Overlooked influences on visual working memory performance.

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“C’est pas loin, hein?

Faites mieux, merci.”

- Jean-Luc Mélenchon

Chapter 1

General Introduction

1.1 Visual working memory

1.1.1 The role of visual working memory

Every awake wide-eyed second of our lives, a myriad of visual inputs enters our eyes and is transmitted to our brain. In concert with selective attention, visual working memory is one of the mechanism used to make sense of this constantly changing flow of information (Aagten-Murphy & Bays, 2018; Schneider, 2013; Tsubomi et al., 2013). This system is severely limited in its capacity (Awh et al., 2007; Cowan, 2001; Luck & Vogel, 2013), and is considered to be the major bottleneck of visual processing. Thus, at each instant we perceive only a fraction of the available information (Rensink, 2004; Simons & Levin, 1997; Simons & Rensink, 2005). While intuition might lead us to believe that visual working memory is simply a storage unit used only for recollection (effectively reducing it to visual short-term memory), it is effectively a hub where maintenance and manipulation of visual information occurs on the short-term (Baddeley, 2003; Ma et al., 2014), to then proceed to long-term memory or to be used on-the-fly to guide our behavior (Cisek & Kalaska, 2010; Desimone & Duncan, 1995; Forsberg et al., 2021; Olivers et al., 2011; Rösner et al., 2022; Schurgin, 2018; van Ede & Nobre, 2023).

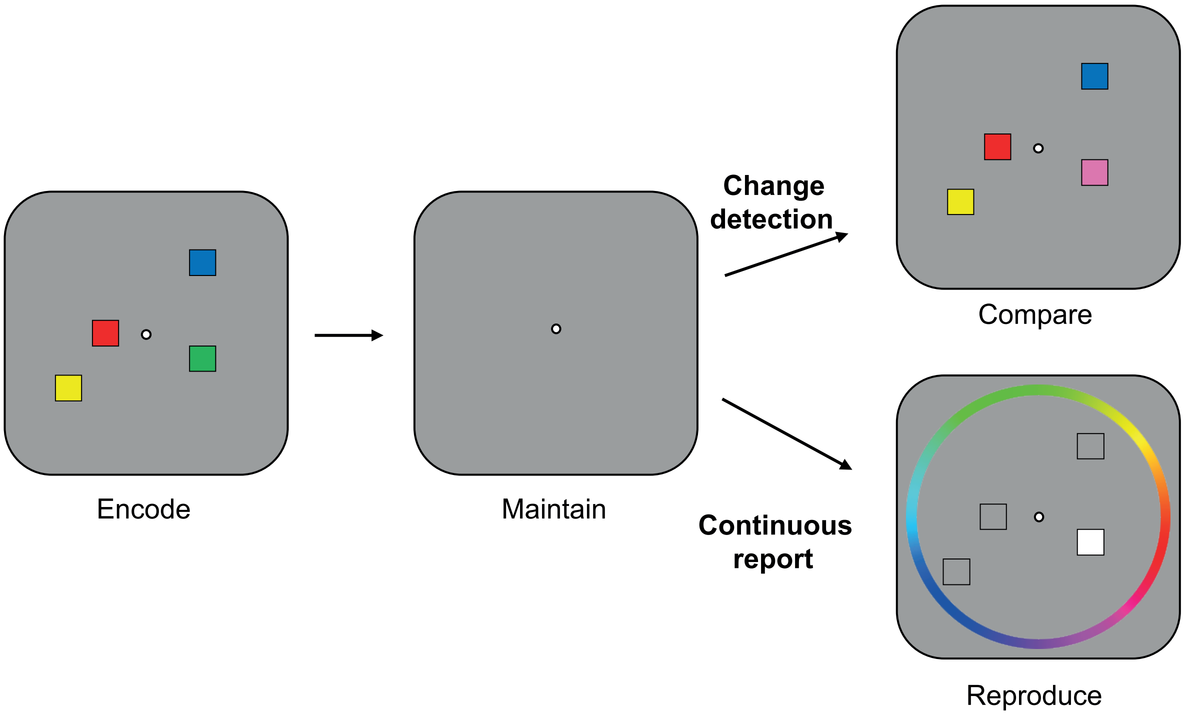
Therefore, content entering visual working memory must be encoded very fast, but remain flexible and adaptable to changes in the visual environment. These representations must also stay accessible for potential use by other relevant processes. One concrete example of visual working memory's usefulness is how it seamlessly bridges perceptual and temporal gaps evoked by ocular movements. If we experience vision as a continuous percept (as opposed to a discretized one), that is owing to visual working memory temporarily maintaining information that the eyes have shifted away from (and is thus not perceptually available) so that we can access it and easily attend to it again (Franconeri et al., 2013; Hollingworth et al., 2008).

1.1.2 The nature of visual working memory

The nature of the storage unit of visual working memory has been (and still is) a very lively scientific debate for nearly three decades. Early theories speculated that working memory stores information in "slots" or discrete units (Cowan, 2001; Luck & Vogel, 1997, 2013; Zhang & Luck, 2008), that is objects are encoded in an all-or-nothing fashion. If an object enters visual working memory, all its features are stored within one slot. A seminal study supporting this theory was conducted by Luck & Vogel (1997), where they found that participants could only recall approximately four colors or four orientations at one time, but that it was also possible to retain both the color and orientation of four objects. Therefore, integrated objects (that is, with their features bound together) seemed to be stored rather than the individual sum of their features. These integrated objects would then each occupy one slot in visual working memory. While still relevant to the current debate, this conception of visual working memory is regularly challenged (Ma et al., 2014; Schurgin et al., 2020; Williams et al., 2022).

Historically, the task used to quantify memory capacity was the change detection task (Luck & Vogel, 1997; Pashler, 1988, see Figure 1, top). In this task, a memory display composed of two to eight targets (e.g., colored squares) was presented for a short duration. Then after a

Figure 1: The typical visual working memory tasks.



Note. Two types of visual working memory tasks. In the change detection task (top), participants must remember the "encode" display, which then disappears during the "maintain" phase. Then at the "compare" display onset, they must decide whether one target has changed color (here: yes). The continuous report task (bottom) starts as the change detection task, however, when the "reproduce" display appears, participants must choose the target's color (here: green) on the colorwheel.

short delay without the targets, the targets reappeared but one of the targets might have changed compared to the previous display (e.g., a previously blue square becoming red in the second display). Participants then had to make a binary decision whether one target had changed or not.

In 2004, Wilken and Ma introduced a new task: the continuous report (or continuous recall) task (Figure 1, bottom). This task starts as the change detection task, with a few targets presented to the participant. However, at the recall stage, instead of deciding whether one target had changed, participants had to reproduce the feature of the target (e.g., by selecting the color of the target by clicking on a colorwheel). This new task allowed for a much more fine-grained measure of visual working memory content (much closer to a continuous measure, hence the name of the task). With the emergence of this new task it became possible and easy (that is, with less need to rely on model parameter estimates) to measure not only the memory capacity, but also its precision.

Shortly after this task emerged, another popular framework for conceptualizing visual working memory was developed: the continuous resource theory (Bays et al., 2009; Bays et al., 2011; Ma et al., 2014; van den Berg et al., 2012). In this model, visual working memory is not composed of discrete slots anymore, but of a continuous limited resource. Within this framework, it becomes theoretically possible to store a lot of items with a very poor resolution, or to have one item stored so precisely that it hogs all the resource. Moreover, given the flexible nature of visual working memory, it is also possible to internally reduce the precision of one (or more) item after encoding to enhance performance for other more relevant items (e.g., because of a retro-cue; see Bays et al., 2011).

All these debates and models are concerned with the nature of visual working memory after successful encoding but not necessarily with the reason objects enter or do not enter visual working memory. Moreover, information overload is surely not the only reason visual working memory sometimes fails. It may be that some information is never even selected to enter visual working memory. Therefore, understanding these reasons is necessary to fully characterize visual working memory.

1.2 Visual attention and visual working memory

1.2.1 Visual working memory and visual attention are co-dependent

An intuitive (and productive) approach to understand factors influencing visual working memory is to relate it to visual attention (Awh & Jonides, 2001; Gazzaley & Nobre, 2012; Oberauer, 2019). Visual attention relies on visual working memory probably as much as visual working memory relies on visual attention. When shifting your attention to visually explore a scene, it seems reasonable to think that you want to process the objects you are attending. Ergo the attentional selection of information is not a purpose in itself.

For instance, when biking through the city, you do not simply move your gaze to the "stop" sign or to the pedestrian that might or might not cross the street, but you also process these. After processing it once, you probably do not need to re-attend to the "stop" sign, given its immobile nature, but you rather want to attend again to the pedestrian who might at some point finally decide to cross the street. Thus, keeping track of items you have attended and their nature is behaviorally relevant. As exposed above, both these processing and short-term storage roles are the purview of visual working memory. Thus, looking at which factors impact visual attention (and visual search) performance is a reasonable way to find new determinants of visual working memory performance. Moreover, these two processes rely partly on the same frontal and parietal neuronal pathways (Awh & Jonides, 2001; Awh et al., 1999; LaBar et al., 1999).

1.2.2 Priority maps

Visual search research often considers that bottom-up influences emerging from the stimuli (i.e., the visual input), and top-down influences originating from the observer (e.g., task goals) are combined into a priority map in order to guide attention to the relevant objects (Bundesen et al., 2005, 2011; Duncan & Humphreys, 1989; Fecteau & Munoz, 2006; Li, 2002; H. R. Liesefeld & Müller, 2021; H. R. Liesefeld et al., 2016; Sauter et al., 2018; Wolfe, 1994, 2007, 2021; Zelinsky & Bisley, 2015). It seems also reasonable to conceptualize the priority map as a filter, a selection bottleneck, which weeds out most visual "noise" so that the information that reaches further processing centers is relevant (or at least likely to be relevant) and worthy of the limited visual working memory resource allocation (regardless of this resource's nature).

The priority map can also include other components, some of which are not easily categorized as part of the top-down/bottom-up dichotomy. Notably, scene grammar (Boettcher et al., 2018; Draschkow & Võ, 2017), prior history (Awh et al., 2012) and reward (Anderson et al., 2011) have been proposed to contribute to the construction of the priority map. Recently, this framework, which is typically employed to understand selective attention, has been applied to visual working memory research to explain performance variations (H. R. Liesefeld et al., 2020; Lorenc et al., 2021; Zelinsky & Bisley, 2015).

1.3 Known influences

Given its capacity limitation much of the research has focused on finding determinants explaining variations in visual working memory performance. This is indeed crucial to help us understand what enters and what stays in this restricted hub that is visual working memory.

The number of objects that need to be stored (set size) is probably the most obvious influence on visual working memory performance, and it is also one the most studied and modeled. One of the first experiments to demonstrate the limited capacity of visual working memory did so by manipulating set size (Luck & Vogel, 1997). Other influences excluded, performance in the change-detection task stays relatively stable until set size reaches around three or four objects. Beyond this limit, change-detection performance usually drops close to random for the additional items. It should however be noted, that set size is generally detrimental only when we increase the total number of targets and not simply the number of items in the memory display. That is, placing many irrelevant gray squares does not hinder visual working memory performance if the task is to remember vividly colored squares. As in visual search, some non-targets can easily be filtered out and these might even help to improve performance if they can form a "background" from which the targets pop-out (see **Chapter 2.2** of the present dissertation Constant and Liesefeld, 2021).

Though not commonly conceptualized as either top-down or bottom-up, set size is probably closer to a bottom-up effect (that is, emanating from the memory display and its configuration, rather than the observer's task goals). Some other bottom-up components, such as target complexity also influence memory performance (Alvarez & Cavanagh, 2004). The more complex the targets, the fewer of them can be remembered (see Ngiam et al., 2019 for a counter-argument). The effect of target complexity can be related to that of set size, in the sense that when people need to encode more features about the object, this increases their memory load (depending on the framework, the object might need to occupy more than one slot, or requires more of the continuous but limited memory resource). However, with large set sizes, target similarity can be used as a way to improve performance through the creation of interitem representations that can be converted to a unitary representation of several items (Bae et al., 2014; Brady & Alvarez, 2015; H. R. Liesefeld & Müller, 2019; H. R. Liesefeld et al., 2019). For instance, two squares that are close in space and in color might be grouped together to ease processing. The relational structure between these items is also usually preserved (e.g., which square was "greener" than the other).

Top-down factors are also among the often investigated predictors of visual working memory performance (Bays et al., 2011; Bundesen et al., 2011; Dube et al., 2017; Emrich et al., 2017; Gazzaley & Nobre, 2012; Griffin & Nobre, 2003; A. M. Liesefeld et al., 2014; Sauseng et al., 2009; Vogel et al., 2005). For instance, the relevant object can be probed with an informative cue (that is, it indicates the target on e.g., 75% of the trials, and a non-target on the remaining 25%) that can be located before, during or after the memory display (Yoo et al., 2018). The performance for the cued target increases proportionally with the cue's informativeness (i.e., a 90% valid cue will have more impact than a 55% valid one), while the performance for the non-cued targets suffers. Another way to increase relevance is to present different colored shapes but to ask participant to remember the color of only one kind of shape or increase the value of a particular shape (Dube et al., 2017; Klink et al., 2017). If the shapes are dissimilar enough, participants will successfully ignore most non-relevant objects (i.e., distractors) thus allowing only the relevant items to be processed in visual working memory.

1.4 Overlooked influences

There are still a lot of factors for which the impact has only been hypothesized or informally observed but was not investigated in detail. Internal factors, which are harder to quantify, such as emotions are among these overlooked factors that might influence visual working memory performance. Two studies have for instance shown that externally induced negative emotions can enhance visual working memory performance (Spachtholz et al., 2014; Xie & Zhang, 2016) though this has recently been challenged (Souza et al., 2021). However, whether emotions induced by the task itself can influence visual working memory performance was, to my knowledge, only speculated but not rigorously examined (Luck, 2014; Rouder et al., 2008). For this reason, we collaborated with researchers from the Educational Psychology department of the LMU München to investigate the association between emotions induced by a visual working memory task and task-performance (**Chapter 2.1**).

A second factor which had, surprisingly, been overlooked is (visual) salience. Salience is the cornerstone of the bottom-up components of the priority map. Something is deemed salient when it pops out from its surroundings. Many features can elicit this standing out effect, such as, for instance, a difference in orientation, color, size, movement or flicker (and flicker frequency) between the salient stimulus and its surroundings. In natural scenes, we often make the experience of salience with colors, the natural world being mostly green and blue, reddish colors are particularly salient in many cases. Thus, manufactured objects which must be noticed are often designed with these colors, some examples are "stop" signs, buoys or airplane "black boxes" (which are actually orange). In the laboratory setting, it's been shown that salient stimuli often attract attention automatically, and that ignoring or overriding this attraction is effortful or requires specific conditions (Theeuwes, 1991, 2004, 2018). Accordingly, it feels very intuitive and at the same time almost trivial to wonder whether salience does have an impact on visual working memory performance. Yet this was vastly overlooked in past research and we filled this gap by designing a new visual working memory task (**Chapter 2.2**).

Finally, building on the inference that priority maps are an intuitive and efficient way to predict visual working memory performance, top-down factors that are part of the priority map should also influence visual working memory. Even further, the relative weight of these factors compared to bottom-up factors is uncharted territory. In **Chapter 2.3**, we mixed top-down factors (goal-driven and experience-driven) with the task designed in **Chapter 2.2** to diagnose their contribution and relative importance compared to the bottom-up salience effects on visual working memory performance.

Chapter 2

Cumulative thesis

The following section contains three original studies: Two peer-reviewed studies, published in high-impact journals (**Chapter 2.1** and **2.2**) and one preprinted manuscript (**Chapter 2.3**).

2.1 Unintended emotions in the laboratory: Emotions incidentally induced by a standard visual working memory task relate to task performance

The corresponding manuscript was published in *Journal of Experimental Psychology: General*:

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For copyrights reasons, the present version is the accepted manuscript (i.e., post-print), formatted by me.

For this publication, I was involved in the following:

- Methodology
- Programming the experiments
- Data collection
- Data analysis
- Data curation
- Review and editing of the manuscript
- Formatting

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Unintended Emotions in the Laboratory: Emotions Incidentally Induced by a Standard Visual Working Memory Task Relate to Task Performance

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Abstract

The ability to temporarily hold information in visual working memory (VWM) is among the most crucial and most extensively examined human cognitive functions. Here, we empirically confirm previous speculations (1) that a standard VWM task arouses emotions in participants and (2) that these task-induced emotions are related to VWM performance. In a first qualitative study (N = 19), by adapting a qualitative method of inquiry, the think-aloud technique, we found that the task induced different positive and negative emotions, such as joy and anger, which varied on the inter- as well as on the intra-individual level. The emotional experiences seemed to be tied to the implicit achievement requirement of the VWM task (getting it right vs. wrong). Encouraged by these findings, two quantitative studies (N = 45, and N = 44, respectively) revealed that VWM performance was positively linked to joy and pride, and negatively linked to anger, frustration and boredom on the inter- and on the intra-individual level. Notably, these emotions were also affected by an experimental manipulation of task difficulty (set-size 4 vs. 8). Further, the findings from Study 3 were replicated in a fourth high-powered online study (N = 110). This research is the first to demonstrate that a task designed to measure VWM in itself triggers emotions, specifically achievement emotions, which, in turn, are linked with VWM performance. Our findings suggest that these task-induced emotions should be considered as potential confounding variables in future research on VWM and in cognitive research in general.

Keywords: visual working memory, achievement emotions, task-induced emotions

Visual working memory (VWM), which can be defined as "the active maintenance of visual information to serve the needs of ongoing tasks" (Luck & Vogel, 2013, p. 392), is crucial in everyday life (Alloway & Alloway, 2010; Conway et al., 2003; Fukuda et al., 2010). Researchers have developed computer-based VWM tasks, such as the change detection task (Luck & Vogel, 1997; Pashler, 1988) or the continuous color-report task (Wilken & Ma, 2004; Zhang & Luck, 2008), which have been shown to provide reliable and valid VWM estimates of individuals' VWM capacities (Johnson et al., 2013; Kyllingsbæk & Bundesen, 2009). Studies using these tasks have brought about valuable insights into the basic functioning of human visual memory (Luck & Vogel, 2013). However, this research tradition is dominated by experimental designs where (typically small) sample means are compared across experimental conditions, and any inter- and intra-individual differences are typically considered as "noise" (Kanai & Rees, 2011; Vogel & Awh, 2008). In the present contribution, we propose that participants and their complexity may have been oversimplified in such existing research paradigms. Although oversimplification is a crucial ingredient of research in general, looking into the "noise" can also be fruitful, and it can even be crucial if it proves to be confounded with experimental manipulations of interest or if it affects the validity of the measures. Specifically, we propose to take into consideration one important human factor: the emotions participants feel while performing experimental laboratory tasks (see also Dukes et al., 2021). We sense that typical prior research seems to view participants as machines who enter the laboratory and perform VWM tasks as successfully as their "hardware" (i.e., their VWM capacity) allows, while neglecting the task-induced emotional experiences. To the authors' knowledge, there is currently no research on how participants feel during VWM tasks in the laboratory, that is the emotions which emerge *as a result of performing the task itself*, and whether these emotions, in turn, are systematically linked with VWM performance, thus potentially biasing capacity estimates.

There are some hints in the literature that emotions induced by the VWM task may be linked to individual differences in VWM performance (Luck, 2014; Rouder et al., 2008). Those are predominantly informal observations and largely speculative, which, to our knowledge, have not been researched systematically. There is substantial empirical evidence, however, that externally induced emotional states influence participants' VWM performance (Spachtholz et al., 2014; Xie and Zhang, 2016, but see Souza et al., 2021). Therefore, it is likely that, to the degree that emotional experiences occur as a result of performing the VWM task, they may well be linked with VWM performance.

The aim of the present research was twofold: (1) to establish whether participants experience emotions during a VWM task, which are induced by the task itself, and (2) if this was the case, to explore how these incidentally induced emotions are related to VWM performance.

To answer these research questions, we followed a mixed-method approach, by first conducting a qualitative study using an approach based on the think aloud method (van Someren et al., 1995) to investigate whether participants experienced any task-induced emotions during a VWM task in the laboratory, and if so, which emotions those were (some authors also refer to this as "emote-aloud," see e.g., D'Mello and Graesser, 2012). In three further quantitative studies, we explored the link between self-reported discrete task-induced emotions and VWM performance, from an inter-individual and intra-individual perspective. Our reasoning for these studies is outlined in the following.

We have no known conflict of interest to disclose.
Sara Laybourn
Anne C. Frenzel
Martin Constant
Heinrich R. Liesefeld
Martin Constant and Heinrich R. Liesefeld are now at the Department of Psychology, University of Bremen, Germany
Preliminary results of Study 1 were presented as a poster at the TeaP conference ("Tagung experimentell arbeitender Psychologen") in London, England, in April 2019. This study was not preregistered.
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Emotions and Visual Working Memory

Emotions are generally defined as multi-component processes, including affective, motivational, cognitive, physiological, and expressive components (Mulligan & Scherer, 2012), which can influence our thoughts, behaviors, and performance (Beal et al., 2005). Research has shown that emotions also influence higher cognitive functions, such as memory. In research regarding long-term memory, it is well established that the emotions experienced at the time of memory formation influence how the memory is stored (e.g., LaBar and Cabeza, 2006). In addition, there is also a specific body of literature which explored the effects of emotions on working memory, specifically VWM. However, these findings are somewhat ambiguous, as we briefly outline below.

When studying the effect of emotional states on VWM, negative, positive and/or neutral emotional states are typically induced prior to the VWM task. In doing so, some researchers have found evidence that negative emotional states relate to poorer working memory performance. For instance, Figueira et al. (2017) showed that participants' contralateral delay activity (CDA) amplitudes were significantly lower in a negative emotional condition as compared to a neutral emotional condition. CDA is an electrophysiological index of VWM processing, which has been shown to correlate with the amount of information stored in working memory (Luria et al., 2016; Vogel & Machizawa, 2004). Further, on an intra-individual level, Brose et al. (2014) found that daily variations in participants' mood (measured over a 100 day period) related to working memory performance. Specifically, negative affect was negatively linked with spatial working memory performance. The authors also found that variations in positive affect were positively linked to working memory performance.

Digging deeper into the potential effects of emotional states on working memory performance, some authors proposed to explore potentially differential effects on the quality versus quantity of visual performance. For instance, Spachtholz et al. (2014) randomly assigned participants to a condition inducing either neutral or negative emotions prior to performing the continuous color-report task. Results showed that the number of remembered items was lower in the negative-emotion condition but VWM performance in terms of quality (precision of color memory) increased. The authors concluded that emotional state leads to a tradeoff between quantity and quality in terms of VWM performance, with negative emotional states favoring quality over quantity. However, those effects were not fully confirmed by Xie and Zhang (2016): manipulating emotional state on a trial by trial basis via presentation of IAPS pictures (International Affective Picture System, Lang et al., 1997), they found that self-reported negative emotion yields higher VWM precision, but this time without any concurrent decrease in VWM capacity (see also Long et al., 2020, who found such a tradeoff). However, a large-scale attempt to replicate those findings failed to find any evidence of an enhancing effect of self-reported negative emotion on either precision or capacity with seven experiments in three different labs and with participants from four different countries (Souza et al., 2021).

Overall, when considering the results discussed above, it seems there is some indication for the relevance of emotional states in VWM performance. However, the results are not straightforward and attempts to replicate the findings yield even more ambiguous results. Importantly, this existing research rests mainly on studies which induced emotional states prior to the VWM task (either block-/session-wise or trial-wise). Not only may such emotion induction procedures lack ecological validity, but more importantly, they are ineffective in exploring another, potentially more relevant factor: the emotions participants experience because of the VWM task itself. These may be systematically linked with performance, and may also differ across experimental conditions, thus creating an important potential confound and posing a threat to the validity of the VWM performance scores. To the authors' knowledge, no study to date has explored these assumptions.

Despite the eminent lack of systematic research into potential links between incidentally induced emotions and VWM performance scores, some researchers from the VWM community hint towards the possibility that tasks designed to measure cognitive functions may induce emotions in participants, and that these emotions in turn may be linked to participants' performance. For instance, in his book on event-related potentials (ERPs), Luck (2014) states the following: "ERP experiments tend to be long and boring, with trial after trial of the same basic task. To ensure that you are collecting the highest quality data possible, it is important to keep your subjects happy and relaxed. If they are unmotivated or become bored, they may not pay close attention to their performance, weakening your effects" (p. 144). Also the classical VWM tasks are typically lengthy, requiring participants to go through multiple-trial-blocks of either change detection or active color recall, which typically take up to 45 minutes or more to complete. To the authors' knowledge, whether or not these tasks are generally not enjoyable or evoke boredom in participants because they are long and repetitive is based purely on introspection or speculation, and has never been explored systematically. Moreover, the presumption that such task-induced emotions may also have an effect on the obtained results has not been tested.

Further, researchers in the field of VWM have conveyed their thoughts on possible task-induced emotions and how these emotions may be linked to participants' performance. For instance, Rouder and colleagues (2008) found that some participants performed worse than expected on difficult as opposed to easy trials of a VWM task, and they concluded that this may have been the case because some participants were "intimidated" by the difficult trials (p. 5978). Similarly, Spachtholz et al. (2014) speculated that differences in VWM performance may "be brought about unintentionally by cues such as affective state that signal requirements of the current situation" (p. 1455).

Overall, it seems highly likely that engaging in a VWM task triggers emotional experiences in participants. It has been speculated that they may be perceived as boring or intimidating, yet we argue they may also be experienced as challenging and engaging. The first goal of the present research was therefore to explore what participants feel when participating in a typical VWM task.

Our second goal was to explore the links between emotions induced by a VWM task and VWM performance. If prior speculations are correct and emotional experiences occur because of certain characteristics of the VWM task (i.e., difficult trials, see Rouder et al., 2008), these emotions may be potentially confounding variables distorting the VWM performance estimates.

Evidence from more applied, educational psychology has demonstrated that engaging in tasks can trigger emotional experiences, which in turn are linked with performance. A brief overview of these results is given in the following.

Task-induced Emotions and their Link with Performance

Emotions are thought to be activated by individual appraisals of specific objects or events (Mulligan & Scherer, 2012). Tasks and activities can also act as objects, which trigger emotional experiences. For instance, people experience joy when engaging in an activity that they appraise as pleasant, either because they receive an extrinsic reward for their engagement in the task, such as praise, or because the task itself is rewarding to the individual (Csikszentmihalyi, 2000). Specifically, task enjoyment is thought to play a major role in different concepts such as flow experience (Csikszentmihalyi, 2000), intrinsic motivation (Deci & Ryan, 1991), and achievement motivation (Dweck & Elliott, 1983) – concepts which are important for performance.

The role of task-induced emotions in cognitive performance is commonly studied in academic settings. Here, the research focus lies mainly on achievement or epistemic emotions. Achievement emotions can either relate to achievement outcomes, such as exam results, or to achievement-related activities, such as studying or class participation (Pekrun et al., 2011). By definition, achievement emotions emerge as a result of achievement outcomes, that is, success entails positive emotions, and failure entails negative emotions. In addition, achievement emotions can be assumed to influence learners' cognitive resources, motivation, strategy use, and self-regulated learning such that they in turn predict achievement outcomes (Goetz & Hall, 2013). Research on achievement emotions has shown consistently that negative achievement emotions, such as shame and anger, are linked negatively with performance (e.g., Pekrun and Perry, 2014) whereas positive achievement emotions, such as joy and pride, correlate positively with performance (e.g., Pekrun, Lichtenfeld, et al., 2017). In longitudinal research designs, it has been shown that those achievement emotion—performance links are driven by reciprocal causation, with emotions and performance predicting each other over time (Pekrun, Lichtenfeld, et al., 2017; Putwain et al., 2018).

The cognitive characteristics of a task can also induce emotional experiences. These emotions are known as epistemic emotions (Pekrun & Stephens, 2012; Pekrun, Vogl, et al., 2017). The object focus of epistemic emotions is knowledge and knowledge generation (Brun et al., 2008), which can trigger different discrete emotions, such as surprise, curiosity, and confusion (Vogl et al., 2019, 2020). Epistemic emotions also have been linked to cognitive performance. For instance, research has found that epistemic emotions predicted processes in self-regulated learning, which in turn predicted complex mathematical problem solving (Muis, Psaradellis, et al., 2015) and learning outcomes on climate change (Muis, Pekrun, et al., 2015).

Further, working on such cognitive tasks has been found to arouse subjective experiences of high mental effort and corresponding mental fatigue during experimental task execution (Gergelyfi et al., 2015; Hopstaken et al., 2015, 2016). These mental states are not classically considered emotional states like anger or pride, but they in fact are closely conceptually related in that they may be experienced as aversive and have specific physiological components.

It becomes apparent that tasks can trigger emotions in people, which in turn are linked with how they perform on these tasks. However, to date, these processes have – to our knowledge – not been examined, nor considered, in laboratory settings designed to measure VWM functions.

The Present Study

We report the results of four consecutive studies. In Study 1, we sought to explore qualitatively what participants feel when performing a VWM task (Research Question (RQ) 1a). In doing so, our goal was to discern discrete emotions that participants may experience, such as joy, pride, anger, and boredom. Further, we sought to explore which aspects of the VWM task triggered these discrete emotions (RQ 1b).

Studies 2 and 3 used a quantitative design to explore, whether and how task-induced emotions are linked to VWM performance, both on an inter-individual level (Study 2; RQ 2a), and on an intra-individual level (Study 3; RQ 2b). Additionally, in Study 3, we explored whether a typical experimental manipulation (set-size) had any systematic effects on the emotions experienced during the task. Study 4 was a high-powered replication (N = 110) of Study 3 that also exploratorily addressed a few interesting subsidiary questions that came up during the review process.

The research reported herein was conducted in accordance with the ethical standards expressed in the Declaration of Helsinki and has received a formal waiver of ethical approval by the ethics committee of the Department of Psychology, LMU München. Participation was voluntary and written informed consent was obtained from all participants for each study. The data files can be found on the Open Science Framework (Laybourn et al., 2020).

Study 1

To explore which discrete emotions are experienced when engaging in a VWM task, participants in this study were asked to verbalize their feelings and any related thoughts thereof while performing the continuous color-report task (Zhang & Luck, 2008). This approach is based on the think aloud method by van Someren et al. (1995), which is traditionally used when trying to identify and understand underlying processes in problem solving by encouraging participants to verbalize their thoughts and strategies while trying to solve a certain problem. We deemed it suitable also for identifying the emotional experiences and related thoughts thereof participants encountered when performing a VWM task (see also e.g., D'Mello and Graesser, 2012, who refer to this as "emote-aloud").

We chose the continuous color-report task as it is a well-established paradigm used in VWM research and has consistently been reported as a highly reliable method for estimating individual differences in VWM. The task involves memorizing multiple, shortly presented visual stimuli (typically two or more colored squares, the sample array), and then, after a short retention period of around 1s, being prompted to recall one of them (the test array; here, a thick black frame indicates which of the squares from the sample array should be recalled) by selecting the color of the prompted square on a continuous color wheel which surrounds the test array (see Figure 1).

Methods

Sample

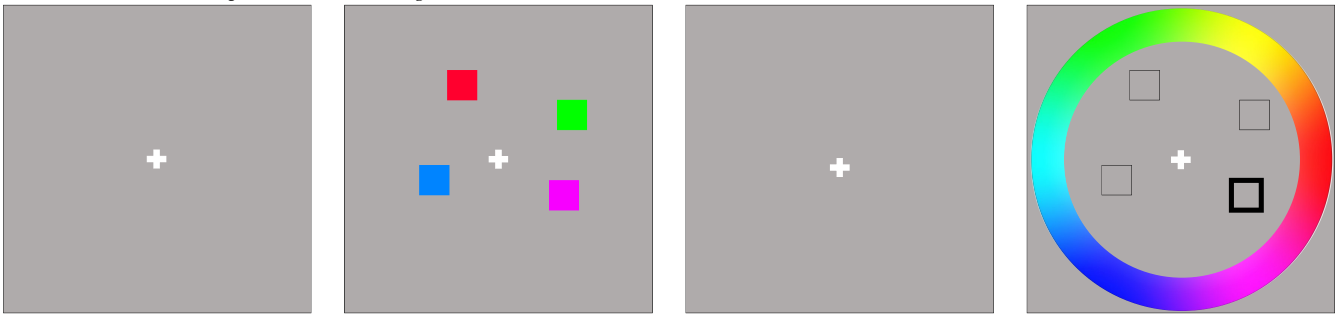
Participants of this study were N = 19 (11 female; M_{age} = 30.21; SD = 8.49), who all stated not to be color-blind and to have normal or corrected-to-normal vision.

Continuous Color-Report Task Specifications

All stimuli were generated in MATLAB using the *Psychophysics Toolbox*. Stimuli were presented on 24" TFT-LCD monitors (ASUS VG248QE, 1920×1080 pixels, 60 Hz) at a viewing distance of approximately 70 cm. The to-be-remembered stimuli were five colored squares (1 x 1°) on a dark grey background (RGB: 60, 60, 60), which randomly (with a distance of at least 1.5° between each) appeared at

Figure 1

Continuous Color-Report Task Showing Set Size 4



least 2° from the white fixation cross (0.5°) within a rectangular region with a width and height of 10 × 9°, centered on the fixation cross. Colors were randomly drawn from a circle with a radius of 40 in a luminance plane of the CIE 1976 L*a*b* color space (L* = 63, center: a* = 9, b* = 27, illuminant: D65, 2° standard observer).

All trials followed the same order: After the fixation cross was briefly presented for 1000 ms (inter-trial interval), the sample array appeared for 1000 ms containing five colored squares. After a 1000 ms delay interval, participants were presented with the test array, which remained until a response was given. Responses were not timed. In keeping with the traditional paradigm, performance feedback was not provided.

Procedure and Think Aloud Protocol Transcription

Participants performed the task alone in the laboratory with only the researcher present. First, participants were given the opportunity to familiarize themselves with the VWM task by reading a short introduction to the task and performing a practice block containing 20 trials. The actual VWM task consisted of two blocks, each containing 165 trials.

The first block served the purpose of the participants' full habituation of the tasks' procedure before asking them to emote aloud during the task, thus in this block, participants did the task in silence. During the second block, the emote aloud procedure was introduced. To this end, participants were prompted with the following instructions: "You will now complete another block of trials, just like the one you have just completed. During this next block, we ask you to please verbalize any feelings or thoughts you are experiencing during the task". The resulting monologue was recorded and later transcribed verbatim. If required, the researcher reminded participants to "think and feel aloud". Overall, participants took approximately between 45 and 90 minutes to complete the task.

Analysis and Coding Reliability

Data analysis was carried out on the basis of qualitative content analysis proposed by Mayring (2014) using the open access web-application QCAmap (Mayring & Fenzl, 2014).

As to the authors' knowledge, there are no prior findings regarding participants' affective states when performing a VWM task in the laboratory, categories needed to be extracted from the textual material itself, using the content analytical technique of inductive category formation (Mayring, 2014).

To determine what participants felt when performing a VWM task (RQ 1a), we categorized all text passages in which "participants referred to emotional states experienced during the VWM task" (selection criterion). Next, categories were phrased as "specific emotional states or personal feelings, which participants referred to during the VWM task" (level of abstraction).

To explore which aspects of the VWM task triggered these discrete emotions (RQ1b), the selection criterion was set to text passages in which "participants explicitly referred to or hinted at reasons, sources or processes related to the emotional states or feelings experienced/perceived during the VWM task". Categories were phrased as "specific reasons, sources or processes affecting or leading to participants' emotional states and feelings experienced/perceived during the VWM task" (level of abstraction). Further details of the coding procedure can be found in the Supplemental Material.

In order to establish the degree of reliability for the category system and reproducibility of the categorizations, a subsample of six randomly chosen interviews (approx. 33% of the entire material) were coded by two independent coders. The coders reached substantial agreement for both research questions (RQ1a: K = .79 (95% CI, .68 to .89), p > .01; RQ1b: K = .72 (95% CI, .61 to .82), p > .01).

Table 1

Discrete Emotions Stated by Participants During a VWM Task in Order of Frequency

Discrete emotion	Frequency by participants	Absolute count
Anger	8 participants	24
Frustration	7 participants	20
Joy	7 participants	17
Boredom	6 participants	9
Tension/Nervousness	3 participants	3
Confusion	2 participants	2
Desperation	2 participants	5
Hope	2 participants	3
Same	1 participant	2
Disappointment	1 participant	1
Uncertainty	1 participant	1
Anxiety	1 participant	1

Results and Discussion

Overall, 12 discrete emotions were identified (see Table 1). The most frequently stated emotions were anger (stated by eight participants), frustration (seven participants), joy (seven participants), and boredom (six participants). Participants varied in terms of how many different emotions they reported during the task (ranging from one to six emotions) and how often they reported to experience them (ranging from one to nine times).

These findings confirm previous speculations and provide first empirical evidence that participants experience emotions during a VWM task, which occur because of the task itself. This is in line with emotion research proposing that emotions can be triggered by (cognitive characteristics of) a task (Pekrun, Vogl, et al., 2017).

In regards to RQ1b, 10 categories were identified, which involved underlying processes associated with participants' emotional experiences during the VWM task (see Table 2). Participants' *self-expectations regarding the VWM task* were identified most frequently to be related to their emotional experiences (eleven participants, referred to 28 times). The majority of the coded passages in this category indicated that participants wanted and also expected to do well on the task, as it was perceived initially as a simple task. However, the task proved to be more difficult than expected. This led to participants experiencing negative emotions, such as anger ("You get angry when you don't know it because this isn't really that difficult, actually", Participant D).

Eleven participants perceived the *VWM task as challenging in a negative sense*. Here, participants reported the VWM task as being stressful or overwhelming for them and resulting in negative emotions for the individual, as is illustrated by the following examples: "I always try to remember, more or less, the general color. And when each one is different, then I am out of my depth. . . . That just makes me angry" (Participant C).

"But sometimes, I don't know, sometimes the time to look at the colors is too short and then I get desperate because I try to recite the colors and to see which ones come in pairs and when there are many different colors, all of a sudden nothing works anymore." (Participant G)

Six participants referred to being *dissatisfied with the VWM task design*, which mainly resulted in frustration: "What's also frustrating is the cross in the middle of the screen" (Participant A). One participant reported to experience boredom: "Because this is the second round, you just start noticing that it is starting to be boring, yes, because it is always the same thing" (Participant K).

Participants' *general judgement of the VWM task* (six participants) pertained to the general attitude they reported having towards the task. For instance, some participants referred to the task as being "pointless" or "silly" (Participant K), others compared the task to a game (Participant M) or an exam situation (Participant P). A *change in motivation* was also referred to by six participants, especially towards the end of the VWM task: "For some reason I'm, I'm starting to notice that it doesn't matter to me that much anymore, I am not clicking anywhere specific anymore" (Participant S).

Pertaining to the category *social comparison*, six participants wondered how they were performing in comparison to the other participants: "I'm always asking myself, if I am that bad or if the others are also this bad." (Participant P). One participant stated to be angry for comparing their own achievement to those of others.

Four participants referred to *missing performance feedback*, which was mainly associated with interest: "It would be interesting to know your score, at the end. Maybe, I don't know, a smiley face indicating whether you were right or wrong" (Participant D).

Four participants also referred to a *missing time reference*, which seemed to be frustrating, as the following example illustrates: "You don't know when it'll be over. I think that's what's bugging me" (Participant E).

Three participants perceived the *VWM task as challenging in a positive sense*. Here, participants mainly reported that the VWM task fueled their ambition to perform well, but when they did not, they experienced negative emotions, for example:

"I am still ambitious. It's not as if I would stop doing this straight away. I want to continue doing this and I want to do well at this and I try every time again and again. But somehow you still are disappointed when you don't know the answer." (Participant D)

Finally, three participants referred to *strategies to improve their achievement*: "You start and build themes and then you wait and see, and then you try and do it well" (Participant E).

Table 2

Underlying Processes Regarding Emotional Experiences in Order of Frequency

Underlying process	Frequency by participants	Absolute count
Self-expectations	11 participants	28
VWM task is challenging (negative sense)	11 participants	23
General judgment of the VWM task	6 participants	27
Dissatisfaction with the VWM task design	6 participants	12
Change in motivation	6 participants	11
Social comparison	6 participants	10
Referring to missing performance feedback	4 participants	9
Referring to missing time reference	4 participants	7
VWM task is challenging (positive sense)	3 participants	8
Thoughts on strategies to improve achievement	3 participants	3

It is worth noting that the think and emote aloud method relied upon participants to be able to register what they are thinking and feeling on a meta-cognitive level and to translate these complex internal processes into words for a third party to understand. A few participants seemed to struggle with this in that they did not verbalize any emotional experiences, others described the think aloud task itself as a source for certain emotional experiences. Yet we took great care not to categorize emotional experiences which were triggered by the think aloud method.

Overall, the results showed that participants experienced an array of different discrete emotions while performing the continuous color-report task, which varied between individuals – some seemed to enjoy the task more, yet others found it frustrating. It also became evident that participating in the continuous color-report task implied going through highly intra-individually varying emotional states – at some points during the experimental block, participants were activated, engaged, and enjoying it, while next they had trouble focusing, worried about their achievement, and became frustrated.

Only few statements pertained to epistemic emotions, such as confusion (Vogl et al., 2020), and some emotions seemed to have been triggered by certain experimental design features we had realized (no performance feedback, no explicit breaks). Most importantly, though, it became evident that the dominating theme of most participants' thinking while engaging in the continuous color-report task was subjective success and failure. This confirms speculations expressed earlier for example by Rouder and colleagues (2008) that some participants can be "intimidated" by the task, and Spachtholz et al. (2014) who conjectured that the VWM task can "signal requirements" which trigger emotions in the participants. Clearly, the key task requirement built into a memory task such as the continuous color-report task is to remember the "correct" color, so participants are fully aware that they can fail versus succeed at each trial. As such, a key insight from this qualitative study was that this task clearly places participants into an achievement situation. That is, participants find themselves in a situation where judgments regarding achieving or failing against some standard, be it task-based, self-based, or other based (Elliot et al., 2011) are dominant.

Study 2

Previous research has demonstrated that emotions induced prior to a VWM task can affect VWM performance. In a second study, we sought to establish whether emotions, which were induced by the VWM task itself, were also systematically linked to VWM performance. To this end, participants performed the continuous color-report task and were asked to rate their emotional experiences during the task immediately after. We opted for such a summative, retrospective task emotion assessment in order to minimize any disruptions during the task.

Taking up the results of Study 1, we chose to assess joy, anger, frustration, and boredom. As joy was the only positive emotion explicitly labeled by the participants in Study 1, and we sought to assess diverse discrete emotions also of positive valence (Pekrun, 2018; Posner et al., 2005), we chose to additionally include pride in this study. Pride is an important self-conscious emotion and a prototypical achievement emotion tightly linked with appraisals of task success (Lagattuta & Thompson, 2007), and given the situational salience of achievement we had identified in Study 1, we deemed it promising to further investigate the link between this emotion and VWM performance.

Method

Sample

Forty-seven individuals initially participated in this study (31 female; M_{age} = 26.09; SD = 3.85) who all stated not to be color-blind and to have normal or corrected-to-normal vision. They received either course credit or monetary compensation for their time.

Two individuals were excluded from further analysis due to substantial missing data in the self-reported emotions and technical difficulties during the VWM task. No participants were excluded due to extremely poor performance. The final sample of this study thus was N = 45 (30 female; M_{age} = 26.24; SD = 3.86).

Procedure, Stimuli and Measurements

Procedure. Participants familiarized themselves with the VWM task by performing a short practice block containing 30 trials, which started either with 15 trials displaying four squares followed by 15 trials displaying eight squares, or vice versa. The actual task contained 240 trials, which were arranged in alternating blocks of 30 trials each, displaying either four- or eight-square arrays (set-size; starting size counterbalanced). At the end of the VWM task, participants were prompted to fill in a paper-and-pencil questionnaire asking them to report, retrospectively, how they felt during the VWM task.

Continuous Color-Report Task. We employed the same task as in Study 1, except that we deliberately introduced variability in the difficulty of the task by using two different sample array set-sizes: four or eight colored squares. We did so because on the one hand, we wanted participants to be fairly comfortable with the task during certain phases of the experiment (set-size 4). On the other hand, we wanted to place them systematically in demanding achievement situations (set-size 8; e.g., Rouder et al., 2008), as results from Study 1 indicated that emotions participants experienced during the VWM task were linked to its achievement requirements. Further, it is common to vary set-size in paradigms designed to measure VWM. No performance feedback was provided and responses were not timed. Participation length for the 240 trials ranged between 25 and 35 minutes, approximately.

VWM performance was operationalized by computing the absolute angular distance (in degrees) between the probed item's color (on the color wheel) and the selected color (henceforth: recall error) for each participant.

Emotion Ratings via Paper-and-Pencil Questionnaire. To assess participants' emotions regarding the VWM task, we asked participants to rate five items concerning the emotions they experienced during the VWM task (*I enjoyed the task*, *I felt proud*, *I felt angry*, *I was frustrated*, *I felt bored*) on a five-point Likert type scale ranging from strongly disagree to strongly agree. These judgments were made immediately after finishing the experiment.

Results and Discussion

As expected, there were no significant effects of set-size order on either recall error or self-reported emotions (all ts < .81, all ps > .37) and we therefore do not consider this group factor further. An overview of the descriptive statistics for the emotion measures in Study 2 can be found in Table 3.

As the emotions were rated with single items on a 5-point Likert scale, thus not affording an interval-scale measurement level, we obtained Spearman's correlation coefficient for VWM performance and the emotions joy, pride, anger, frustration, and boredom to explore the link between task-induced emotions and VWM performance (recall error) on an inter-individual level (RQ2a; see Table 4). Results indicated that there was a significant negative association between recall error and joy ($r_s = -.34$, 95% BCa CI [−.606, −.017], p = .02) and pride ($r_s = -.30$, 95% BCa CI [−.602, .015], p = .04). Further, there were significant positive associations between recall error and anger (r_s = .32, 95% BCa CI [.026, .561], p = .03), frustration (r_s = .34, 95% BCa CI [.048, .555], p = .03), and boredom (r_s = .33, 95% BCa CI [.017, .57], p = .03)[1].

The results imply that the better participants performed on the VWM task relative to others, the more joy and pride they experienced. However, when participants performed more poorly on the task relative to others, they experienced more anger, frustration and boredom. Importantly, though, these are purely correlative findings, so we hasten to caution the reader (and ourselves) not to interpret these findings as causal relations; emotions might affect performance, performance might affect emotions or there might be a third variable that affects both emotions and performance. Even more likely, the correlation might be due to a complex reciprocal interaction between performance, emotions, and maybe additional variables (as discussed in more detail in the Introduction and General Discussion sections with regard to Pekrun's (2006) control-value theory).

Study 3

The results from Study 1 had suggested that not only did the participants differ from one another, that is, on an inter-individual level, with respect to their task-induced emotions during the VWM task (as followed up upon in Study 2), but also, single individuals seemed to experience widely ranging levels of emotions during the task. Additionally, Study 1 had revealed that participants were mostly preoccupied with their subjective performance during the task, and the emotions they experienced could be largely classified as achievement emotions. Following up on this, in Study 3, we sought to explore whether task difficulty (i.e., set-size) had an effect on participants' emotions, and we aimed to assess the intra-individual variation of emotional experiences during the continuous color-report task execution. Further, we aimed to explore whether and how these varying emotions related to VWM performance, on

[1] We confirmed that all those effects were significant (p < .05) even when adopting the Benjamini-Hochberg procedure for ruling out false discoveries.

Table 3

Descriptive Statistics for Emotional Measures in Studies 2, 3, and 4

	Study 2 (N = 45)		Study 3 (N = 44)				Study 4 (N = 110)					
	Single retrospective measure		Mean score across the blockwise measures				Single retrospective measure		Mean score across the blockwise measures			
	Median	Range	M (SD)	Range	Skew.	Kurt.	Median	Range	M (SD)	Range	Skew.	Kurt.
Joy	3.0	1–5	2.5 (0.73)	1–4	−0.17	−0.35	3.0	1–5	2.62 (1.02)	1–5	0.49	−0.34
Pride	2.0	1–5	2.1 (0.67)	1–3.5	0.07	−0.85	2.0	1–5	2.22 (0.77)	1–5	1.08	2.01
Anger	2.0	1–4	1.9 (0.90)	1–4.3	0.71	−0.48	2.0	1–5	2.08 (0.98)	1–4.6	0.66	−0.32
Frustration	3.0	1–5	2.4 (0.93)	1–4.9	0.47	0.07	3.0	1–5	2.76 (1.20)	1–5	0.19	−0.70
Boredom	3.0	1–5	2.9 (0.88)	1.1–4.8	0.17	−0.51	3.0	1–5	3.02 (1.17)	1–5	−0.10	−0.98

an intra-individual level. To this end, in Study 3, we asked participants to rate their emotional experiences at multiple time points during the VWM task. In other words, we sought to explore whether any dynamics of the participants' emotions across the course of the experiment, as assessed through multiple emotion ratings after short experimental sub-blocks, co-fluctuated with the dynamics of the performance across those sub-blocks, within the participants.

Method

Sample

Forty-six individuals (26 female; M_{age} = 25.57; SD = 3.86) initially participated in this study, who all stated not to be color-blind and to have normal or corrected-to-normal vision. They received either course credit or monetary compensation for their time.

One person was excluded from further analysis due to substantial missing data in the self-reported emotions and one participant was excluded due to extremely poor performance (average recall error of more than two standard deviations above the mean), indicating poor study commitment and thus low overall data quality. The final sample of the study thus was N = 44 (24 female; M_{age} = 25.50; SD = 3.89).

Procedure, Stimuli, and Measurements

Procedure. We largely adopted the same procedure as described in Study 2. The key difference was that in this study, participants were prompted to rate the emotion items presented to them in a paper-and-pencil questionnaire several times within the experiment (after each block of 30 trials displaying either four- or eight-square arrays), as we sought to assess the potential intra-individual variability in emotions regarding the VWM task execution in the course of the experiment.

Continuous Color-Report Task. We adopted the same continuous color-report task as described in Study 2, and operationalized VWM performance in terms of recall error accordingly. We thus obtained recall error for each block of 30 trials.

Emotion Ratings via Paper-and-Pencil Questionnaire. To assess participants' emotions regarding the VWM task on an intra-individual level, we asked participants "*How are you currently feeling?*" at eight time points during the VWM task. At each time point participants were asked to rate five items concerning the emotions they experienced during the VWM task (*I am enjoying the task*, *I feel proud*, *I feel angry*, *I am frustrated*, *I feel bored*) on a five-point Likert type scale ranging from strongly disagree to strongly agree.

Analysis Approach

We calculated random intercept, fixed-slope models for each emotion/recall error combination. For this analysis, all emotion and recall error scores were transformed into z-scores, so that the within-person regression parameters could be interpreted as standardized correlations, to allow for comparability between the results from this study and Study 2.

Results and Discussion

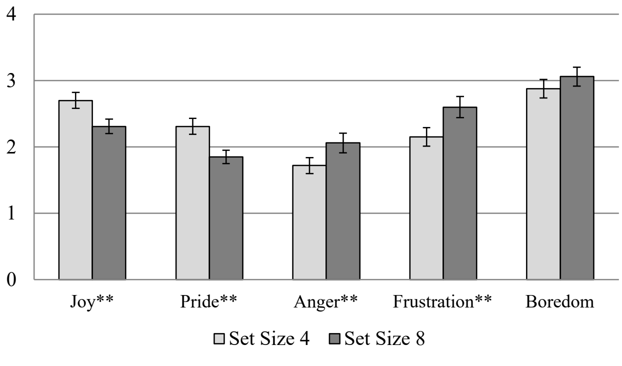
Descriptive statistics of all emotion measures in Study 3 are shown in Table 3. As in Study 2, there were no significant between-person effects of set-size order on either recall error or self-reported emotions (all ts < 1.52, all ps > .14). Further, to test whether the multiple emotion ratings affected VWM performance, an independent-samples t-test was calculated using participants' average recall error from Study 2 (M = 47.02, SD = 8.54) and Study 3 (M = 47.75, SD = 10.89). Results yielded no significant difference between the two sample means ($t(87) = -0.35$, p = .73, d = −0.07).

Next, we explored effects of set-size. As could be expected, paired-sample t-tests showed significant effects of set-size on recall error ($t(43) = -24.17$, p < .01, d_z = −3.64) thus, easier blocks (i.e., arrays with four squares) were associated with better performance (M_4 = 35.70, SD_4 = 10.49; M_8 = 59.79, SD_8 = 12.22). Regarding the emotions, paired-samples t-tests further showed significant effects of set-size on joy ($t(43)$ = 4.66, p < .01, d_z = 0.70), pride ($t(43)$ = 5.96, p < .01, d_z = 0.90), anger ($t(43) = -3.91$, p < .01, d_z = −0.59) and frustration ($t(43) = -5.00$, p < .01, d_z = −0.75), indicating that the variation in task difficulty affected how participants felt while performing the VWM task. Specifically, when confronted with set-size 4, participants experienced more enjoyment (M_4 = 2.70, SD_4 = 0.82) and pride (M_4 = 2.32, SD_4 = 0.79) than when confronted with set-size 8 (joy: M_8 = 2.31, SD_8 = 0.74; pride: M_8 = 1.85, SD_8 = 0.65). Further, participants experienced less anger (M_4 = 1.72, SD_4 = 0.82) and frustration (M_4 = 2.15, SD_4 = 0.91) when confronted with set-size 4 than with set-size 8 (anger: $M_8 = 2.06$, $SD_8 = 1.02$; frustration: $M_8 = 2.60$, $SD_8 = 1.04$). The effect of set-size on boredom did not reach significance ($t(43) = -1.97$, $p = .06$, $d_z = -0.30$; $M_4 = 2.88$, $SD_4 = 0.95$; $M_8 = 3.06$, $SD_8 = 0.91$; see Figure 2).

Regarding the relationship between performance and emotions, results showed that every discrete emotion significantly correlated with recall error on the intra-individual level (see Table 4). Specifically, joy and pride were significantly negatively linked with recall error, indicating that when a participant performed better on a block of 30 trials than on the other blocks, they enjoyed it more, and were more proud, relative to the other blocks. Vice versa, when participants experienced more of those positive emotions during a block, they performed better on the task on that particular block relative to the other blocks. In turn, anger, frustration, and boredom were significantly positively linked with recall error, implying that the worse a participant performed on a particular block the more they experienced those negative emotions during that block, and vice versa. Finally, taking into consideration that set-size also had a strong effect on the emotions, in a last analysis step, we additionally considered set-size in our analyses. This implied exploring whether, even in blocks of the same difficulty, participants' emotions varied, and whether this variation in task experiences was systematically related to performance. Intriguingly, the effects remained significant for all discrete emotions except for anger (see Table 4). This implies that anger was strongly driven by task difficulty. However, participants' fluctuations in joy and pride across the experiment were still significantly negatively related with their performance in the task, and their fluctuations in frustration and boredom were positively related with performance above and beyond the performance variability induced by the array size manipulation.

Figure 2

Effects of Set Size on Emotions in Study 3



Note. $^{**}p < .01$; error bars display ± one standard error.

Study 4

This study was designed as a high-powered replication of Study 3 (intra-individual links between emotions and performance). Due to the COVID-19 pandemic, data collection in the laboratory was not possible. The study was therefore moved from a laboratory to

Table 4

Spearman Correlations from Study 2 and Intra-Personal Correlations from Study 3 and 4 between Emotions and Recall Error

	Study 2		Study 3			Study 3 (controlling for set size)			Study 4			Study 4 (controlling for set size)			Study 4 (controlling for set size and pre-experimental mood)		
	r_s	95% CI	r	SE_β	95% CI	r	SE_β	95% CI	r	SE_β	95% CI	r	SE_β	95% CI	r	SE_β	95% CI
Joy	−.34*	−.61, −.02	−.31**	.05	−.42, −.21	−.11**	.04	−.18, −.04	−.29**	.04	−.37, −.21	−.11**	.03	−.18, −.05	−.11**	.03	−.18, −.05
Pride	−.30*	−.60, .02	−.42**	.05	−.53, −.32	−.16**	.04	−.23, −.08	−.38**	.04	−.45, −.30	−.19**	.03	−.25, −.14	−.20**	.03	−.25, −.14
Anger	.32*	.03, .56	.25**	.06	.12, .37	.07	.04	.01, .15	.26**	.04	.18, .34	.10**	.03	.04, .16	.10**	.03	.05, .16
Frustration	.34*	.05, .55	.38**	.06	.26, .50	.16**	.04	.08, .24	.33**	.04	.25, .40	.13**	.03	.07, .19	.13**	.03	.07, .19
Boredom	.33*	.02, .57	.21**	.06	.10, .32	.13**	.04	.06, .20	.15**	.04	.07, .23	.05	.03	−.006, .11	.05	.03	−.007, .11

Note. Intraindividual correlations in Study 3 and 4 were obtained via two-level hierarchical models.
$^{*}p < .05$ $^{**}p < .01$

an online environment and data was collected via the data collection platform Prolific (thus drawing from a different population). Otherwise we aimed to replicate Study 3 as closely as possible. The functionality of the online environment for the assessment of both the continuous color-report paradigm as well as self-report items of emotional experiences after each 30-trial sub-block was piloted.

In addition to the emotion ratings after each block, we also included further "overall retrospective" emotion rating items at the very end of the experimental session. We were unsure whether participants were able to sufficiently abstract from their current emotional state when answering these items after having been probed for their current emotional state multiple times during the experiment. If they were able to do so, this would provide a relatively cost-free opportunity to additionally replicate Study 2 conceptually, because the additional rating would not affect the main data of interest (related to the replication of Study 3).

As a further extension of this replication, we had participants fill out the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) before the start of the experiment. This would allow us to take their pre-experimental mood into account as well. As such, we could explore whether mood before the experiment had any effects on performance, and whether the task-induced emotion—performance links as demonstrated in Study 3 would persist above and beyond any such effects of mood.

Method

Sample

We used the effect of set-size on boredom in Study 3 ($d_z = -0.30$), which had just failed to reach significance, to determine the necessary sample size for this replication. Using *G*Power* aiming at power $1 - \beta = .9$; $\alpha = .05$ for this effect, we obtained a required N of 97. Administering the study online via Prolific involved making batches of experimental slots available at several standardized time slots, which would not necessarily always fill up. We further anticipated that we could not include all initial participants in our analyses due to exclusion criteria, potential technical problems in the online data collection environment, or other factors and therefore slightly oversampled. Our final initial sample (before exclusion) was $N = 124$ participants (43 females, 1 other; $M_{age} = 26.47$; $SD = 7.76$).

We took advantage of Prolific's option to preclude participants from study-participation due to certain factors. Therefore, all participants reported not to be color-blind and to have normal or corrected-to-normal vision. One participant was excluded from the study due to technical problems, which lead to substantial missing data. We applied the same exclusion rule for sorting out participants based on extremely low performance as in Study 3 (recall error of more than two standard deviations above the mean), indicating poor study commitment and thus low overall data quality. On that basis, four participants were excluded from further analyses. Further nine participants were excluded for taking too long on the experiment overall (more than two standard deviations above the mean experiment duration, i.e., more than 86 minutes), an exclusion rule we deemed necessary given the highly uncontrolled digital setting. The final sample included for analysis was thus $N = 110$ participants (38 female; $M_{age} = 26.56$; $SD = 7.92$), thus slightly oversampling relative to the required N as implied by the power analysis for the reasons stated above.

Procedure, Stimuli, and Measurements

Procedure. Data collection occurred online via Prolific. First, participants were prompted to rate items on the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) before they were introduced to the same continuous color-report task used in studies 2 and 3. Identical to the procedure in Study 3, after a short practice block of 30 trials (15 of each set-size), participants performed the experimental block of 240 trials consisting of 30 trials each in a row with array size 4 or 8. As results from both Study 2 and 3 yielded no significant effects of set-size starting order on either recall error or self-reported emotions, this was not counterbalanced in the present study and all participants started with set-size 4. As in Study 3, after each of these sub-blocks of 30 trials, participants were prompted to rate the emotion items; this time presented to them on the screen in the online environment. Different from Study 3, attempting to potentially also replicate our findings from Study 2, at the very end of the block of 240 trials, participants were prompted to report, retrospectively, how they felt during the entire experiment. Participants received monetary compensation for their time. The various measures are described in more detail in the following.

Continuous Color-Report Task. We adopted the same continuous color-report task as described in Studies 2 and 3. VWM performance was operationalized in terms of recall error accordingly. We obtained the average recall error for each block of 30 trials (for the intra-individual analyses) and the overall average recall error after 240 trials (for the inter-individual analyses).

Positive and Negative Affect Schedule. To assess participants' mood prior to the VWM task, the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) was used. The PANAS is suitable to either measure trait affectivity (personal tendencies to experience generally positive vs. negative affect) or state affect (i.e., momentary positive versus negative affect/mood). It includes 20 items, ten of which are positive (e.g. *interested*, *inspired*, *active*) and ten are negative (e.g., *distressed*, *hostile*, *jittery*). For the present purpose, we used the state instructions, asking participants to "Indicate to what extent you feel this way right now, that is, at the present moment." Responses were given on a five-point Likert type scale ranging from *very slightly or not at all* to *extremely*.

Emotion Ratings during the VWM task. Exactly as in Study 3, to assess participants' emotions regarding the VWM task on an intra-individual level, we asked participants, "*How are you currently feeling?*" after each sub-block (eight times in total). At each time point participants were asked to rate five items concerning the emotions they experienced during the VWM task (*I am enjoying the task*, *I feel proud*, *I feel angry*, *I am frustrated*, *I feel bored*) on a five-point Likert type scale ranging from *strongly disagree* to *strongly agree*.

Overall Emotion Ratings of the VWM task. Exactly as in Study 2, we asked participants to retrospectively rate their emotions after they completed the entire VWM task by asking, "When looking back across the entire memory task: how were you feeling during the task?" Participants again rated five items (*I enjoyed the task*, *I felt proud*, *I felt angry*, *I was frustrated*, *I felt bored*) on a five-point Likert type scale ranging from *strongly disagree* to *strongly agree*.

Results and Discussion

To explore whether the online setting had any effects, we tested average recall error means from Study 3 against recall error means from Study 4. Participants of this online study performed slightly better overall (M = 43.25, SD = 12.28) than participants of the comparable laboratory study (Study 3, M = 47.75, SD = 10.89), $t(152) = 2.12$, $p = .04$, $d = 0.38$.).

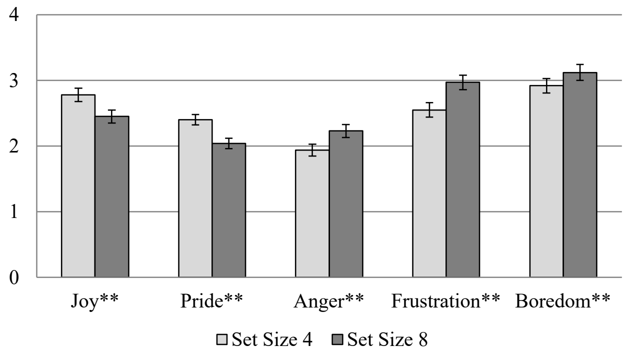
An overview of the descriptive statistics for the emotion measures in Study 4 can be found in Table 3. Somewhat disappointingly, but not unexpectedly (see above), the Spearman's correlation coefficients for overall VWM performance and the overall retrospective emotion judgements for joy, pride, anger, frustration, and boredom ($r_s = -.06/-.11/.16/.04/.05$; $p = .53/.24/.11/.66/.61$; respectively) did not reach statistical significance. Thus, simply adding an extra question at the end of the experiment did not serve the purpose of replicating Study 2. This is likely due to a crucial change in the study design (which was introduced because our main aim was to replicate Study 3): As opposed to Study 2, where participants performed the VWM task without any interruption and were asked to rate one item regarding their achievement emotions towards the task in one single retrospect across the entire experimental block, participants in Study 4 were asked to continually rate their current emotional experiences eight times within the VWM task, before rating the overall emotion item retrospectively. It appears that the multiple question rating interfered with the final retrospective question. Maybe this made the variation of set-size and corresponding emotional variation particularly salient to the participants, or they were unable to sufficiently abstract from their current emotional state after getting used to report exactly this.

In order to replicate the findings from Study 3, we again calculated random intercept, fixed-slope models for each emotion/recall error combination, using the emotion and recall error z-scores, to allow for comparability. Results showed that, as in Study 3, every discrete emotion significantly correlated with recall error on the intra-individual level (see Table 4). For joy, pride, anger, and frustration this also held true when controlling for set-size. For boredom, the correlation with recall error was no longer significant when controlling for set size. Additionally, in a third step of our multilevel regression analyses, we also considered mood before the experiment on the inter-person level (level 2), which did not alter the results (see Table 4). In sum, results of Study 3 were fully replicated for enjoyment and pride (positive intra-individual links with performance) and frustration (negative intra-individual links with performance). Intriguingly, in contrast to Study 3, the negative anger—performance link now remained significant when controlling for set-size (as well as mood), but the boredom—performance link proved no longer significant with this control in this high-powered study.

Paired-samples t-tests also replicated the findings from Study 3 that set-size had a significant effect on each of the emotions (joy: $t(109) = 8.10$, $p < .01$, $d_z = 0.77$; $M_4 = 2.78$, $SD_4 = 1.04$, $M_8 = 2.45$, $SD_8 = 1.05$; pride: $t(109) = 8.54$, $p < .01$, $d_z = 0.81$; $M_4 = 2.40$, $SD_4 = 0.79$, $M_8 = 2.05$, $SD_8 = 0.81$; anger: $t(109) = -6.22$, $p < .01$, $d_z = -0.59$; $M_4 = 1.94$, $SD_4 = 0.91$, $M_8 = 2.23$, $SD_8 = 1.10$); frustration: $t(109) = -7.27$, $p < .01$, $d_z = -0.69$; $M_4 = 2.55$, $SD_4 = 1.12$, $M_8 = 2.97$, $SD_8 = 1.16$; including boredom: $t(109) = -5.14$, $p < .01$, $d_z = -0.48$, $M_4 = 2.92$, $SD_4 = 1.16$, $M_8 = 3.12$, $SD_8 = 1.21$). Thus, the non-significance of an effect of set-size on boredom in Study 3 (on which we had based the power analysis to determine the sample size in Study 4) was indeed simply a power issue that was resolved in Study 4. These results indicate once more that the variation in task difficulty affected how participants felt while performing the VWM task (see Figure 3).

Figure 3

Effects of Set Size on Emotions in Study 4



Note. **$p < .01$; error bars display ± one standard error.

General Discussion

The present research aimed to explore whether participants experience emotions during a VWM task, which are induced by the task itself, and which discrete emotions these are. Next, and most importantly, we sought to demonstrate that such incidentally emotions were systematically linked with VWM performance (positive links for pleasant emotions, negative links for unpleasant emotions). To this end, we conducted an exploratory qualitative study, followed up by three confirmative quantitative studies. In addition to demonstrating the existence of emotion/performance covariance, our studies showed that task difficulty (i.e., set-size) has an effect on the emotions participants experience during task execution. As expected, higher set-size resulted in increased unpleasant and decreased pleasant emotions during the task.

VWM Tasks Induce Achievement Emotions

While there have been previous speculations about (predominantly negative) emotions occurring during typical lab-based cognitive performance tasks (Luck, 2014; Rouder et al., 2008), the present research was the first to systematically explore these assumptions. Our qualitative results from Study 1 revealed that participants experienced various different discrete emotions, both negative and positive in valence, during a VWM task, while overall negative emotions were mentioned more frequently than positive emotions. Interestingly, these emotional experiences not only varied between individuals, in that some participants experienced more joy and others more anger, but also within them: Participants experienced a range of varying emotions, while performing this laboratory task, for instance switching from joy, to boredom, to anger, and back to joy again during the course of one single experimental block. Importantly, though, joy, anger and frustration clearly were the most dominant emotional experiences reported by the participants in Study 1, whereas, by comparison, boredom was reported less frequently. This is an important finding of the present study in and of itself: While researchers in this field seemed to have been concerned with participant boredom, our results indicate that this seems to be less problematic than previously assumed, at least for the continuous color-report task examined here.

Beyond identifying which discrete emotions the participants experienced during the VWM task, we also employed qualitative content analysis to classify participants' think aloud utterances pertaining to potential reasons for their current emotional experiences. Across the various categories for triggers of emotions identified by this approach, one striking overarching theme emerged from this analysis: Participants seemed to be constantly aware that they could either succeed or fail at the VWM task (i.e., recalling the correct/exact color of the probed square versus failing to do so), and a clear majority of their thoughts centered around corresponding achievement appraisals. By implication, the predominant type of emotions participants experience during the examined VWM task seem to be achievement emotions (Pekrun, Lichtenfeld, et al., 2017).

It is worth noting that within the think-aloud transcripts, it became apparent that some participants hinted towards using certain strategies in order to enhance their performance on the VWM task such as verbalization of the colors (Souza & Skóra, 2017), grouping (Morey, 2019), and ensemble representations (e.g., Brady and Alvarez, 2015; Liesefeld and Müller, 2019), and they expressed varying degrees of mind wandering (e.g., Robison and Unsworth, 2018). As this was not the focus of our research question, we did not further follow up on those observations. However, it may be interesting to explore in more detail how those phenomena are linked with task-induced emotions in future research. Furthermore, it is worth noting that some participants expressed frustration about the fact that they did not get performance feedback; thus they apparently felt that the task would be more satisfying if performance feedback was provided. Instead, we would actually expect that provision of performance feedback would intensify any emotional experiences during the task (positive after success feedback, negative after failure feedback), thus yet exacerbating the potential emotion—performance links. We therefore deliberately decided against providing any performance feedback in the present study to see whether even in that situation, participants would experience achievement emotions. Future research may explore effects of performance feedback on task-induced emotions during cognitive tasks, and potential corresponding effects on task performance and emotion—performance covariation.

When realizing that the continuous color-report task has such strong task-inherent achievement requirements, which trigger achievement emotions in the large majority of participants, it seems helpful to consider Pekrun's (2006) control-value theory of achievement emotions to better understand the possible underlying processes of emotion elicitation during VWM task performance. In this theory, Pekrun proposes that individuals vary in their emotional experiences depending on their appraisals concerning the achievement activity and its outcome, in terms of subjective control appraisals (which correspond with judgments of whether one can succeed at the task) and subjective value (which correspond with judgments of how important it is to succeed on the task). More specifically, Pekrun (2006, 2018) proposes that control appraisals determine the valence of emotions (e.g., enjoyment or pride in case of high control, anger, frustration or anxiety in case of low control), and value appraisals boost the emotional intensity (stronger with higher value). As such, the present findings imply that as long as participants truly commit to the task – i.e., they accept that selecting the correct color is important, and continually monitor their own performance by judging whether or not they think they got it right – both negative and positive achievement emotions are bound to occur during the task. Yet, this also implies that participants will vary in the levels of task-induced achievement emotions, depending on how much importance they attach to selecting the correct color, and how successful they sense they are at doing so.

Large Array Sizes Increase Negative Task Emotions and Decrease Positive Task Emotions

A key finding of the present research was that emotional processes involved in performing a VWM task were influenced by task difficulty, with larger set size being associated with decreased positive and increased negative emotions. This was shown in Study 3 for the emotions joy, pride, anger and frustration. This finding was replicated using a larger sample in Study 4, where the effect of set-size on boredom also reached significance (more boredom for set size 8 than set size 4). The variation of set-sizes is a common practice by many researchers who use the continuous color-report task, and our findings suggest that the emotions induced by varying set-sizes might be a confound that has not yet been sufficiently considered. Rouder et al. (2008) speculated that some participants may be intimidated by the harder trials, which in turn may harm their VWM performance. The present study is the first to provide evidence that participants experience more positive emotions and less negative emotions for smaller compared to larger set-sizes.

Again, control-value theory (Pekrun, 2006, 2018) provides the theoretical underpinning for explaining this finding: with larger set-sizes, the participants' control over succeeding at the task decreases. Given that a set-size of eight clearly exceeds the VWM capacity of a large proportion of participants, their chances of remembering the correct color are low, and thus their subjective appraisals of whether they can succeed at the task are bound to be poor. As a result, negative achievement emotions emerge. In contrast, easier trials (e.g., set-size 4) are appraised by the participants as more controllable, resulting in more pleasant task emotions. A key implication of the present study is thus that the task emotions affected by set-size represent an essential potential confound in any study that seeks to explore any effects of set-size in the context of VWM research.

Task Emotions and VWM Performance are Systematically Linked

The second and overarching goal of the present research was to quantify the links between task-induced emotions and performance. Overall, our findings implied that there are positive links between pleasant emotions and VWM performance, and negative links between unpleasant emotions and VWM performance. These systematic emotion—performance links were demonstrated both across individuals (Study 2), and within individuals (Studies 3 and 4). It is worth noting that our attempt to conceptually replicate the Study

2 findings by adding an overall retrospective emotion rating at the very end of the experiment (in addition to the repeated emotion ratings within the experimental block) failed. We suppose that adding this question to the design of Study 4 did not provide the same measurement as obtained in Study 2, because performing similar ratings with regard to the current emotional experience multiple times throughout the experiment, unfortunately but not unexpectedly, affects how participants perform the final rating.

The emotion—performance links as demonstrated in our studies are consistent with previous research demonstrating that positive emotions are associated with enhanced working memory performance (e.g., Brose et al., 2014) and negative affect with decreased performance (Figueira et al., 2017). Importantly, these results are correlational and as such do not allow to draw any causal implications. Based on claims and corresponding findings from field studies in applied academic contexts (e.g., Pekrun, Lichtenfeld, et al., 2017), we find it plausible that emotions and performance are linked through reciprocal causation, meaning that both causal directions exist. Taking task enjoyment as an example, on the one hand, doing well on the task causes participants to experience joy, but on the other hand, enjoying the task also leads to participants doing well, as it boosts their task motivation and willingness to invest effort, and focuses their attention on the task.

As mentioned above, participants were not provided with any feedback on their task achievement, so they did not know for certain how well or how poorly they were doing. However, participants seemed to have a good sense of their task achievement, as they often commented on their overall success rate and subjective success at individual trials in Study 1, which might indicate that they know when they have forgotten a probed item and therefore have to guess. Further, in Study 2, results showed the better participants performed relative to others, the more they reported enjoying the task and feeling proud, and the poorer they performed relative to others, the more they reported anger, frustration, and boredom. Studies 3 and 4 further confirmed that those emotion/performance links also emerged on the intra-individual level. In other words, the dynamics of participants' emotions across the course of the experiment, as assessed through multiple emotion ratings after short experimental sub-blocks, co-fluctuated with the dynamics of the performance across those sub-blocks, within the participants: the better the participants did at a certain point within the experimental block, the better they felt at this moment, while when they performed more poorly, negative emotions were aroused within them. In turn, assuming reciprocal causation, this correlative pattern also implies that the better participants felt during task execution, the higher they performed.

We propose that such reciprocal causation between task performance and task emotions should result, in case of task success, in upward spirals, and in the case of task failure, in downward spirals. Specifically, we propose that those participants who truly have higher capacity will quickly get a subjective feeling of doing well on the task, which makes them joyous. In turn, we suppose that this task enjoyment boosts their sense of challenge and opportunity to perform during task, and as a result, they do even better at it. In contrast, those participants who have lower capacity will quickly get a subjective feeling of doing poorly on the task, which makes them angry and frustrated. This anger and frustration will undermine their task performance. At best, they will keep trying, complying with the task requirement asking them to recall the correct color. However, they may also, for the sake of emotion regulation (c.f. Gross, 2002), re-appraise the situation and decide that doing well on the task is not so important for them. This then may result in decreased task commitment, which further undermines their performance.

We believe that there is an important implication of these possible reciprocally spiraling emotion-performance links which seem to be initiated during classical VWM tasks, such as the continuous color-report task (or even during cognitive tasks in general), due to their strong task-inherent achievement requirement. We suggest that thus-obtained capacity scores are dually biased due to the emotional processes just described: They are positively biased, the higher the true capacity, and negatively biased, the lower the true capacity, thus resulting in an overestimation of inter-individual variability in task performance (Vogel & Awh, 2008). This may not be the case for every participant, as individuals may vary in responding to the task-inherent achievement requirements, that is, in how much they value solving the task correctly. Future research may follow up on this notion we see implied by our findings by systematically exploring the emotional responses of low versus high achievers in VWM and how this influences VWM performance (see also Fukuda et al., 2010; Luck and Vogel, 2013).

In sum, the present results provide substantial evidence to confirm earlier speculations about VWM tasks inducing certain emotional experiences in participants. These task-induced emotions are systematically linked with VWM performance and this may be worth considering in future cognitive and VWM research. As researchers, we would like participants to be more like machines sometimes, so we can examine their "hardware" most accurately. However, it seems that human functioning is more complex and highly interacts with emotional experiences, so that future research needs to account for task-induced emotions.

Context of Research

In an ongoing collaboration, we combine theories and findings of two very different fields of study within the same discipline: educational and general psychology. In particular, the reported study combines ACF's expertise in achievement emotions (e.g., Frenzel et al., 2018, forthcoming), a construct traditionally researched in applied academic settings, with HRL's expertise in visual working memory (e.g., Constant and Liesefeld, 2021; Liesefeld et al., 2020; Liesefeld and Müller, 2019), typically researched in basic lab contexts. By our interdisciplinary approach, we were able to gain novel insights into both constructs, which bear important implications for both basic visual working memory research and applied achievement emotion research. In future research, we aim to further inspect these implications for both fields of study.

References

Alloway, T. P., & Alloway, R. G. (2010). Investigating the predictive roles of working memory and IQ in academic attainment. *Journal of Experimental Child Psychology*, *106*(1), 20–29. https://doi.org/10/cjfxwk

Beal, D. J., Weiss, H. M., Barros, E., & MacDermid, S. M. (2005). An episodic process model of affective influences on performance. *Journal of Applied Psychology*, *90*(6), 1054–1068. https://doi.org/10/b8q45n

Brady, T. F., & Alvarez, G. A. (2015). No evidence for a fixed object limit in working memory: Spatial ensemble representations inflate estimates of working memory capacity for complex objects. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *41*(3), 921–929. https://doi.org/10/ggt428

Brose, A., Lövdén, M., & Schmiedek, F. (2014). Daily fluctuations in positive affect positively co-vary with working memory performance. *Emotion*, *14*(1), 1–6. https://doi.org/10/f22drg

Brun, G., Doğuoğlu, U., & Kuenzle, D. (Eds.). (2008). *Epistemology and emotions*. Ashgate.

Constant, M., & Liesefeld, H. R. (2021). Massive effects of saliency on information processing in visual working memory. *Psychological Science*, *32*(5), 682–691. https://doi.org/10/gjk9jh

Conway, A. R., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences*, *7*(12), 547–552. https://doi.org/10/c8jjx5

Csikszentmihalyi, M. (2000). *Beyond boredom and anxiety: Experiencing flow in work and play*. Jossey-Bass Publishers.

Deci, E. L., & Ryan, R. M. (1991). A motivational approach to self: Integration in personality. In *Nebraska Symposium on Motivation, 1990: Perspectives on motivation* (pp. 237–288). University of Nebraska Press.

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction*, *22*(2), 145–157. https://doi.org/10/fv2b3c

Dukes, D., Abrams, K., Adolphs, R., Ahmed, M. E., Beatty, A., Berridge, K. C., Broomhall, S., Brosch, T., Campos, J. J., Clay, Z., Clément, F., Cunningham, W. A., Damasio, A., Damasio, H., D'Arms, J., Davidson, J. W., de Gelder, B., Deonna, J., de Sousa, R., … Sander, D. (2021). The rise of affectivism. *Nature Human Behaviour*, *5*(7), 816–820. https://doi.org/10/gkhxms

Dweck, C. S., & Elliott, E. S. (1983). Achievement motivation. In M. Hetherington (Ed.), *Socialization, personality, and social development* (pp. 643–691). Wiley.

Elliot, A. J., Murayama, K., & Pekrun, R. (2011). A 3 × 2 achievement goal model. *Journal of Educational Psychology*, *103*(3), 632–648. https://doi.org/10/ch6d89

Figueira, J. S. B., Oliveira, L., Pereira, M. G., Pacheco, L. B., Lobo, I., Motta-Ribeiro, G. C., & David, I. A. (2017). An unpleasant emotional state reduces working memory capacity: Electrophysiological evidence. *Social Cognitive and Affective Neuroscience*, *12*(6), 984–992. https://doi.org/10/f9zrwj

Frenzel, A. C., Becker-Kurz, B., Pekrun, R., Goetz, T., & Lüdtke, O. (2018). Emotion transmission in the classroom revisited: A reciprocal effects model of teacher and student enjoyment. *Journal of Educational Psychology*, *110*(5), 628–639. https://doi.org/10/ggb623

Frenzel, A. C., Goetz, T., & Loderer, K. (forthcoming). Emotions and emotion regulation. In P. Schutz & K. R. Muis (Eds.), *Handbook of Educational Psychology* (4th ed.). Routledge/Taylor-Francis.

Fukuda, K., Vogel, E., Mayr, U., & Awh, E. (2010). Quantity, not quality: The relationship between fluid intelligence and working memory capacity. *Psychonomic Bulletin & Review*, *17*(5), 673–679. https://doi.org/10/dwkkc6

Gergelyfi, M., Jacob, B., Olivier, E., & Zénon, A. (2015). Dissociation between mental fatigue and motivational state during prolonged mental activity. *Frontiers in Behavioral Neuroscience*, *9*. https://doi.org/10/ghs9ww

Goetz, T., & Hall, N. C. (2013). Emotion and achievement in the classroom. In *International guide to student achievement* (pp. 192–195). Routledge/Taylor & Francis Group.

Gross, J. J. (2002). Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology*, *39*(3), 281–291. https://doi.org/10/dhr5xt

Hopstaken, J. F., van der Linden, D., Bakker, A. B., & Kompier, M. A. J. (2015). A multifaceted investigation of the link between mental fatigue and task disengagement: Mental fatigue and task disengagement. *Psychophysiology*, *52*(3), 305–315. https://doi.org/10/f63dqp

Hopstaken, J. F., van der Linden, D., Bakker, A. B., Kompier, M. A. J., & Leung, Y. K. (2016). Shifts in attention during mental fatigue: Evidence from subjective, behavioral, physiological, and eye-tracking data. *Journal of Experimental Psychology: Human Perception and Performance*, *42*(6), 878–889. https://doi.org/10/f8qpsg

Johnson, M. K., McMahon, R. P., Robinson, B. M., Harvey, A. N., Hahn, B., Leonard, C. J., Luck, S. J., & Gold, J. M. (2013). The relationship between working memory capacity and broad measures of cognitive ability in healthy adults and people with schizophrenia. *Neuropsychology*, *27*(2), 220–229. https://doi.org/10/f4sct8

Kanai, R., & Rees, G. (2011). The structural basis of inter-individual differences in human behaviour and cognition. *Nature Reviews Neuroscience*, *12*(4), 231–242. https://doi.org/10/cv46sf

Kyllingsbæk, S., & Bundesen, C. (2009). Changing change detection: Improving the reliability of measures of visual short-term memory capacity. *Psychonomic Bulletin & Review*, *16*(6), 1000–1010. https://doi.org/10/c32bch

LaBar, K. S., & Cabeza, R. (2006). Cognitive neuroscience of emotional memory. *Nature Reviews Neuroscience*, *7*(1), 54–64. https://doi.org/10/bk9dcz

Lagattuta, K. H., & Thompson, R. A. (2007). The development of self-conscious emotions: Cognitive processes and social influences. In *The self-conscious emotions: Theory and research* (pp. 91–113). Guilford Press.

Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (1997). *International Affective Picture System (IAPS): Technical manual and affective ratings*. https://doi.org/10/hcrv

Laybourn, S., Frenzel, A. C., Constant, M., & Liesefeld, H. R. (2020). Unintended Emotions in the Laboratory: Emotions Incidentally Induced by a Standard Visual Working Memory Task Relate to Task Performance. https://osf.io/dr62j/

Liesefeld, H. R., Liesefeld, A. M., Sauseng, P., Jacob, S. N., & Müller, H. J. (2020). How visual working memory handles distraction: Cognitive mechanisms and electrophys-

iological correlates. *Visual Cognition*, *28*(5-8), 372–387. https://doi.org/10/gg5vsv
Liesefeld, H. R., & Müller, H. J. (2019). Current directions in visual working memory research: An introduction and emerging insights. *British Journal of Psychology*, *110*(2), 193–206. https://doi.org/10/gfvm2p
Long, F., Ye, C., Li, Z., Tian, Y., & Liu, Q. (2020). Negative emotional state modulates visual working memory in the late consolidation phase. *Cognition and Emotion*, *34*(8), 1646–1663. https://doi.org/10/ghp84s
Luck, S. J. (2014, May 30). *An introduction to the Event-Related Potential technique* (2nd ed.). A Bradford Book.
Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10/cqwttd
Luck, S. J., & Vogel, E. K. (2013). Visual working memory capacity: From psychophysics and neurobiology to individual differences. *Trends in Cognitive Sciences*, *17*(8), 391–400. https://doi.org/10/39v
Luria, R., Balaban, H., Awh, E., & Vogel, E. K. (2016). The contralateral delay activity as a neural measure of visual working memory. *Neuroscience & Biobehavioral Reviews*, *62*, 100–108. https://doi.org/10/f8dp5m
Mayring, P. (2014). *Qualitative content analysis: Theoretical foundation, basic procedures and software solution*.
Mayring, P., & Fenzl, T. (2014). *QCAmap. A software for qualitative content analysis*. https://www.qcamap.org/
Morey, C. C. (2019). Perceptual grouping boosts visual working memory capacity and reduces effort during retention. *British Journal of Psychology*, *110*(2), 306–327. https://doi.org/10/ghs9vm
Muis, K. R., Pekrun, R., Sinatra, G. M., Azevedo, R., Trevors, G., Meier, E., & Heddy, B. C. (2015). The curious case of climate change: Testing a theoretical model of epistemic beliefs, epistemic emotions, and complex learning. *Learning and Instruction*, *39*, 168–183. https://doi.org/10/ggd6zw
Muis, K. R., Psaradellis, C., Lajoie, S. P., Di Leo, I., & Chevrier, M. (2015). The role of epistemic emotions in mathematics problem solving. *Contemporary Educational Psychology*, *42*, 172–185. https://doi.org/10/gnv4rg
Mulligan, K., & Scherer, K. R. (2012). Toward a Working Definition of Emotion. *Emotion Review*, *4*(4), 345–357. https://doi.org/10/gf7nr3
Pashler, H. (1988). Familiarity and visual change detection. *Perception & Psychophysics*, *44*(4), 369–378. https://doi.org/10/d3h3b6
Pekrun, R. (2006). The Control-Value Theory of Achievement Emotions: Assumptions, Corollaries, and Implications for Educational Research and Practice. *Educational Psychology Review*, *18*(4), 315–341. https://doi.org/10/d6rrq9
Pekrun, R. (2018). Control-value theory: A social-cognitive approach to achievement emotions. In G. A. D. Liem & D. M. McInerney (Eds.), *Big theories revisited 2: A volume of research on sociocultural influences on motivation and learning.* Information Age Publishing.
Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ). *Contemporary Educational Psychology*, *36*(1), 36–48. https://doi.org/10/djzhcs
Pekrun, R., Lichtenfeld, S., Marsh, H. W., Murayama, K., & Goetz, T. (2017). Achievement Emotions and Academic Performance: Longitudinal Models of Reciprocal Effects. *Child Development*, *88*(5), 1653–1670. https://doi.org/10/gbw6vg
Pekrun, R., & Perry, R. P. (2014). Control-value theory of achievement emotions. In *International handbook of emotions in education* (pp. 120–141). Routledge/Taylor & Francis Group.
Pekrun, R., & Stephens, E. J. (2012). Academic emotions. In K. R. Harris, S. Graham, T. Urdan, S. Graham, J. M. Royer, & M. Zeidner (Eds.), *APA educational psychology handbook, Vol 2: Individual differences and cultural and contextual factors.* (pp. 3–31). American Psychological Association. https://doi.org/10/bdqx6d
Pekrun, R., Vogl, E., Muis, K. R., & Sinatra, G. M. (2017). Measuring emotions during epistemic activities: The Epistemically-Related Emotion Scales. *Cognition and Emotion*, *31*(6), 1268–1276. https://doi.org/10/ghphct
Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and Psychopathology*, *17*(03). https://doi.org/10/d6f7tr
Putwain, D. W., Becker, S., Symes, W., & Pekrun, R. (2018). Reciprocal relations between students' academic enjoyment, boredom, and achievement over time. *Learning and Instruction*, *54*, 73–81. https://doi.org/10/gdbvxc
Robison, M. K., & Unsworth, N. (2018). Cognitive and contextual correlates of spontaneous and deliberate mind-wandering. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(1), 85–98. https://doi.org/10/gcx8th
Rouder, J. N., Morey, R. D., Cowan, N., Zwilling, C. E., Morey, C. C., & Pratte, M. S. (2008). An assessment of fixed-capacity models of visual working memory. *Proceedings of the National Academy of Sciences*, *105*(16), 5975–5979. https://doi.org/10/fngr7w
Souza, A. S., & Skóra, Z. (2017). The interplay of language and visual perception in working memory. *Cognition*, *166*, 277–297. https://doi.org/10/gbm62h
Souza, A. S., Thaler, T., Liesefeld, H. R., Santos, F. H., Peixoto, D. S., & Albuquerque, P. B. (2021). No evidence that self-rated negative emotion boosts visual working memory precision. *Journal of Experimental Psychology: Human Perception and Performance*, *47*(2), 282–307. https://doi.org/10/ghwzjb
Spachtholz, P., Kuhbandner, C., & Pekrun, R. (2014). Negative affect improves the quality of memories: Trading capacity for precision in sensory and working memory. *Journal of Experimental Psychology: General*, *143*(4), 1450–1456. https://doi.org/10/f6c5dp
van Someren, M. W., Barnard, Y. F., & Sandberg, J. A. C. (1995). The think aloud method: A practical guide to modelling

cognitive processes. *Information Processing & Management*, *31*(6), 906–907. https://doi.org/10/fdzb2d

Vogel, E. K., & Awh, E. (2008). How to exploit diversity for scientific gain: Using individual differences to constrain cognitive theory. *Current Directions in Psychological Science*, *17*(2), 171–176. https://doi.org/10/bcd74p

Vogel, E. K., & Machizawa, M. G. (2004). Neural activity predicts individual differences in visual working memory capacity. *Nature*, *428*(6984), 748–751. https://doi.org/10/dpb3j5

Vogl, E., Pekrun, R., Murayama, K., & Loderer, K. (2020). Surprised–curious–confused: Epistemic emotions and knowledge exploration. *Emotion*, *20*(4), 625–641. https://doi.org/10/gjp858

Vogl, E., Pekrun, R., Murayama, K., Loderer, K., & Schubert, S. (2019). Surprise, curiosity, and confusion promote knowledge exploration: Evidence for robust effects of epistemic emotions. *Frontiers in Psychology*, *10*, 2474. https://doi.org/10/gngt82

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070. https://doi.org/10/ck3

Wilken, P., & Ma, W. J. (2004). A detection theory account of change detection. *Journal of Vision*, *4*(12), 11. https://doi.org/10/bkrxvz

Xie, W., & Zhang, W. (2016). Negative emotion boosts quality of visual working memory representation. *Emotion*, *16*(5), 760–774. https://doi.org/10/f848bj

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233–235. https://doi.org/10/c693sk

Supplemental Material

Information on Transcription of "Think Aloud" Protocols

1. Use "P:" or "R:", respectively, to indicate that the participant/researcher is talking
2. Transcribe verbatim, except when the participant recites colors. Summarize this by adding the following to the transcription: "recites colors"
3. Pauses in participants' monologues are not noted
4. Fillers such as "erm" do not need to be transcribed
5. Include non-verbal utterances, such as laughing or coughing, in brackets and in italics
6. Replace names of people, towns or any other such information with "XYZ"

Coding Scheme

Data regarding researcher questions (RQ) 1a and 1b were analyzed using and inductive procedure (Mayring, 2014), as, to the authors' knowledge, there are no prior findings regarding these research questions. Therefore, categories needed to be extracted from the textual material itself on the basis of a predefined selection criterion and level of abstraction (see Table S1 and Table S2).

RQ1a: What do participants feel when performing a VWM task?

Selection Criterion. Select all text passages in which participants referred to any sort of emotional states experienced during the VWM task. Do not select any references to emotional states that pertain to the think-aloud task (e.g., "It stresses me out to talk and perform the task at the same time").

Level of Abstraction. Categories are formulated as specific emotional states or personal feelings, which participants referred to during the VWM task.

RQ1b: Which aspects of the VWM task trigger these discrete emotions?

Selection Criterion. Select all text passages in which participants explicitly referred to or hinted at reasons, sources or processes related to the emotional states or feelings experienced/perceived during the VWM task.

Level of Abstraction. Categories are formulated as specific reasons, sources or processes affecting or leading to participants' emotional states and feelings experienced/perceived during the VWM task.

Table S1

Coding Scheme for RQ1a

Category Definition	Anchor Examples	Coding Guidelines
Anger	That just makes me angry.	Clear meaning component in the text; Multiple responses allowed (applies to all categories here)
Frustration	It's really frustrating	
Joy	I'm enjoying this; I was happy about that	
Boredom	It's always the same thing; It's starting to get boring	
Tension/Nervousness	It's probably because of nerves.	
Confusion	I'm a bit confused.	
Desperation	I get desperate	
Hope	I think it's better now, I hope I'll do better.	
Shame	I'm a bit ashamed.	
Disappointment	I'm disappointed when I don't know it (the correct color).	
Uncertainty	I feel uncertain and that's not pleasant.	
Anxiety	I feel afraid of not doing it right.	

Table S2

Coding Scheme for RQ1b

Category Definition	Anchor Examples	Coding Guidelines
Self-expectations	This isn't really that difficult.	Clear meaning component in the text; Multiple responses allowed (applies to all categories here)
VWM task is challenging (negative sense)	I'm out of my depth.	
General judgement of the VWM task	At the end of the day, it's just like a game.	
Dissatisfaction with the VWM task design	It's always the same thing.	
Change in motivation	It doesn't matter to me that much anymore.	
Social comparison	I'm always asking myself, if I'm that bad or if the others are also this bad.	
Referring to missing performance feedback	It would be interesting to know your score.	
Referring to missing time reference	You don't know when it'll be over.	
VWM task is challenging (positive sense)	I want to continue doing this and I want to do well.	
Thoughts on strategies to improve achievement	You start and build themes.	

2.2 Massive effects of saliency on information processing in visual working memory

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 The main manuscript here is the published version, and I formatted the supplements.

For this publication, I was involved in the following:

- Conceptualization
- Methodology
- Programming the experiments
- Data collection
- Data analysis
- Data curation
- Initial draft of the manuscript
- Review and editing of the manuscript
- Creation of the figures
- Formatting

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Massive Effects of Saliency on Information Processing in Visual Working Memory

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Abstract
Limitations in the ability to temporarily represent information in visual working memory (VWM) are crucial for visual cognition. Whether VWM processing is dependent on an object's saliency (i.e., how much it stands out) has been neglected in VWM research. Therefore, we developed a novel VWM task that allows direct control over saliency. In three experiments with this task (on 10, 31, and 60 adults, respectively), we consistently found that VWM performance is strongly and parametrically influenced by saliency and that both an object's relative saliency (compared with concurrently presented objects) and absolute saliency influence VWM processing. We also demonstrated that this effect is indeed due to bottom-up saliency rather than differential fit between each object and the top-down attentional template. A simple computational model assuming that VWM performance is determined by the weighted sum of absolute and relative saliency accounts well for the observed data patterns.

Keywords
visual short-term memory, priority map, attention, visual search, visual perception, open data, open materials, preregistered

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Visual working memory (VWM) is a crucial hub in the processing of visual information, and its limitations are strongly related to general cognitive ability (Fukuda et al., 2010). Variation in VWM performance is typically interpreted in terms of some limited commodity (slots or resources; Cowan, 2001; Liesefeld & Müller, 2019a; Luck & Vogel, 2013; Ma et al., 2014), but alternative interpretations exist (Emrich et al., 2017; Oberauer & Lin, 2017). Identifying influences on VWM performance is of high applied and theoretical relevance because of its central role in theories of visual cognition.

It has been extensively demonstrated that how well an object is memorized hinges on its behavioral relevance, that is, on the explicit intention to favor one or several objects (top-down influences; Emrich et al., 2017; Souza & Oberauer, 2016). How VWM processing might differ for equally relevant objects because of contextual features of these objects themselves (bottom-up influences) has been largely neglected. In fact, all current models assume that, apart from random variation, all equally relevant objects within a display are processed equally well or have the same chance of being processed. This assumption seems reasonable for highly controlled, abstract stimuli but might not hold for somewhat more naturalistic stimuli and for the everyday use of VWM in complex real scenes.

It is well known from the visual attention literature that factors other than top-down goals influence the allocation of processing resources (Awh et al., 2012; Liesefeld et al., 2018; Wolfe & Horowitz, 2017). A particularly strong influence on object processing that is largely neglected in the VWM literature is bottom-up saliency. An object is salient if at least one of its features stands out, such as the blackness of a black sheep in a flock of white sheep. More technically, saliency is largely determined by local feature contrast (Nothdurft, 1993): Via lateral inhibition (i.e., at the same hierarchical level

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of visual processing), neurons with overlapping tuning curves (i.e., coding similar features) mutually suppress each other (*lateral iso-feature suppression*; Li, 2002); the resulting net activity is highest for features that differ maximally from their immediate surroundings, because the respective neuronal activity receives little suppression. Because saliency has a strong and parametric influence on object processing in visual search (Liesefeld et al., 2016), it seems likely that salient objects are also prioritized for VWM processing.

In the rare cases in which the influence of object saliency on VWM processing has been studied, the design did not allow manipulating each object's saliency independently (Rajsic et al., 2016) or confounded saliency with the discriminability of the to-be-remembered feature. Klink et al. (2017), for example, had participants remember the orientation of Gabor gratings and manipulated saliency by varying the Gabor contrast (see Fig. 1a; see also Knops et al., 2014). In line with an effect of saliency, the lower the contrast, the worse the VWM performance. However, varying the contrast also influences the discriminability of the to-be-remembered orientation because the Gabor grating increasingly merges with the background for lower contrasts. In fact, in psychophysical studies, Gabor contrast is often used to scale discrimination difficulty (e.g., Alvarez & Cavanagh, 2008). These and other confounds also affect studies using quasinatural stimuli (which are by definition not well-controlled; for a review, see Santangelo, 2015). Nevertheless, these studies indicate that saliency has some influence on VWM processing.

To study the influence of saliency on VWM encoding under controlled conditions, we developed a task that deconfounds the saliency of target objects and discriminability of to-be-remembered features and allows the researcher to manipulate each object's saliency continuously and independently (see Fig. 1b). With this novel task, we conducted three experiments in which participants had to remember the color of three target objects. These three targets were always equally likely to be probed but differed in saliency either within or across displays. Our results show a strong impact of bottom-up saliency on how well equally relevant objects are stored in VWM.

Statement of Relevance

The amount of visual information arriving each moment from our eyes is impossible to process to any reasonable extent by any limited system, and human visual processing abilities are severely limited indeed; the major bottleneck for visual processing is called visual working memory (VWM). Using a novel task design, we demonstrated that the selection problem is solved in part by preferably processing the most prominent objects within a scene. How well an object is processed in VWM is determined both by how much it stands out and by how strong the other competitors in the scene are. This study brings VWM research one step closer to the highly complex real world and reveals that saliency has a major impact on VWM processing that is easily overlooked in the traditionally very abstract VWM paradigm.

Experiment 1

Method

In many VWM studies, participants hold the colors of a bunch of isolated objects in mind for a short retention period and then have to decide whether one of the objects changed color in a second display (*change detection*) or reproduce the color of a probed object (*continuous report*). A wide variety of versions of this basic design exist, but the focus on isolated (i.e., highly salient) objects is common to virtually all of them (see Fig. 1d). To open up the VWM paradigm to the well-controlled examination of saliency effects, we developed a novel VWM task in which we can directly, gradually, and independently manipulate each object's saliency while keeping the discriminability of the to-be-remembered features and the objects' behavioral relevance untouched. This design also enables the use of modern computational models and neuroimaging methods.

We built on our previous experience from visual attention research to develop the task. In particular, Liesefeld et al. (2016) devised a visual search task that allowed a gradual manipulation of the search target's saliency (see also Nothdurft, 1993) and showed that search becomes faster as a continuous function of target saliency. By placing a tilted target bar into a dense array of vertical nontarget bars and adapting the tilt of the target bar (and therefore the contrast between target and nontargets), we were able to control target saliency to any desired precision. Liesefeld et al. (2017) showed that in this design, processing priority (measured by the order of attention allocations) is almost perfectly determined by object saliency.

Here, we translated this design to the study of VWM by employing memory displays featuring a dense array of vertical nontarget bars into which three differently tilted and randomly colored target bars were placed (see Fig. 1b). Participants had to remember the target bars' colors in order to later reproduce one of them. In

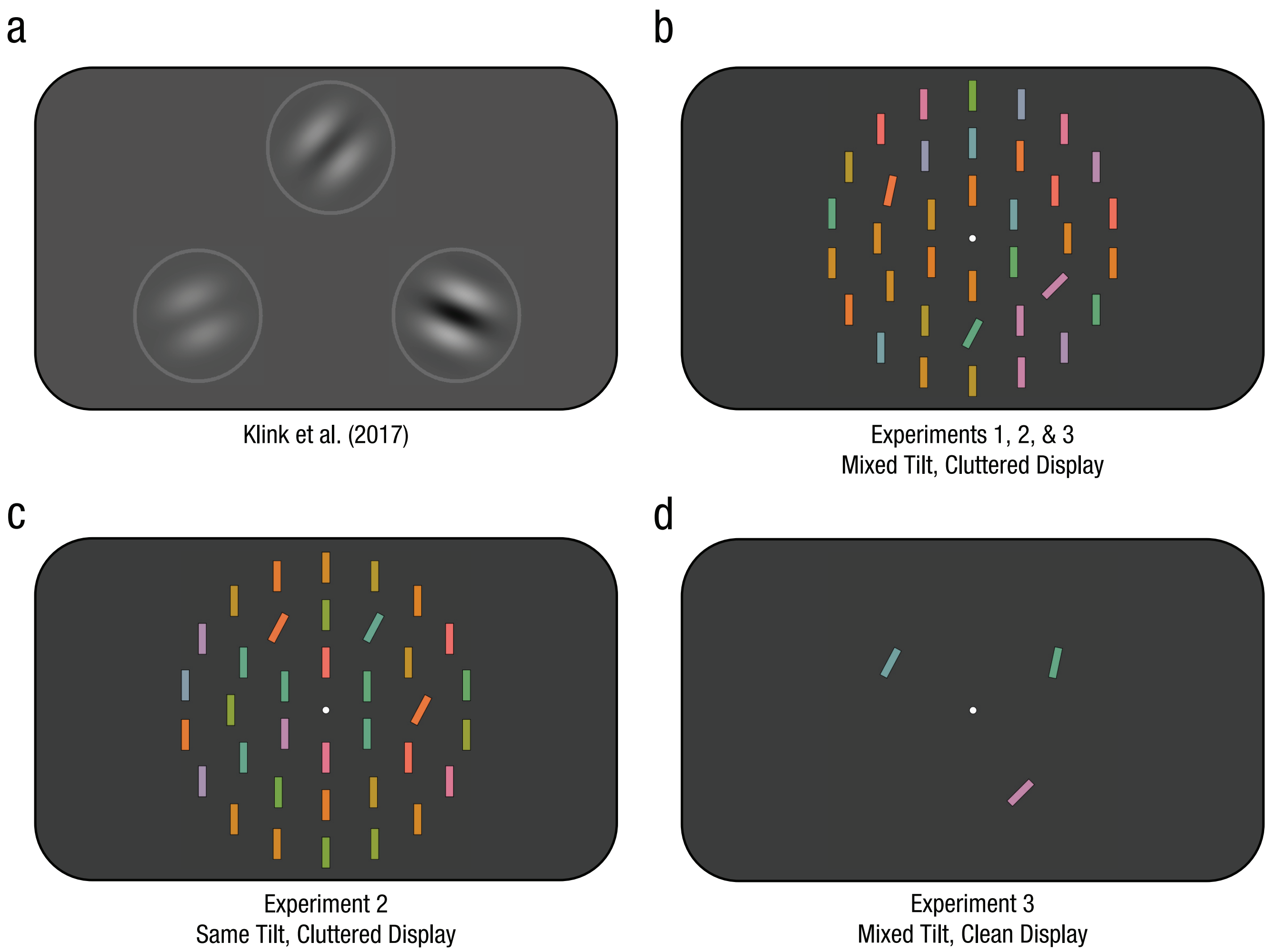

Fig. 1. A typical example of previous manipulations of saliency and design of the present memory displays. Klink et al. (2017) had participants remember the orientations of Gabor gratings and manipulated saliency via the gratings' contrasts (a); note how the contrast also influences the discriminability of the to-be-remembered orientations. In our novel task design (b and c; Experiments 1–3), participants have to remember the colors of three tilted target bars to later reproduce one of these colors, and saliency is manipulated via target tilt. Using the same tilt for all three of the target bars in Experiment 2 (c) equated the bars' relative saliency within each display. Removing the vertical nontarget bars in Experiment 3 (d) rendered all target bars highly salient (leaving only the isolated colored objects that are often used in studies of visual working memory).

order not to make color dominate the contrast (and therefore determine saliency), we also drew the nontarget bars in random (completely irrelevant) colors.

The critical deviation from previous research on VWM is that our displays are cluttered with irrelevant vertical nontarget bars. As explained above, this is necessary to control the saliency of the relevant bars because saliency of an object depends on its relationship to its immediate surroundings. This is not an artificial change to the task, though. It mimics a feature of the real world: Hardly any natural environment consists of well-isolated relevant objects, but the real world is cluttered with many objects that are irrelevant for the task at hand (e.g., Hollingworth, 2008). Also note that in Liesefeld et al.'s (2016) study, even targets with a 12° tilt (the smallest tilt employed in the present study) produced clear pop-out, that is, participants were able to almost exclusively process the target bar and completely ignore the vertical nontarget bars. Thus, the vertical bars are sufficiently less salient than even the 12°-tilted bars, so that they likely do not significantly compete for VWM processing as distractors in other designs would (Liesefeld et al., 2014; Vogel et al., 2005; for a review, see Liesefeld et al., 2020).

Participants. For each experiment, sample size was determined via sequential testing with Bayes factors (BFs), following the recommendations by Schönbrodt and Wagenmakers (2018; for details, see the Supplemental Material available online). The critical tests determining the stopping rule were directional (and thus conducted one-tailed; see https://osf.io/ktp6n for the preregistration). These tests examined whether VWM performance (the mean absolute angular distance between correct and selected response, i.e., *recall error*) would decrease with object saliency (tilt). This resulted in a sample of 10 adults with normal or corrected-to-normal vision (age: M = 26.3 years, SD = 3.37; four female; all right-handed).

Procedure and design. After a 1-s fixation dot, the memory display (see Fig. 1b) was presented for 350 ms. This display consisted of a dense array of vertical nontarget bars among which were three differently tilted (12°, 28°, 45°) target bars. The colors of all bars (both target and nontarget) were randomly chosen. Participants task was to remember the target bars' color. The memory display was followed by another 1-s fixation dot (delay period). A response display was then presented; this display contained a color wheel and outlined placeholder bars at the locations of each bar from the memory display. One of the placeholders was filled in black to indicate which bar to report (hereafter, *probe*), and participants were instructed to report the color they remembered for that bar by using the computer mouse to select a point on the color wheel. After each response, a feedback line appeared at the correct location on the color wheel to show the participant the correct response (and, by implication, how far off the actual response was).

Each participant completed a total of 600 trials divided into blocks of 30 trials each. Each condition (i.e., tilt of the probe) was randomly presented 200 times (10 times per block).

Data analysis. In addition to the t tests discussed in the Participants section, we report Bayes factors quantifying the evidence for the alternative over the null hypothesis (BF_{10}, BF_{+0}, or BF_{-0}) or the null over the alternative hypothesis (BF_{01}). For directional tests, we report the corresponding BF_{+0} or BF_{-0} (which place zero probability on negative or positive effects, respectively), rather than the undirectional BF_{10}.

Results

As expected, our manipulation of saliency had a huge and reliable impact on VWM performance (see Fig. 2): Despite all three objects being equally relevant, recall error was higher for 12° probes (M = 59.07°, between-participants 95% confidence interval [CI] = [50.04, 68.10]) than for 28° probes (M = 41.84°, 95% CI = [32.81, 50.86]), $t(9)$ = 6.56, p < .001, d_z = 2.07, 95% CI = [0.93, 3.19], BF_{+0} = 551.51, and higher for 28° probes than for 45° probes (M = 28.14°, 95% CI = [19.12, 37.17]), $t(9)$ = 4.66, p < .001, d_z = 1.47, 95% CI = [0.54, 2.37], BF_{+0} = 70.6. Effect sizes were so huge that despite the relatively small sample size (which we had defined as the minimum in our preregistration), the BFs indicated overwhelming evidence for both differences. This finding demonstrates that VWM performance is strongly and parametrically dependent on saliency.

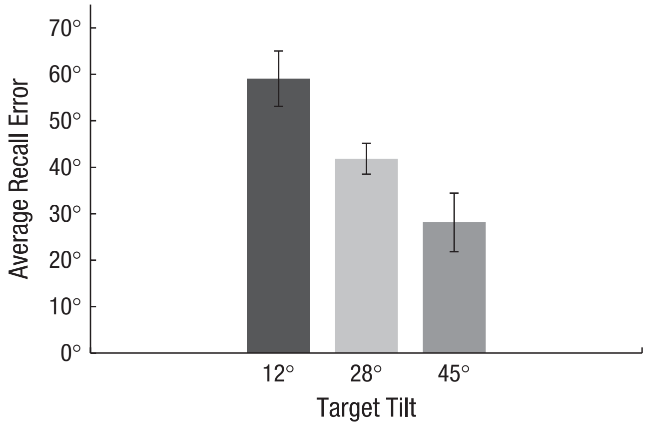

Fig. 2. Results from Experiment 1: average recall error (i.e., mean absolute difference between correct responses and given responses) for each of the three target tilts. Error bars represent 95% within-participants confidence intervals.

Fitting the data to the Zhang and Luck (2008) model revealed that the probability that the probed item was in memory (p_{mem}) differed significantly between 12° probes (M = 44.08%, 95% CI = [32.25, 55.89]) and 28° probes (M = 68.89%, 95% CI = [57.06, 80.71]), $t(9)$ = 6.37, p < .001, d_z = 2.01, 95% CI = [0.89, 3.10], BF_{10} = 227.57, and between 28° and 45° probes (M = 86.41%, 95% CI = [74.58, 98.23]), $t(9)$ = 4.10, p = .003, d_z = 1.30, 95% CI = [0.42, 2.14], BF_{10} = 18.18 (see the Supplemental Material for details on the model and model parameters). However, the memory precision (as estimated in terms of the standard deviation of a von Mises distribution) did not significantly differ between 12° probes (M = 26.93°, 95% CI = [22.31, 31.55]) and 28° probes (M = 25.99°, 95% CI = [21.37, 30.61]), $t(9)$ = 0.315, p = .760, d_z = 0.10, 95% CI = [−0.52, 0.72], BF_{01} = 3.10, or between 28° and 45° probes (M = 23.91°, 95% CI = [19.29, 28.53]), $t(9)$ = 1.29, p = .230, d_z = 0.41, 95% CI = [−0.25, 1.04], BF_{01} = 1.68. Even though this evidence for the absence of an effect on memory precision is only moderate or indecisive, respectively, it is clear that potential effects on precision cannot explain the overwhelming evidence for an effect of saliency on recall error (BF_{+0} = 551.51 and BF_{+0} = 70.6).

Experiment 2

Saliency might influence VWM processing in two nonexclusive ways. First, objects compete for VWM processing, so the most salient object within a display is eventually remembered best. This effect depends on the object's relation to other objects in the display, and we therefore refer to it as an effect of *relative saliency*.

Second, processing of more salient objects might be enhanced regardless of what else is in the display—an effect of *absolute saliency*. In visual search, the absolute saliency of a single target affects processing difficulty (Liesefeld et al., 2016; Nothdurft, 1993), but little is known about the effects of relative saliency with multiple target objects.

Method

To disentangle the two potential effects of saliency, we ran an experiment that compared the mixed-tilt displays of Experiment 1 with displays containing three bars of the same tilt. An effect of absolute saliency would predict that even in displays with only 12°-tilted bars (12° same-tilt displays), each 12°-tilted bar is remembered worse than each 45°-tilted bar in 45° same-tilt displays. If relative saliency contributed to the effect of saliency observed in Experiment 1, the 45°-tilted object was processed particularly well (beyond the effect of absolute saliency) by virtue of the other two tilted bars being less salient. Correspondingly, the 12°-tilted object then was processed particularly poorly because the other two tilted bars were more salient. By contrast, when all targets within a display are equally salient, the degree of VWM processing should be equal for all of them. This means that each 45°-tilted object in a display with only 45°-tilted objects among vertical bars would be remembered less well than the 45°-tilted object competing with the 28°- and 12°-tilted object in mixed-tilt displays. Conversely, each 12°-tilted object in a display with only 12°-tilted objects would be remembered better than the 12°-tilted object competing with the 28°- and 45°-tilted objects in Experiment 1. Thus, demonstrating that performance decreases from mixed- to same-tilt displays for 45°-tilted objects and increases for 12°-tilted objects would constitute proof of an influence of relative saliency on VWM performance.

In Experiment 2, the preregistered tests determining the stopping rule for the sequential testing procedure examined whether recall error would decrease with object saliency (as in Experiment 1) for both same- and mixed-tilt displays and also whether recall error would differ between same- and mixed-tilt displays even for the same probe tilt (see https://osf.io/d8t62 for the preregistration). We predicted an increase for 45° probes and a decrease for 12° probes. This resulted in a sample of 31 adults with normal or corrected-to-normal vision (age: M = 26.4 years, SD = 5.44; 25 female; four left-handed). Experiment 2 was modeled after Experiment 1, with the crucial difference being that one of two types of memory displays could be presented on each trial. Mixed-tilt displays were identical to the displays of Experiment 1 (see Fig. 1b) in all relevant aspects. Same-tilt displays were similar to mixed-tilt displays except that the tilted bars all shared the same tilt (12°, 28°, or 45°).

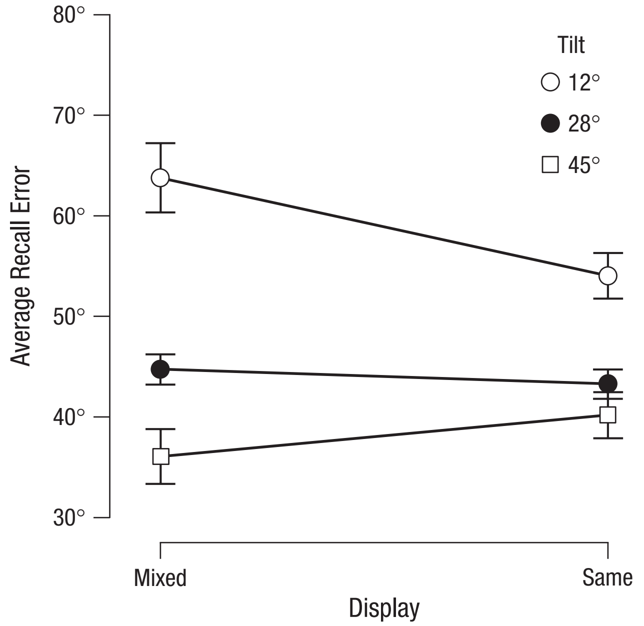

Fig. 3. Results from Experiment 2: average recall error (i.e., mean absolute difference between correct responses and given responses) as a function of display condition and target tilt. Error bars represent 95% within-participants confidence intervals.

Each participant completed a total of 600 trials divided into blocks of 30 trials each. Each condition (i.e., Type of Display × Tilt of the Probe) was randomly presented 100 times.

Results

The mixed-tilt condition of Experiment 2 replicated the results of Experiment 1 (see Fig. 3): Recall error was higher for 12° probes (M = 63.77°, 95% CI = [58.94, 68.59]) than for 28° probes (M = 44.74°, 95% CI = [39.92, 49.57]), $t(30) = 10.57$, $p < .001$, $d_z = 1.90$, 95% CI = [1.30, 2.49], $BF_{+0} = 1.44 \times 10^9$, and higher for 28° probes than for 45° probes (M = 36.06°, 95% CI = [31.24, 40.89]), $t(30) = 5.83$, $p < .001$, $d_z = 1.05$, 95% CI = [0.60, 1.48], $BF_{+0} = 1.68 \times 10^4$.

Crucially, and as expected, performance was better for 12° probes, $t(30) = 6.02$, $p < .001$, $d_z = 1.08$, 95% CI = [0.63, 1.52], $BF_{+0} = 2.69 \times 10^4$, and worse for 45° probes, $t(30) = -2.88$, $p = .004$, $d_z = -0.52$, 95% CI = [−0.89, −0.13], $BF_{-0} = 11.56$, in same-tilt compared with mixed-tilt displays. This difference was weak and unreliable only for 28° probes (for which we had no specific hypotheses, as mentioned in our preregistration; see https://osf.io/d8t62), $t(30) = 1.57$, $p = .128$, $d_z = 0.28$, 95% CI = [−0.08, 0.64], $BF_{01} = 1.75$. Indeed, VWM recall performance for a particular object depends on the object's relative saliency with respect to the other objects in the scene.

Even though the effect of probed-target tilt was weaker for same- than for mixed-tilt displays, it was still present, indicating an effect of absolute saliency on top of the effect of relative saliency. In particular, recall error was higher for 12° same-tilt displays (M = 54.02°, 95% CI = [49.20, 58.85]) than for 28° same-tilt displays (M = 43.29°, 95% CI = [38.47, 48.12]), $t(30) = 7.79$, $p < .001$, $d_z = 1.40$, 95% CI = [0.90, 1.89], $BF_{+0} = 2.39 \times 10^6$, and higher for 28° same-tilt displays than for 45° same-tilt displays (M = 40.19°, 95% CI = [35.37, 45.02]), $t(30) = 3.10$, $p = .002$, $d_z = 0.56$, 95% CI = [0.17, 0.93], $BF_{+0} = 18.85$ (see Fig. 3). Replicating Experiment 1, results from the Zhang and Luck (2008) mixture model again showed that saliency mainly influenced p_{mem} in both same- and mixed-tilt displays (see the Supplemental Material).

Computational Modeling

One might argue that the observed effects of target tilt are not due to differential bottom-up saliency but, rather, to differential fit between each object and the top-down attentional template used to select target objects (e.g., Duncan & Humphreys, 1989; Geng & Witkowski, 2019). In particular, when participants look for tilted objects, their attentional template in our study might be matched best by the 45°-tilted object, followed by the 28°-tilted object, despite all objects being equally relevant. Such an attentional template might be optimal because it minimizes the match between the search template and the vertical (0°) nontarget objects, thus potentially minimizing interference (Geng & Witkowski, 2019).

Method

To test how well the two conflicting explanations account for the data from Experiment 2, we used computational modeling. In particular, we devised two novel models that implement the two potential accounts for the observed data pattern. First, the saliency model attempts to account for the data by a mixture of absolute and relative saliency; the degree to which relative saliency has an influence is a free parameter estimated from the data (w_{rel}). Second, the alternative optimal-template model posits that the different target bars differentially match the top-down template. Importantly, rather than deciding a priori on the value of the template, we included template tilt as a free parameter so that the optimization algorithm could estimate the unobservable template tilt from the observed behavioral data (for a detailed description of both models, see the Supplemental Material).

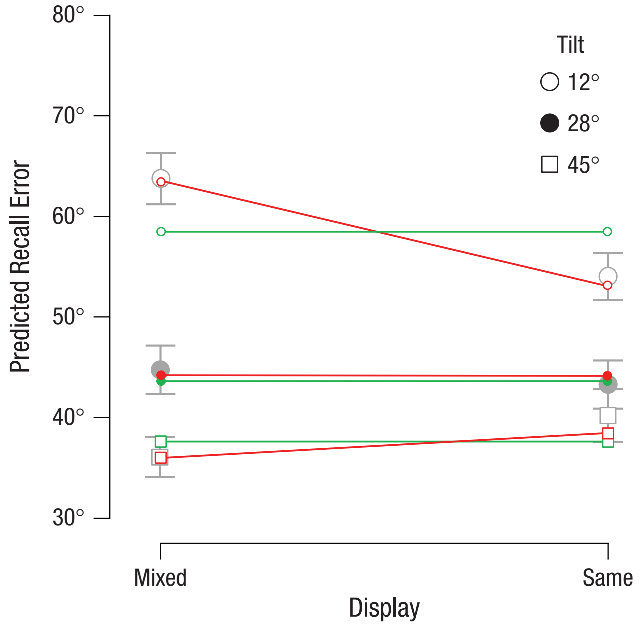

Fig. 4. Predictions of our preferred saliency model (red) and the alternative optimal-template model (green) as a function of display condition and target tilt. For comparison, mean empirical data are plotted in gray (error bars indicate ±1 *SE*).

Results

Comparing the fit of both models with the data of Experiment 2 (see Fig. 4), we found that the saliency model well outperformed the optimal-template model. In particular, the optimal-template model failed to account for the difference between same- and mixed-tilt displays. Thus, performance in Experiment 2 is best explained by variation in saliency. Notably, to account for the data, the saliency model has to assume a positive influence of relative saliency ($w_{rel} > 0$), thus providing further support for this novel assumption.

Experiment 3

The model was devised after Experiment 2 was conducted and analyzed to rule out the possibility (brought forward by a reviewer) that our data might also be explained by participants employing some attentional template. To additionally provide an empirical test with a priori hypotheses, we preregistered and ran Experiment 3 (see https://osf.io/f9c72 for the preregistration). We reasoned that if differential fit between the objects and an attentional template explains our results, the effect of tilt should remain when the vertical bars are removed (clean displays[1]; see Fig. 1d) because the tilted bars still differentially fitted to this assumed attentional template. By contrast, our explanation in terms of saliency predicts that removing the task-irrelevant vertical bars renders all tilted bars highly and almost equally salient because local feature contrast is high for all three bars when presented in isolation (see the Method section for Experiment 1). In contrast to the cluttered displays of Experiment 1, clean displays should result in a strong decrease or even a complete absence of the effect of tilt.

Method

Experiment 3 was conducted online (for details, see the Supplemental Material). The preregistered *t* tests determining the stopping rule for the sequential testing procedure examined whether recall error would decrease with object saliency in displays with vertical nontarget bars (cluttered displays; mixed-tilt targets as in Experiments 1 and 2) and whether the effect of tilt was lower in clean displays compared with cluttered displays. A third noncritical hypothesis was that the effect of tilt might be fully absent in clean displays. This sequential testing procedure (for details, see the Supplemental Material and the preregistration) resulted in a sample of 60 adults with normal or corrected-to-normal vision (age: M = 25.6 years, SD = 6.20; 23 female; four left-handed).

Experiment 3 was modeled after Experiment 1, with the critical difference being that one of two types of memory displays could be presented on each trial. Cluttered displays were identical to the displays of Experiment 1 (see Fig. 1b) in all relevant aspects. Clean displays contained only the three tilted bars (i.e., the task-irrelevant vertical nontarget bars were removed) but were otherwise identical to cluttered displays. Each participant completed a total of 150 trials divided into blocks of 50 trials. Each condition (i.e., Type of Display × Tilt of the Probe) was randomly presented 25 times.

Results

For cluttered displays, we replicated the results of Experiments 1 and 2 (mixed-tilt displays; see Fig. 5): Recall error was higher for 12° probes (M = 71.64°, 95% CI = [68.10, 75.18]) than for 28° probes (M = 48.56°, 95% CI = [45.02, 52.10]), $t(59) = 11.74$, $p < .001$, d_z = 1.52, 95% CI = [1.14, 1.88], $BF_{+0} = 2.63 \times 10^{14}$, and higher for 28° probes than for 45° probes (M = 35.30°, 95% CI = [31.76, 38.84]), $t(59) = 6.11$, $p < .001$, $d_z = 0.79$, 95% CI = [0.50, 1.08], $BF_{+0} = 3.18 \times 10^5$. Crucially, and as expected, the effect of tilt decreased in clean displays compared with cluttered displays for 12° probes compared with 28° probes, $t(59) = -10.01$, $p < .001$, d_z = −1.29, 95% CI = [−1.63, −0.95], $BF_{-0} = 2.69 \times 10^4$, and for 28° probes compared with 45° probes, $t(59) = -5.06$, $p < .001$, $d_z = -0.65$, 95% CI = [−0.93, −0.37], BF_{-0} = 8024.60. Finally, there was no significant effect of tilt,

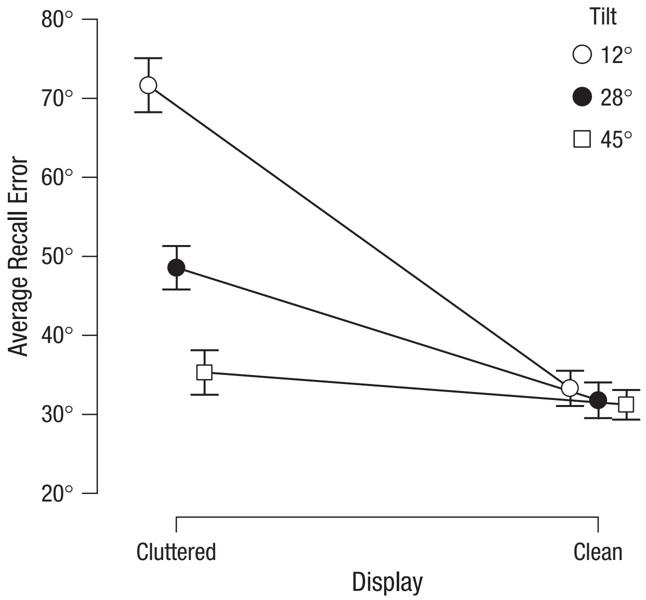

Fig. 5. Results from Experiment 3: average recall error (i.e., mean absolute difference between correct responses and given responses) as a function of display condition and target tilt. Error bars represent 95% within-participants confidence intervals.

and there was even some evidence for the absence of this effect, in clean displays for 12° probes (M = 33.31°, 95% CI = [29.78, 36.85]) compared with 28° probes (M = 31.79°, 95% CI = [28.25, 35.33]), $t(59) = 1.17$, p = .247, $d_z = 0.15$, 95% CI = [−0.10, 0.40], $BF_{01} = 3.71$, and moderate evidence for the absence of an effect for 28° probes compared with 45° probes (M = 31.23°, 95% CI = [27.70, 34.77]), $t(59) = 0.46$, $p = .650$, $d_z = 0.06$, 95% CI = [−0.19, 0.31], $BF_{01} = 6.41$. This pattern indicates that the effect of target tilt is not due to differential match between the objects and an attentional template but, rather, due to variation in saliency.

General Discussion

We set out to demonstrate an influence of saliency on performance in a VWM task, an influence that has not yet been acknowledged in any current model of VWM processing. Experiment 1 indeed provided overwhelming evidence for the existence of this effect by showing that how well an object's color is remembered is largely determined by how much it differs in tilt from its immediate surroundings (local feature contrast). Experiment 2 demonstrated that both relative and absolute saliency contribute to the effect of saliency. Finally, a newly devised computational model and Experiment 3 demonstrated that the effect of target tilt is indeed explained by saliency rather than differential fit between each object and some attentional template. How saliencies of multiple relevant objects interact has—to the best of our knowledge—not yet been systematically examined, and an observation of an effect of relative saliency is therefore new not only for the VWM community but also for the visual cognition community in general.

Many theories of visual search (e.g., Duncan & Humphreys, 1989; Fecteau & Munoz, 2006; Liesefeld & Müller, 2019b, 2020; Wolfe, 2021) assume a preattentive spatial representation of the visual scene coding for relevance at each location and informing a second, attentive-processing stage. This assumption is needed to explain how second-stage focal attention can be allocated to the most promising objects in view without analyzing each object in detail first. This preattentive *priority map* is thought to be influenced by task goals and experiences (top-down) as well as saliency (bottom-up). We propose that the very same priority map supporting visual search might also determine VWM processing (Bundesen et al., 2011; Liesefeld et al., 2020). Findings from the present study and those manipulating each object's relevance (e.g., Emrich et al., 2017) can be integrated using the priority-map concept: Although previous studies manipulated top-down influences, we are the first to systematically manipulate bottom-up contributions (i.e., saliency) to preattentive-priority-map activations in a VWM task.

There are many potential mechanisms by which first-stage priority (and, thus, saliency) could theoretically impact second-stage VWM processing. First, it might influence VWM encoding directly (in particular without the allocation of focal attention) or via the allocation of an attentional resource (Emrich et al., 2017). Second, encoding and attention allocation could be conceived of as serial (one object is processed or attended after the other) or parallel (all objects are processed or attended at once; Bundesen et al., 2011; Sewell et al., 2014). Third, priority might affect how much (if any) information about each object is processed or how much of a limited (quantized or continuous) VWM resource it receives (Ma et al., 2014; Vogel et al., 2006). Fourth, priority might additionally influence third-stage postselective and postencoding processes, such as how fast attention is disengaged from a processed object to continue with the next object in line (see Sauter et al., 2021) or how well a processed object is stored (e.g., by attaining a special state; Oberauer & Lin, 2017; Olivers et al., 2011). All kinds of combinations between these mechanisms seem theoretically possible, and we will speculate on some in turn.

Our exploratory Zhang and Luck (2008) mixture-model analysis indicated that saliency mainly affects whether an item is encoded (p_{mem}) rather than the precision of encoding (standard deviation of the von Mises distribution). If mixture modeling is valid (for a critical view, see Ma, 2018), this finding somewhat constrains the range of potential mechanisms by which saliency (as represented on a first-stage, preattentive priority map) is translated into VWM performance: If, at the second stage, all objects are processed in parallel, one would assume that information on each object accrues continually with a slower rate for less salient objects (e.g., Moran et al., 2016). The mixture-modeling finding would then indicate that an object is stored in full when a certain amount of information is accumulated (Bundesen et al., 2011) because, otherwise, we should have observed an effect on memory precision. Alternatively, second-stage encoding might proceed serially, starting at the most salient target object and sometimes not reaching the least salient target object (Wolfe, 2021; e.g., because focal attention needs to be allocated sequentially to encode each object).

Another implication from our study is that previous studies might have unintentionally induced and misinterpreted disguised effects of saliency. Data from the same-tilt condition of Experiment 2 indicate that less information was remembered in low-saliency compared with high-saliency displays (the effect of absolute saliency). One could easily misinterpret this effect as a decrease in VWM capacity from high- to low-saliency displays. However, this would be theoretically awkward because a fixed limit is the core assumption behind both slot theories and flexible-resource theories of VWM alike (for an alternative, see Oberauer & Lin, 2017). Actually, this effect recalls other findings that processing difficulty of an object class correlates with how many objects of that class can be held in VWM: Manipulating object complexity, Alvarez and Cavanagh (2004) showed that visual search rate (as a measure of processing difficulty) predicts VWM capacity for the respective object class. They argued that search rate and VWM capacity were related by the objects' informational content, which would affect how long it takes to process each item in visual search and how much of the limited VWM capacity it consumes. In light of the present results, it seems equally likely, though, that the two measures are more directly related by the saliency-dependent ease of processing each object. For example, processing of the first low-saliency/high-complexity objects might take so long (see the third-stage mechanisms discussed above) that on some trials, no time is left to process the remaining objects in the display (e.g., in our same-tilt displays, only two of the three 12° objects might have been processed on some trials). Crucially, in our study, this cannot be explained by the to-be-encoded informational content (which was the same for each object) but must be due to the saliency of the object carrying that information. Thus, effects of object complexity on VWM performance observed in earlier studies might alternatively be explained as effects of saliency. More complex objects might be less salient in their respective displays and therefore take longer to process (irrespective of their informational content). Along similar lines, our findings might trigger reevaluations of further influential findings from VWM studies using relatively complex stimuli.

Transparency

Action Editor: Krishnankutty Sathian
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Author Contributions
H. R. Liesefeld developed the study concept. M. Constant programmed the experiments, supervised data collection, and analyzed the results. Both authors contributed to the study design and interpreted the data. H. R. Liesefeld drafted the manuscript, and M. Constant provided critical revisions. Both authors approved the final manuscript for submission.
Declaration of Conflicting Interests
The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.
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Open Practices
All data, experimental programs, and analysis scripts have been made publicly available via OSF and can be accessed at https://osf.io/bpavz/files. The design and analysis plans for the three experiments were preregistered at https://osf.io/ktp6n (Experiment 1), https://osf.io/d8t62 (Experiment 2), and https://osf.io/f9c72 (Experiment 3). This article has received the badges for Open Data, Open Materials, and Preregistration. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797620975785

Note

1. We thank Nelson Cowan for suggesting these displays at the Virtual Working Memory 2020 Symposium.

References

Alvarez, G. A., & Cavanagh, P. (2004). The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science*, *15*(2), 106–111. https://doi.org/10/b88gs7

Alvarez, G. A., & Cavanagh, P. (2008). Visual short-term memory operates more efficiently on boundary features than on surface features. *Perception & Psychophysics*, *70*(2), 346–364. https://doi.org/10/dbs6k7

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. https://doi.org/10/f34nps

Bundesen, C., Habekost, T., & Kyllingsbæk, S. (2011). A neural theory of visual attention and short-term memory (NTVA). *Neuropsychologia*, *49*(6), 1446–1457. https://doi.org/10/b8863z

Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, *24*(1), 87–114. https://doi.org/10/ddq83h

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458. https://doi.org/10/ck4p2t

Emrich, S. M., Lockhart, H. A., & Al-Aidroos, N. (2017). Attention mediates the flexible allocation of visual working memory resources. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(7), 1454–1465. https://doi.org/10/gbn3xj

Fecteau, J., & Munoz, D. (2006). Salience, relevance, and firing: A priority map for target selection. *Trends in Cognitive Sciences*, *10*(8), 382–390. https://doi.org/10/fb66m9

Fukuda, K., Vogel, E., Mayr, U., & Awh, E. (2010). Quantity, not quality: The relationship between fluid intelligence and working memory capacity. *Psychonomic Bulletin & Review*, *17*(5), 673–679. https://doi.org/10.3758/17.5.673

Geng, J. J., & Witkowski, P. (2019). Template-to-distractor distinctiveness regulates visual search efficiency. *Current Opinion in Psychology*, *29*, 119–125. https://doi.org/10/gg5vtp

Hollingworth, A. (2008). Visual memory for natural scenes. In S. J. Luck & A. Hollingworth (Eds.), *Visual memory* (pp. 123–162). Oxford University Press.

Klink, P. C., Jeurissen, D., Theeuwes, J., Denys, D., & Roelfsema, P. R. (2017). Working memory accuracy for multiple targets is driven by reward expectation and stimulus contrast with different time-courses. *Scientific Reports*, *7*(1), Article 9082. https://doi.org/10/gbtwp7

Knops, A., Piazza, M., Sengupta, R., Eger, E., & Melcher, D. (2014). A shared, flexible neural map architecture reflects capacity limits in both visual short-term memory and enumeration. *The Journal of Neuroscience*, *34*(30), 9857–9866. https://doi.org/10/f6fskg

Li, Z. (2002). A saliency map in primary visual cortex. *Trends in Cognitive Sciences*, *6*(1), 9–16. https://doi.org/10/bjs32m

Liesefeld, A. M., Liesefeld, H. R., & Zimmer, H. D. (2014). Intercommunication between prefrontal and posterior brain regions for protecting visual working memory from distractor interference. *Psychological Science*, *25*(2), 325–333. https://doi.org/10/f5344z

Liesefeld, H. R., Liesefeld, A. M., Pollmann, S., & Müller, H. J. (2018). Biasing allocations of attention via selective weighting of saliency signals: Behavioral and neuroimaging evidence for the dimension-weighting account. In T. Hodgson (Ed.), *Processes of visuospatial attention and working memory* (Vol. 41, pp. 87–113). Springer International Publishing. https://doi.org/10/dc5q

Liesefeld, H. R., Liesefeld, A. M., Sauseng, P., Jacob, S. N., & Müller, H. J. (2020). How visual working memory handles distraction: Cognitive mechanisms and electrophysiological correlates. *Visual Cognition*, *28*(5–8), 372–387. https://doi.org/10/gg5vsv

Liesefeld, H. R., Liesefeld, A. M., Töllner, T., & Müller, H. J. (2017). Attentional capture in visual search: Capture and post-capture dynamics revealed by EEG. *NeuroImage*, *156*, 166–173. https://doi.org/10/gbsjqj

Liesefeld, H. R., Moran, R., Usher, M., Müller, H. J., & Zehetleitner, M. (2016). Search efficiency as a function of target saliency: The transition from inefficient to efficient search and beyond. *Journal of Experimental Psychology: Human Perception and Performance*, *42*, 821–836. https://doi.org/10/ggbnjc

Liesefeld, H. R., & Müller, H. J. (2019a). Current directions in visual working memory research: An introduction and emerging insights. *British Journal of Psychology*, *110*(2), 193–206. https://doi.org/10/gfvm2p

Liesefeld, H. R., & Müller, H. J. (2019b). Distractor handling via dimension weighting. *Current Opinion in Psychology*, *29*, 160–167. https://doi.org/10/ggbnjd

Liesefeld, H. R., & Müller, H. J. (2020). Modulations of saliency signals at two hierarchical levels of priority computation revealed by spatial statistical distractor learning. *Journal of Experimental Psychology: General*. Advance online publication. https://doi.org/10.1037/xge0000970

Luck, S. J., & Vogel, E. K. (2013). Visual working memory capacity: From psychophysics and neurobiology to individual differences. *Trends in Cognitive Sciences*, *17*(8), 391–400. https://doi.org/10/39v

Ma, W. J. (2018). *Problematic usage of the Zhang and Luck mixture model*. bioRxiv. https://doi.org/10/ggbpq3

Ma, W. J., Husain, M., & Bays, P. M. (2014). Changing concepts of working memory. *Nature Neuroscience*, *17*(3), 347–356. https://doi.org/10/gd8cbs

Moran, R., Zehetleitner, M., Liesefeld, H. R., Müller, H. J., & Usher, M. (2016). Serial vs. parallel models of attention in visual search: Accounting for benchmark RT-distributions. *Psychonomic Bulletin & Review*, *23*(5), 1300–1315. https://doi.org/10/gbgdk6

Nothdurft, H.-C. (1993). The role of features in preattentive vision: Comparison of orientation, motion and color cues. *Vision Research*, *33*(14), 1937–1958. https://doi.org/10/d6fw5n

Oberauer, K., & Lin, H.-Y. (2017). An interference model of visual working memory. *Psychological Review*, *124*(1), 21–59. https://doi.org/10/f9mhb2

Olivers, C. N. L., Peters, J., Houtkamp, R., & Roelfsema, P. R. (2011). Different states in visual working memory: When it guides attention and when it does not. *Trends in Cognitive Sciences*, *15*(7), 327–334. https://doi.org/10/fcfxg6

Rajsic, J., Sun, S. Z., Huxtable, L., Pratt, J., & Ferber, S. (2016). Pop-out and pop-in: Visual working memory advantages for unique items. *Psychonomic Bulletin & Review*, *23*(6), 1787–1793. https://doi.org/10/f9hf36

Santangelo, V. (2015). Forced to remember: When memory is biased by salient information. *Behavioural Brain Research*, *283*, 1–10. https://doi.org/10/f67dgp

Sauter, M., Hanning, N. M., Liesefeld, H. R., & Müller, H. J. (2021). Post-capture processes contribute to statistical learning of distractor locations in visual search. *Cortex*, *135*, 108–126. https://doi.org/10.1016/j.cortex.2020.11.016

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. *Psychonomic Bulletin & Review*, *25*(1), 128–142. https://doi.org/10/gcsk2r

Sewell, D. K., Lilburn, S. D., & Smith, P. L. (2014). An information capacity limitation of visual short-term memory. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(6), 2214–2242. https://doi.org/10/gg5fn7

Souza, A. S., & Oberauer, K. (2016). In search of the focus of attention in working memory: 13 years of the retro-cue effect. *Attention, Perception, & Psychophysics*, *78*(7), 1839–1860. https://doi.org/10/f83nvs

Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*(7067), 500–503. https://doi.org/10/drbpg5

Vogel, E. K., Woodman, G. F., & Luck, S. J. (2006). The time course of consolidation in visual working memory. *Journal of Experimental Psychology: Human Perception and Performance*, *32*(6), 1436–1451. https://doi.org/10/c2vrp7

Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*. Advance online publication. https://doi.org/10.3758/s13423-020-01859-9

Wolfe, J. M., & Horowitz, T. S. (2017). Five factors that guide attention in visual search. *Nature Human Behaviour*, *1*(3), Article 0058. https://doi.org/10/gftcnc

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233–235. https://doi.org/10/c693sk

Supplement

Supplementary Methods

Participants

For each experiment, sample size was determined via sequential testing with Bayes factors, following the recommendations by Schönbrodt and Wagenmakers (2018). This recently developed sequential testing procedure with preregistered hypotheses continues data collection until a pre-defined level of evidence in terms of Bayes factors in favor of or against each preregistered hypothesis is reached and thereby ensures that strong evidence for either the presence or the absence of each relevant effect is gained. In our preregistration, we set a minimum of 10 and a maximum of 60 participants in the laboratory Experiments 1 and 2. For Experiment 3, which was conducted online and was shorter, we set a minimum of 20 and a maximum of 100 participants (*BF*s were evaluated after each batch of 20 participants). We stopped testing when sufficient evidence for either the null or the alternative ($BF \geq 6$) was reached, which was achieved for each critical test.

All participants provided informed consent prior to the respective experiment, reported normal or corrected-to-normal visual acuity and normal color vision and were naïve as to the purpose of the study. They received either course credits or monetary remuneration (9 €/h) in Experiments 1 and 2. Experiment 3 was run online and recruitment was done via Prolific (https://prolific.co/). Participants were paid 1.50£ for around 15 minutes of their time. All experimental procedures were approved by the ethics committee of the Department Psychology and Pedagogics at LMU. In Experiments 1 and 2, no participant was excluded from the analyses and two trials of one participant (0.33%) were dropped in each experiment because of a delay in memory-display offset. Three participants of Experiment 2 had already participated in Experiment 1 and three others had participated in another related experiment.[1] In Experiment 3, eight participants were excluded. As specified during recruitment, these eight participants were not compensated and were replaced.

Stimuli

For Experiment 1 and 2, stimuli were displayed on a 24” TFT-LCD monitor (ASUS VG248QE, 1920x1080 pixels, 60 Hz) at a viewing distance of 70 cm. The testing room was pitch dark and there were between one and four participants in each testing session. For Experiment 1, OpenSesame 3.2.7 (Mathôt et al., 2012) with the PsychoPy backend was used for stimulus presentation. For CIE L*a*b* conversion to sRGB, the colormath Python package was used. Experiment 2 and 3 were written in JavaScript and HTML5, using the d3.js library for color conversion. Experiment 2 was run in Mozilla Firefox (68.0) and the online Experiment 3 was run on participants’ computers using various browsers. For Experiment 3, participants’ display size and distance from the screen were estimated via the methods of Li et al. (2020). We used a central fixation dot (white; 0.18° in Experiments 1 and 0.16° in Experiments 2 and 3) against a gray background (RGB: [60, 60, 60], L* = 25.3, 14.2 cd/m² for Experiment 1 and 2). The sample display consisted of 33 vertical and 3 differently tilted (12°, 28° and 45°) colored bars subtending a visual angle of 1.30 × 0.33° each. The bars were arranged in three concentric rings (2°, 4° and 6° radius) with respectively 6, 12 and 18 bars on each. The relevant (tilted) bars were presented at a randomly chosen position on the middle ring. Colors were randomly drawn from a circle in a luminance plane of the CIE 1976 L*a*b* color space (L* = 63, center: a* = 9, b* = 27, illuminant: D65, 2° standard observer) with a radius of 40 (Mean ΔE2000 between two adjacent colors: 0.43). These parameters were chosen to ensure that all colors could be mapped onto the 24-bits sRGB color space. CIE L*a*b* is a device-independent color space based on the opponent color theory that aspires to be perceptually uniform, taking into account the specificities of the human color vision system (for a more detailed overview, see Fairchild, 2013). The color wheel (360 colors; randomly rotated in 30° steps) used to give the response had a width of 0.66° and a radius of 8°, 7.8°, or 7.1° in Experiments 1, 2 and 3, respectively. While the mouse hovered on the color wheel, the probe dynamically changed color according to the mouse position.

Analysis

Our analyses focus on the mean average absolute distance between the correct and the selected color (*recall error*). For statistical analyses, JASP 0.13.1 (JASP Team, 2020) was used with default settings for the Bayesian priors. Directed Bayesian *t* tests were conducted to analyze the differences between the different tilts. The *BF* quantifies the support for a hypothesis (first subscript) over another (second subscript), regardless of whether these models are correct. The subscript “0” always refers to the null hypothesis (H_0). When conducting undirected (two-sided) tests, the subscript “1” refers to the alternative hypothesis (H_1). When conducting directed (one-sided) tests, instead of “1”, the subscripts “+” or “–” were used depending on the direction of the hypothesis (H_+ or H_-, respectively). Throughout the results, we will report the BF for the most favored hypothesis (e.g., if the null is more probable, BF_{01} will be reported), as we find it most intuitive to interpret.

We also conducted the traditional (frequentist) significance tests for reference and report effect sizes (Cohen’s d_z) followed by their respective 95% *CI*s in brackets. Finally, as an exploratory analysis, we fitted the data from Experiment 1 and 2 – separately per participants and condition – to the mix-

[1] Withholding these participants from the analyses did not influence the pattern of results.

ture model of Zhang and Luck (2008).[2] This model (which is not without critiques, see Ma, 2018) assumes that the recall error arises from two sources represented by two parameters. The first parameter is the probability that the probed object is present in memory (p_{mem}). If the probed object is not in memory, the response will be made randomly. If the probed object is in memory, the second parameter reflects the precision of its representation (*sd*; higher *sd*s indicate lower precision). We extracted these parameters (Table S1; using MemToolbox; Suchow et al., 2013, https://memtoolbox.org/) and ran statistical analyses on them (Table S2). The below tables show the results for Experiment 2; the respective analyses for Experiment 1 are described in the main article. Due to the low number of trials per condition (25), we did not apply mixture-modeling to the data of Experiment 3.

Supplementary Results

Table S1

Descriptive statistics for mixture-model parameters estimated from data of Experiment 2.

Parameter	Condition	*M*	*SD*	95% *CI* Lower	95% *CI* Upper
	Experiment 2 – *Mixed* Displays				
p_{mem}	12°	40.09%	20.67	32.50	47.67
	28°	66.41%	19.41	59.29	73.53
	45°	75.02%	15.53	69.32	80.72
sd	12°	29.75°	12.95	25.00	34.50
	28°	27.84°	10.43	24.01	31.66
	45°	23.63°	4.65	21.92	25.33
	Experiment 2 – *Same* Displays				
p_{mem}	12°	52.51%	18.71	45.65	59.38
	28°	68.39%	21.67	60.44	76.34
	45°	71.82%	21.94	63.77	79.87
sd	12°	26.53°	8.60	23.37	29.68
	28°	27.74°	8.30	24.70	30.79
	45°	26.76°	6.52	24.37	29.15

Details on Computational Modeling

Saliency model

The core of our saliency model is given by Equation 1, which states that an object *i*'s total saliency (s_{total}) is determined by the weighted (w_{rel}) sum of its absolute ($s_{abs(i)}$) and relative ($s_{rel(i)}$) saliency:

$$s_{total} = s_{abs(i)} + w_{rel} \cdot s_{rel(i)} \tag{1}$$

To keep the model as simple as possible, we assumed that the degree of tilt (t_i) (with respect to the non-targets) directly translates into an object's individual saliency ($s_{ind(i)}$). This sufficiently approximates the true transfer function for the present purposes as demonstrated by the model fit (see Table S3 and Fig. 4 in the main document).

We implemented relative saliency as the object's individual saliency divided by the sum of all *k* objects' saliencies (including the object's own saliency; *divisive normalization*, Bays, 2014; Liesefeld & Müller, 2021):

$$s_{rel} = \frac{s_{ind(i)}}{\sum_{j=1}^{k} s_{ind(j)}} = \frac{t_i}{\sum_{j=1}^{k} t_j}; i, j = 1, ..., k \tag{2}$$

Absolute saliency was defined as the individual saliency normalized by the maximal saliency (in the present design, saliency would be maximal for 90° tilted bars):

$$s_{abs(i)} = \frac{s_{ind(i)}}{s_{max}} = \frac{t_i}{90} \tag{3}$$

Template Model

Template mismatch (d_i) was defined as the difference between the tilt of the template (as estimated from the data via the free parameter t_t) and the individual tilt of each object (t_i):

$$d_i = |t_t - t_i|;\ \text{with } 0 \leq t_t \leq 180 \text{ and } d_i \leq 90 \tag{4}$$

Model fitting

To relate total saliency to performance in the present task (recall error averaged across participants, *re*) for the purpose of fitting the models to the empirical data, we used (out of convenience and to keep our modeling simple and agnostic with regard to the exact mechanisms linking saliency/template mismatch and VWM recall performance) a power-law function with the free parameters α and β (as we did in other contexts before, Liesefeld et al., 2016):

$$re_i = \alpha \cdot s_{total(i)}{}^{\beta} \tag{5}$$

If we had used the same transfer function for the template model, a $d_i = 0$ (i.e., a perfect template match) would predict $re = 0$. Thus, to predict non-perfect performance even for perfect template matches, we had to give this model extra flexibility by including an intercept term as a fourth free parameter:

$$re_i = \alpha \cdot d_i{}^{\beta} + \gamma \tag{6}$$

[2] Due to a technical mistake only the response and the correct answer were stored for Experiment 2, so that we could not apply other, more advanced models (e.g., Bays, 2014; Oberauer & Lin, 2017; van den Berg et al., 2012).

Table S2

Paired samples t *tests on mixture-model parameters for Experiment 2.*

Comparison	$t(30)$	Cohen's d_z	BF	Favors
		Mixed displays		
p_{mem} – 12° vs. 28°	-9.66^{***}	−1.73 [−2.29, −1.17]	9.83e+7	H_1
p_{mem} – 28° vs. 45°	-4.71^{***}	−0.85 [−1.25, −0.43]	456.21	H_1
sd – 12° vs. 28°	0.87	0.16 [−0.20, 0.51]	3.68	H_0
sd – 28° vs. 45°	2.41^{*}	0.43 [0.06, 0.80]	2.26	H_1
		Same displays		
p_{mem} – 12° vs. 28°	-6.84^{***}	−1.23 [−1.69, −0.75]	1.11e+5	H_1
p_{mem} – 28° vs. 45°	−1.83	−0.33 [−0.69, 0.04]	1.19	H_0
sd – 12° vs. 28°	−0.68	−0.12 [−0.47, 0.23]	4.23	H_0
sd – 28° vs. 45°	0.73	0.13 [−0.22, 0.48]	4.07	H_0
		Mixed vs. *Same* displays		
p_{mem} – 12°	4.38^{***}	0.79 [0.38, 1.19]	201.01	H_1
p_{mem} – 28°	−0.73	0.13 [−0.48, 0.22]	4.09	H_0
p_{mem} – 45°	1.36	0.24 [−0.12, 0.60]	2.27	H_0
sd – 12°	1.04	0.19 [−0.17, 0.54]	3.19	H_0
sd – 28°	0.04	0.01 [−0.35, 0.36]	5.22	H_0
sd – 45°	-2.26^{*}	−0.48 [−0.85, −0.10]	3.70	H_1

Note. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

The values of free parameters (w_{rel}, α, and β, or t_i, α, β and γ, respectively) were determined by a simplex routine (Nelder & Mead, 1965) as implemented as *fminsearch* in MATLAB, minimizing the sum of the squared differences between empirical and predicted recall performance (SS) per Tilt × Display Type cell (averaged across participants).

Modeling results and interpretation

As shown in Fig. 4 of the main article, our saliency model quite accurately reproduced the observed data pattern. This model also accounts well for the data pattern in Experiment 3 (not shown). Notably, parameters α and β cannot affect the predicted data pattern, because the exact same transformation is applied to each total-saliency estimate from each cell of the respective experimental design. That is, the only free parameter used to account for the observed pattern is w_{rel}. By contrast, the template model failed to account for the difference between *mixed* and *same* displays (i.e., it cannot account for the effect of relative saliency) despite having one more free parameter than the saliency model (i.e., despite being less parsimonious).

Parameter estimates for the two models are given in Table S3. It is interesting to note that the estimated template is 42.40°, thus, quite close to the maximal target tilt (45°). Furthermore, w_{rel} was estimated at 0.57. A w_{rel} considerably above zero confirms an influence of relative saliency beyond the influence of absolute saliency on VWM performance.

Table S3

*Estimated parameters of two simple models linking either saliency (*relative *and* absolute*) or match between each object and an*
(optimal) template to recall error in Experiment 2.

Model	w_{rel}	t_t	α	β	γ	SS
Saliency	0.57	–	33.32	−0.42	–	3.61
Template	–	40.35	0.39	1.22	35.56	57.11

References

Bays, P. M. (2014). Noise in neural populations accounts for errors in working memory. *Journal of Neuroscience*, *34*(10), 3632–3645. https://doi.org/10/gfwfbw

Fairchild, M. D. (2013). *Color appearance models* (3rd ed.). John Wiley & Sons, Inc. https://doi.org/10/dc5n

JASP Team. (2020). *JASP* (Version 0.13.1). https://jasp-stats.org/

Li, Q., Joo, S. J., Yeatman, J. D., & Reinecke, K. (2020). Controlling for Participants' Viewing Distance in Large-Scale, Psychophysical Online Experiments Using a Virtual Chinrest. *Scientific Reports*, *10*(1), 904. https://doi.org/10/ggpbsf

Liesefeld, H. R., & Müller, H. J. (2021). Modulations of saliency signals at two hierarchical levels of priority computation revealed by spatial statistical distractor learning. *Journal of Experimental Psychology: General*, *150*(4), 710–728. https://doi.org/10/gqdh98

Liesefeld, H. R., Moran, R., Usher, M., Müller, H. J., & Zehetleitner, M. (2016). Search efficiency as a function of target saliency: The transition from inefficient to efficient search and beyond. *Journal of Experimental Psychology: Human Perception and Performance*, *42*, 821–836. https://doi.org/10/ggbnjc

Ma, W. J. (2018). Problematic usage of the Zhang and Luck mixture model. *bioRxiv*. https://doi.org/10/ggbpq3

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*, *44*(2), 314–324. https://doi.org/10/ft2dgc

Nelder, J. A., & Mead, R. (1965). A Simplex method for function minimization. *The Computer Journal*, *7*(4), 308–313. https://doi.org/10/bkqf

Oberauer, K., & Lin, H.-Y. (2017). An interference model of visual working memory. *Psychological Review*, *124*(1), 21–59. https://doi.org/10/f9mhb2

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. *Psychonomic Bulletin & Review*, *25*(1), 128–142. https://doi.org/10/gcsk2r

Suchow, J. W., Brady, T. F., Fougnie, D., & Alvarez, G. A. (2013). Modeling visual working memory with the MemToolbox. *Journal of Vision*, *13*(10), 9. https://doi.org/10/ggbnjj

van den Berg, R., Shin, H., Chou, W.-C., George, R., & Ma, W. J. (2012). Variability in encoding precision accounts for visual short-term memory limitations. *Proceedings of the National Academy of Sciences*, *109*(22), 8780–8785. https://doi.org/10/f3trn3

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233–235. https://doi.org/10/c693sk

2.3 Effects of salience are long-lived and stubborn

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For this manuscript, I was involved in the following:

- Conceptualization
- Methodology
- Programming the experiments
- Data collection
- Data analysis
- Data curation
- Initial draft of the manuscript
- Review and editing of the manuscript
- Creation of the figures
- Formatting

Effects of salience are long-lived and stubborn

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Abstract

Salience is a core determinant of attentional processing. Although information on salience has been shown to dissipate within a few hundred milliseconds, we recently observed massive effects of salience on the delayed recall from visual working memory (VWM) more than 1300 ms after stimulus onset. Here, we manipulated presentation duration of the memory display and found that effects of salience, albeit decreasing over time, were still markedly present after 3000 ms (2000 ms presentation; Exp. 1). In an attempt to overrule this persistent influence of salience we made less salient stimuli more relevant (by rewarding their prioritized processing in Exp. 2 or by probing them more often in Exp. 3). Participants were unable to reliably prioritize low-salience stimuli. Thus, our results demonstrate that effects of salience or their repercussions have surprisingly long-lasting effects on cognitive performance that reach even relatively late processing stages and are difficult to overrule by volition.

Statement of Relevance

Objects that stand out from their surround often grasp attention. This effect of salience has been used to avoid harm. For instance, safety equipment is often made of reflective material with bright unnatural colors (e.g., a lifebuoy). However, previous reports of effects of salience lasting for only a few hundred milliseconds being quickly overridden by goal-driven processes, render this effort questionable: why bother if salience plays a role only for a glimpse? The present study shows that effects of salience last for a long time; even after 3 seconds and more they are not completely overridden by experience or volition. Thus, salience plays a much larger role for human cognition than has been previously assumed.

Keywords: Saliency, Guidance, Attentional priority, Visual short-term memory

Research on visual attention and on visual search in particular has long demonstrated that the allocation of *attentional* resources is based both on top-down and bottom-up factors (Awh et al., 2012; Corbetta & Shulman, 2002; Wolfe, 2021). The major bottom-up factor for attentional resource allocation is salience. Salience arises mainly from the local feature contrast of a given stimulus and its surroundings (Liesefeld et al., 2016; Nothdurft, 1993); stimuli with a high level of salience subjectively stand out from their environment (Liesefeld et al., 2020; Wang & Theeuwes, 2020). It is assumed that salience drives overt and covert allocations of attention in the absence or in the service of a specific task (Itti & Koch, 2001). When stimuli share the same task relevance, salience determines the order of attention allocation (Christie et al., 2018; Woodman & Luck, 1999) and, under certain conditions, salience can even overrule task relevance (Liesefeld et al., 2022; Liesefeld et al., 2017).

While salience is a major driving factor of attention, it has been claimed that its effects are short-lived (Donk & van Zoest, 2008; van Heusden et al., 2022). Specifically, these bottom-up effects would quickly be relegated by top-down control effects (de Vries et al., 2011; van Zoest & Donk, 2006; van Zoest et al., 2004) or, under the right conditions, even be mitigated before their expression (Einhäuser et al., 2008; Folk & Remington, 1998; Gaspelin & Luck, 2018).

Considering this tension between the high behavioral importance of salience and the apparent short-livedness of its effects, we'd like to point out that research on salience focuses almost exclusively on covert or overt (eye movements) shifts of attention, which are short-lived phenomena themselves. Recently, we have shown that salience can influence visual working memory (VWM), a much longer lasting cognitive mechanism; we presented memory arrays with colored bars for 350 ms and one out of 3 tilted bars was probed for recall after a 1000-ms retention interval (see Figure 1 and https://doi.org/jbgf). Targets differed in salience, but were equally likely to be probed at recall thus, top-down factors cannot be responsible for any observed effects. Still, VWM recall performance more than 1300 ms after the memory display onset was heavily affected by salience (Constant and Liesefeld, 2021; see also Klink et al., 2017).

Therefore, even if effects of salience on attentional processes and eye movements are short-lived, their repercussions at later processing stages, such as VWM, might affect behavior much more deeply than would be expected based on the findings from the attention community alone. In fact, VWM is considered the major cognitive bottleneck of visual processing with effects on even later stages such as object recognition, long-term memory formation, and action control (Liesefeld et al., 2020; Liesefeld & Müller, 2019; Rösner et al., 2022; van Ede & Nobre, 2023), so that any effect on VWM processing has strong implications for many cognitive functions and applied settings.

On that background, we wanted to see how stable effects of salience are, that is, how long after display onset they would affect behavior (Exp. 1) and how resistant they are against opposing top-down influences (Exps. 2 and 3). Results indicate that effects of salience are long-lived and quite resistant to top-down manipulations.

Experiment 1

In the first experiment, we evaluated how different presentation times (14 ms — 2000 ms) would impact the effect of salience on VWM performance. Potentially, the 350 ms presentation time plus 1000 ms retention interval might not have been enough time to see the dissipation of salience effects observed in attentional tasks (Donk & van Zoest, 2008; van Heusden et al., 2022). We expected (preregistration: https://osf.io/byr2v) the effects of salience to decrease with increasing presentation time (i.e., the longer an array is presented the less salience should affect VWM performance).

Results

The Bayesian Repeated-Measures ANOVA favored the most complete model (Presentation Time + Tilt + Presentation Time × Tilt) over all others, BF_M = 1.28e+10 (For the frequentist RM ANOVA, all $p_s < .001$ (two main effects and the interaction); see OSF repository for full ANOVA reports).

For each presentation time, the recall error for 12° probes was significantly higher than for 45°, even when the array was presented for 2000 ms (Figure 2 and Table 1; see OSF repository for descriptive statistics).

Discussion

Experiment 1 shows that the effect of salience on VWM performance is extremely long-lasting: even after 2000 ms presentation and 1000 ms retention, it was not completely relegated by top-down control. While the tilted bars all share the same relevance, performance remains biased in favor of the most salient bar.

Interestingly, even at the lowest presentation time (14 ms), the most salient target was recalled quite precisely. In fact, the recall error for 45° probes at 14 ms was lower than 12° probes' recall error at all presentation times but 2000 ms. Certainly, some of the information on 45° targets was collected from iconic memory after display offset (note that we did not employ masking), but it is still impressive that the difference in salience between 12° and 45° is worth more than 1000 ms of presentation time in terms of VWM performance ($M_{45°/14\text{ ms}}$ = 46.67° ± 2.64 lies in between $M_{12°/1000\text{ ms}}$ = 53.24° ± 4.92 and $M_{12°/2000\text{ ms}}$ = 38.76° ± 5.14).

Experiment 2

Experiment 1 indicates that top-down control cannot overcome the effect of salience within any reasonable time frame, so that an ideal distribution of VWM resources across target objects with different degrees of salience in a display can never be achieved. An alternative explanation would be that overcoming the effect of salience requires effort and participants were not sufficiently motivated to invest that effort. To increase their motivation, we added a monetary reward to the experiment and lower-salience targets were rewarded more than higher-salience targets.

With this manipulation, participants should be highly incentivized to focus their available resources on less salient targets to maximize their gains. As we believe that implementing top-down control takes more than a few hundred milliseconds, we expected (preregistration: https://osf.io/fxwyp) an effect of salience for displays presented for 350 ms. If top-down control can fully overrule the effect of salience, we expect a reversal of the pattern (according to the behavioral relevance) at 2000 ms. No performance

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All experiments reported here were preregistered on OSF. The preregistrations, experimental programs, analysis scripts, and data files can be found at: https://osf.io/xq2ng/

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Data from Experiments 1 and 3 were presented at the Vision Sciences Society meeting 2020 and 2022 (Constant and Liesefeld, 2020; Liesefeld, Constant & Oberauer, 2022). Data from Experiment 2 was also presented at the Vision Sciences Society meeting 2022.

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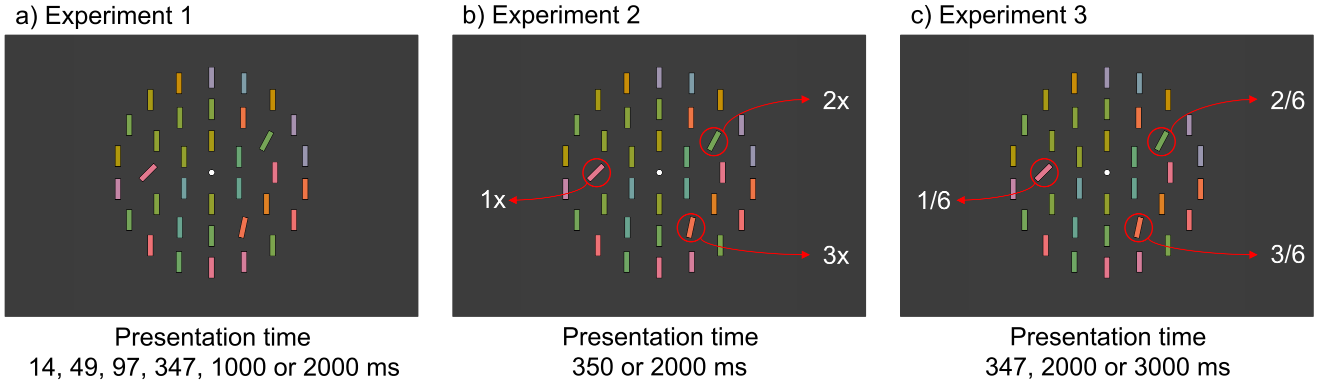
Figure 1

Memory displays used in the present study.



Note. Participants had to remember the color of only the tilted target bars. They were informed that vertical bars were completely irrelevant and these bars were never probed. In the present study the presentation time of the memory array was varied, followed by a fixed 1000 ms retention interval and a recall probe (see https://doi.org/jbgf). Participants' task was to indicate on a color wheel the color the probed (filled) bar had in the memory array. (a) In Experiment 1, each target (tilted bar) was equally relevant. (b) In Experiment 2, a performance-based bonus was awarded on each trial and multiplied by a factor dependent on target tilt (3x for 12°, 2x for 28°, 1x for 45°). (c) In Experiment 3, the probability that a target was probed depended on its tilt (3/6 of the trials for 12°, 2/6 for 28°, 1/6 for 45°).

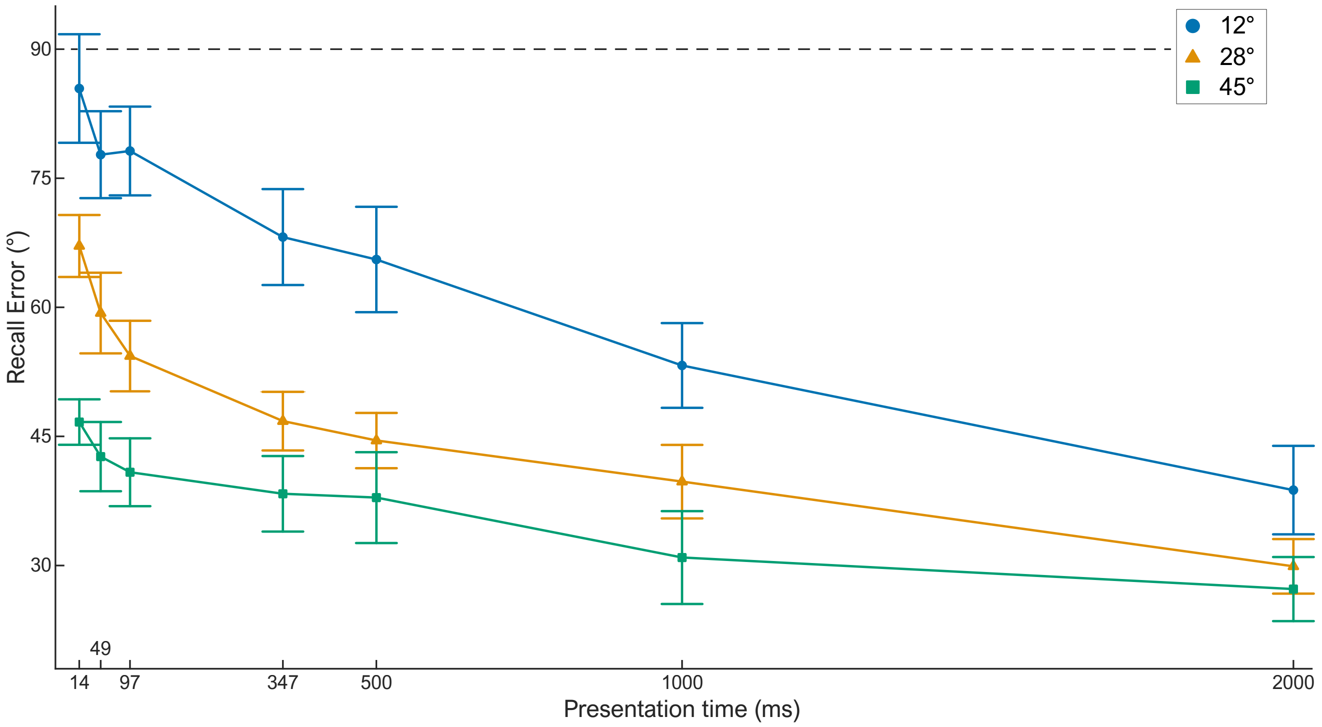
Table 1

Paired Samples t *Tests for Experiment 1.*

Presentation Time	Comparison	$t(15)$	p	Hedges' g_z	BF_{+0}
14 ms	12° > 28°	4.89	< .001	1.16 [0.63, 2.05]	316.33
	28° > 45°	11.37	< .001	2.70 [1.88, 4.30]	2.59e+6
	12° > 45°	11.56	< .001	2.74 [1.92, 4.37]	3.22e+6
49 ms	12° > 28°	5.54	< .001	1.31 [0.76, 2.26]	935.97
	28° > 45°	7.66	< .001	1.81 [1.18, 2.99]	2.49e+4
	12° > 45°	11.10	< .001	2.63 [1.83, 4.21]	1.94e+6
97 ms	12° > 28°	7.57	< .001	1.80 [1.17, 2.96]	2.20e+4
	28° > 45°	5.95	< .001	1.41 [0.85, 2.41]	1851.30
	12° > 45°	11.54	< .001	2.74 [1.91, 4.37]	3.14e+6
347 ms	12° > 28°	7.21	< .001	1.71 [1.10, 2.84]	1.30e+4
	28° > 45°	3.02	.004	0.72 [0.22, 1.44]	12.36
	12° > 45°	7.38	< .001	1.75 [1.13, 2.90]	1.66e+4
500 ms	12° > 28°	5.93	< .001	1.41 [0.84, 2.40]	1774.43
	28° > 45°	2.45	.013	0.58 [0.09, 1.26]	4.82
	12° > 45°	6.26	< .001	1.48 [0.91, 2.51]	3009.04
1000 ms	12° > 28°	4.68	< .001	1.11 [0.59, 1.97]	218.08
	28° > 45°	3.29	.003	0.78 [0.28, 1.52]	19.39
	12° > 45°	5.47	< .001	1.30 [0.75, 2.24]	839.64
2000 ms	12° > 28°	3.50	.002	0.83 [0.33, 1.59]	28.09
	28° > 45°	1.69	.056	0.40 [−0.09, 1.02]	1.53
	12° > 45°	3.52	.002	0.83 [0.34, 1.59]	29.01

Figure 2

Results from Experiment 1.



Note. Targets were equally task-relevant. Dotted line indicates chance level. Error bars reflect 95% within-participant confidence intervals (Cousineau, 2005; Morey, 2008).

difference for the three targets at 2000 ms would indicate an attenuation, but not a full elimination of the effect of salience.

Results

As expected, recall error was significantly higher for 12°- (63.06° ± 5.07) than 28°- (41.96° ± 3.80) probes at 350 ms presentation time, $t(19) = 8.29$, $p < .001$, $g_z = 1.78$ [1.21, 2.76], $BF_{+0} = 3.02e+5$ (see Figure 3). Similarly, it was also higher for 28°- than 45°- (30.20° ± 3.81) probes at this presentation time, $t(19) = 4.52$, $p < .001$, $g_z = 0.97$ [0.51, 1.66], $BF_{+0} = 261.47$.

Contrary to our expectation that top-down control can overcome or at least balance an effect of salience given enough time, at 2000 ms presentation time, recall error was still significantly higher for 12°- (30.61° ± 2.82) compared to 28°- (25.86° ± 3.19) probes, $t(19) = 3.00$, $p = .004$, $g_z = 0.64$ [0.20, 1.24], $BF_{+0} = 13.08$ and also when compared to 45° probes (24.11° ± 2.73), $t(19) = 3.39$, $p = .002$, $g_z = 0.73$ [0.28, 1.35], $BF_{+0} = 27.77$. There was however no longer a significant difference between 28°- and 45°- probes, $t(19) = 1.22$, $p = .119$, $g_z = 0.26$ [−0.18, 0.77], $BF_{0+} = 1.30$.

Discussion

It turns out that even when heavily incentivized to preferentially process less salient targets, participants cannot overcome the effect of salience, even at 2000 ms. Compared to Experiment 1, the effect seems somewhat attenuated at 2000 ms, but it's far from the reversal (better performance for the much more valuable 12°) that should have occurred if top-down control was able to dominate salience.

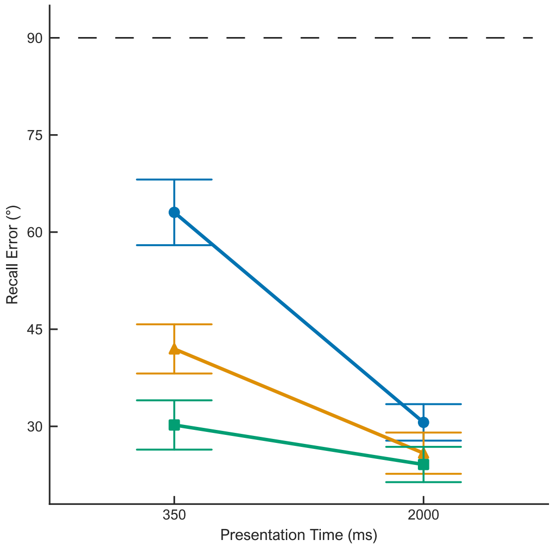
Experiment 3

It has been argued that prior experience constitutes an even stronger influence on attention allocation than observers' goals (Theeuwes, 2018). Specifically, if a certain feature or location has recently been behaviorally relevant (*intertrial priming*) or is, on average, more behaviorally relevant across a longer time period (*statistical learning*), objects with that feature or at that location increase in priority and therefore compete more vigorously for attention allocations. The same might be true for competition for VWM resources.

In Experiment 3, we boosted the less salient targets' priority by increasing the probability that they would be probed at the recall stage. As participants were told to prioritize less

Figure 3

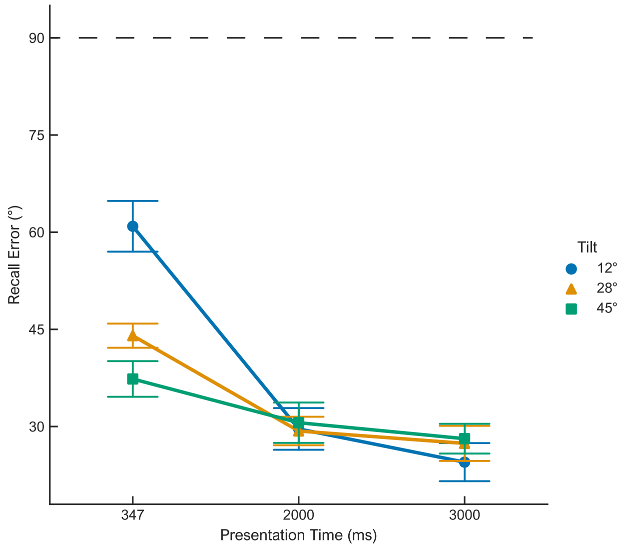
Results from Experiment 2.



Note. Participants were monetarily incentivized to prioritize processing of the least salient (12°) target. Dotted line indicates chance level. Error bars reflect 95% within-participant confidence intervals (Cousineau, 2005; Morey, 2008).

Figure 4

Results from Experiment 3.



Note. The least salient target (12°) was probed three times more often than the most salient target (45°). Dotted line indicates chance level. Error bars reflect 95% within-participant confidence intervals (Cousineau, 2005; Morey, 2008).

salient targets and that these were probed more often, influences from goals and experiences were aligned and should therefore constitute a maximally strong counterforce against salience. Furthermore, we added a third, even longer, presentation duration of 3000 ms to give top-down processes even more time to develop their full potential. We predicted (preregistration: https://osf.io/d7ku2) that participants would not be able to override the salience effect for memory displays presented for 347 ms but might be able to negate or even reverse it with longer presentation times (2000 & 3000 ms).

Results

As expected, recall error was significantly higher for 12°- (60.91° ± 3.92) than 28°- (44.02° ± 1.87) probes at 347 ms presentation time (Figure 4 and Table 2). Similarly, it was also higher for 28°- than 45°- (37.34° ± 2.75) probes at this presentation time. At 2000 ms presentation time, recall error was not significantly higher in 12°- (29.63° ± 3.22) compared to 28°- (29.31° ± 2.20) probes, nor in 28°- compared to 45°- (30.59° ± 3.12) probes. Finally, at 3000 ms recall error was not significantly lower for 12°- (24.50° ± 2.94) compared to 28°- (27.40° ± 2.71) probes nor for 28°- compared to 45°- (28.12° ± 2.30) probes. When comparing 12° and 45° at 3000 ms, performance was a little better for 12° targets.

The 12° target was thus processed slightly better than the behaviorally much less relevant 45° target (M_{diff} = -3.62° ± 4.51) but this reversal is far from convincing statistically: the *BF* is in the indecisive range (*BF* = 1.44) indicating almost no evidence for a difference; the *p* value also does not survive FDR correction ($p = .261$, corrected for 9 tests; Benjamini and Yekutieli, 2001).

To assert whether performance had reached ceiling, we ran an exploratory paired samples *t* test between the mean performance in the best condition (12°, 3000 ms) and the mean performance in the baseline block. The mean performance in the baseline block (M = 11.44°, 95% between-participant CI = 1.05) was significantly better than for the 12°, 3000 ms condition, $t(35) = 11.88$, $p < .001$, $g_z = 1.94$ [1.47, 2.64], BF_{10} = 9.47e+10.

Discussion

In Experiment 3, we observed weak evidence for the reversal expected if top-down influences can override and dominate effects of salience. Yet, it took participants 3000 ms to “implement” top-down control, which provides much leeway for extraneous strategies to be employed (see General Discussion).

At 2000 ms presentation time, already much longer than in typical VWM experiments, effects of salience and the top-down effects induced in Experiment 3 seem to have hit an equilibrium, with evidence (in terms of *BF*s) for the ab-

Table 2

Paired Samples t *Tests for Experiment 3.*

Presentation Time	Comparison	$t(35)$	p	Hedges' g_z	BF	Favors
347 ms	12° > 28°	10.32	< .001	1.68 [1.25, 2.32]	4.73e+9	H_+
	28° > 45°	4.23	< .001	0.69 [0.35, 1.11]	323.82	H_+
	12° > 45°	9.03	< .001	1.47 [1.07, 2.06]	1.77e+8	H_+
2000 ms	12° > 28°	0.15	.442	0.02 [−0.31, 0.36]	4.97	H_0
	28° > 45°	−0.96	.828	−0.16 [−0.51, 0.17]	10.14	H_0
	12° > 45°	−0.36	.640	−0.06 [−0.40, 0.28]	7.21	H_0
3000 ms	12° < 28°	−1.31	.100	−0.21 [−0.57, 0.12]	1.43	H_0
	28° < 45°	−0.49	.314	−0.08 [−0.42, 0.25]	3.67	H_0
	12° < 45°	−1.79	.041	−0.29 [−0.66, 0.04]	1.44	H_-

sence of effects of these manipulations. It seems interesting to relate this situation to the recently proposed "attentional limbo" where (overt) attention allocations apparently were not affected by either salience nor task relevance and which occurred around 250 ms after display onset (van Heusden et al., 2022). By comparison, VWM performance at 350 ms presentation time (which actually manifested more than 1350 ms after display onset) was still heavily dominated by salience.

General Discussion

In three experiments, we have tried to overcome effects of salience on VWM performance. It has been proposed that the effects of salience are short-lived because top-down control replaces bottom-up orienting after a few hundred milliseconds (Donk & van Zoest, 2008; van Heusden et al., 2022). In contrast to this clear prediction, our Experiment 1 showed salience effects on VWM performance for several seconds, that is, an order of magnitude longer than expected based on previous work. Enhancing the relevance of less salient targets with monetary incentives (Exp. 2) or by probing them more often (Exp. 3) did not erase effects of salience for up to 2 seconds of memory-array presentation. As task goals and prior experience (Awh et al., 2012) were aligned in these experiments, we conclude that neither of these top-down influences is able to overrule effects of salience (see also, Melcher & Piazza, 2011). Only with 3-s presentation duration in Exp. 3 were the effects of salience slightly reversed in favor of less salient targets. This *slight* reversal still indicates residual effects of salience, because full top-down control would have caused a *strong* reversal, that is, much better performance for less salient targets.

Indeed, previous studies have shown that top-down manipulations with presentation times shorter than 2000 ms can have strong effects on VWM performance for equally salient stimuli (Bays et al., 2011; Dube et al., 2017; Emrich et al., 2017; Klink et al., 2017; Ravizza et al., 2021; see also, Ravizza and Conn, 2022). Some of these studies have also looked at the interplay of salience, presentation time and top-down influences, but none of them contained a non-confounded and direct manipulation of to-be-remembered stimuli's salience (for a discussion, see Constant & Liesefeld, 2021).

Although salience affected performance even at the longest presentation times, less salient targets benefitted most from increased presentation times. It is therefore possible that the effect of salience could disappear with even longer presentation time (see Klink et al., 2017, Exp. 3). However, with such long presentation times, we likely do not measure pure VWM anymore, as participants probably supplement their VWM performance with other strategies such as verbalization (Overkott & Souza, 2022) that might not be affected by salience. They might also actively suppress information on the most salient object and resample from the less salient object, a process unlike what is traditionally assumed (or possible) in research on VWM and which probably does not play much of a role for the rapidly changing visual stimulation in real life.

The apparent discrepancy between our findings and Donk & van Zoest (2008; see also van Heusden et al., 2022) can be resolved by differentiating between direct effects of salience on attention allocation and indirect effects on later cognitive processes. It is possible that focal attention quickly moves on after visiting the most salient stimulus. However, being attended first might endow stimuli with a head start in the race for VWM resources (Bundesen, 1990; Ravizza et al., 2016) that is effective early on (Exp. 1, 14-ms condition) and takes several seconds to outrun for the less salient stimuli even when reinforced by top-down influences (Exps. 2 and 3). Thus, while the effects of salience on attention allocations might be short-lived, they have long-lasting repercussions that are hard to overcome. As VWM is considered the bottleneck for further visual and conceptual processing, these repercussions might have even later repercussions that are yet to be discovered.

Materials and Methods

Participants

For each experiment, sample size was determined via sequential testing with Bayes factors (*BF*), following the recommendations by Schönbrodt and Wagenmakers (2018) with a minimum of 10 and a maximum of 60 participants for Experiment 1 and 3, and 100 for Experiment 2. We stopped testing when sufficient evidence for either the null or the alternative ($BF \geq 6$) was reached for each critical test.

Stimuli, procedure & design

For Experiment 1 and 3, stimuli were displayed on a color-calibrated (120 cd/m² D65 whitepoint) 24" TFT-LCD monitor (ASUS VG248QE, 1920×1080 pixels, 144 Hz) at a viewing distance of 70 cm. The testing room was pitch dark and there were between one and four participants in each testing session. OpenSesame 3.2.8 (Mathôt et al., 2012) with the PsychoPy (Peirce, 2008) backend was used for stimulus presentation. Experiment 2 was coded in HTML and JavaScript. For this experiment, screen size and distance from the screen were estimated using the virtual chinrest method (Li et al., 2020).

Each trial began with the presentation of a central fixation dot (white, 0.18° radius) against a gray background (L* = 25.3, 14 cd/m²). After 1000 ms, a memory display was presented, consisting of 33 vertical and 3 tilted (12°, 28° and 45°) colored bars each subtending a visual angle of 1.30 × 0.33° (see Figure 1). The bars were arranged in three concentric rings (2°, 4° and 6° radius) with respectively 6, 12 and 18 bars on each. The relevant (tilted) bars were always presented on the middle ring.

Colors were randomly drawn from a circle in a luminance plane of the CIE 1976 L*a*b* color space (L* = 63, center: a* = 9, b* = 27, illuminant: D65, 2° standard observer) with a radius of 40 (Mean ΔE2000 between two adjacent colors: 0.43). These parameters were chosen to ensure that all colors could be mapped onto the 24-bits sRGB color space. CIE L*a*b* is a device-independent color space based on the opponent color theory (Hering, 1964) that aspires to be perceptually uniform, taking into account the specificities of the human color vision system (for a more detailed overview, see Fairchild, 2013).

The memory display (duration depending on the experiment) was followed by a delay period of 1000 ms during which only the fixation dot was shown. A response display was then presented containing a randomly rotated (30° steps) color wheel (360 colors) and outlined placeholder bars at the location of each bar from the memory display. One of the placeholders was filled in black to indicate which bar to report (also called *probe* in the rest of this paper), and participants were instructed to report the color they remembered for that bar by using the computer mouse to select a point on the color wheel. The color wheel had a width of 0.66° and a radius of 8°. While the mouse hovered on the color wheel, the probe dynamically changed color according to the mouse position.

Analysis

Our analyses focus on the mean absolute angular distance between the correct and the selected color (called *recall error* in the rest of this paper). As stated in our preregistrations, participants with an average recall error above 80° were excluded. Unless otherwise stated descriptive statistics are reported as mean ± 95% within-participant confidence interval (Cousineau, 2005; Cousineau & O'Brien, 2014; Morey, 2008).

Statistical analyses were performed with custom Python scripts and validated with JASP 0.16.3 (JASP Team, 2020; Love et al., 2019) with default settings for the priors. We did not implement the Bayesian directed *t* tests nor Bayesian ANOVAs in Python, thus we used the results from JASP. Bayesian repeated-measures ANOVAs and planned directed Bayesian *t* tests (Rouder et al., 2009) were conducted to analyze the differences between the conditions.

BayesFactors (*BF*) quantify the support for a hypothesis (first subscript) over another (second subscript), regardless of whether these models are correct. The subscript "0" always refers to the null hypothesis (H_0). When conducting undirected (two-sided) tests, the subscript "1" refers to the alternative hypothesis (H_1). When conducting directed (one-sided) tests, instead of "1", the subscripts "+" or "–" were used depending on the direction of the hypothesis (H_+ or H_-, respectively). Throughout the results, we reported the *BF* for the most favored hypothesis from the test we ran (e.g., if we ran a non-directed test and the null was more probable, BF_{01} was reported instead of BF_{10}), as we find it most intuitive to interpret. We also reported the traditional (frequentist) significance tests for reference and the effect sizes (mainly Hedges' g_z [Hedges, 1981; Hedges and Olkin, 1985], the unbiased equivalent of Cohen's d_z [Cohen, 1988]) followed by their 95% *CI* in brackets (Fitts, 2020; Goulet-Pelletier & Cousineau, 2018, 2019).

Experiment 1

The critical tests determining the stopping rule for Experiment 1 examined whether VWM performance (*recall error*) would decrease with object salience (tilt). This resulted in a sample of 16 healthy human adults (Mean age: 26.88 ± 1.34 [*s.e.m.*], 9 females, 1 left-handed) who received either course credits or monetary remuneration (9€/h). In this and all following experiments, all participants provided informed consent prior to the experiment, reported normal or corrected-to-normal visual acuity and normal color vision and were naïve as to the purpose of the study, and the experimental procedures were approved by the ethics committee of the Department Psychology and Pedagogics at LMU München. No participant was excluded.

In Experiment 1, the memory display was presented for either 14, 49, 97, 347, 500, 1000 or 2000 ms and all targets were equally relevant.

Each participant completed a total of 1050 trials divided into blocks of 42 trials. Each condition (i.e., Tilt of the probe × Presentation time) was randomly presented 50 times (twice per block). After each response, a feedback line appeared at the correct location on the color wheel to show the correct response (and, by implication, how far off the actual response was) to the participant.

Experiment 2

In Experiment 2 the critical tests determining the stopping rule for the sequential testing procedure examined: (1) whether the directional effect of salience was present at 350 ms presentation time and (2) whether it disappeared at 2000 ms presentation time. This resulted in a sample of 20 healthy human adults (Mean age: 27.40 ± 1.31 [*s.e.m.*], 8 females, 2 left-handed). Experiment 2 was run online (participant recruitment via Prolific) and was modeled after Experiment 1 with two key differences:

1. There were only two presentation times: 350 ms and 2000 ms.
2. Participants received points (which were converted to a monetary reward) based on their recall error and the tilt of the probe.

For the 45° probes (base formula), the number of points awarded decreased linearly from 8 (for a 0° recall error) to 0 (for 89° recall error) in 90 steps. All responses with a recall error equal to or above 90° were penalized with -1 point. Crucially, in order to incentivize prioritized processing of less salient targets, the reward and penalty were multiplied by 2 for 28° probes (from 16 to 0, penalty = -2), and for 12° probes they were multiplied by 3 (from 24 to 0, penalty = -3). Participants were made aware of these multipliers at the start of the experiment and the points earned on a given trial (rounded to 1 decimal) were shown simultaneously with the correct response after each trial (see https://doi.org/jbgg for an example of the task).

Participants' base compensation was estimated for 45 minutes of task duration and amounted to 4.5£. The monetary reward was awarded after all participants completed the experiment and was computed to average at 2£ (i.e., 45 % of the base compensation). Given that participants on Prolific take part in experiments mainly for the money, this should be a very strong incentive to bias performance in favor of the more strongly rewarded/penalized 12° objects.

Each participant completed a total of 300 trials divided into blocks of 50 trials. Each condition (presentation time × tilt of the probe) was randomly presented 50 times. One participant was excluded and replaced due to poor performance (average recall error ≥ 80°), thus the final sample size was still 20 participants.

Experiment 3

In Experiment 3, the critical tests determining the stopping rule for the sequential testing procedure examined whether the differences in recall error between the different tilts became smaller, or even reverted, as presentation time increased. However, due to the COVID-19 pandemic, testing had to be stopped earlier than originally planned in the preregistration and, because of a change in affiliation, we could not resume testing in the laboratory. We can nonetheless draw conclusions from the present results. This resulted in a sample of 37 healthy human adults. One participant was excluded from the analyses, in accordance with the exclusion criteria defined in our preregistration (mean recall error > 80°), thus the final sample was composed of 36 participants (Mean age: 25.70 ± 1.31 [*s.e.m.*], 24 females, 6 left-handed).

Experiment 3 was again modeled after Experiment 1 with the following differences:

1. The presentation times of the memory display were 347, 2000 or 3000 ms.
2. Less salient targets were probed with a higher probability.

In particular, the 12° tilted bar was probed on 3/6 of the trials, the 28° bar was probed on 2/6 of the trials and the 45° bar was probed on the remaining 1/6 of the trials. Participants were made aware (and reminded each block) that the 12° bar was more likely to be probed than the 28° bar and that the 28° bar was also more likely to be probed than the 45° bar.

Each participant completed a total of 900 trials divided into blocks of 36 trials. Each presentation time was randomly presented 300 times (12 times per block). Within each presentation time, each tilt was probed 150, 100 or 50 times (18, 12 or 6 times per block) in accordance with the aforementioned probabilities.

Moreover, at the end of the experiment, an additional block of 36 trials was run, in which a single vertical bar was presented 2° above the fixation dot for 2 seconds and participants had to recall its color. The colors of the targets were the same for all participants (from 0° to 350° on the colorwheel, in steps of 10°) but the order of presentation was randomized. This additional block (which we call the baseline block) provides us with an estimate of the maximally achievable performance for each participant.

Data availability

All analysis, experiment and data files as well as preregistrations are available on OSF (https://osf.io/xq2ng/).

References

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. https://doi.org/10/f34nps

Bays, P. M., Gorgoraptis, N., Wee, N., Marshall, L., & Husain, M. (2011). Temporal dynamics of encoding, storage, and reallocation of visual working memory. *Journal of Vision*, *11*(10), 6–6. https://doi.org/10/fm6m38

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *The Annals of Statistics*, *29*(4). https://doi.org/10/fjzj8p

Bundesen, C. (1990). A theory of visual attention. *Psychological Review*, *97*(4), 523–547. https://doi.org/10/b8djmr

Christie, G. J., Spalek, T. M., & McDonald, J. J. (2018). Salience drives overt selection of two equally relevant visual targets. *Attention, Perception, & Psychophysics*, *80*(6), 1342–1349. https://doi.org/10/gdzd2c

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Routledge. https://doi.org/10/vv3

Constant, M., & Liesefeld, H. R. (2021). Massive effects of saliency on information processing in visual working memory. *Psychological Science*, *32*(5), 682–691. https://doi.org/10/gjk9jh

Constant, M., & Liesefeld, H. R. (2020). The role of saliency for visual working memory in complex visual scenes. *Journal of Vision*, *20*(11), 499. https://doi.org/10/fgf4

Corbetta, M., & Shulman, G. L. (2002). Control of goal-directed and stimulus-driven attention in the brain. *Nature Reviews Neuroscience*, *3*(3), 201–215. https://doi.org/10/brm459

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson's method. *Tutorials in Quantitative Methods for Psychology*, *1*(1), 42–45. https://doi.org/10/b9z7

Cousineau, D., & O'Brien, F. (2014). Error bars in within-subject designs: A comment on Baguley (2012). *Behavior Research Methods*, *46*(4), 1149–1151. https://doi.org/10/f6vdsw

de Vries, J. P., Hooge, I. T. C., Wiering, M. A., & Verstraten, F. A. J. (2011). How longer saccade latencies lead to a competition for salience. *Psychological Science*, *22*(7), 916–923. https://doi.org/10/djpmkq

Donk, M., & van Zoest, W. (2008). Effects of salience are short-lived. *Psychological Science*, *19*(7), 733–739. https://doi.org/10/d3cn5x

Dube, B., Emrich, S. M., & Al-Aidroos, N. (2017). More than a filter: Feature-based attention regulates the distribution of visual working memory resources. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(10), 1843–1854. https://doi.org/10/gb2z76

Einhäuser, W., Rutishauser, U., & Koch, C. (2008). Task-demands can immediately reverse the effects of sensory-driven saliency in complex visual stimuli. *Journal of Vision*, *8*(2), 2. https://doi.org/10/cpt8wt

Emrich, S. M., Lockhart, H. A., & Al-Aidroos, N. (2017). Attention mediates the flexible allocation of visual working memory resources. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(7), 1454–1465. https://doi.org/10/gbn3xj

Fairchild, M. D. (2013). *Color appearance models* (3rd ed.). John Wiley & Sons, Inc. https://doi.org/10/dc5n

Fitts, D. A. (2020). Commentary on "A review of effect sizes and their confidence intervals, Part I: The Cohen's d family": The degrees of freedom for paired samples designs. *The Quantitative Methods for Psychology*, *16*(4), 281–294. https://doi.org/10/gk3rr4

Folk, C. L., & Remington, R. (1998). Selectivity in distraction by irrelevant featural singletons: Evidence for two forms of attentional capture. *Journal of Experimental Psychology: Human Perception and Performance*, *24*(3), 847–858. https://doi.org/10/b79dkk

Gaspelin, N., & Luck, S. J. (2018). The role of inhibition in avoiding distraction by salient stimuli. *Trends in Cognitive Sciences*, *22*(1), 79–92. https://doi.org/10/gcr98d

Goulet-Pelletier, J.-C., & Cousineau, D. (2018). A review of effect sizes and their confidence intervals, Part I: The Cohen's d family. *The Quantitative Methods for Psychology*, *14*(4), 242–265. https://doi.org/10/gkzn9m

Goulet-Pelletier, J.-C., & Cousineau, D. (2019). Corrigendum to "A review of effect sizes and their confidence intervals, Part I: The Cohen's d family". *The Quantitative Methods for Psychology*, *15*(1), 54–54. https://doi.org/10/gk3pvk

Hedges, L. V. (1981, Summer). Distribution theory for Glass's estimator of effect size and related estimators. *Journal of Educational Statistics*, *6*(2), 107. https://doi.org/10/dbqn45

Hedges, L. V., & Olkin, I. (1985). *Statistical methods for meta-analysis*. Academic Press.

Hering, E. (1964). *Outlines of a theory of the light sense.* (L. M. Hurvich & D. Jameson, Trans.). Harvard University Press.

Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews Neuroscience*, *2*(3), 194–203. https://doi.org/10/chw2bk

JASP Team. (2020). *JASP* (Version 0.16.3). https://jasp-stats.org/

Klink, P. C., Jeurissen, D., Theeuwes, J., Denys, D., & Roelfsema, P. R. (2017). Working memory accuracy for multiple targets is driven by reward expectation and stimulus contrast with different time-courses. *Scientific Reports*, *7*(1), 9082. https://doi.org/10/gbtwp7

Li, Q., Joo, S. J., Yeatman, J. D., & Reinecke, K. (2020). Controlling for participants' viewing distance in large-scale, psychophysical online experiments using a virtual chinrest. *Scientific Reports*, *10*(1), 1–11. https://doi.org/10/ggpbsf

Liesefeld, H. R., Liesefeld, A. M., & Müller, H. J. (2022). Preparatory control against distraction is not feature-based. *Cerebral Cortex*, *32*(11), 2398–2411. https://doi.org/10/gmxwhc

Liesefeld, H. R., Liesefeld, A. M., Sauseng, P., Jacob, S. N., & Müller, H. J. (2020). How visual working memory handles distraction: Cognitive mechanisms and electrophysiological correlates. *Visual Cognition*, *28*(5-8), 372–387. https://doi.org/10/gg5vsv

Liesefeld, H. R., Liesefeld, A. M., Töllner, T., & Müller, H. J. (2017). Attentional capture in visual search: Capture and post-capture dynamics revealed by EEG. *NeuroImage*, *156*, 166–173. https://doi.org/10/gbsjqj

Liesefeld, H. R., Moran, R., Usher, M., Müller, H. J., & Zehetleitner, M. (2016). Search efficiency as a function of target saliency: The transition from inefficient to efficient search and beyond. *Journal of Experimental Psychology: Human Perception and Performance*, *42*, 821–836. https://doi.org/10/ggbnjc

Liesefeld, H. R., & Müller, H. J. (2019). Current directions in visual working memory research: An introduction and emerging insights. *British Journal of Psychology*, *110*(2), 193–206. https://doi.org/10/gfvm2p

Love, J., Selker, R., Marsman, M., Jamil, T., Dropmann, D., Verhagen, J., Ly, A., Gronau, Q. F., Smíra, M., Epskamp, S., Matzke, D., Wild, A., Knight, P., Rouder, J. N., Morey, R. D., & Wagenmakers, E.-J. (2019). **JASP**: Graphical statistical software for common statistical designs. *Journal of Statistical Software*, *88*(2). https://doi.org/10/ggbnjf

Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*, *44*(2), 314–324. https://doi.org/10/ft2dgc

Melcher, D., & Piazza, M. (2011). The role of attentional priority and saliency in determining capacity limits in enumeration and visual working memory (D. C. Burr, Ed.). *PLoS ONE*, *6*(12), e29296. https://doi.org/10/frfx2t

Morey, R. D. (2008). Confidence intervals from normalized data: A correction to Cousineau (2005). *Tutorials in Quantitative Methods for Psychology*, *4*(2), 61–64. https://doi.org/10/ggbnjg

Nothdurft, H.-C. (1993). The role of features in preattentive vision: Comparison of orientation, motion and color cues. *Vision Research*, *33*(14), 1937–1958. https://doi.org/10/d6fw5n

Overkott, C., & Souza, A. S. (2022). Verbal descriptions improve visual working memory but have limited impact on visual long-term memory. *Journal of Experimental Psychology: General*, *151*(2), 321–347. https://doi.org/10/gmtn9d

Peirce, J. W. (2008). Generating stimuli for neuroscience using PsychoPy. *Frontiers in Neuroinformatics*, *2*. https://doi.org/10/bg3jd8

Ravizza, S. M., & Conn, K. M. (2022). Gotcha: Working memory prioritization from automatic attentional biases. *Psychonomic Bulletin & Review*, *29*(2), 415–429. https://doi.org/10/gkskcv

Ravizza, S. M., Pleskac, T. J., & Liu, T. (2021). Working memory prioritization: Goal-driven attention, physical salience, and implicit learning. *Journal of Memory and Language*, *121*, 104287. https://doi.org/10/gqp53c

Ravizza, S. M., Uitvlugt, M. G., & Hazeltine, E. (2016). Where to start? Bottom-up attention improves working memory by determining encoding order. *Journal of Experimental Psychology: Human Perception and Performance*, *42*(12), 1959–1968. https://doi.org/10/f9dkfd

Rösner, M., Sabo, M., Klatt, L.-I., Wascher, E., & Schneider, D. (2022). Preparing for the unknown: How working memory provides a link between perception and anticipated action. *NeuroImage*, *260*, 119466. https://doi.org/10/gqq56c

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian *t* tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, *16*(2), 225–237. https://doi.org/10/b3hsdp

Schönbrodt, F. D., & Wagenmakers, E.-J. (2018). Bayes factor design analysis: Planning for compelling evidence. *Psychonomic Bulletin & Review*, *25*(1), 128–142. https://doi.org/10/gcsk2r

Theeuwes, J. (2018). Visual selection: Usually fast and automatic; seldom slow and volitional. *Journal of Cognition*, *1*(1), 29. https://doi.org/10/ggrs42

van Ede, F., & Nobre, A. C. (2023). Turning attention inside out: How working memory serves behavior. *Annual Review of Psychology*, *74*(1). https://doi.org/10/gqq56b

van Heusden, E., van Zoest, W., Donk, M., & Olivers, C. N. L. (2022). An attentional limbo: Saccades become momentarily non-selective in between saliency-driven and relevance-driven selection. *Psychonomic Bulletin & Review*. https://doi.org/10/gqhwkp

van Zoest, W., & Donk, M. (2006). Saccadic target selection as a function of time. *Spatial Vision*, *19*(1), 61–76. https://doi.org/10/b4nsn2

van Zoest, W., Donk, M., & Theeuwes, J. (2004). The role of stimulus-driven and goal-driven control in saccadic visual selection. *Journal of Experimental Psychology: Human Perception and Performance*, *30*(4), 746–759. https://doi.org/10/b63pph

Wang, B., & Theeuwes, J. (2020). Salience determines attentional orienting in visual selection. *Journal of Experimental Psychology: Human Perception and Performance*, *46*(10), 1051–1057. https://doi.org/10/gj6bdw

Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, *28*(4), 1060–1092. https://doi.org/10/gh2s45

Woodman, G. F., & Luck, S. J. (1999). Electrophysiological measurement of rapid shifts of attention during visual search. *Nature*, *400*(6747), 867–869. https://doi.org/10/bc68bs

Chapter 3

General Discussion

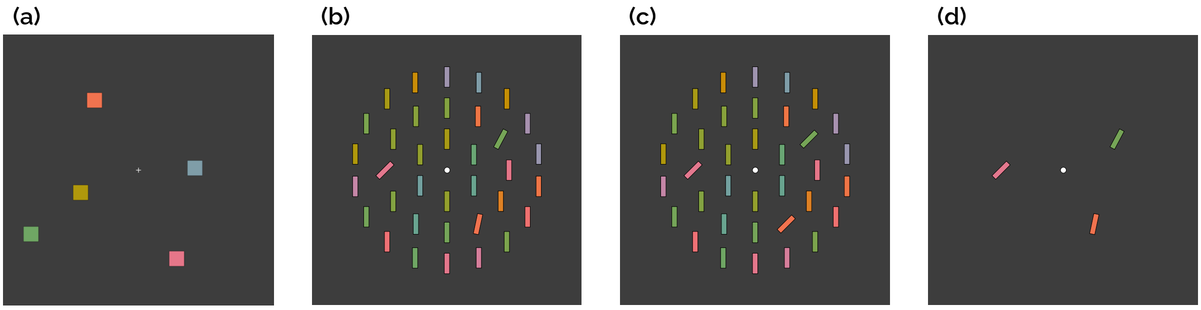
3.1 Summary of the findings

3.1.1 Study 1

In the present dissertation, several understudied factors of visual working memory performance have been examined and their influence has been evaluated. The first study (**Chapter 2.1**: Laybourn et al., 2022) was conducted in collaboration with researchers from the Educational Psychology department of the LMU München. We investigated across four experiments with medium to high sample sizes (19, 45, 44 and 110 participants in experiments 1, 2, 3 and 4 respectively) what emotions were induced by a visual working memory task in the laboratory, and how these influenced visual working memory performance.

This was motivated by the feeling that we, researchers, often act as if our participants are data-producing "machines" who perform the task as optimally and successfully as possible. After accepting the premise that it is not the case (in other words, that our participants are humans with affects, even in the laboratory; Dukes et al., 2021), it becomes not so far-fetched to imagine that participants' emotions (and their fluctuations during the task) can influence their visual working memory performance, thus contributing both to the between- and

Figure 2: Memory displays used in the different studies of this dissertation.



(a) Study 1 — (b) Study 2 & 3 *Mixed/Cluttered displays* — (c) Study 2 *Same* displays — (d) Study 2 *Clean* displays

Note. (a) Memory displays of Study 1 (**Chapter 2.1**). In Experiment 1, there were 5 targets (as shown here), in Experiments 2, 3 and 4 there were 4 or 8 square targets. (b) *Mixed/Cluttered* displays presented in Study 2 (**Chapter 2.2**) and 3 (**Chapter 2.3**). The targets each have a different orientation. (c) *Same* displays presented in Experiment 2 of Study 2. The targets share the same tilt in a given display (here 45°). (d) Clean displays presented in Experiment 3 of Study 2. The targets do not differ in salience anymore; the colored targets equally pop out from the gray background. Note that in (b), (c) and (d), the targets were always presented in the middle ring (eccentricity: 4 degrees of visual angle from fixation).

within-participant variability of these measurements.

The first experiment was a qualitative study, exploring what participants felt during a visual working memory task (continuous recall task with a set size of 5 targets, Figure 2a). The second, third and fourth experiments were quantitative experiments also with a continuous recall task but with a variable set size of either 4 or 8 targets (block design). In the second experiment, emotions were assessed once at the end of the task and significant correlations with task performance were observed, positive emotions being associated to a better task-performance and negative emotions to a worse task-performance. In the third experiment, emotions were assessed at the end of each block. Participants reported stronger negative emotions after difficult blocks (set size 8) and stronger positive emotions after easy blocks (set size 4). Task performance was associated with the emotions with the same pattern as in Experiment 2. Finally, Experiment 4 was a high-powered replication of Experiment 3 and the results were overall similar, thus confirming that emotions induced by a visual working memory task are linked to task-performance.

3.1.2 Study 2

The second study (**Chapter 2.2**) of this dissertation was our first step to demonstrate that the priority map concept can be used to explain (some) variations of visual working memory performance. In this study, we focused on the major bottom-up component of the priority map that is salience.

For that purpose, we designed a new task inspired from the visual search literature (e.g., H. R. Liesefeld et al., 2017), with a dense array of vertical non-targets and three tilted targets (continuous color recall task). This is, to our knowledge, the first study to use a memory display where salience is not confounded with the to-be-remembered feature. In other words, varying the salience of the targets (via their tilt) does not affect the discriminability of the to-be-remembered feature (color; as would for instance, increasing their size or reducing their contrast). The memory displays were presented for 350 ms in all experiments, which is neither particularly short nor long for this kind of task.

In the first experiment, the targets each had a different tilt (12°, 28° and 45°, see Figure 2b) and thus a different salience. The more salient the target was, the more precise the observers' responses were. We attributed this result to an effect of both *absolute* and *relative* salience; the absolute salience of a target being its local feature contrast (i.e., how much it pops out from the background; here from the vertical non-targets) and the relative salience being its salience compared to the other targets (e.g., the 12° target is less salient than the 28°). With the second experiment, we wanted to disentangle the effects of *relative* and *absolute* salience.

Therefore, in the second experiment, half of the memory displays were similar to Experiment 1 with targets differently tilted (*mixed* displays, unveiling relative salience) and the other half was composed of displays where the three targets shared the same tilt (*same* displays, unveiling absolute salience, Figure 2c). In the same displays, the competition between the targets was therefore not influenced by salience. Experiment 2 replicated the results of Experiment 1 (which had revealed combined effects of relative and absolute salience) but also demonstrated that absolute salience by itself plays a role in the distribution or availability of visual working memory resources. To further support the differential impact of relative and absolute salience, we also devised a computational model which showed that these results could not be attributed to an attentional template match (Duncan & Humphreys, 1989; Geng & Witkowski, 2019). The attentional template theory would predict that participants search for a template (e.g., 40°) and that the targets close to this template are found/processed more easily than those far away.

This was further supported by Experiment 3, in which half of the displays were *cluttered mixed* displays (similar to Experiment 1) and the other half were *clean mixed* displays (Figure 2d) where the vertical non-targets were removed. Consequently, each target's salience was equal in the *clean* displays (since they had no surroundings to create salience differences). If memory performance was due to the match of the target to an attentional template, then the performance differences should have persisted in *clean* displays, which they did not.

3.1.3 Study 3

In the last study (**Chapter 2.3**), we examined how robust the bottom-up effects of salience were to top-down control. All the experiments used *cluttered mixed* displays only. In the first experiment, we manipulated the presentation time of the memory display from 14 ms to 2000 ms. In visual search tasks, a common assumption is that effects of salience are short-lived and that top-down mechanisms can quickly override them (Donk & van Zoest, 2008; van Zoest & Donk, 2006; van Zoest et al., 2004). If this also applied to a visual working memory task, then the effects of salience on performance should disappear when enough time is provided to encode the equally-relevant targets (here for instance, with 1000 ms and 2000 ms presentation time). We observed that effects of salience got weaker with increasing presentation times, but were still present even at 2000 ms. Hence, the effects of salience might not be so short-lived after all in visual working memory tasks. In the second experiment, we presented the targets for 350 ms or 2000 ms, but we manipulated the targets' relevances. We used a reward paradigm in which more precise responses awarded more money. The relevance was manipulated by applying a multiplier to the reward that was inversely linked to the salience (i.e., less salient targets had a higher reward multiplier). So, it was more beneficial for the observers to focus on the less salient targets. However, the effects of salience persisted both with 350 ms and 2000 ms of presentation time.

As it was demonstrated in visual search tasks that experience-driven effects are usually stronger than goal-driven ones, we designed our last experiment with a manipulation that would also induce such an effect. In this experiment, less salient targets were made more relevant by probing them more often. Importantly, the participant knew that this was the case, thus we could induce both a goal-driven effect (by virtue of the participants' cognizance of the manipulation) and an experience-driven effect since observers were exposed more often to less salient probes. In this experiment we used three presentation times, 350 ms, 2000 ms and 3000 ms, to maximize the chances to observe an effect of our manipulations. Here, we found that the effect of salience disappeared at 2000 ms, and even slightly reversed at 3000 ms. We therefore conclude from this study that the effects of salience on visual working memory performance are long-lived and rather hard to get rid of, thus colliding with some of the conclusions from the visual search literature. This finding also reveals that visual working memory tasks can be an efficient way to study visual attention and to expand our knowledge of the priority map.

3.1.4 Overall summary

In short, the findings from the three studies can be shortly summarized as such:

1. **Influence of achievement emotions**: Achievement emotions induced by visual working memory tasks are linked to task performance. Positive emotions are positively linked and negative emotions are negatively linked to task performance.

2. **Influence of *relative* salience**: In a dense (complex) display, the *relative* salience of each target is a major predicting factor of task performance. The more salient targets are recalled more precisely than the less salient ones (see Fig. 2 of **Chapter 2.2**). In a sense, the more salient targets are winning the competition against less salient targets.

3. **Influence of *absolute* salience**: To remove the bias in the aforementioned competition, we equated the targets' saliencies and the effects of (*absolute*) salience remained. Performance for displays with more salient targets was better than for displays with less salient targets (see Fig. 3 of **Chapter 2.2**). Thus, on top of winning the competition (*relative* salience), how much an object stands out from its surroundings (*absolute* salience) also has a strong influence on performance.

4. **Interaction between salience and encoding time:** Varying the presentation time of the memory display revealed that the effect of salience appears almost instantaneously and remains (though weaker) even with long encoding times (see Fig. 2 of **Chapter 2.3**).

5. **Interaction between salience, presentation time and conflicting task-goals**: Conflicting task-goals (i.e., decreasing the more salient targets' relevance) were not enough to counteract the effects of salience at relatively short presentation time. The goal-driven manipulation remained inefficient even at long presentation times (see Fig. 3 of **Chapter 2.3**), while the combined goal- and experience-driven manipulation successfully erased the effect of salience with long presentation times (see Fig. 4 of **Chapter 2.3**). However, this merely compensated the effect of salience rather than fully dominating it.

3.2 Future research directions

Taking the results of Study 1 into account, it appears likely that gamification of the visual working memory task could improve overall performance. Indeed, this should elicit stronger positive achievement emotions and reduce negative achievement emotions (Lei et al., 2022). However, to date, a recent preprint (Mystakidou & van den Berg, 2020) in which a visual working memory task was gamified showed that gamification improved motivation but not task performance. To empirically solidify (or disqualify) this finding, this design could be adapted to different visual working memory tasks, while also monitoring more closely how gamification impacts the inducement of achievement emotions throughout the experiment.

Now that it is demonstrated that salience is a major influence on visual working memory performance, it becomes possible to build new theories and validate older ones, notably by adapting our novel task. For instance, EEG data from two experiments (manuscript in preparation, results presented in several national and international conferences) seem to indicate that salience does not, as one might assume, impact visual working memory only because of an attentional preference, but might also speed up the rate at which information is encoded. It also challenges the popular idea that the contralateral delay activity (CDA) reflects only the number of items into visual working memory, but not the precision of the items' representation (Luria et al., 2016).

Our task could be combined with the pro-/anti- retro-cue paradigm (van Ede et al., 2020) to examine whether flexible reprioritization of targets in working memory is affected by their salience. Pre-cues could also be used in an attempt to override or enhance the effect of salience on a trial-by-trial basis. This pre-cue could be an attentional template (showing the tilt of the target) or a location cue (pointing to the location of the target). Another possibility to further understand the effect of salience would be to reveal the display's spatial organization before any memory content is shown. This would minimize the chance that the target was simply not found on some trials and allow to disentangle the "visual search" component of the salience effect from other components.

To conclude, the results from this dissertation can also be envisioned as an appeal to caution. The influences that were examined here have so far been neglected from most research, at best being relegated to a potential source of noise and at worst being totally ignored. What I have shown here is that these factors do have a strong impact on visual working memory performance. The now-revealed effect of salience can provide a lens to re-examine previous results and their interpretation, and researchers should be cautious not to involuntarily introduce salience variations that could prove to be a confounding factor later on.

Bibliography (General Introduction and General Discussion)

Aagten-Murphy, D., & Bays, P. M. (2018). Functions of memory across saccadic eye movements. In T. Hodgson (Ed.), *Current Topics in Behavioral Neurosciences: Processes of Visuo-spatial Attention and Working Memory*. Springer. https://doi.org/10/dc5p

Alvarez, G. A., & Cavanagh, P. (2004). The capacity of visual short-term memory is set both by visual information load and by number of objects. *Psychological Science*, *15*(2), 106–111. https://doi.org/10/b88gs7

Anderson, B. A., Laurent, P. A., & Yantis, S. (2011). Value-driven attentional capture. *Proceedings of the National Academy of Sciences*, *108*(25), 10367–10371. https://doi.org/10/c6pdx8

Awh, E., Barton, B., & Vogel, E. K. (2007). Visual working memory represents a fixed number of items regardless of complexity. *Psychological Science*, *18*(7), 622–628. https://doi.org/10/c544j9

Awh, E., Belopolsky, A. V., & Theeuwes, J. (2012). Top-down versus bottom-up attentional control: A failed theoretical dichotomy. *Trends in Cognitive Sciences*, *16*(8), 437–443. https://doi.org/10/f34nps

Awh, E., & Jonides, J. (2001). Overlapping mechanisms of attention and spatial working memory. *Trends in Cognitive Sciences*, *5*(3), 119–126. https://doi.org/10/dz73cr

Awh, E., Jonides, J., Smith, E. E., Buxton, R. B., Frank, L. R., Love, T., Wong, E. C., & Gmeindl, L. (1999). Rehearsal in spatial working memory: Evidence from neuroimaging. *Psychological Science*, *10*(5), 433–437. https://doi.org/10/bjgcp3

Baddeley, A. (2003). Working memory: Looking back and looking forward. *Nature Reviews Neuroscience*, *4*(10), 829–839. https://doi.org/10/bz2gwb

Bae, G.-Y., Olkkonen, M., Allred, S. R., Wilson, C., & Flombaum, J. I. (2014). Stimulus-specific variability in color working memory with delayed estimation. *Journal of Vision*, *14*(4), 7. https://doi.org/10/f54rc8

Bays, P. M., Catalao, R. F. G., & Husain, M. (2009). The precision of visual working memory is set by allocation of a shared resource. *Journal of Vision*, *9*(10), 7. https://doi.org/10/c46n7t

Bays, P. M., Wu, E. Y., & Husain, M. (2011). Storage and binding of object features in visual working memory. *Neuropsychologia*, *49*(6), 1622–1631. https://doi.org/10/d6xj73

Boettcher, S. E. P., Draschkow, D., Dienhart, E., & Võ, M. L.-H. (2018). Anchoring visual search in scenes: Assessing the role of anchor objects on eye movements during visual search. *Journal of Vision*, *18*(13), 11. https://doi.org/10/gqc3z5

Brady, T. F., & Alvarez, G. A. (2015). Contextual effects in visual working memory reveal hierarchically structured memory representations. *Journal of Vision*, *15*(15), 6. https://doi.org/10/f76w3m
Bundesen, C., Habekost, T., & Kyllingsbæk, S. (2005). A neural theory of visual attention: Bridging cognition and neurophysiology. *Psychological Review*, *112*(2), 291–328. https://doi.org/10/cgcpn9
Bundesen, C., Habekost, T., & Kyllingsbæk, S. (2011). A neural theory of visual attention and short-term memory (NTVA). *Neuropsychologia*, *49*(6), 1446–1457. https://doi.org/10/b8863z
Cisek, P., & Kalaska, J. F. (2010). Neural mechanisms for interacting with a world full of action choices. *Annual Review of Neuroscience*, *33*(1), 269–298. https://doi.org/10/btntfd
Constant, M., & Liesefeld, H. R. (2021). Massive effects of saliency on information processing in visual working memory. *Psychological Science*, *32*(5), 682–691. https://doi.org/10/gjk9jh
Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, *24*(1), 87–114. https://doi.org/10/ddq83h
Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, *18*(1), 193–222. https://doi.org/10/bmcht5
Donk, M., & van Zoest, W. (2008). Effects of salience are short-lived. *Psychological Science*, *19*(7), 733–739. https://doi.org/10/d3cn5x
Draschkow, D., & Võ, M. L.-H. (2017). Scene grammar shapes the way we interact with objects, strengthens memories, and speeds search. *Scientific Reports*, 7(1), 16471. https://doi.org/10/gcnx5f
Dube, B., Emrich, S. M., & Al-Aidroos, N. (2017). More than a filter: Feature-based attention regulates the distribution of visual working memory resources. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(10), 1843–1854. https://doi.org/10/gb2z76
Dukes, D., Abrams, K., Adolphs, R., Ahmed, M. E., Beatty, A., Berridge, K. C., Broomhall, S., Brosch, T., Campos, J. J., Clay, Z., Clément, F., Cunningham, W. A., Damasio, A., Damasio, H., D'Arms, J., Davidson, J. W., de Gelder, B., Deonna, J., de Sousa, R., … Sander, D. (2021). The rise of affectivism. *Nature Human Behaviour*, *5*(7), 816–820. https://doi.org/10/gkhxms
Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review*, *96*(3), 433–458. https://doi.org/10/ck4p2t
Emrich, S. M., Lockhart, H. A., & Al-Aidroos, N. (2017). Attention mediates the flexible allocation of visual working memory resources. *Journal of Experimental Psychology: Human Perception and Performance*, *43*(7), 1454–1465. https://doi.org/10/gbn3xj
Fecteau, J., & Munoz, D. (2006). Salience, relevance, and firing: A priority map for target selection. *Trends in Cognitive Sciences*, *10*(8), 382–390. https://doi.org/10/fb66m9
Forsberg, A., Adams, E. J., & Cowan, N. (2021, January 1). The role of working memory in long-term learning: Implications for childhood development. In K. D. Federmeier (Ed.), *Psychology of Learning and Motivation* (pp. 1–45, Vol. 74). Academic Press. https://doi.org/10/h2xq
Franconeri, S. L., Alvarez, G. A., & Cavanagh, P. (2013). Flexible cognitive resources: Competitive content maps for attention and memory. *Trends in Cognitive Sciences*, *17*(3), 134–141. https://doi.org/10/f4sbwj

Gazzaley, A., & Nobre, A. C. (2012). Top-down modulation: Bridging selective attention and working memory. *Trends in Cognitive Sciences*, *16*(2), 129–135. https://doi.org/10/fxprkn

Geng, J. J., & Witkowski, P. (2019). Template-to-distractor distinctiveness regulates visual search efficiency. *Current Opinion in Psychology*, *29*, 119–125. https://doi.org/10/gg5vtp

Griffin, I. C., & Nobre, A. C. (2003). Orienting attention to locations in internal representations. *Journal of Cognitive Neuroscience*, *15*(8), 1176–1194. https://doi.org/10/bt2j36

Hollingworth, A., Richard, A. M., & Luck, S. J. (2008). Understanding the function of visual short-term memory: Transsaccadic memory, object correspondence, and gaze correction. *Journal of Experimental Psychology: General*, *137*, 163–181. https://doi.org/10/fqxcqf

Klink, P. C., Jeurissen, D., Theeuwes, J., Denys, D., & Roelfsema, P. R. (2017). Working memory accuracy for multiple targets is driven by reward expectation and stimulus contrast with different time-courses. *Scientific Reports*, 7(1), 9082. https://doi.org/10/gbtwp7

LaBar, K. S., Gitelman, D. R., Parrish, T. B., & Mesulam, M. .-. (1999). Neuroanatomic overlap of working memory and spatial attention networks: A functional MRI comparison within subjects. *NeuroImage*, *10*(6), 695–704. https://doi.org/10/dn23g9

Laybourn, S., Frenzel, A. C., Constant, M., & Liesefeld, H. R. (2022). Unintended emotions in the laboratory: Emotions incidentally induced by a standard visual working memory task relate to task performance. *Journal of Experimental Psychology: General*, *151*(7), 1591–1605. https://doi.org/10/hh3g

Lei, H., Wang, C., Chiu, M. M., & Chen, S. (2022). Do educational games affect students' achievement emotions? Evidence from a meta-analysis. *Journal of Computer Assisted Learning*, *38*(4), 946–959. https://doi.org/10/gqhbpb _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcal.12664.

Li, Z. (2002). A saliency map in primary visual cortex. *Trends in Cognitive Sciences*, *6*(1), 9–16. https://doi.org/10/bjs32m

Liesefeld, A. M., Liesefeld, H. R., & Zimmer, H. D. (2014). Intercommunication between prefrontal and posterior brain regions for protecting visual working memory from distractor interference. *Psychological Science*, *25*(2), 325–333. https://doi.org/10/f5344z

Liesefeld, H. R., Liesefeld, A. M., Sauseng, P., Jacob, S. N., & Müller, H. J. (2020). How visual working memory handles distraction: Cognitive mechanisms and electrophysiological correlates. *Visual Cognition*, *28*(5-8), 372–387. https://doi.org/10/gg5vsv

Liesefeld, H. R., & Müller, H. J. (2021). Modulations of saliency signals at two hierarchical levels of priority computation revealed by spatial statistical distractor learning. *Journal of Experimental Psychology: General*, *150*(4), 710–728. https://doi.org/10/gqdh98

Liesefeld, H. R., Liesefeld, A. M., & Müller, H. J. (2019). Two good reasons to say 'change!' – ensemble representations as well as item representations impact standard measures of VWM capacity. *British Journal of Psychology*, *110*(2), 328–356. https://doi.org/10/ggbnjb

Liesefeld, H. R., Liesefeld, A. M., Töllner, T., & Müller, H. J. (2017). Attentional capture in visual search: Capture and post-capture dynamics revealed by EEG. *NeuroImage*, *156*, 166–173. https://doi.org/10/gbsjqj

Liesefeld, H. R., Moran, R., Usher, M., Müller, H. J., & Zehetleitner, M. (2016). Search efficiency as a function of target saliency: The transition from inefficient to efficient search and beyond. *Journal of Experimental Psychology: Human Perception and Performance*, *42*, 821–836. https://doi.org/10/ggbnjc

Liesefeld, H. R., & Müller, H. J. (2019). Current directions in visual working memory research: An introduction and emerging insights. *British Journal of Psychology*, *110*(2), 193–206. https://doi.org/10/gfvm2p

Lorenc, E. S., Mallett, R., & Lewis-Peacock, J. A. (2021). Distraction in visual working memory: Resistance is not futile. *Trends in Cognitive Sciences*, *25*(3), 228–239. https://doi.org/10/ghrncr

Luck, S. J. (2014). *An introduction to the event-related potential technique* (Second edition). The MIT Press.

Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, *390*(6657), 279–281. https://doi.org/10/cqwttd

Luck, S. J., & Vogel, E. K. (2013). Visual working memory capacity: From psychophysics and neurobiology to individual differences. *Trends in Cognitive Sciences*, *17*(8), 391–400. https://doi.org/10/39v

Luria, R., Balaban, H., Awh, E., & Vogel, E. K. (2016). The contralateral delay activity as a neural measure of visual working memory. *Neuroscience & Biobehavioral Reviews*, *62*, 100–108. https://doi.org/10/f8dp5m

Ma, W. J., Husain, M., & Bays, P. M. (2014). Changing concepts of working memory. *Nature Neuroscience*, *17*(3), 347–356. https://doi.org/10/gd8cbs

Mystakidou, M., & van den Berg, R. (2020). More motivated but equally good: No effect of gamification on visual working memory performance. *bioRxiv*, 2020.01.12.903203. https://doi.org/10/gk2mjh

Ngiam, W. X. Q., Khaw, K. L. C., Holcombe, A. O., & Goodbourn, P. T. (2019). Visual working memory for letters varies with familiarity but not complexity. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *45*(10), 1761–1775. https://doi.org/10/gk4nrd

Oberauer, K. (2019). Working memory and attention – a conceptual analysis and review. *Journal of Cognition*, *2*(1), 36. https://doi.org/10/gf6bx5

Olivers, C. N. L., Peters, J., Houtkamp, R., & Roelfsema, P. R. (2011). Different states in visual working memory: When it guides attention and when it does not. *Trends in Cognitive Sciences*, *15*(7), 327–334. https://doi.org/10/fcfxg6

Pashler, H. (1988). Familiarity and visual change detection. *Perception & Psychophysics*, *44*(4), 369–378. https://doi.org/10/d3h3b6

Rensink, R. A. (2004). Visual sensing without seeing. *Psychological Science*, *15*(1), 27–32. https://doi.org/10/brg48z

Rösner, M., Sabo, M., Klatt, L.-I., Wascher, E., & Schneider, D. (2022). Preparing for the unknown: How working memory provides a link between perception and anticipated action. *NeuroImage*, *260*, 119466. https://doi.org/10/gqq56c

Rouder, J. N., Morey, R. D., Cowan, N., Zwilling, C. E., Morey, C. C., & Pratte, M. S. (2008). An assessment of fixed-capacity models of visual working memory. *Proceedings of the National Academy of Sciences*, *105*(16), 5975–5979. https://doi.org/10/fngr7w

Sauseng, P., Klimesch, W., Heise, K. F., Gruber, W. R., Holz, E., Karim, A. A., Glennon, M., Gerloff, C., Birbaumer, N., & Hummel, F. C. (2009). Brain oscillatory substrates of visual short-term memory capacity. *Current Biology*, *19*(21), 1846–1852. https://doi.org/10/fb975q

Sauter, M., Liesefeld, H. R., Zehetleitner, M., & Müller, H. J. (2018). Region-based shielding of visual search from salient distractors: Target detection is impaired

with same- but not different-dimension distractors. *Attention, Perception, & Psychophysics*, *80*(3), 622–642. https://doi.org/10/gc64rc
Schneider, W. X. (2013). Selective visual processing across competition episodes: A theory of task-driven visual attention and working memory. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *368*(1628), 20130060. https://doi.org/10/f5gzs7
Schurgin, M. W. (2018). Visual memory, the long and the short of it: A review of visual working memory and long-term memory. *Attention, Perception, & Psychophysics*, *80*(5), 1035–1056. https://doi.org/10/gdv52k
Schurgin, M. W., Wixted, J. T., & Brady, T. F. (2020). Psychophysical scaling reveals a unified theory of visual memory strength. *Nature Human Behaviour*, *4*(11), 1156–1172. https://doi.org/10/gg9384
Simons, D. J., & Levin, D. T. (1997). Change blindness. *Trends in Cognitive Sciences*, *1*(7), 261–267. https://doi.org/10/bq9qc7
Simons, D. J., & Rensink, R. A. (2005). Change blindness: Past, present, and future. *Trends in Cognitive Sciences*, *9*(1), 16–20. https://doi.org/10/d49rp5
Souza, A. S., Thaler, T., Liesefeld, H. R., Santos, F. H., Peixoto, D. S., & Albuquerque, P. B. (2021). No evidence that self-rated negative emotion boosts visual working memory precision. *Journal of Experimental Psychology: Human Perception and Performance*, *47*(2), 282–307. https://doi.org/10/ghwzjb
Spachtholz, P., Kuhbandner, C., & Pekrun, R. (2014). Negative affect improves the quality of memories: Trading capacity for precision in sensory and working memory. *Journal of Experimental Psychology: General*, *143*(4), 1450–1456. https://doi.org/10/f6c5dp
Theeuwes, J. (1991). Cross-dimensional perceptual selectivity. *Perception & Psychophysics*, *50*(2), 184–193. https://doi.org/10/ch3qrr
Theeuwes, J. (2004). Top-down search strategies cannot override attentional capture. *Psychonomic Bulletin & Review*, *11*(1), 65–70. https://doi.org/10/ds3bp8
Theeuwes, J. (2018). Visual selection: Usually fast and automatic; seldom slow and volitional. *Journal of Cognition*, *1*(1), 29. https://doi.org/10/ggrs42
Tsubomi, H., Fukuda, K., Watanabe, K., & Vogel, E. K. (2013). Neural limits to representing objects still within view. *Journal of Neuroscience*, *33*(19), 8257–8263. https://doi.org/10/f4vz7w
van den Berg, R., Shin, H., Chou, W.-C., George, R., & Ma, W. J. (2012). Variability in encoding precision accounts for visual short-term memory limitations. *Proceedings of the National Academy of Sciences*, *109*(22), 8780–8785. https://doi.org/10/f3trn3
van Ede, F., Board, A. G., & Nobre, A. C. (2020). Goal-directed and stimulus-driven selection of internal representations. *Proceedings of the National Academy of Sciences*, *117*(39), 24590–24598. https://doi.org/10/ghbtt9
van Ede, F., & Nobre, A. C. (2023). Turning attention inside out: How working memory serves behavior. *Annual Review of Psychology*, *74*(1). https://doi.org/10/gqq56b
van Zoest, W., & Donk, M. (2006). Saccadic target selection as a function of time. *Spatial Vision*, *19*(1), 61–76. https://doi.org/10/b4nsn2
van Zoest, W., Donk, M., & Theeuwes, J. (2004). The role of stimulus-driven and goal-driven control in saccadic visual selection. *Journal of Experimental Psychology: Human Perception and Performance*, *30*(4), 746–759. https://doi.org/10/b63pph
Vogel, E. K., McCollough, A. W., & Machizawa, M. G. (2005). Neural measures reveal individual differences in controlling access to working memory. *Nature*, *438*(7067), 500–503. https://doi.org/10/drbpg5

Wilken, P., & Ma, W. J. (2004). A detection theory account of change detection. *Journal of Vision*, *4*(12), 11. https://doi.org/10/bkrxvz
Williams, J. R., Robinson, M. M., Schurgin, M., Wixted, J., & Brady, T. F. (2022). You can't "count" how many items people remember in working memory: The importance of signal detection-based measures for understanding change detection performance. *PsyArXiv*. https://doi.org/10/h2xr
Wolfe, J. M. (1994). Guided Search 2.0 A revised model of visual search. *Psychonomic Bulletin & Review*, *1*(2), 202–238. https://doi.org/10/cdwjzg
Wolfe, J. M. (2007). Guided Search 4.0: Current progress with a model of visual search. In *Integrated models of cognitive systems* (pp. 99–119). Oxford University Press. https://doi.org/10/gftcmp
Wolfe, J. M. (2021). Guided Search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, *28*(4), 1060–1092. https://doi.org/10/gh2s45
Xie, W., & Zhang, W. (2016). Negative emotion boosts quality of visual working memory representation. *Emotion*, *16*(5), 760–774. https://doi.org/10/f848bj
Yoo, A. H., Klyszejko, Z., Curtis, C. E., & Ma, W. J. (2018). Strategic allocation of working memory resource. *Scientific Reports*, *8*(1), 1–8. https://doi.org/10/gfnbqd
Zelinsky, G. J., & Bisley, J. W. (2015). The what, where, and why of priority maps and their interactions with visual working memory. *Annals of the New York Academy of Sciences*, *1339*(1), 154–164. https://doi.org/10/ggbnjn
Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233–235. https://doi.org/10/c693sk

List of publications

- **Constant, M.**, & Liesefeld, H. R. (2022) Effects of salience are long-lived and stubborn. *PsyArXiv*. https://doi.org/jbpx (Preprint)
- Liesefeld, H., **Constant, M.**, & Oberauer, K. (2022). The consequences of effects of saliency are long-lived (and stubborn). *Journal of Vision*, 22(14), 4206. https://doi.org/jsvx (Conference abstract)
- **Constant, M.**, & Liesefeld, H. R. (2022). Examining the effect of saliency on EEG markers of attention allocation and maintenance in a visual-working-memory task. *Journal of Vision*, 22(14), 3512. https://doi.org/jsvw (Conference abstract)
- Laybourn, S., Frenzel A. C., **Constant M.**, Liesefeld, H. R. (2022). Unintended emotions in the laboratory: Emotions incidentally induced by a standard visual working memory task predict task performance. *Journal of Experimental Psychology: General, 151*(7), 1591–1605. https://doi.org/hh3g
- **Constant, M.**, & Liesefeld, H. R. (2021). Massive effects of saliency on information processing in visual working memory. *Psychological Science*, *32*(5), 682–691. https://doi.org/gjk9jh
- **Constant, M.**, & Liesefeld, H. R. (2020). The role of saliency for visual working memory in complex visual scenes. *Journal of Vision*, *20*(11), 499. https://doi.org/fgf4 (Conference abstract)
- **Constant, M.**, & Mellet, E. (2018). The impact of handedness, sex, and cognitive abilities on left–right discrimination: A behavioral study. *Frontiers in Psychology*, *9*. https://doi.org/gdbb4f

DECLARATION OF AUTHOR CONTRIBUTIONS

Massive effects of saliency on information processing in visual working memory

Martin Constant: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing - original draft, and Writing - review & editing.

Heinrich R. Liesefeld: Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Software, Supervision, Writing - original draft, and Writing - review & editing.

Effects of salience are long-lived and stubborn

Martin Constant: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing - original draft, and Writing - review & editing.

Heinrich R. Liesefeld: Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, and Writing - review & editing.

Unintended emotions in the laboratory: Emotions incidentally induced by a standard visual working memory task relate to task performance

Sara Laybourn: Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing - original draft, and Writing - review & editing.
Anne C. Frenzel: Conceptualization, Formal analysis, Funding acquisition, Methodology, Project administration, Supervision, and Writing - review & editing.
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Martin Constant: Formal analysis, Investigation, Methodology, Software, Visualization, and Writing - review & editing.

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