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Behavioral and electrophysiological evidence for the flexible recruitment of feature- and object-based processing in visual working memory comparison

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ABSTRACT

Previous research is inconclusive on when visual working memory (VWM) can be object-based or feature-based. Prior event-related potential (ERP) studies using change detection tasks have found that amplitudes of the N200—an ERP index of VWM comparison— are sensitive to changes in both relevant and irrelevant features, suggesting a bias toward object-based processing. To test whether VWM comparison processing can operate in a feature-based manner, we aimed to create circumstances that would support feature-based processing by: 1) using a strong task-relevance manipulation, and 2) repeating features within a display. Participants completed two blocks of a change detection task for four-item displays in which they were told to respond to color changes (task relevant) but not shape changes (task irrelevant). The first block contained only task-relevant changes to create a strong task-relevance manipulation. In the second block, both relevant and irrelevant changes were present. In both blocks, half of the arrays contained within-display feature repetitions (e.g. two items of the same color or shape). We found that during the second block, N200 amplitudes were sensitive to task-relevant but not irrelevant features regardless of repetition status, consistent with feature-based processing. However, analyses of behavioral data and N200 latencies suggested that object-based processing was occurring at some stages of VWM processing on task-irrelevant feature change trials. In particular, task-irrelevant changes may be processed after no task-relevant feature change is revealed. Overall, the results from the current study suggest that the VWM processing is flexible and can be either object- or feature-based.

Efficient processing of visual information likely involves filtering out irrelevant information to focus on task-relevant information (Brady, Konkle, Oliva, & Alvarez, 2009; Cowan, 2001). Furthermore, to detect visual changes in the environment, perceptual representations must be compared to representations stored in visual working memory (VWM) (Simons, 2000; Simons & Rensink, 2005). The extent to which task-irrelevant information is filtered out during this comparison process may be determined by how representations are processed for a given VWM task. For example, in a change detection task where participants are instructed to detect changes in color but disregard changes in shape, it could be beneficial to use a feature-based strategy that involves processing only color information. Feature-based processing models suggest that when VWM processing is biased toward individual features, VWM capacity is determined by the number of features presented (Bays, Wu, & Husain, 2011; Fougnie & Alvarez, 2011; Li, Qian, & Liang, 2018; Meyerhoff, Jardine, Stieff, Hegarty, & Franconeri, 2021; Niklaus, Nobre, & van Ede, 2017; van Lamsweerde, Beck, & Johnson, 2016; Wheeler & Treisman, 2002; van Lamsweerde and Beck, 2015). Moreover, task-irrelevant features can be filtered out because each feature can be processed individually. By contrast, object-based processing models propose that VWM capacity can be determined by the number of objects presented (Awh, Barton, & Vogel, 2007; Gao et al., 2016; Gu et al., 2022; Luck & Vogel, 1997; Shen, Tang, Wu, Shui, & Gao, 2013; Vogel, Woodman, & Luck, 2001; Yin et al., 2011, 2012). Under this view, individual features of an item are necessarily bound to that single item, and processing an item leads to processing all its features regardless of task relevance.

Although the current state the literature does not strongly support a

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purely object-based model or a purely feature-based model, it is not fully understood under which circumstances object- or feature-based processing is prioritized or supported (see Schneegans & Bays, 2019 for review). In the current study, we examine event-related potentials (ERPs) during a change detection task to examine the potential for flexibility in processing level (feature or object) depending on the stage of processing.

VWM processing involves several stages, and feature- or object-based processing biases could occur at different stages. To successfully detect a change to a visual stimulus, the stimulus's original state (i.e., pre-change display) must be attended to and encoded into VWM. This representation must then be maintained in VWM until the post-change information is encountered. Next, a comparison process must occur in which the pre-change representation is compared to the post-change representation. Finally, a decision/response process occurs during which, if the signal created by the comparison process is higher than a threshold, a "change response" is generated, and if not, a "no change response" is generated (Beck, Peterson, & Angelone, 2007; Hyun, Woodman, Vogel, Hollingworth, & Luck, 2009; Mitroff, Simons, & Levin, 2004; Simons, 2000; Simons & Rensink, 2005; Wilken & Ma, 2004). It is possible that the encoding, maintenance, or comparison stages in processing can be either feature- or object-based.

Evidence regarding when feature-based VWM processing can be supported comes from studies investigating how feature repetition within a display can be used to improve VWM performance. Specifically, change detection improvements are found when task-relevant features are shared by multiple items within a single display (Meyerhoff et al., 2021; van Lamsweerde et al., 2016; van Lamsweerde & Beck, 2015). This suggests that, under some circumstances, VWM processing can operate in a feature-based manner (Meyerhoff et al., 2021; van Lamsweerde et al., 2016; van Lamsweerde & Beck, 2015). For example, if presented with a display containing a blue square, a blue circle, a red triangle, and a green star and required to detect a color change, it would be beneficial to group processing of the two blue features together at the cost of processing irrelevant features such as shape. This grouping can be primarily bottom-up if the gestalt grouping cues are strong (e.g., Diaz et al., 2021), but top-down influences (stimuli with a prior history of grouping or explicit instructions to group) can also lead to stimuli being grouped based on features (Balaban and Luria, 2016; Rabbitt et al., 2017). It has not yet been determined which stage of VWM processing benefits from grouped processing of repeated task-relevant features. Therefore, even if grouping does not occur initially at encoding, a benefit of feature repetition for task-relevant features can potentially occur at the maintenance and/or comparison stages.

Findings from other change detection studies have shown evidence for prioritization of object-based processing. For example, Yin et al. (2012) examined task-irrelevant feature processing during a change detection task involving colored shapes. Participants were first presented with displays of three colored shapes for 200 ms in a pre-change array (e.g., blue circle, red square, green star) and told to remember and detect only shape changes and to ignore color changes. After a 1000 ms delay, a post-change display was presented with one of four change types: task-relevant (color) change, task-irrelevant (shape) change, both shape and color change, or no-change. Change detection response times (RTs) were longer for task-irrelevant change trials (Yin et al., 2012). In addition, a previous study reported that change detection accuracy was impaired when both color and shape changed in the same trial (Yin et al., 2011). The authors interpreted the findings from these studies as evidence that both task-relevant and task-irrelevant features were processed in VWM.

To gain insight into which stage(s) of processing are biased toward object- or feature-based processing, Yin et al. (2011, 2012) also analyzed event-related potentials (ERPs) elicited during the four types of post-change displays. In both studies, it was found that amplitudes of the anterior N200 component were equivalent among trials with task-relevant changes, task-irrelevant changes, and both-changes, and all three change types elicited larger (more negative) N200 amplitudes than no-change trials. The anterior N200 is an ERP component that has been linked to the detection of mismatching information in VWM comparison (e.g., the comparison of an incoming stimulus to an active working memory representation (for review, see Folstein and Van Petten, 2008; see also Mao & Wang, 2008; Wang et al., 2004; Zhang et al., 2003). Based on these results, Yin et al. (2011, 2012) concluded that task-irrelevant features are automatically processed during the comparison stage of VWM (Yin et al., 2011, 2012), which is consistent with object-based processing accounts.

In addition to the N200, Yin et al. (2012) found differences in a late positive component (LPC or P300),[2] which was also greater for change than no-change trials with no effect of change task-relevance. The LPC is believed to reflect the summation of multiple subcomponents, each with different properties and eliciting conditions. In the context of change detection, differences between change- and no-change trials may largely reflect the P3b subcomponent, which is elicited by target stimuli in a variety of tasks that involve signal detection (Luck & Kappenman, 2011). Traditionally, the P3b was believed to reflect processes involved in stimulus evaluation, such as attention to the contents of working memory (Fabiani, Karis, & Donchin, 1986; Polich, 2007), working memory load or effort (Gunseli et al., 2014) or context updating (Donchin, 1981; Donchin & Coles, 1988). More recent evidence suggests that the P3b may reflect response-related processes, such as reactivating the link between a stimulus and its corresponding button press (Verleger et al., 2017; Verleger, 2020). Regardless of the precise interpretation of these effects, the fact that the LPC was equivalent for irrelevant and irrelevant changes in Yin et al. (2012) suggests that object-based processing persisted beyond the comparison stage.

1. The current study

In summary, evidence from previous research is mixed as to when processing in VWM is biased toward feature-based (Bays, Wu, & Husain, 2011; Fougnie & Alvarez, 2011; Li, Qian, & Liang, 2018; Meyerhoff, Jardine, Stieff, Hegarty, & Franconeri, 2021; Niklaus, Nobre, & van Ede, 2017; van Lamsweerde, Beck, & Johnson, 2016; van Lamsweerde and Beck, 2015; Wang et al., 2016, 2017;Wheeler & Treisman, 2002) or object-based processing (Awh, Barton, & Vogel, 2007; Gao et al., 2016; Luck & Vogel, 1997; Shen, Tang, Wu, Shui, & Gao, 2013; Vogel, Woodman, & Luck, 2001; Yin et al., 2011, 2012), suggesting that processing can be flexible. Understanding when and how individuals engage in object- or feature-based processing is essential to encourage efficient information processing. In the current study, we examine ways in which stages of VWM processing can be dynamically tailored to be either feature- or object-based to meet the needs of specific stimulus characteristics and task demands (Schneegans & Bays, 2019; see also van Lamsweerde et al., 2016; Wang et al., 2016; for behavioral evidence of such flexibility). We also examined whether, despite previous findings consistent with object-based processing (Yin et al., 2011, 2012), VWM comparison can be feature-based under appropriate circumstances.

We modeled the current study after Yin et al. (2011, 2012) but made two changes to promote feature- rather than object-based processing. First, we included change detection trials with within-display feature repetition. As previously mentioned, feature repetition is one factor that may encourage feature-based VWM processing. When multiple items share a feature, representations can be grouped by perceptual connection, such as color and shape at the same location/object (e.g., blue square; Luck & Vogel, 1997) or by feature similarity, such as similar colors (e.g., two blue shapes; Peterson & Berryhill, 2013). This "grouping" can bias VWM processing toward task-relevant features by

[2] Here we use the term LPC rather than P300 for consistency with Yin (2012) as well as to explicitly acknowledge that scalp activity associated with this measure reflects multiple subcomponents (e.g, Barry et al., 2020).

allowing attention to be spread across similar items, thereby maximizing VWM processing efficiency during the encoding and attention processing stages (Bateman, Ngiam, & Birney, 2018; Brady, Konkle, Oliva, & Alvarez, 2009; Erlikhman, Keane, Mettler, Horowitz, & Kellman, 2013; Kasai, Moriya, & Hirano, 2011; Meyerhoff, Jardine, Stieff, Hegarty, & Franconeri, 2021; Niklaus, Nobre, & van Ede, 2017; van Lamsweerde, Beck, & Johnson, 2016; Wannig, Stanisor, & Roelfsema, 2011; van Lamsweerde and Beck, 2015). To assess maintenance capacity, change detection accuracy was transformed into a VWM capacity estimate using Cowan's K formula. Increased capacity estimates on repeated-feature trials containing a task-relevant change would suggest that VWM can be biased toward feature-based processing. Feature repetition could also bias later stages of working memory processing, such as the comparison stage. It is likely more efficient to compare the post-change array to a feature in VWM only once (for a single "grouped" representation) rather than multiple times (for each object). Therefore, improvements in change detection performance for task-relevant trials due to feature repetition would be evidence that such repetition can serve to bias VWM toward feature-based processing.

Our second fundamental design change involved strengthening the task-relevance manipulation by including an initial block of trials where *only* the task-relevant feature changed, and thus there were no task-irrelevant change trials. We reasoned that automatic processing of both task-relevant and task-irrelevant information (a hallmark of object-based processing) may be more likely to occur in situations in which the task-irrelevance manipulation is relatively weak. Indeed, this seems to have been the case in Yin et al. (2011, 2012). Although participants in these studies were told only to detect one type of change (e.g., color changes in Yin et al., 2011 and shape changes in Yin et al., 2012), all types of change trials (e.g., color and shape changes) were included throughout these studies, potentially limiting participants' ability to focus only on the features meant to be task relevant. Developing a strong manipulation of task relevance may be integral to creating a situation where VWM processing is feature-based.

As in Yin et al. (2011, 2012), in addition to comparing accuracy and reaction times across trial types, we also examined ERPs elicited by the post-change displays to isolate effects on the comparison stage as indexed by frontal N200 amplitudes. A finding that both task-relevant and task-irrelevant change trials elicit a more negative N200 amplitude than no-change trials would suggest that object-based processing occurred during the comparison stage of VWM despite our attempts to encourage feature-based processing. By contrast, feature-based VWM processing will be evidenced if task-irrelevant changes elicit a minimal N200, similar to the no-change trials. The latter pattern of results, taken together with those of Yin et al. (2011, 2012), would not only suggest that VWM processing is flexible at the comparison stage, but would point to two possible moderators of this flexibility that could be targeted in future research.

2. Methods

2.1. Participants

Twenty-six psychology students (5 male and 21 female) from Louisiana State University participated in the current study. The average age of participants was 20 years (range = 18 – 23). Four participants' data were removed due to not completing the experiment, and one participant's data was removed due to excessive EEG artifacts. Thus, twenty-one participants were included in the final analysis. Based on an initial power analysis from a behavioral pilot (change type x feature repetition, $n_p^2 = .47$), 16 participants were required to achieve a power of .80. More participants were recruited than required to account for any potential data loss due to incomplete experiments or excessive EEG artifacts. No data were analyzed prior to the completion of data collection. All participants had normal or corrected-to-normal vision and normal color vision. All participants received either course credit or $10/hr for participating in this experiment.

2.2. Design

The study employed a 2 (feature repetition: repeated-feature, unique-feature) x 4 (change type: task-relevant, task-irrelevant, both-change, no-change) repeated measures design.

2.3. Stimuli and apparatus

The experiment was programmed in Experiment Builder (SR Research), and ERPs were recorded using a BioSemi ActiveTwo system.

Stimuli consisted of four-item displays, with each display containing a unique combination of one of 12 abstract shapes and one of eight colors (Fiser and Aslin, 2001; see Figs. 1a and 1b). No two items were identical on a given display. Items in the pre-and post-change displays were presented randomly in one of four quadrants, each 2.16° away from the center of the screen. Each item had a horizontal visual angle of 2.12° and a vertical visual angle of 2.09°. For <u>no-change</u> trials, all four color-shape combinations remained the same from pre- to post-change displays. For each of the other three change types, one item's shape and/or color changed from the pre- to post-change display. For <u>task-relevant change</u> (color change) trials, the color of one item changed, but all other features remained the same. <u>Task-irrelevant change</u> (shape change) trials included one shape change, while all other features remained the same. Finally, the same item would change both color and shape during <u>both-change</u> trials. Examples of these trial types are shown in Fig. 1a.

The location of the changed item was randomly determined between one of the four quadrants. On average, 94 change trials contained a change from the first quadrant, 86 changes were made from the second, 96 in the third quadrant, and 83 from the fourth quadrant. Participants were also presented with an equal number of <u>repeated-feature</u> and <u>unique-feature</u> trials, presented in a random order. For <u>repeated-feature</u> trials, two different shapes shared the same color, two different colors shared the same shape, and one item had a unique color and shape (see Fig. 1b). However, there were never two identical items (same color and same shape for both items). For example, a pre-change display could include a blue circle, a blue square, a green square, and a yellow triangle. The locations of the stimuli with repeated features were randomized on each trial, with an equal probability of the repeated stimuli appearing in any one of the four quadrants. For <u>unique-feature</u> trials, each item had a unique shape and a unique color.

2.4. Procedure

The methodology for the current study was adapted from Yin et al. (2012) with the addition of block 1 containing only task-relevant change trials and the addition of displays with repeated features. Participants completed 720 change detection trials, divided into two blocks of 240 and 480 trials, respectively. In both blocks, participants were instructed to detect a change in color to one of the four stimuli. Participants were never explicitly told that shape may change, only to detect a color change. The purpose of block 1 was to strengthen the task-relevance manipulation. Thus, block 1 contained 120 task-relevant changes (color change) and 120 no-change trials, but no task-irrelevant or

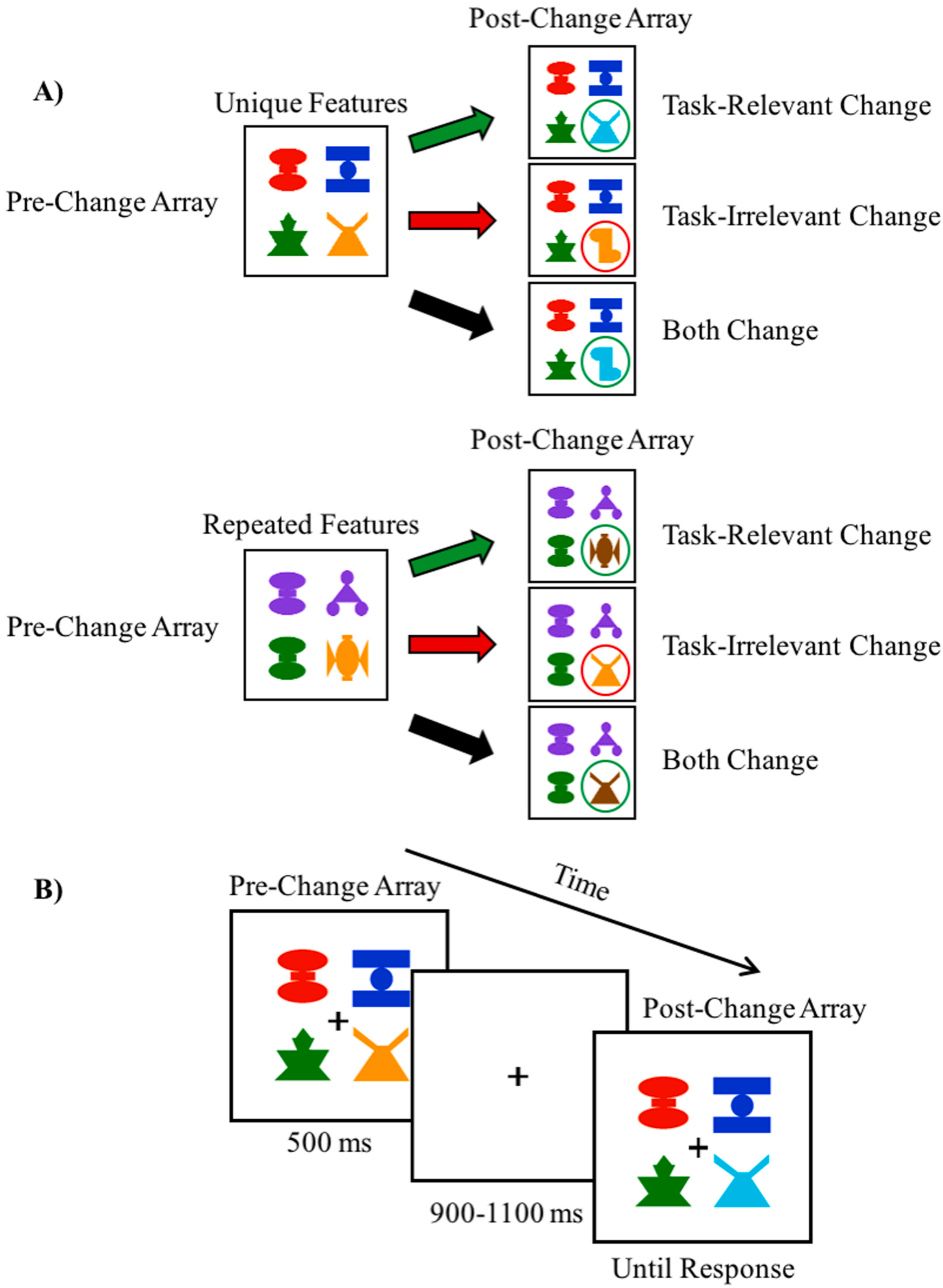

Fig. 1. A) Example of each possible condition during change detection. The changed item was chosen randomly from the four pre-change items. B) Example of one experimental trial.

both-change trials. In block 2, by contrast, an equal number of task-relevant, task-irrelevant, no-change, and both-change trials were included. An example trial is shown in Fig. 1b. A fixation cross was presented in the center of the screen in between trials and each trial was initiated with a key response by the participant. After a 200 – 300 ms delay, participants were presented with one four-item display for

500 ms (pre-change display), followed by a fixation cross for 900 – 1100 ms.[3] The post-change display followed the blank screen, which remained on the screen until the response (see Fig. 1). Participants were instructed to respond "change" when the color changed (task-relevant change and both-change trials) and "no change" when the color did not change (task-irrelevant change and no-change trials). For both blocks, half of the displays within each trial type contained a within-display feature repetition (repetition trials), and half did not (unique trials). Breaks were included throughout the experiment after every 120 trials (two breaks during block 1; four breaks during block 2).

2.5. Electrophysiological recordings

Continuous EEG was recorded throughout the experiment from 32 Ag/AgCL electrodes at locations corresponding to the 10–20 system. Additional electrodes were placed on the right and left mastoids, below the center of the eye, and on each outer canthus. EEG data were recorded at a sampling rate of 512 Hz with a bandpass filter of 0.16–50 Hz. Before statistical analyses, an additional bandpass filter with half-amplitude cutoffs of 0.1–30 Hz was applied using a Butterworth impulse response function and a 12 dB/octave roll-off. ERPs were time-locked to the onset of the post-change array. Data were online referenced to the BioSemi CMS/DRL electrodes and were referenced again offline to the average of the right and left mastoids.

Epochs were 1100 ms long, time-locked to the onset of the post-change displays, with a time window of – 200 – 900 ms. The mean amplitude of the 200 ms prior to stimulus onset (time point 0) was used for baseline correction. To detect ocular artifacts, bipolar channels were created to represent the difference between: 1) the left vertical EOG and channel Fp1; 2) the right vertical EOG and channel Fp2; and 3) the left and right horizontal EOG channels. To screen for trials with horizontal eye movements, blinks, or excessive muscle movements, we performed an initial round of artifact detection using a simple rejection threshold of + /- 100 μV on any scalp channels and a step-like artifact threshold of + /- 60 μV on the bipolar vertical or bipolar horizontal eye channels. These thresholds were then adjusted for individual participants as needed based on visual inspection by a researcher blind to the assignment of trials to conditions (see Luck, 2014, for justification of the use of the individualized thresholds). For datasets in which < 25% of trials contained artifacts (n = 20), all trials with artifacts were excluded from the analysis. Data from the remaining participant were subject to independent components analysis (ICA)[4] using the runica algorithm implemented in EEGLAB (Bell & Sejnowski, 1995; Lee, Girolami, & Sejnowski, 1999; Amari et al., 1997). Two eyeblink components were manually identified and removed from the EEG for this participant. After blink component removal, we did an additional screening of the data for trials containing artifacts due to saccades, muscle activity, or residual eyeblinks. An average of 12.5% of trials (range = 2.9–22.5%) were excluded from each participant. The mean number of trials included in the analysis for each condition ranged from 38 to 45 (min = 19, max = 57). Only correct trials were included in ERP analyses.

2.6. Electrophysiological analysis strategy: planned

Prior studies vary in the time windows chosen to analyze the N200 and LPC components, making it difficult to select specific analysis windows a priori (see Luck & Gaspelin, 2017, for further discussion of this issue). Thus, we took a data-driven approach to selecting our analysis windows by first conducting a mass univariate analysis with cluster-based permutation tests, which identifies broad spatiotemporal clusters that differ according to the conditions of interest while holding the family-wise alpha rate at 0.05. This cluster-based mass univariate approach has the advantage of being data-driven and less constrained by a priori selections regarding analysis windows and electrode sites, while still maintaining statistical power to detect differences (Fields and Kuperberg, 2020). We used the Mass Univariate ERP Toolbox (Groppe et al., 2011) and Factorial Mass Univariate ERP Toolbox (Fields, 2017) to conduct a repeated-measures ANOVA on ERPs elicited by the post-change arrays with the factors of change type (task-relevant, task-irrelevant, both-change, no-change) and feature repetition (repeated-feature, unique-feature) including all 32 electrode channels and all time windows from 0 to 900 ms. Electrodes within 5.45 cm of each other were considered spatial neighbors, and adjacent time points were considered temporal neighbors. Following the cluster-based permutation approach, neighboring F-statistics with uncorrected p-values ≤ 0.05 were grouped into clusters. The F-statistics within each cluster were summed together to calculate the cluster mass. To assign a p-value to each cluster, the cluster masses of the data are compared to an estimate of the null distribution based on 10,000 within-subject permutations. These analyses were supplemented with traditional spatiotemporal-based analyses of ERP amplitudes over combinations of electrode clusters and time windows that emerged as significant in the mass univariate analysis.

2.7. Electrophysiological analysis strategy: exploratory

As described below, visual inspection of the grand average waveforms suggested possible latency differences across conditions in the N200 component, with the irrelevant-change condition peaking close to the end of the 300–400 ms analysis window. Thus, we supplemented our planned analyses of mean amplitudes with exploratory analyses of peak amplitudes over the same frontal cluster from 300 to 450 ms. Peak amplitudes were measured from difference waves formed by subtracting the ERPs for the no-change condition from each of the three other condition and using ERPLAB functions to find a local negative peak over 3 consecutive points within the 300–450 ms time window (see Luck, 2014, for discussions of why the use of difference waves is preferable for measuring peak amplitudes). If no local peak was found, the absolute negative peak over this window was used. Although peak amplitude tends to be a less reliable measure than mean amplitude, it is better suited for comparing amplitudes among conditions with different latencies. Because the N200 is a negative-going component, we defined peak amplitude as the largest negative local peak over at least three time points.

3. Behavioral results

For block 1, a 2 × 2 repeated measure analysis of variance (ANOVA) was conducted with change type (task-relevant, no-change) and feature repetition (repeated-features, unique-features) as within-subject factors. For block 2, separate 2 × 2 repeated measures ANOVAs were conducted for trials where the correct response was "change" (task-relevant and both-change) and for trials where the correct response was "no change" (task-irrelevant and no-change) with change type and feature repetition as within-subject factors. Paired samples t-tests were used to follow up on significant main effects and interactions. Specifically, we were interested in the difference between levels of feature repetition across change types.

[3] Note that this is a shorter pre-post retention interval than the 4000 ms interval that was used in Yin et al. (2011). We chose this retention interval because it is more typical of change detection studies, including studies in which the N200 is measured (Luck & Vogel, 1997; van Lamsweerde et al., 2016; Vogel et al., 2001; Yin et al., 2012). Importantly, Yin et al. (2012) replicated the key ERP results of Yin et al. (2011) using a 1000 ms retention interval, so it is unlikely that differences between our findings and those of Yin et al. (2011, 2012) are related to our retention interval.

[4] Given that ICA can never perfectly isolate artifactual from neural sources and that the N200 component is maximal over frontal electrode sites close to the eyes, we chose to be sparing with our use of ICA to minimize the risk of data distortion. We re-ran all analyses using a rejection-only version of the dataset for the one participant who received ICA and found the results to be unchanged.

3.1. Change detection accuracy

Change detection accuracy was calculated as the proportion of trials that received a correct response. For task-relevant change and both-change trials, the correct response was “change,” and for task-irrelevant change and no-change trials, the correct response was “no change.” Therefore, “change” responses made to task-irrelevant and no-change trials were classified as “false alarms”, whereas “no change” responses to these trials were classified as “correct rejections”. “Change” responses made to task-relevant and both-change trials were classified as “hits”, whereas “no change” responses to these trials were classified as “misses”. Proportions of hits and false alarms are displayed in Fig. 2.

Block 1.

Block 1 only included task-relevant and no-change trials. A main effect of change type emerged, by which accuracy was higher for no-change trials ($M = 0.92$, $SD = 0.08$) compared to task-relevant change trials ($M = 0.82$, $SD = 0.14$), $F(1, 20) = 11.70$, $p = .003$, $\eta_p^2 = .37$. There was also a main effect of feature repetition, with higher accuracy for repeated-feature trials ($M = 0.90$, $SD = 0.09$) compared to unique-feature trials ($M = 0.84$, $SD = 0.15$), $F(1, 20) = 30.06$, $p < .001$, $\eta_p^2 = .60$. Importantly, an interaction between change type and feature repetition was observed, $F(1, 20) = 14.40$, $p = .001$, $\eta_p^2 = .42$. Paired samples t-tests were conducted to examine the difference between repeated and unique trials for task-relevant and no-change trials separately. For task-relevant change trials, performance for repeated-feature trials ($M = 0.87$, $SD = 0.09$) was significantly higher than for unique-feature trials ($M = 0.77$, $SD = 0.15$), $t(20) = 5.98$, $p < .001$, $d = 1.30$. However, for no-change trials, there was no difference in false alarm rate between repeated-feature ($M = 0.07$, $SD = 0.07$) and unique-feature trials ($M = 0.08$, $SD = 0.09$), $t(20) = 0.79$, $p = .44$, $d = 0.17$. This non-significant effect may be due to ceiling performance for no-change trials, for which accuracy was > 90% (see Fig. 2). The accuracy results from block 1 replicate previous research (van Lamsweerde et al., 2016; van Lamsweerde & Beck, 2015) by demonstrating that feature repetition does improve performance.

Block 2.

The 2 × 2 ANOVA exploring false alarms for task-irrelevant and no-change trials revealed a main effect of change type, such that the false alarm rate was lower for no-change trials ($M = 0.09$, $SD = 0.08$) compared to task-irrelevant trials ($M = 0.18$, $SD = 0.13$), $F(1, 20) = 25.50$, $p < .001$, $\eta_p^2 = .56$. No main effect of feature repetition was revealed, with no difference in false alarm rate between repeated-feature trials ($M = 0.13$, $SD = 0.11$) and unique-feature trials ($M = 0.14$, $SD = 0.10$), $F(1, 20) = 1.53$, $p = .23$, $\eta_p^2 = .07$. Finally, the interaction between change type and feature repetition was not significant, $F(1, 20) = 0.63$, $p = .44$, $\eta_p^2 = .03$. Overall, these results suggest that task-irrelevant change trials led to significantly more false alarms (18%) compared to no-change trials (9%), suggesting that at least some amount of object-based processing occurred.

The 2 × 2 ANOVA comparing hit rates for trials for which the correct response was “change” (task-relevant and both-change trials) revealed a main effect of change type, with a significantly higher proportion of hits on both-change trials ($M = 0.86$, $SD = 0.09$) compared to task-relevant change trials ($M = 0.82$, $SD = 0.12$), $F(1, 20) = 10.07$, $p < .05$, $\eta_p^2 = .33$. There was also a significant main effect of feature repetition, with repeated-feature trials ($M = 0.89$, $SD = 0.08$) leading to a higher hit rate than unique-feature trials ($M = 0.79$, $SD = 0.08$), $F(1, 20) = 32.01$, $p < .001$, $\eta_p^2 = .62$. Finally, the interaction between change type and feature repetition was significant, $F(1, 20) = 14.86$, $p < .001$, $\eta_p^2 = .43$. To explore this interaction, paired samples t-tests were conducted to compare the effect of change type for repeated and unique trials. If task-irrelevant features are processed, we would expect both-change trials to differ from relevant-change trials. For repeated-feature trials, the t-test revealed no significant difference between task-relevant change trials ($M = 0.89$, $SD = 0.09$) and both-change trials ($M = 0.89$, $SD = 0.07$), $t(20) = 0.27$, $p = .79$, $d = 0.06$. However, for unique-feature trials, the hit rate was significantly higher for both-change trials ($M = 0.83$, $SD = 0.11$) compared to task-relevant change trials ($M = 0.76$, $SD = 0.16$), $t(20) = 3.79$, $p = .001$, $d = 0.83$. These results suggest that when both task-relevant and task- irrelevant features are present, irrelevant features are more likely to be processed on unique- rather than repeated-feature trials, consistent with the notion that feature repetition can encourage feature-based processing.

4. Change detection accuracy: Cowan’s *K*

Feature-repetition may improve efficiency of working memory maintenance by means of “grouping” task-relevant features. To assess VWM capacity, change detection accuracy was converted into a K estimate using Cowan’s (2001) formula, $K = N\,(H - FA)$. Cowan’s K was analyzed only for trials in Block 2 that contained a task-relevant feature change. Four measures were created to assess capacity estimates (Relevant Hits – No-Change FAs; Both-Change Hits – Irrelevant Change FAs). To measure the ability to discriminate color-change from no-change trials, the difference between task-relevant change trial hits and no-change trial false alarms was calculated for repeated- and unique-feature trials separately. Next, the difference between task-irrelevant change and both-change trials was calculated to measure how the

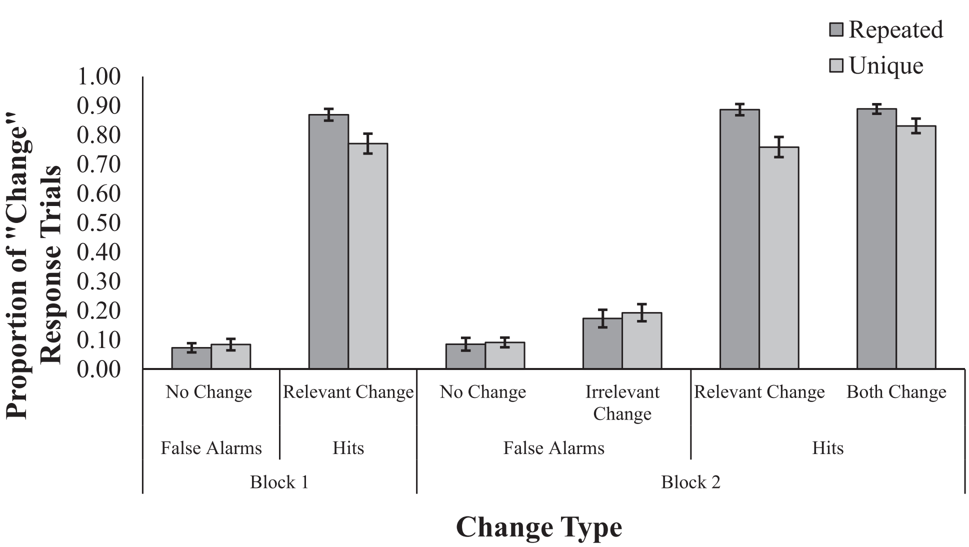

Fig. 2. False alarms and hits for trials in which a “change” response was made, separated by feature repetition and change type. No-change and task-irrelevant change trials display false alarms (1 – correct rejections). Task-relevant and both-change trials display hit rate. In Block 1, there was an effect of feature repetition. In Block 2, more false alarms were made on task-irrelevant trials than no-change trials. Change type did not affect the hit rate when features were repeated. Both-change trials had a higher hit rate than task-relevant change trials when features were unique. Error bars denote standard error.

presence of a task-irrelevant feature change impacts VWM capacity. We corrected for instances in which no false alarms were made by adding 0.5 to each hit and false alarm rate and then dividing the result by N + 1, where N is the number of trials (Snodgrass & Corwin, 1988). All hits and false alarm measures were calculated separately for repeated- and unique-feature trials.

There was a main effect of change type, with a higher estimated VWM capacity for task-relevant change trials ($M = 2.86$, $SD = 0.66$) compared to both-change trials ($M = 2.66$, $SD = 0.65$), $F(1, 20) = 6.53$, $p = .02$, $\eta_p^2 = .25$. Additionally, there was a main effect of feature repetition, with repeated-feature trials ($M = 2.95$, $SD = 0.63$) leading to higher predicted VWM capacity compared to unique-feature trials ($M = 2.57$, $SD = 0.68$), $F(1, 20) = 28.23$, $p < .001$, $\eta_p^2 = .59$. The interaction between feature repetition and change type was not significant, $F(1, 20) = 3.58$, $p = .07$, $\eta_p^2 = .15$. These results suggest that when feature-based processing is encouraged with feature repetition, participants are able to store more in VWM (Fig. 3).

4.1. Change detection response times

Response times (RTs) were examined for correct change detection trials only (Fig. 4). ***Block 1***.

In block 1, there was no main effect of change type, $F(1, 20) = 1.61$, $p = .22$, $\eta_p^2 = .07$. The main effect of feature repetition was also not significant, $F(1, 20) = 0.40$, $p = .54$ $\eta_p^2 = .02$, nor was the interaction between change type and feature repetition $F(1, 20) = 0.26$, $p = .61$, $\eta_p^2 = .01$. Thus, there was no evidence that feature repetition impacts RTs.

Block 2.

For no-change and task-irrelevant change trials (correct response is “no change”), there was a main effect of change type, with task-irrelevant change trials ($M = 1044.46$ ms, $SD = 337.38$ ms) leading to significantly longer RTs than no-change trials ($M = 892.11$ ms, $SD = 236.25$ ms), $F(1, 20) = 57.40$, $p < .001$, $\eta_p^2 = .74$. No main effect of feature repetition was revealed, with similar RTs for both repeated-feature trials ($M = 965.85$ ms, $SD = 291.58$ ms) and unique-feature trials ($M = 970.73$ ms, $SD = 309.06$ ms), $F(1, 20) = 0.15$, $p = .70$, $\eta_p^2 = .01$. Finally, the interaction between change type and feature repetition was not significant, $F(1, 20) = 0.14$, $p = .71$, $\eta_p^2 = .01$. The main effect of change type suggests that the task-irrelevant feature change impacted the correct rejection response, suggesting that in the absence of a task-relevant feature change, the task-irrelevant feature change was processed to some extent.

For task-relevant and both-change trials (correct response is “change”), there was no main effect of change type, with similar change detection RTs for both task-relevant change trials ($M = 908.02$ ms, $SD = 242.40$ ms) and both-change trials ($M = 913.14$ ms, $SD = 246.49$ ms), $F(1, 20) = 0.23$, $p = .64$, $\eta_p^2 = .01$. The main effect of feature repetition was also non-significant, with similar RTs between repeated-feature trials ($M = 904.96$ ms, $SD = 233.11$ ms) and unique-feature trials ($M = 916.20$ ms, $SD = 257.34$ ms), $F(1, 20) = 0.59$, $p = .45$, $\eta_p^2 = .03$. Finally, the interaction between change type and feature repetition was not significant, $F(1, 20) = 0.82$, $p = .38$, $\eta_p^2 = .04$. Overall, these results suggest that RTs are insensitive to the presence of a task-irrelevant feature change on trials that also contained a task-relevant feature change.

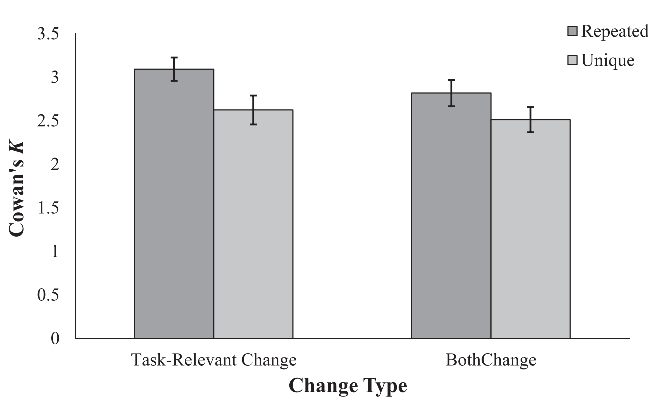

Fig. 3. Estimated VWM capacity, Cowan’s *K,* for trials containing a task-relevant change separated by feature repetition. No-change trial false alarms were subtracted from task-relevant change trial hits. Task-irrelevant change trial false alarms were subtracted from both-change trial hits. The main effect of change type and feature repetition was significant. Error bars denote standard error.

5. ERP results

5.1. Planned analyses

5.1.1. Mass univariate analyses

For the cluster-based mass permutation analysis, no clusters emerged with a significant main effect of feature repetition ($ps > 0.052$) nor a change type x feature repetition interaction ($ps > 0.67$). However, a significant main effect of change type emerged in a single, broadly distributed cluster from 257 to 688 ms ($p < .001$). The cluster’s temporal peak was at 432 ms (temporal mass = 468 ms), and the spatial peak was at electrode P4 (spatial mass = P03). As shown in Fig. 4, however, this cluster appeared to have two distinct subregions: one that spanned from approximately 300 to 400 ms over frontal electrodes, consistent with the timing and scalp distribution of the N200 component, and a second temporally overlapping subregion with a parieto-occipital focus from approximately 300 to 600 ms, consistent with the LPC. For this reason, we chose to follow up on the mass univariate results by conducting spatiotemporal averaging-based analyses for 1) the 300 – 400 ms time window (N200) averaged over a cluster of frontal electrodes (Fp1, Af3, F7, F3, Fz, F4, F8, Af4, Fp2); and 2) the 300 – 600 ms time window (LPC) averaged over a cluster of parietal and occipital electrodes (P7, P3, Pz, Po3, O1, Oz, O2, Po4, P4, P8). These analyses consisted of 4 (change type: task-relevant, task-irrelevant, both-change, no-change) x 2 (feature repetition: repeated-feature, unique-feature) repeated measures ANOVAs over the mean amplitude of each cluster over each time window. Although no main effects or interactions involving repetition were found in the mass univariate analysis, we included repetition as a factor in this analysis in case such effects were present but not detected due to the conservative nature of the mass univariate analysis. The Greenhouse-Geisser correction for non-sphericity was applied to effects that involved more than two levels (main effects of change type and change-type x repetition interactions).

Spatiotemporal Average-Based Analysis: 300 – 400 ms (N200). Regarding the frontal N200 analyses, the main effect of feature repetition was non-significant $F(1, 20) = 1.15$, $p = .30$, $\eta_p^2 = .05$, with no significant N200 amplitude differences between repeated-feature ($M = -0.74$, $SD = 3.88$) and unique-feature trials ($M = -1.14$, $SD = 3.19$). However, a significant main effect of change type emerged, $F(2.85, 57.01) = 5.80$, $p = .002$, $\eta_p^2 = .22$ (see Figs. 5, 7, & 8). Follow-up paired t-tests revealed that N200 amplitudes were larger (more negative) for both task-relevant change ($M = -1.71$, $SD = 3.62$) and both-change trials ($M = -1.50$, $SD = 3.85$), relative to no-change trials ($M = -0.003$, $SD = 3.63$); $ts = 3.38$ and 3.21; $ps = 0.003$ and $.004$, respectively, $ds = 0.74$ and 0.70. Additionally, both task-relevant change and both-change trials produced larger N200 amplitudes compared to irrelevant-change trials ($M = -0.55$, $SD = 3.68$), $ts = 2.52$ and 2.25, $ps = 0.02$ and $.04$, respectively, $ds = 0.55$ and 0.49. N200 amplitudes did not differ between task-irrelevant change and no-change trials, $t(20) = 1.04$, $p = .31$, $d = 0.23$, nor between task-relevant change and both-change trials, $t(20) = 0.47$, $p = .64$, $d = 0.10$. The interaction between repetition and change type was not significant, $F(2.81, 56.28) = 1.74$, $p = .17$, $n_p^2 = .08$. In summary, the N200 results suggest that, at least during the VWM comparison process, participants successfully filtered out the task-irrelevant dimension regardless of feature repetition or response type

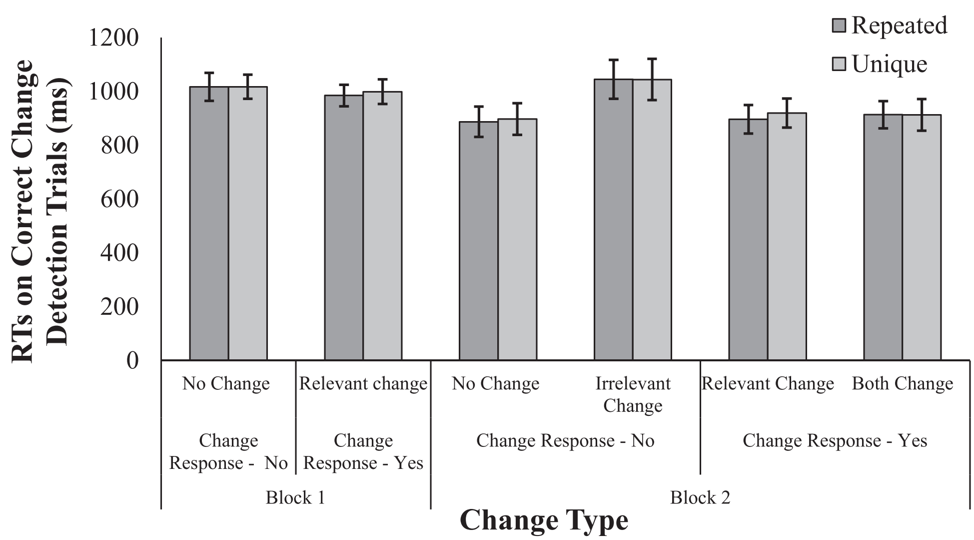

Fig. 4. Response times for correct change detection trials separated by feature repetition and change type. Task-irrelevant change trials produced significantly longer RTs than all other change trial types. Error bars denote standard error.

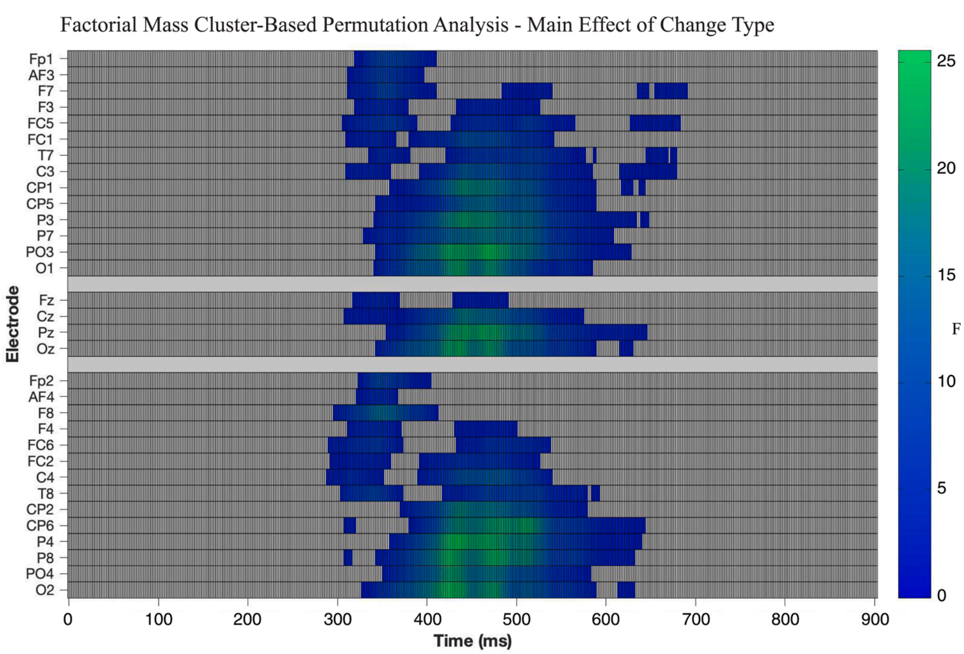

Fig. 5. Raster diagram representing the results of the cluster-based permutation test, which included all electrodes and all time points between 0 and 900 ms. Electrode groupings along the y-axis correspond to left hemisphere (top group), midline (middle group) and right hemisphere electrodes (bottom group). Within each group, electrodes are listed in descending order of anteriority. Colored rectangles indicate electrodes and time points that were included in the cluster with a significant main effect of change type. No clusters showed a significant main effect of feature repetition or a change type x feature repetition interaction.

("change"/"no change"). These results suggest that VWM processing can be feature-based during the comparison stage.

Spatiotemporal Average-Based Analysis: 300 – 600 ms (LPC). The results of the LPC analyses closely mirror those of the N200. As with the N200, no main effect of feature repetition was found on LPC amplitudes ($M = 9.19$, $SD = 3.02$; $M = 8.74$, $SD = 3.19$ for repetition and unique trials, respectively), $F(1, 20) = 2.04$, $p = .17$, $\eta_p^2 = .09$. However, a significant main effect of change type was present, $F(2.30, 46.06) = 15.14$, $p < .001$, $\eta_p^2 = 0.43$ (see Fig. 6, 7, & 8). Follow-up paired t-tests revealed that, relative to no-change trials ($M = 8.12$, $SD = 2.50$), LPC amplitudes were significantly larger for both task-relevant change ($M = 9.87$, $SD = 3.60$), $t(20) = 3.42$, $p = .003$, $d = 0.75$, and both-change trials, ($M = 10.17$, $SD = 3.90$), $t(20) = 3.81$, $p = .001$, $d = .83$. Task-relevant change trials elicited significantly larger amplitudes compared to task-irrelevant change trials ($M = 7.71$, $SD = 2.91$), $t(20) = 5.74$, $p < 0.001$, $d = 1.25$. Finally, the difference in LPC amplitudes between both-change trials and task-relevant change trials was not significant, $t(20) = 0.90$, $p = .38$, $d = 0.20$, nor was the difference between no-change trials and task-irrelevant change trials, $t(20) = 0.96$, $p = .35$, $d = 0.21$. The interaction between repetition and change type was not significant, $F(2.44, 48.75) = 0.83$, $p = .47$, $\eta_p^2 = .04$. Overall, these results are consistent with feature-based processing.

5.2. Exploratory analyses

Overall, the results of our primary analyses suggest that the type of comparison processing attributed to the N200 was absent for task-irrelevant features. However, visual inspection of Fig. 7, as well as of the difference waves formed by subtracting ERPs for no-change trials from those of each of the other conditions (Fig. 8) suggest another possibility: namely, that N200 potentials evoked by task-irrelevant change trials occurred later than those evoked by the other two change conditions, and thus were less well-captured by our analysis window.

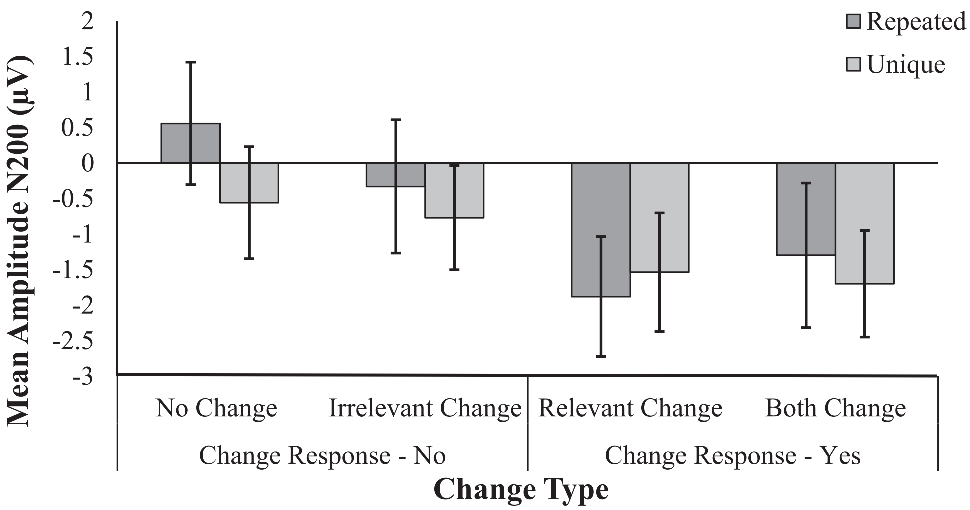

Fig. 6. Mean amplitudes for the N200 separated by feature repetition and change type. Task-irrelevant change trials produced minimal N200 amplitudes. Error bars denote standard error.

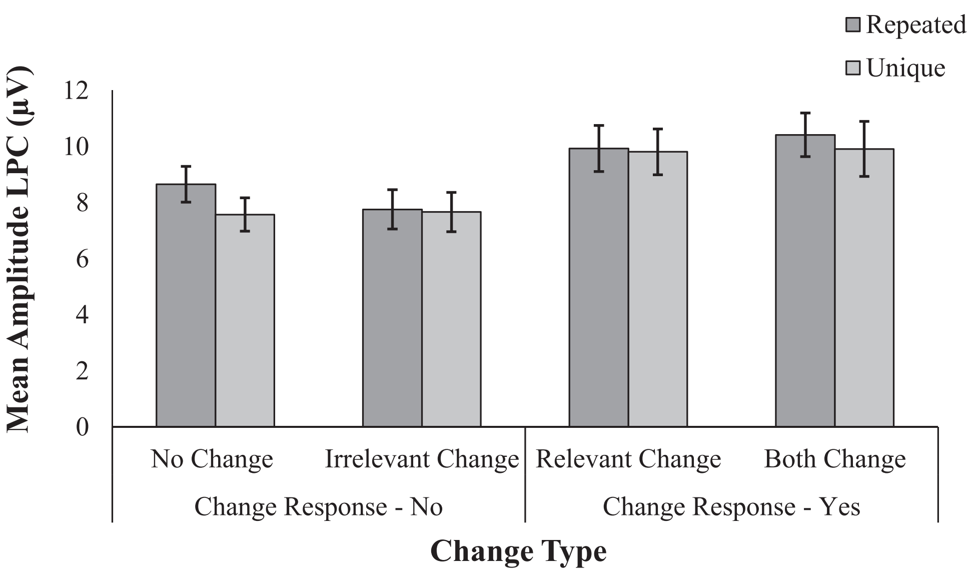

Fig. 7. Mean amplitudes for the LPC separated by feature repetition and change type. Task-irrelevant change trials produced smaller LPC amplitudes than trials containing a task-relevant change. Error bars denote standard error.

To further explore this possibility, we conducted a series of one-sample t-tests with Bonferroni-corrected p-values to determine whether the peak amplitude of each difference wave over the frontal electrode cluster between 300 and 450 ms was reliably different from zero (e.g., was the peak N200 amplitude generated by each change type reliably different from that generated by no-change). Using a Bonferroni corrected alpha of .017, all three comparisons were significant. For the relevant-none difference wave, the peak amplitude was − 3.36 uV, *SD* = 2.35, $t(20) = 6.55$, $p < .001$, $d = 1.43$. For the irrelevant-none difference wave, the peak amplitude was − 2.03 uV, *SD* = 2.05, $t(20) = 4.54$, $p < .001$, $d = 0.99$. For the both-none difference wave, the peak amplitude was − 3.08 uV, *SD* = 2.63, $t(20) = 5.99$, $p < .001$, $d = 1.31$.

We next conducted a repeated-measures ANOVA with the single factor of difference type (relevant-none, irrelevant-none, both-none) to compare across the three conditions. The effect was significant, $F(1.99, 39.77) = 4.31$, $p = .02$, $\eta_p^2 = 0.18$, reflecting a greater difference for task-relevant than for task-irrelevant changes, $t(20) = 2.83$, $p = .01$, $d = 0.62$ and as well as a greater difference for both-change than task-irrelevant changes, $t(20) = 2.12$, $p = .047$, $d = 0.46$. The difference between task-relevant and both-change trials was non-significant, $t(20) = 0.60$, $p = .56$, $d = 0.13$.

In summary, the results of these exploratory peak amplitude analyses are in partial agreement with those of the mean amplitude analyses. Both sets of analyses converge to suggest that: 1) N200 amplitudes are larger for task-relevant change and both-change displays relative to task-irrelevant change displays, and 2) task-relevant change displays elicit comparable N200 amplitudes to both-change displays. However, while mean amplitude analyses revealed no significant difference between irrelevant-change and no-change trials, examination of peak amplitudes raises the possibility that the N200 potentials evoked by irrelevant-change trials were delayed and attenuated, but not eliminated. As discussed further below, this pattern mirrors that of the behavioral results in suggesting that the presence of a task-relevant feature can be an important determinant of whether VWM comparison is object- or feature-based.

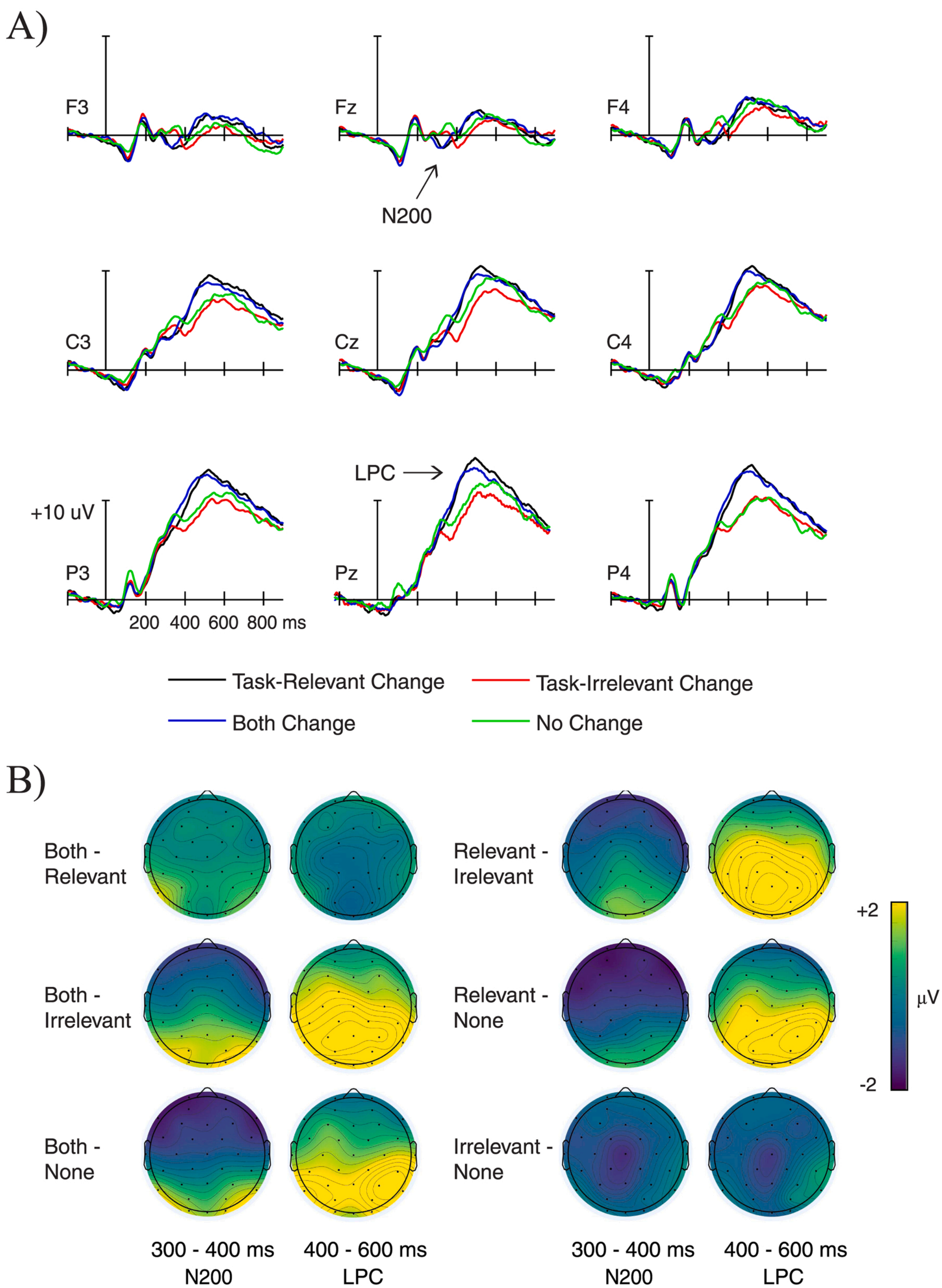

Fig. 8. A) Grand average ERP waveforms time-locked to the post-hange arrays in Block 2 for task-relevant (color) change trials, task-irrelevant (shape) change trials, both-change trials, and no-change trials. Waveforms are plotted positive-up and are shown for nine electrode locations, including frontal (F3, Fz, F4), central (C3, Cz, C4), and parietal sites (P3, Pz, P4). B) Topographical plots of differences among conditions over the time window of interest. Waveforms and topographical plots are collapsed across levels of feature repetition.

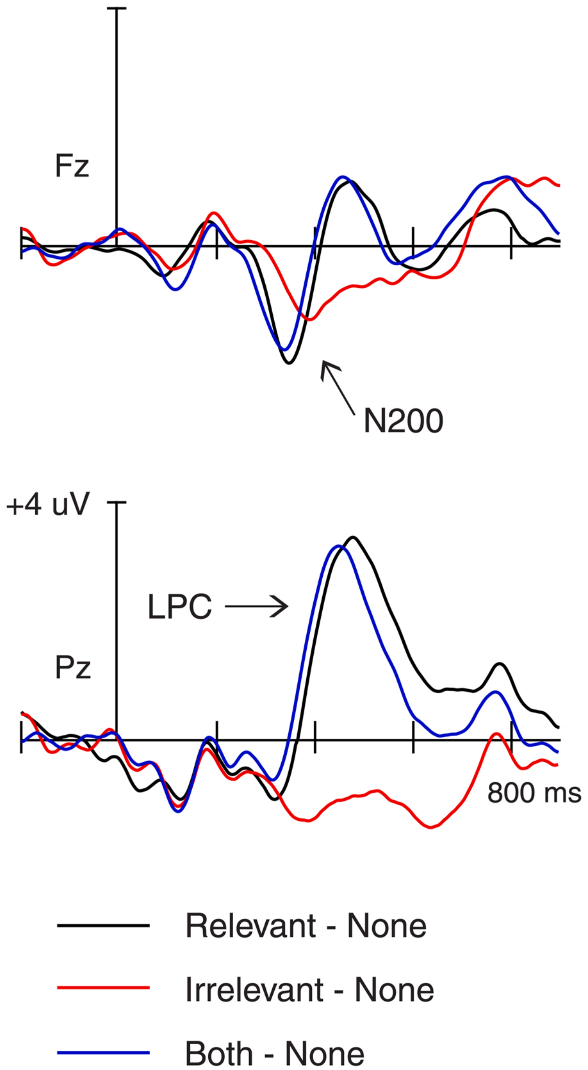

Fig. 9. Waveforms depicting the subtraction between relevant- and no-change trials (black), irrelevant- and no-change trials (red), and both- and no-change trials (blue). Waveforms are plotted positive up and are shown for one frontal midline electrode (Fz) and one parietal midline electrode Pz).

6. Discussion

Previous research has provided mixed evidence as to when VWM is biased toward feature- versus object-based processing (Awh, Barton, & Vogel, 2007; Bays, Wu, & Husain, 2011; Fougnie & Alvarez, 2011; Gao et al., 2016; Gu et al., 2022; Li, Qian, & Liang, 2018; Luck & Vogel, 1997; Meyerhoff, Jardine, Stieff, Hegarty, & Franconeri, 2021; Niklaus, Nobre, & van Ede, 2017; Shen, Tang, Wu, Shui, & Gao, 2013; van Lamsweerde, Beck, & Johnson, 2016; Vogel, Woodman, & Luck, 2001; van Lamsweerde and Beck, 2015; Wang et al., 2016, 2017; Wheeler & Treisman, 2002; Yin et al., 2011, 2012). Prior evidence from ERP research supports the idea that the comparison stage of VWM is biased toward object-based processing (Yin et al., 2011, 2012). The goal of this study was to examine the extent to which the processing of task-irrelevant features in VWM comparison can be feature-based under appropriately conducive circumstances. We attempted to create such circumstances by 1) having features repeat within a display so that feature-based processing would be more efficient and 2) using a strong task-relevance manipulation by including an initial block (block 1) in which all change trials were task-relevant.

Both behavioral and electrophysiological data suggests that we were successful in creating a situation conducive to feature-based processing. Performance in block 1 was high, suggesting that participants were able to focus on the task-relevant change. In addition, in both blocks 1 and 2, feature repetition improved change detection accuracy. Indeed, for trials containing a task-relevant change with repeated features in block 2, neither the hit rate nor response times differed between task-relevant change and both-change trials. N200 and LPC amplitudes were also comparable between task-relevant and both-change trials regardless of feature repetition. Overall, these data suggest that when a task-relevant feature is present, feature-based processing can be encouraged when features repeat within a display and a sufficiently strong manipulation of task-relevance has been established (as we did with block 1).

We found a different pattern of results for trials that did not contain task-relevant feature changes (no-change and task-irrelevant change trials). Specifically, both reaction time and false alarm rates were higher for task-irrelevant change relative to no-change trials. Moreover, while our planned ERP analyses revealed no differences in either the N200 or LPC between these trial types, exploratory analyses suggested that there may have been a later N200 difference between task-irrelevant change and no-change trials, implying that the comparison stage for task-irrelevant changes may have been delayed but not eliminated. Finally, unlike on trials containing a task-relevant change, neither accuracy nor reaction times on target-absent trials was facilitated by feature repetition. Altogether, these results suggest that the balance of feature- and object-based processing differed according to whether a change was present along the task-relevant feature.

There are multiple stages of VWM processing that contribute to change detection performance, including 1) attention and encoding, 2) maintenance, 3) comparison, 4) decision/response (Beck, Peterson, & Angelone, 2007; Simons, 2000; Simons & Rensink, 2005; Wilken & Ma, 2004). Our behavioral and ERP results provide clues as to how VWM processing stage(s) can flexibly switch between object based and feature based processing. Behaviorally, evidence of feature-based processing was found only on trials containing a task-relevant change. This finding rules out the possibility that the pre-change displays were processed in a purely feature-based manner, because both shape and color information were available at the onset of the post-change array. On the other hand, N200 amplitudes did not differ between both-change and task-relevant change trials suggesting that by the time VWM comparison took place, feature-based processing had been engaged, at least for trials containing a task-relevant change. Finally, there was no evidence of object-based processing for either trial type during the LPC. The timing and scalp distribution of the LPC effects shown here suggest a strong contribution of the P3b subcomponent. The functional significance of the P3b is a matter of considerable debate, with hypotheses ranging from memory storage to stimulus-response reactivation (for review see Verleger, 2020). Regardless, the lack of a difference in LPC amplitudes between task-irrelevant change and no-change trials suggests that stage(s) of processing reflected by this component were also applied in a feature-based manner.

Our ERP results stand in contrast with those of previous work. In at least two prior change detection studies (Yin et al., 2011, 2012), task-relevant and task-irrelevant feature changes elicited equivalent N200 amplitudes, suggesting that VWM comparison was object-based. As with the N200, Yin et al. (2012) found no differences in mean LPC amplitude between task-relevant and task-irrelevant stimuli, suggesting that post-comparison evaluation and/or response processes were applied equally to both types of stimuli. Again, we propose that the differences between our results and those of Yin et al. (2011, 2012) stemmed from our efforts to create conditions conducive to feature-based processing. In the case of change detection, object-based processing may be the most efficient strategy when participants are not in a strong task-relevance mindset and thus have difficulty filtering out conspicuous changes to task-irrelevant features. However, once this mindset is established—and particularly in conjunction with within-display feature repetition—feature-based processing is more efficient and thus is “adopted” by certain stages of VWM.

As an important caveat, while we tried to align our work as closely as possible with Yin (2011, 2012) aside from the task-relevancy induction and inclusion of feature repetition, it remains possible that other, unaccounted for differences between our study and theirs also contributed to differences in our results. Future research that manipulates these factors within the same study would provide a more conclusive demonstration that object- and feature-based comparison processes can be deployed flexibly, not only across trial types, but also for the same trial type under different types of task relevance.

The current study also contributes to understanding the facilitative effect of within-display feature repetition on change detection performance (Meyerhoff et al., 2021; van Lamsweerde et al., 2016; van Lamsweerde & Beck, 2015). This, too, was specific to trials containing a task-relevant change: hit rates were higher on trials in which features were repeated, but false alarms were unaffected. However, this behavioral pattern was not mirrored in the ERPs elicited by the post-change array, which were entirely unaffected by feature repetition. One possibility is that the processes involved in "grouping" along the task-relevant feature occurred partially or entirely during the pre-change array or were otherwise distributed in such a way that was not well time-locked to the onset of the post-change array. By this account, the fact that feature repetition only affected the hit rate could reflect an uneven effect of grouping on the ability to detect task-relevant changes versus the ability to ignore task-irrelevant changes, rather than reflecting differences in whether grouping occurred in the first place. Indeed, capacity estimates revealed larger Cowan's K for repeated- compared to unique-feature trials, suggesting that participants stored more in VWM on repeated trials. Larger capacity estimates under conditions of feature repetition indicate that the beneficial effects of repetition on performance may stem in part from more efficient processing of the pre-change display, which may explain why the beneficial effects of feature repetition were not accompanied by changes to the N200 or LPC elicited by the post-change array. Future research designed specifically to examine encoding processes could shed additional light on this issue.

It is worth noting that the N200 effects reported here and in previous work using change detection (Yin et al., 2011, 2012) bear some resemblance to the visual mismatch negativity (vMMN), which occurs over a similar time window but with an occipital rather than anterior scalp distribution. However, these two components have different functional properties. The vMMN is sensitive to violations of incidentally learned environmental regularities (e.g., "deviant" stimuli, such as an occasional asymmetry in a stream of symmetric patterns; Kecskés-Kovács et al., 2013) and is famously insensitive to whether or not the information occurs within the focus of attention (Czigler, 2014; Stefanics, Kreml Ã¡Ä ek, & Czigler, 2015). By contrast, the anterior N200 is elicited by attended deviance from an active working memory template, which can be intentionally updated with new goal information (Folstein and Van Petten, 2008). The cognitive processes indexed by the N200 are thus more relevant to change detection, which requires working memory templates to be updated on a trial-by-trial basis.

Finally, although our study focused largely on flexible trade-offs between object- and feature-based processing in the comparison stage of VWM, this may not be the earliest stage that can manifest such flexibility. It would be interesting for future research to examine measures of other stages such as encoding and maintenance (for example, via the contralateral delay ERP component; e.g., Woodman & Vogel, 2008) to directly test this possibility and broaden the understanding of sources of flexibility in how information is processed in VWM. Nonetheless, the current study provides the first electrophysiological evidence that feature-based processing can be engaged during the comparison stage, while raising the possibility that the balance of feature- and object-based processing may depend on the strength of the task-relevance manipulation. As such, this study demonstrates that increased attention to the role of task demands may help to reconcile discrepant findings in the debate regarding when object- or feature-based processing in VWM occurs.

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Data Availability

Data will be made available on request.

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