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SHORT REPORT

Memory benefits when actively, rather than passively, viewing images

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Abstract
Serial visual presentations of images exist both in the laboratory and increasingly on virtual platforms such as social media feeds. However, the way we interact with information differs between these. In many laboratory experiments participants view stimuli passively, whereas on social media people tend to interact with information actively. This difference could influence the way information is remembered, which carries practical and theoretical implications. In the current study, 821 participants viewed streams containing seven landscape images that were presented at either a self-paced (active) or an automatic (passive) rate. Critically, the presentation speed in each automatic trial was matched to the speed of a self-paced trial for each participant. Both memory accuracy and memory confidence were greater on self-paced compared to automatic trials. These results indicate that active, self-paced progression through images increases the likelihood of them being remembered, relative to when participants have no control over presentation speed and duration.

Keywords Self-paced · Passive viewing · Image memorability · Attention · Memory

Introduction

Serial visual presentation designs are widely used to examine temporal cognitive processing, and provide a wealth of knowledge about attention and memory (Chun & Potter, 1995; Dux & Marois, 2009; Potter & Levy, 1969; Witkowski & Spence, 2012). Increasingly, serial visual presentation designs are incorporated into technology we frequently encounter, such as social media feeds that require a user to scroll through content. However, in laboratory experiments participants often have no control over stimulus duration or presentation rate, which contrasts with the way we interact with social media or similar platforms. Here we ask – does actively advancing through images affect our memory for them compared to passive viewing? Exploring such relationships may reveal cognitive mechanisms that differ for active compared to passive presentations, as well as the degree to which lab-based measures generalize to real-life tasks (Baror & He, 2021; Endsley, 2017).

Allowing viewers to control the rate of presentation likely changes the way that information is processed, which makes the literature gap in this space surprising (Baror & He, 2021). Nevertheless, several related literatures suggest that actively self-pacing through stimuli may enhance memory for stimuli. For example, previous work has identified links between action and cognition (Gibson, 1979; Hommel, 2010; Zmigrod & Hommel, 2013), and a growing body of literature indicates that active engagement with stimuli can benefit perception and memory (Afrooz et al., 2018; Berberian et al., 2012; Craddock et al., 2011; Ichikawa & Masakura, 2006; Kinder & Buss, 2021; Knoblich & Flach, 2001; Maruya et al., 2007; Voss et al., 2011; Yebra et al., 2019; but see Chen & Tsoi, 1988; Hine & Tasaki, 2019; Russell & Chaparro, 2001; Tenhundfeld & Witt, 2020). In a modified go/no-go task, stimuli paired with go responses requiring action (a button press) were remembered better than stimuli paired with no-go responses requiring no action (Yebra et al., 2019; see also Kinder & Buss, 2021). Self-pacing through information may also benefit attention. For example, the "attentional boost effect" reveals memory

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benefits for stimuli when they are paired with responses made to other task-relevant target stimuli, such as better memory for scene images when they happen to coincide with colored dots that require a participant response (Swallow & Jiang, 2010, 2013). Furthermore, when participants had volitional control to self-explore through stimuli in a visual array, they remembered stimuli better than participants who passively watched a yoked version of the same display (i.e., the same stimuli presented in the same order and for the same amount of time; Voss et al., 2011). In the current study, we explore whether allowing observers to actively control the speed of image advancement within a visual stream will show similar memory benefits observed in other task domains.

In addition to possible action-related boosts in memory, actively controlling the speed of image presentation may allow participants to calibrate view duration based on image memorability. Some images are more memorable than others (Bainbridge et al., 2017; Isola et al., 2011; Khosla et al., 2015), and research indicates that processes underlying image memorability are related to the perceptual processes that influence memory encoding (Bainbridge et al., 2017). If the view duration of an image varies as a function of image memorability, providing autonomy over the speed of stimuli presentation in a stream may especially benefit memory for less memorable images, compared to stimuli presented at an otherwise matched but uniform speed.

The current study investigates whether actively controlling the pace and duration of stimulus exposure (self-paced trials) improves memory accuracy and confidence compared to when participants have no control over the pace and duration (automatic trials), even when there are no appreciable differences in the actual presentation rate. Research indicates that people can remember many unique scenes when they view them one at a time (Brady et al., 2008; Thunell & Thorpe, 2019), and we chose such stimuli as typical of those encountered in the laboratory as well as on social media. Further, because of the technological implications associated with this design, we included exploratory analyses to assess whether individual differences in attitudes toward technology (Compeau & Higgins, 1995; Merritt et al., 2019) additionally predict how much someone may benefit from the active versus passive presentation of images. We hypothesized that participants' memory accuracy and confidence in their memory would be higher on self-paced trials than on automatic trials. We also examined whether individual differences in attitudes towards technology predicted the difference in performance on active (self-paced trials) and passive (automatic trials) conditions.

Method

Participants

Eight hundred and forty-two participants completed the experiment (591 female, 240 male, five non-binary, one genderfluid, four preferred not to say, one did not report; age range = 17–59 years, M = 19.9 years, SD = 5.4 years). Undergraduates enrolled in the PSYC1101 Psychology: Mind and Brain course at The University of Western Australia were invited to voluntarily complete the experiment, which was related to a unit assessment that they could complete regardless of their participation. Data were included in the final dataset only if participants: consented to their data being used for research purposes, completed all experimental trials, completed the experiment during the week allocated for research purposes (before any participant was debriefed about the goals of the study), and self-indicated there was no reason we should not use their data (e.g., if they were distracted). We additionally excluded data from 21 participants who had poor performance accuracy or were not consistently self-pacing on self-paced trials (see *Data screening*). The final sample included 821 participants. The study was approved by the UWA Human Research Ethics Office, Protocol 2022/ET000019 and was not preregistered. The experimental program and anonymized data are available via the Open Science Framework at: https://osf.io/zm78v.

Sample size was determined by the large number of students who volunteered to contribute. In our analyses, we interpret $p < .005$ as significant to reduce the false-positive rate, in line with recent calls to promote reproducibility (Benjamin et al., 2018). A sensitivity analysis with G*Power (Faul et al., 2007) indicated that our within-subject t-tests could detect effect sizes of $d_z = 0.128$ ($N_{\text{final}} = 821$, $\alpha = .005$, power $(1 - \beta) = .80$).

Materials

The experiment was presented online using participants' own computers.

Recognition memory task

A recognition memory task was programmed using Inquisit 6 (Inquisit 6, 2021). The task included 460 scene images sourced from the UCSD Vision and Memory Lab Scene Set (Konkle et al., 2010). The number of images ensured that each image appeared only once in the experiment. The color images depicted an array of different outdoor landscape scenes with no obvious people, animals, or objects present.

Images were presented at a size with equal height and width determined as 25% of the participant's monitor height. All stimuli appeared against a white background.

The task contained 46 trials, divided into four blocks of ten trials plus an additional practice block of six trials at the beginning of the experiment. Every trial was a serial visual presentation of seven landscape images, with no interstimulus interval, such that each image immediately replaced the previous image. The experimental trials included 20 automatic trials (passive condition) and 20 self-paced trials (active condition) distributed equally across blocks in alternating order. The six practice trials included three automatic and three self-paced trials in alternating order. Self-paced and automatic trials differed only in the way images advanced. In self-paced trials, participants pressed the spacebar to advance to the next image in the stream, and were encouraged to advance as fast as they could without compromising accuracy in their later recognition of the images. In automatic trials, participants could not control the image presentation rate, and images were instead presented at a rate determined by the average speed of the previous self-paced trial. Thus, the speed at which participants saw images in self-paced and automatic trials was roughly matched. The sole exception was the first practice trial of the experiment, which was always an automatic trial and presented at a rate of 800 ms per image. Participants were not told that the task worked such that automatic trials were presented at a rate based on the previous self-paced trial.

Despite being self-paced, to ensure that all participants advanced through the experiment at rates that did not differ dramatically, images were set to advance at a base rate of 4 s on self-paced trials. If participants did not advance an image on a self-paced trial by the time 4 s elapsed, the program automatically advanced to the next image. If participants did not advance through any of the images in a self-paced trial, a prompt was presented at the beginning of the next self-paced trial: "Remember: go as fast as you can by using the spacebar on self-paced trials."

Each trial started with a 2-s fixation cross in the center of the display, followed by a 2-s prompt indicating whether the trial was automatic or self-paced (Fig. 1). A 1-s fixation cross then appeared before the serial visual presentation of images was presented at the center of the display. Then another 1-s fixation cross appeared, followed by a response

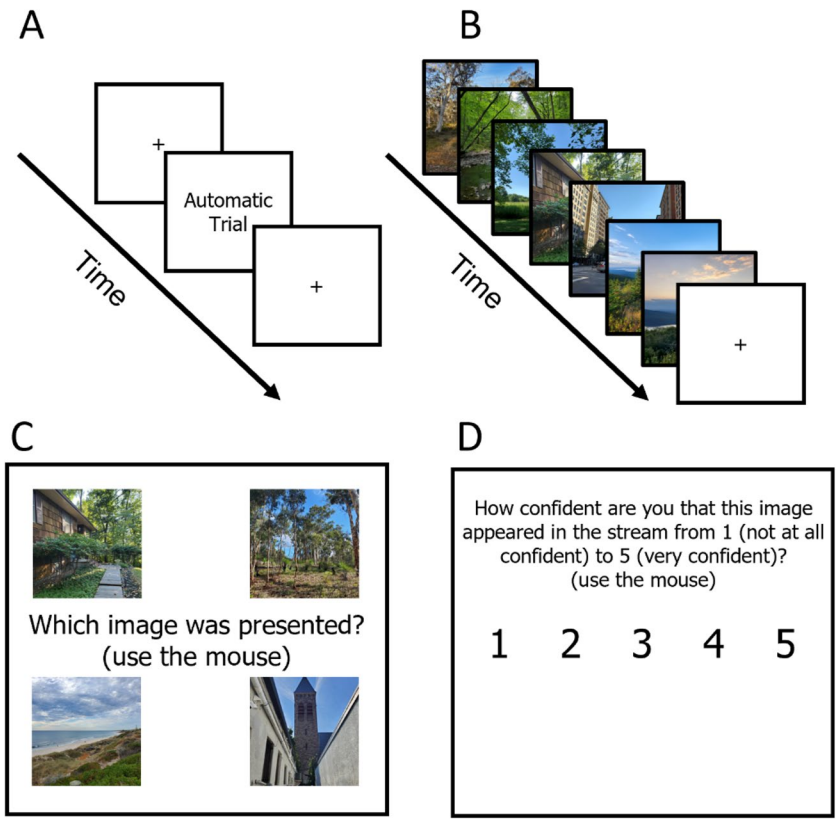

Fig. 1 Recognition memory task trial design. *Note.* On every trial, (**A**) participants were instructed whether the upcoming trial was an automatic or self-paced trial, and then (**B**) saw a stream of images that advanced either automatically or in a self-paced manner. (**C**) Participants then used their mouse to select the familiar image in the recognition memory task, and after making their choice, (**D**) rated their confidence in their decision. Images in this figure were not the same as those in the experiment as they are for illustration purposes only

screen that appeared with four image options – one positioned in each quadrant of the display. Only one of the four options was an image from the previous serial visual presentation trial stream (target image), and the other three images served as foils (i.e., foils had appeared neither in the serial visual presentation nor on any other trial). Participants' task was to click on the familiar image with their mouse.

Images were randomly chosen without replacement from the full set of images such that each was presented only once in the experiment. In the recognition memory task, the serial position of the target image could only be serial position 2, 3, 4, 5, or 6 to minimize primacy or recency effects, but this was not made explicit to participants. The position of the target image on the recognition memory task array was random, such that it was equally likely to appear in any of the four quadrants.

After participants indicated the image they remembered from the stream, they rated their confidence in this decision on a scale of 1 (not at all confident) to 5 (very confident) by mouse click. Following this confidence rating, 1-s feedback indicted whether they were correct or incorrect before the next trial started.

Questionnaire

A questionnaire was administered using Qualtrics. It included items about attitudes toward technology, which participants rated on a scale from "strongly disagree" (1) to "strongly agree" (5). This included statements related to participants' trust in automation (Automation-Induced Complacency Potential Scale (AICP-R); Merritt et al., 2019), such as how likely participants were to double-check tasks that were completed with automation or how much they would be willing to let automation handle their tasks. Additional statements were about technology proficiency (adapted from Compeau & Higgins, 1995), such as how successfully participants thought they could use technology if left on their own, or if someone else showed them how to use it. Participants also provided their self-rated ability on attention-type tasks on a single-item five-point scale from "very weak" (1) to "very strong" (5), an estimate of the average amount of time that they spent on social media per week in the previous 12 months, and the primary device that they use to access social media. Participants then provided demographic information including age and gender, and indicated whether they had normal vision, and if there was any reason we should not use their data.

Procedure

Potential participants were told that they could complete the experiment at any time during a given week. If they chose to complete the experiment, they were directed to a Qualtrics link with a consent form, and then were directed to the Inquisit program to complete the recognition memory task. After completing all trials in the recognition memory task, participants were redirected to Qualtrics to complete the questionnaires. Lastly, participants were told that the goal of the research would be discussed in their class the following week. The experiment took ~15 min to complete.

Results

Data screening

Full datasets were removed from three participants due to poor performance, where their overall memory accuracy was lower than three standard deviations below the mean (less than 25.3% overall memory accuracy). Full datasets were also removed from an additional 18 participants who did not advance through self-paced trial images on ≥ 36.5% of total self-paced images, which was more than three standard deviations above the mean number of self-paced trials that participants tended to self-advance (final $N = 821$).

Self-paced trial behavior

We first examined the speed with which participants advanced through self-paced trials. Participants typically advanced through images faster than the 4-s base rate (on $M = 97.4\%$ of the self-paced images; $SD = 5.5\%$) and at an average speed of 1,166 ms per image ($SD = 547$ ms). Participants were mostly consistent in the amount of time they viewed images within a trial, with an average standard deviation within a trial of $M = 335$ ms ($SD = 164$ ms) while advancing through images.

Memory performance on self-paced versus automatic trials

Within-subjects *t*-tests were used to compare self-paced and automatic trial performance on memory accuracy and confidence ratings (Fig. 2). Memory accuracy was greater on self-paced trials compared to automatic trials, $M_{diff} = 1.55$, 95% CI [.67, 2.43], $t(820) = 3.45$, $p < .001$, $d_z = .12$. Participants' confidence ratings were also higher on self-paced trials compared to automatic trials, $M_{diff} = .14$, 95% CI [.11, 16], $t(820) = 10.60$, $p < .001$, $d_z = .37$. Thus, participants had greater memory accuracy and confidence in their memory on self-paced trials compared to automatic trials.

Individual differences

Our exploratory analyses examined whether individual differences in attitudes towards technology predicted the

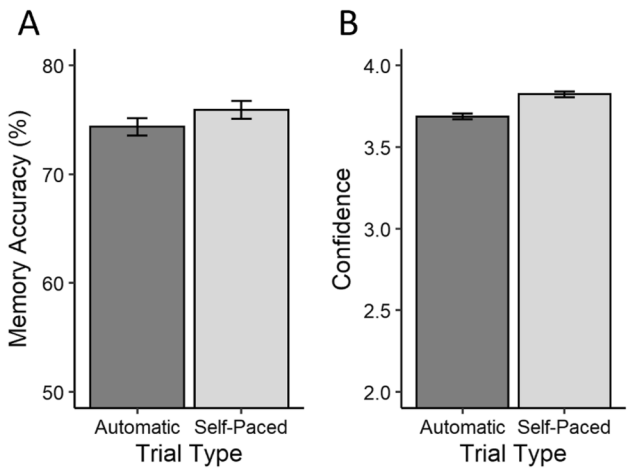

Fig. 2 Memory accuracy and confidence ratings results. *Note*. Both (**A**) memory accuracy and (**B**) confidence ratings were higher on self-paced (active) compared to automatic (passive) trials. Error bars represent 95% within-subjects confidence intervals

benefit of self-paced, relative to automatic, trials. To do this, we calculated benefit scores (self-paced minus automatic) for each participant on memory accuracy and confidence. Neither memory accuracy nor confidence benefits correlated with any of the individual difference measures (self-rated ability, time on social media, trust in automation, or technology proficiency; see Table 1). However, memory accuracy and confidence correlated with one another, such that individuals whose memory accuracy benefited more on self-paced, compared to automatic, trials were more likely to report higher confidence on self-paced, compared to automatic, trials. Further, linear regressions showed that none of the individual differences in attitudes toward technology predicted memory accuracy benefits, $R^2 = .001$, $F(4,815) = .266$, $p = .900$, or memory confidence benefits, $R^2 = .008$, $F(4,815) = 1.58$, $p = .177$. In sum, we found that individual differences in attitudes toward technology did not predict performance on self-paced compared to automatic trials.

Trial and target latencies

Even though automatic trials were matched to the average image advance rate from the previous self-paced trial, inherent qualities in how images were presented could elicit differences. For example, the amount of time that images were presented on automatic trials was based on the total length of the previous self-paced trial divided by the number of images, which left room for rounding differences from self-paced to automatic conditions. When we compared image-viewing duration between automatic and self-paced trials, the total trial length on automatic trials (M = 8,358 ms, SD = 3,802 ms) tended to be around 197 ms longer than self-paced trials (M = 8,161 ms, SD = 3,831 ms), $t(820) = 20.34$, $p < .001$, $d_z = .71$, meaning that images tended overall to be seen for more time on automatic compared to self-paced trials.

Additionally, variability among image presentation times within a self-paced stream meant that the dwell time on some images was longer than others. For example, if target images were visible for longer during self-paced than automatic trials, then this could potentially account for any increased memory for them (i.e., rather than differences in memory performance being driven by whether the presentation rate was under participants' control). However, on average, participants spent 60 ms *less* time viewing the target image on self-paced trials (M = 1,134 ms, SD = 565 ms) compared to automatic trials (M = 1,194 ms, SD = 543 ms), $t(820) = 18.32$, $p < .001$, $d_z = .64$. Thus, a memory benefit on self-paced compared to automatic trials was obtained despite viewing target images for less time.

Table 1 Correlations between individual difference measures

	1.	2.	3.	4.	5.	6.
1. Memory Accuracy Benefit (*self-paced minus automatic*)	—					
2. Memory Confidence Benefit (*self-paced minus automatic*)	**0.407** (< .001)**	—				
3. Trust in Automation	0.010 (.773)	0.041 (.239)	—			
4. Technology Proficiency	0.029 (.404)	0.042 (.228)	**0.172** (<.001)**	—		
5. Self-Rated Ability	0.011 (.744)	-0.051 (.143)	-0.060 (.088)	0.089 (.011)	—	
6. Time on Social Media	0.017 (.619)	-0.035 (.323)	0.083 (.017)	-0.024 (.488)	-0.016 (.639)	—

Pearson correlations (p-values noted in parentheses). Bolded text indicates a significant correlation, ** $p < .005$

Image memorability and performance

In a post hoc analysis, we examined whether image memorability predicted the amount of time that participants dwelled on individual images on self-paced trials. We used the pretrained convolutional neural network "Memnet," which was trained on a large human memorability dataset (60,000 images) to predict image memorability (Khosla et al., 2015). Memnet estimates the memorability of images based on this previous training. Given an image input, it returns a memorability score that has been shown to predict the likelihood that someone would remember the image (Khosla et al., 2015). We obtained image memorability predictions by submitting all 460 images from our experiment to Memnet and normalized resulting memorability predictions to range from zero (lowest predicted image memorability) to one (highest predicted image memorability). We then determined the average dwell time for each image when it was presented on self-paced trials and compared those dwell times to the predicted image memorability scores (see Fig. 3).

A Pearson correlation revealed a significant negative relationship between image memorability and average image dwell time, $r(458) = -.358$, $p < .001$, such that on self-paced trials, dwell time was longer for less memorable images and shorter for more memorable images. This suggests that the speed with which participants actively advanced through images was related to the likelihood of an image being remembered.

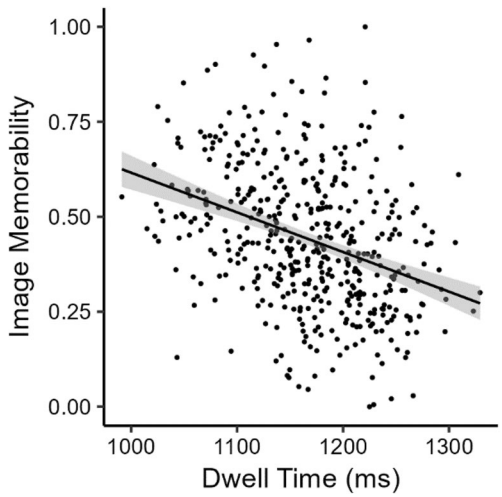

Fig. 3 Image memorability and average dwell time on self-paced trials. *Note.* Each of the 460 images used in this experiment were submitted to "Memnet" to estimate image memorability. Predicted image memorability scores were normalized to range from zero to one (see main text for details). The black line represents the best-fit linear relationship with a 95% confidence interval. Image dwell time (X-axis) in self-paced trials was negatively correlated with Memnet's predicted memorability scores (Y-axis)

Discussion

Many cognitive experiments require participants to passively view stimuli and respond after their presentation. However, visual information is often presented in a way that requires an individual to actively engage with it (Baror & He, 2021). We found improved image recognition and greater memory confidence when participants actively progressed through self-paced trials than when images were passively presented to them at a matched rate on automatic trials. Individual differences in attitudes toward, and experience with, technology did not predict this benefit of self-paced compared to automatic trial advancement. In a post hoc analysis, we found that image memorability correlated with how long participants dwelled on an image in self-paced trials. Together, these findings indicate a benefit for actively, compared to passively, viewing information, and that self-pacing behaviour may reflect strategically allocating resources to images based on intrinsic image memorability. The pattern is consistent with and extends previous literature that indicates greater memory for information that coincides with action (e.g., Swallow & Jiang, 2010; Yebra et al., 2019). These findings also have important implications for the design of both work and personal technology, and suggest that designers should consider active engagement as a way to increase the likelihood of important information being remembered.

Matching the image presentation rate in automatic trials to the average rate in corresponding self-paced trials allowed us to control the amount of time that participants viewed images across conditions. This design ensured that all images were presented at the same rate within an automatic trial, whereas participants could spend longer on some images than others within a given self-paced trial. Notably, the advantage on self-paced trials was despite the target images being viewed for less time than on automatic trials overall. This meant that some individual target images may have been viewed more strategically on self-paced trials but, on average, for less time than on automatic trials. Future research could explore different ways of matching self-paced and automatic trials to further probe related research questions. For example, self-paced and automatic trials could be matched such that dwell time is the same for specific images, rather than blocks of random images.

While our finding that participants' active control over stimulus duration enhanced memory for information echoes research in other contexts (e.g., Afrooz et al., 2018; Berberian et al., 2012; Craddock et al., 2011; Ichikawa & Masakura, 2006; Knoblich & Flach, 2001; Maruya et al., 2007; Voss et al., 2011), it remains unknown what mechanism is responsible and whether it is the same as that

responsible for active benefits in other task domains. Some literature suggests noradrenaline systems enhance memory encoding for stimuli paired with action (e.g., Yebra et al., 2019) and provide attentional benefits for stimuli temporally paired with task-relevant responses (e.g., Swallow & Jiang, 2013), making it possible that the locus coeruleus-noradrenaline system was involved in benefits observed in our study. Others suggest that volitional control can benefit memory through interactions between the hippocampus and neural systems involved in memory processes (Voss et al., 2011). Of course, alternative mechanisms are possible – for example, participants may have been particularly engaged in self-paced trials compared to automatic trials and invested more attention and effort into those trials (e.g., Chun & Turk-Browne, 2007; Körber et al., 2015; Metzger & Parasuraman, 1999; Miller & Unsworth, 2021), such that greater attention given during encoding and retrieval of self-paced trials would benefit memory performance on these trials. Future research may probe the particular mechanisms responsible for the benefit and how this relates to previous findings. As it stands, the current findings are in line with notions that memory of information is not determined by exposure alone, but also by our agency in controlling that exposure.

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Authors' contributions Conceptualization, B.L.K.; methodology, B.L.K., S.B.M., T.G., and V.B.; software, B.L.K.; formal analysis, B.L.K. and V.B.; investigation, B.L.K. and V.B.; resources, B.L.K. and V.B.; writing – original draft preparation, B.L.K.; writing – review and editing, B.L.K., S.B.M., T.G., and V.B. All authors have read and agreed to the published version of the manuscript.

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Data availability Anonymized data and experiment materials are available on OSF: https://osf.io/zm78v

Code availability Experimental code is available on OSF: https://osf.io/zm78v

Declarations

Conflicts of interest/competing interests The authors declare no conflicts of interest.

Ethics approval The study was approved by the UWA Human Research Ethics Office, Protocol 2022/ET000019.

Consent to participate Informed consent was obtained from all participants involved in the study.

Consent for publication We only report data from participants that consented their data to be used for research purposes.

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