

The results of the current study suggest that color and shape information may share VWM resources. A performance tradeoff for shape was found in both experiments: when color changes were most probable, shape performance was reduced compared to when all changes were equally likely. This performance tradeoff also occurred for color in Experiment 2, when participants were explicitly told that shape changes were most likely. These results are not readily explained by the independent stores hypothesis, although they may be explained by the object slot and resolution hypotheses. None of the hypotheses offer alternative explanations about why a change probability effect was found for color and shape but not location. Therefore, this point will not be discussed within the context of these hypotheses.

According to the independent stores hypothesis, features from different dimensions are maintained in separate stores, each with their own independent capacity limit (Bays et al., 2011; Wheeler & Treisman, 2002). Thus, the finding that increased performance in one dimension (e.g., color) may lead to decreased performance in another dimension (shape) is generally incompatible with the independent stores hypothesis.

The object slot hypothesis assumes that multiple features may be stored at no cost if they are part of the same object (Alvarez & Thompson, 2009; Barton, Ester, & Awh, 2009; Fukuda, Awh, & Vogel, 2010; Luck & Vogel, 1997; Vogel et al., 2001). Therefore, this hypothesis does not predict that color and shape from the same object will compete for storage resources (Luck & Vogel, 1997; Vogel et al., 2001; Woodman & Vogel, 2008; Zhang & Luck, 2008). However, it is possible that the results of the current study can be explained not by a tradeoff in capacity, but by a bias in the comparison necessary for accurate change detection (Hollingworth, 2003). If color changes are most likely to occur, color information may be compared first, followed by location and shape information. Presumably, given that VWM representations are lost over time (Posner & Keele, 1967; Zhang & Luck, 2009), the earlier comparisons would lead to the highest level of performance.

The flexible resource hypothesis can predict that increased storage in one feature dimension can be achieved through a cost to another dimension (Alvarez & Cavanagh, 2004; Bays & Husain, 2008; Eng et al., 2005; Fougnie et al., 2010; Olson & Jiang, 2002; Wilken & Ma, 2004; see Jiang, Makovvski, and Shim (2008), for review). Because objects within VWM compete for the same resource, decreasing the load of each object should decrease how much of the resource is consumed by each object (Alvarez & Cavanagh, 2004). The results of the current study would suggest that task-relevant features of an object may be selectively stored, to the exclusion of less probable features. This means that the total amount of information that is stored remains constant, but the task-relevant features may have preferential storage, leading to the tradeoff in performance found in the current study.

5. Conclusion

The results of the current study suggest that participants can use probability information to improve change detection performance for color and shape changes, and that this ability develops quickly. Furthermore, the change probability effect can occur through incidental learning of the change probability information. Finally, a performance tradeoff suggests that using probability information to detect changes in a particular feature dimension may bias VWM resources away from less probable changes. However, the specific mechanism (i.e., biased storage or biased comparisons) needs to be further investigated to determine which hypothesis best explains the results.

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