

Memory failure predicted by attention lapsing and media multitasking

<https://doi.org/10.1038/s41586-020-2870-z>

Received: 31 January 2020

Accepted: 3 August 2020

Published online: 28 October 2020

 Check for updates

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With the explosion of digital media and technologies, scholars, educators and the public have become increasingly vocal about the role that an ‘attention economy’ has in our lives¹. The rise of the current digital culture coincides with longstanding scientific questions about why humans sometimes remember and sometimes forget, and why some individuals remember better than others^{2–6}. Here we examine whether spontaneous attention lapses—in the moment^{7–12}, across individuals^{13–15} and as a function of everyday media multitasking^{16–19}—negatively correlate with remembering. Electroencephalography and pupillometry measures of attention^{20,21} were recorded as eighty young adults (mean age, 21.7 years) performed a goal-directed episodic encoding and retrieval task²². Trait-level sustained attention was further quantified using task-based²³ and questionnaire measures^{24,25}. Using trial-to-trial retrieval data, we show that tonic lapses in attention in the moment before remembering, assayed by posterior alpha power and pupil diameter, were correlated with reductions in neural signals of goal coding and memory, along with behavioural forgetting. Independent measures of trait-level attention lapsing mediated the relationship between neural assays of lapsing and memory performance, and between media multitasking and memory. Attention lapses partially account for why we remember or forget in the moment, and why some individuals remember better than others. Heavier media multitasking is associated with a propensity to have attention lapses and forget.

Fluctuations in spontaneous states of preparatory attention might help to account for fundamental puzzles in neuroscience and behavioural science regarding why humans sometimes remember and sometimes forget, why some cognitively healthy individuals remember better than others and why memory varies as a function of engagement with the modern media landscape. To examine links between attention, goal coding and episodic remembering within individuals, and how they correlate with individual differences and media multitasking (MMT), participants completed a goal-directed episodic memory task during which electroencephalography (EEG) and pupillometry measurements were obtained (Extended Data Fig. 1). Participants also completed separate trait-level questionnaires and a sustained attention task.

We first leveraged retrieval data to investigate whether and how lapses of attention in the moment before remembering correlate with neural signals of goal coding and memory, and behavioural forgetting. Pre-stimulus tonic increases in posterior alpha power from EEG, an expression of release from top-down inhibitory control, and pre-stimulus tonic decreases in pupil diameter from pupillometry, an expression of hypoarousal linked to a locus coeruleus circuit of noradrenaline, are associated with attention lapsing and reduced accuracy on working memory, perceptual discrimination and vigilance tasks, and thus could extend to episodic remembering^{7–12,20,21}. Little is known about the roles that spontaneous fluctuations in attention

have in the representation of retrieval goals and cues, when engaged post-encoding⁵, that govern attempts to remember the past. To assay spontaneous attention lapses, tonic posterior alpha power and pupillometry were extracted from the 1 s preceding the onset of the retrieval goal cue (pre-goal) and object probe (pre-probe) of each trial. To measure the strength of goal coding on three retrieval tasks (conceptual source recognition, perceptual source recognition and novelty detection), goal-cue-locked event-related potentials (ERPs) were extracted from an a priori midfrontal cluster that has been shown^{26,27} to track goal processing. To measure neural signals of recollection- and familiarity-based memory, object-probe-locked ERPs were extracted from a priori left posterior and left midfrontal clusters, which are canonical sites of parietal old versus new (hereafter Parietal Old/New) and early midfrontal old versus new (hereafter FN400) mnemonic components²⁸ (Extended Data Fig. 1b). All assays were z-scored within each run to account for potential time-on-task effects across runs.

Spontaneous changes in attention, just before retrieval goal-cue onset, were correlated with subsequent remembering of studied items (Fig. 1). Specifically, attention lapses early in a trial—marked by pre-goal increases in posterior alpha power and decreases in pupil diameter—were correlated with a greater likelihood of memory failure (misses) compared with success (hits) across the three goal-state conditions (alpha: $b = -0.46$, $z_{6,822} = -3.61$, $P < 0.001$; pupil: $b = 0.36$, $z_{7,197} = 2.18$,

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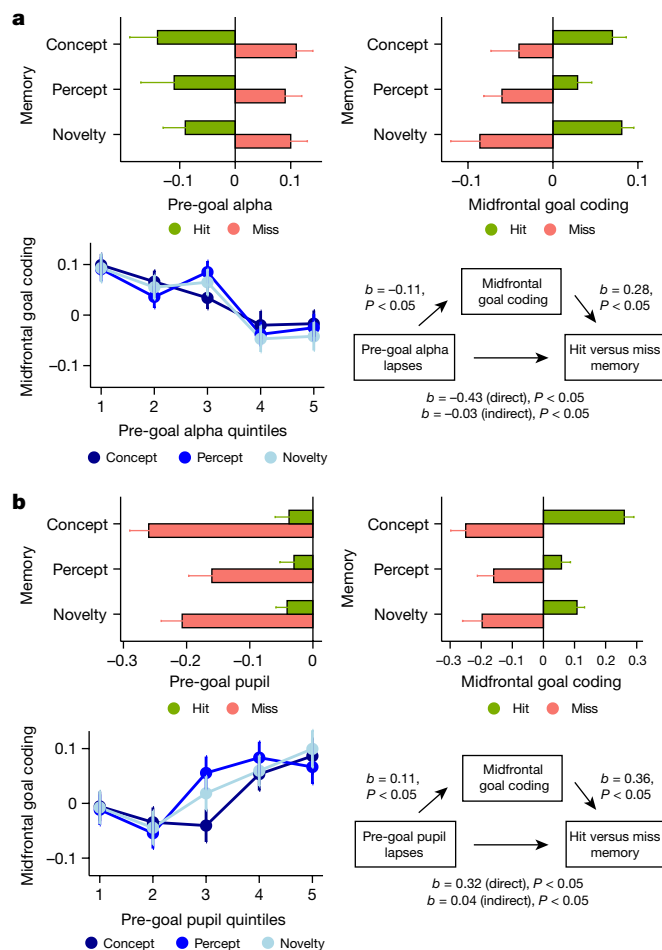


Fig. 1 | Attention, goals and memory in the moment. Pre-goal attention lapses relate to forgetting (misses) versus remembering (hits) across three retrieval goal conditions, and this relationship is partially mediated by goal-coding strength through a midfrontal ERP cluster. **a**, **b**, Attention lapses from alpha (**a**) and pupil (**b**) assays. Bar graphs show mean unweighted standardized betas (data are mean $\pm$ s.e.m.) for the relationships between attention lapses and memory (top left) and midfrontal goal coding and memory (top right), and line graphs (bottom left) show quintiles for mean unweighted standardized betas (data are mean $\pm$ s.e.m.) for the relationships between lapsing and goal coding. Statistical analyses included an interaction term for retrieval goal, and treated lapsing and goal coding continuously in trial-level mixed models. Axis units with decimals show z-scores. The trial-wise mediation models reflect mean weighted standardized betas, with two-sided *P* values (alpha indirect effect: $P = 0.042$ and direct effect: $P = 0.017$; pupil indirect effect: $P = 0.041$ and direct effect: $P = 0.008$). Statistical analysis was performed using *Z*- and *t*-tests, where applicable, without multiple comparison adjustments. $n = 75$ human participants from a single independent experiment.

$P = 0.03$). By contrast, later in a trial, pre-retrieval probe alpha and pupil did not correlate with misses or hits (correct rejections and false alarms were also unaffected; Supplementary Information).

We therefore explored how pre-goal lapses of attention relate to forgetting or remembering. One possibility is that an attention lapse immediately before processing a retrieval goal results in a reduction in the strength of subsequent goal coding, which then influences retrieval. Consistent with this hypothesis, attention lapsing just before goal cuing was significantly correlated with a reduction in the subsequent goal-cue-elicited midfrontal ERP signal (alpha: $b = -0.11$, $t_{6,819} = -2.29$, $P = 0.02$; pupil: $b = 0.11$, $t_{7,194} = 2.09$, $P = 0.04$). Notably, this reduction in goal-state coding in turn significantly correlated with misses or hits across the three goal-state conditions (alpha: $b = 0.28$, $z_{6,823} = 2.23$,

$P = 0.03$; pupil: $b = 0.36$, $z_{7,197} = 2.11$, $P = 0.04$; note: effect sizes (*b* values) between goal coding and memory are not identical by modality owing to trial-level modality-specific artefacts) (Methods). Trial-wise mediation analyses revealed that the relationship between pre-goal attention lapsing and later forgetting was partially explained by the strength of goal coding, and this was the case both when attention was assayed using pre-goal alpha power (Fig. 1a; indirect effect $b = -0.03$ (95% confidence interval = -0.05 , -0.01), direct effect $b = -0.43$, total effect $b = -0.46$) and pupil diameter (Fig. 1b; indirect effect $b = 0.04$ (95% confidence interval = 0.02 , 0.07), direct effect $b = 0.32$, total effect $b = 0.36$). The total, indirect and direct effects were significant in each mediation (*P* values of $P < 0.05$; Methods). These outcomes indicate that moment-to-moment attention lapses before goal cuing correlate with concomitant reductions in goal coding that influence source recollection and novelty detection, and also have significant direct effects on memory.

Beyond memory behaviour, we used EEG to measure neural markers of retrieval and their relation to attention lapsing. Consistent with previously published studies^{6,28}, we first confirmed that, irrespective of attentional state, canonical Parietal Old/New (Extended Data Fig. 2a) and FN400 (Extended Data Fig. 2c) neural signals were observed (see also Extended Data Figs. 3, 4 and Supplementary Information). We next examined whether pre-goal lapses correlated with the magnitude of the Parietal Old/New and FN400 neural signals elicited by the retrieval probe. Focusing on the source-recollection signals in the conceptual- and perceptual-retrieval tasks, we observed a significant interaction between trial-level pre-goal attention lapsing and the magnitude of the Parietal Old/New effect (500–600 ms post-probe) when remembering (hits) versus forgetting (misses) (alpha: $b = -0.14$, $t_{4,041} = -2.16$, $P = 0.03$; pupil: $b = 0.17$, $t_{4,341} = 2.26$, $P = 0.02$) (Extended Data Fig. 2b). Pre-goal lapses were significantly correlated with the strength of the parietal signal on miss trials (alpha: $b = -0.14$, $t_{1,521} = -2.52$, $P = 0.01$; pupil: $b = 0.15$, $t_{1,721} = 2.41$, $P = 0.02$) but not hit trials (alpha: $b < 0.001$, $t_{2,470} = -0.09$, $P = 0.93$; pupil: $b = -0.01$, $t_{2,620} = -0.37$, $P = 0.71$). That is, moment-to-moment increases in alpha power and decreases in pupil diameter correlated with reductions in the Parietal Old/New signal for source-recollection failures (misses), which suggests that fluctuations in attention correlate with sub-threshold recollection responses, which drive forgetting.

Focusing on neural memory signals in the novelty-detection task, a significant interaction was also found between trial-level pre-goal lapsing and the magnitude of the FN400 component (400–500 ms post-probe) when correctly endorsing new items (hits) compared with misses (alpha: $b = 0.17$, $t_{2,771} = 2.18$, $P = 0.03$; pupil: $b = -0.23$, $t_{2,846} = -2.17$, $P = 0.03$) (Extended Data Fig. 2d). Pre-goal lapses were significantly correlated with the strength of FN400 signal for misses (alpha: $b = 0.11$, $t_{974} = 2.03$, $P = 0.04$; pupil: $b = -0.22$, $t_{896} = -2.51$, $P = 0.01$) but for not hits (alpha: $b = -0.07$, $t_{1,797} = -1.41$, $P = 0.16$; pupil: $b = 0.02$, $t_{1,947} = 0.45$, $P = 0.65$). That is, moment-to-moment increases in alpha power and decreases in pupil diameter correlated with increasing positivity in FN400 signal for misses, which drove the signal to appear more like that of an incorrect old rather than a correct new item. These results indicate that attentional fluctuations correlate with neural responses that underpin familiarity-based memory.

Along with the relationship between moment-to-moment lapses and subsequent multimodal signals of memory failures, we assessed whether trait-level differences in the propensity of a lapse in attention could help to explain why some individuals are more likely to forget than others (Fig. 2). Emerging evidence indicates that trait-level differences in sustained attention relate to differences in working memory¹³ and these could therefore extend to long-term memory processes. We first examined how trait-level task-based metrics of preparatory lapsing relate to memory, computing participant-level lapse markers—mean alpha power and pupil diameter variability averaged over all pre-goal retrieval epochs—and behavioural markers of retrieval success

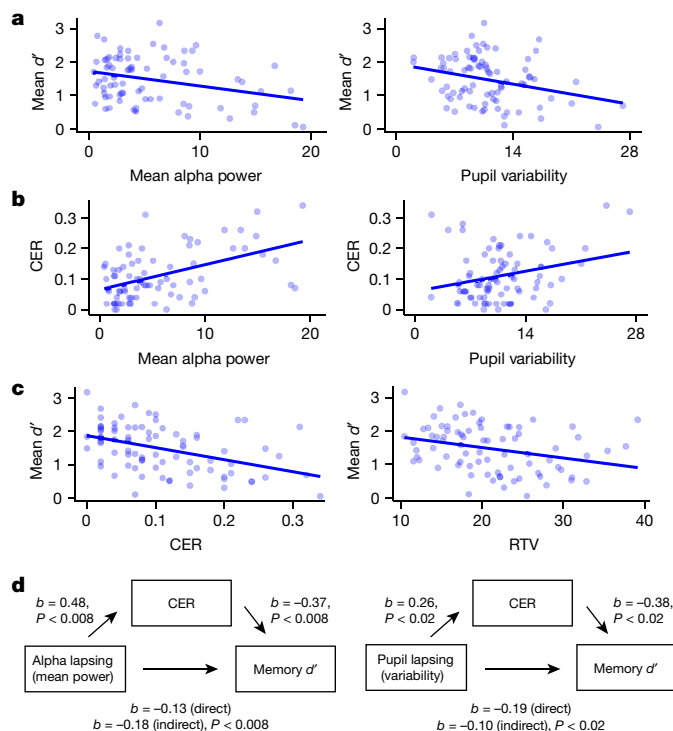


Fig. 2 | Trait-level differences in sustained attention help to explain why individuals are more prone to remembering or forgetting. **a, b,** Greater lapsing is correlated with worse d' on the memory tasks (**a**) and attention on the gradCPT (**b**). **c,** Worse attention on the gradCPT is correlated with worse memory d' . **a–c,** Raw scores are shown. Statistical analyses were performed using z-scores with Pearson correlations. **d,** Formal mediation models with mean standardized betas, and two-sided P values (alpha indirect effect: $P = 0.003$; pupil indirect effect: $P = 0.018$). $n = 75$ participants for alpha data and $n = 80$ participants for all other data from a single independent experiment; the effect sizes between the commission error and d' are therefore not identical for alpha and pupil models (Methods). Statistical analysis was performed using Z- and t -tests, where applicable, without multiple comparison adjustments.

(memory discriminability (d') for each goal-state condition). Higher trait-level alpha power in the absence of external distraction has been associated with release from inhibition, higher pupil variability has been associated with more off-task thoughts and higher d' denotes higher memory accuracy^{7,10}. We found that increases in trait-level mean alpha power and pupil variability were significantly negatively correlated with individual differences in d' (Fig. 2a and Supplementary Information). In addition, we found that individual differences in pre-goal lapses of attention at encoding, assayed from mean alpha power and pupil variability, were significantly correlated with individual differences in pre-goal lapses at retrieval and with memory ability (Extended Data Fig. 5 and Supplementary Information). Notably, when controlling for differences in attention at encoding, a significant relationship remains between individual differences in pre-goal attention at retrieval and remembering (Supplementary Information).

After the experiment, participants also completed an independent task-based assessment of sustained attention (the gradual-onset continuous performance task (gradCPT)²³). Two of its metrics—commission error rate (CER; responses to ‘no-go’ trials) and reaction time variability (RTV; a coefficient of variation on correct responses to ‘go’ trials)—are reliable indicators of trait-level attention lapsing²³. In our sample, trait-level attention lapsing, as assayed by mean alpha power and pupil variability during the memory task, significantly correlated with CER in the gradCPT (alpha: $r = 0.48$, $P < 0.001$; pupil: $r = 0.26$, $P = 0.009$), but not RTV (alpha: $r = 0.18$, $P = 0.065$; pupil: $r = 0.12$, $P = 0.14$) (Fig. 2b). Notably, CER and RTV in the gradCPT were negatively correlated with

d' in the conceptual-retrieval (CER: $r = -0.36$, $P < 0.001$; RTV: $r = -0.21$, $P = 0.03$), perceptual-retrieval (CER: $r = -0.39$, $P < 0.001$; RTV: $r = -0.26$, $P = 0.009$), and novelty-detection (CER: $r = -0.42$, $P < 0.001$; RTV: $r = -0.30$, $P = 0.003$) tasks (Fig. 2c). Thus, trait-level differences in sustained attention are correlated with individual differences in forgetting.

Trait-level mediation analyses further revealed that the relationship between individual differences in lapsing and memory was explained by differences in sustained attention as indexed by CER in the gradCPT (indirect effect with alpha $b = -0.18$ (95% confidence interval = -0.33 , -0.05), direct effect $b = -0.13$, total effect $b = -0.31$; indirect effect with pupil $b = -0.10$ (95% confidence interval = -0.22 , -0.02), direct effect $b = -0.19$, total effect $b = -0.29$) (Fig. 2d). The total and indirect effects were significant in each mediation (P values of $P < 0.02$; Methods). These results indicate that trait differences in sustained attention may explain pre-goal lapsing and memory ability. Confirmatory factor analysis with a trait-level ‘attention’ factor (pupil variability and mean alpha power from the memory task, and CER and RTV from the gradCPT) and a ‘memory’ factor (d' from each retrieval task) also indicated a significant model fit ($\chi^2_{21} = 185.68$, $P < 0.001$) and a significant negative relationship between inattention and memory (covariance = -0.52 , $z = -4.99$, $P < 0.001$).

Given observations that everyday MMT is negatively associated with episodic memory performance¹⁸, we used the current multi-modal approach to also test whether increased forgetting in heavier media multitaskers is correlated with a higher propensity to suffer lapses in attention before goal-directed behaviour. Data on the relationship between laboratory-based assays of cognition (specifically, attention and memory) and real-world MMT behaviour¹⁶—that is, the degree to which an individual engages with multiple media types in a given media consumption hour (for example, watching television while texting)²⁴—are provocative, in part because heavier MMT is associated with reduced working memory and episodic memory even when performing a single task, possibly because of its positive relationship with failures of sustained attention¹⁷ and increased mind wandering^{16,25}. Given that engagement with concurrent streams of media is pervasive in everyday life, there is a need to pinpoint the mechanism or mechanisms that underlie trait-level relationships between MMT and memory. Participants completed an individual differences battery that consisted of several self-report questionnaires, including a modified Media Multitasking Inventory, for which a higher score indicates heavier MMT and a lower score lighter MMT. We first observed that participants who self-reported heavier MMT showed a significantly lower d' during the conceptual-retrieval ($r = -0.32$, $P = 0.002$), perceptual-retrieval ($r = -0.28$, $P = 0.007$) and novelty-detection ($r = -0.32$, $P = 0.002$) tasks (Fig. 3a). Second, heavier MMT was significantly correlated with higher CER ($r = 0.31$, $P = 0.003$) and RTV ($r = 0.30$, $P = 0.003$) in the gradCPT (Fig. 3c), and higher mean pre-goal alpha power ($r = 0.21$, $P = 0.036$) and pupil variability ($r = 0.23$, $P = 0.019$) during the memory tasks (Fig. 3b). The same patterns of findings were exhibited with an extreme-groups approach (Supplementary Information). Finally, a test of trait-level mediation revealed that the relationship between MMT and memory was partially explained by differences in sustained attention as assayed by CER in the gradCPT (indirect effect $b = -0.11$ (95% confidence interval = -0.23 , -0.02), direct effect $b = -0.24$, total effect $b = -0.35$) (Fig. 3d), with the total, indirect and direct effects all showing significance (P values of $P < 0.03$; Methods).

Exploratory factor analysis (that is, a principal component analysis) further revealed that MMT loaded on a ‘sustained attention’ factor extracted from other relevant questionnaires—including measures of spontaneous mind wandering, attention-deficit/hyperactivity disorder (ADHD) and attentional impulsivity. Moreover, we note that MMT was the only self-reported measure that was significantly correlated with all memory and attention metrics (Supplementary Information). Our task-based and self-reported measures indicate that attention lapsing

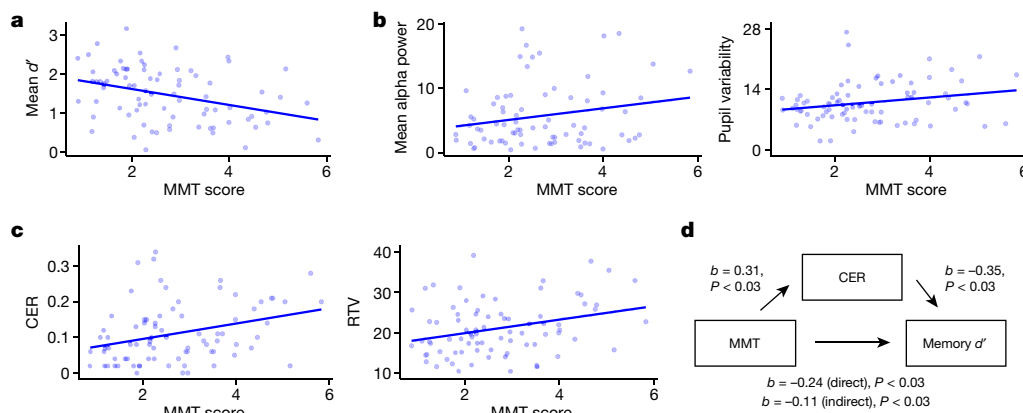


Fig. 3 | Trait-level differences in sustained attention partially explain the negative relationship between MMT and memory. **a, b,** Heavier MMT is correlated with worse d' (**a**) and greater lapsing during retrieval (**b**). **c,** Heavier MMT is correlated with higher commission error and RTV during the gradCPT. **a–c,** Raw scores are shown. Statistical analyses were performed using z-scores with Pearson correlations. **d,** Formal mediation model with mean standardized

betas, and two-sided P values (indirect effect: $P = 0.005$ and direct effect: $P = 0.024$). $n = 75$ participants for alpha data and $n = 80$ participants for all other data from a single independent experiment. Statistical analysis was performed using Z - and t -tests, where applicable, without multiple comparison adjustments.

is one plausible explanation for why heavier MMT is correlated with poorer episodic memory.

To retrieve a memory, a number of neurocognitive processes dynamically interact. Various sources of forgetting at retrieval have been studied, including cue availability, mnemonic interference and memory weakening⁴. Here, we document that when pre-goal lapses of attention occur during retrieval, the strength of goal coding is reduced and forgetting is the price paid. The trial-level relationships were observed between attention lapsing, goal cuing, and hit or miss memory decisions but not correct rejection or false alarm memory decisions in the three retrieval tasks. This novel observation suggests that effects of attention interact with the congruency between one's mnemonic goal and the retrieval cue, perhaps modulating mnemonic evidence as it begins to emerge. Furthermore, the trial-wise mediations and ERP analyses indicate that pre-goal lapses of attention at retrieval have robust direct effects on mnemonic behaviour and neural signals in addition to those attributed to goal cue processing. An interesting possibility is that attention modulates the processing of a contextual cue, or one's retrieval mode, that is leveraged in the moment to remember, which should be explored further by direct assessment. Translating basic science findings to real-world behaviours, we further show that heavier MMT is associated with worse episodic memory, in part, because of a greater propensity to suffer more-frequent or disruptive lapses of attention.

These results highlight how multimodal approaches can advance our understanding of the role of attention in memory at both the trial and trait levels. The independent biological and behavioural metrics converge on the role of attention in partially accounting for mnemonic and MMT differences (for consideration of the relationship to working memory, see Supplementary Information). Another strength is that effects of attention at retrieval are not due to effects of attention at encoding, nor to variable perceptual encoding of goal cues at retrieval (see Supplementary Information).

Future work focused on longitudinal assays that can inform causality²⁹ in terms of whether differences in MMT produce differences in attention (or vice versa) will be important. Adopting complementary multimodal approaches to quantify attention and goal-state coding³⁰ also holds promise for building models of how interactions between attention, goal states, contextual cue processing and memory explain why we sometimes remember and sometimes forget, and why some individuals remember better than others.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at <https://doi.org/10.1038/s41586-020-2870-z>.

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Methods

Data reporting

There was randomization of cues within all task-based assessments, but participants by definition could not be randomized for individual difference assays. The investigators were blinded to allocation during experiments but not during outcome assessment. A sample size of 80 participants was chosen based on previous studies, which showed that this number was adequate for a reliable individual differences approach. For further information, see the 'Reporting Summary'.

Participants

Eighty participants were enrolled in the study (49 female participants; mean age = 21.7 years, s.d. = 1.48, range = 18–26 years). Participants were recruited from online advertisements at Stanford University and the surrounding community, were right-handed, and had normal or corrected-to-normal vision, no history of neurological or psychological impairment and no current medication. All participants provided written informed consent and were compensated US\$60 (US\$15 per hour), in accordance with procedures approved by Stanford's Institutional Review Board. Data from five participants were excluded from trial-level analyses owing to insufficient trial numbers (fewer than 10 hits or fewer than 10 misses in each retrieval goal condition) stemming from technical artefacts and/or task performance. Data from five participants were excluded from trait-level analyses involving alpha power owing to technical artefacts. Thus, 75 participants were retained for all trial-level analytics and trait-level alpha analytics, and 80 participants were retained for all other trait-level analytics.

Experimental design

Participants completed a 4-h session: set-up and instructions (30 min), goal-directed encoding (1 h), goal-directed retrieval (1.5 h) and the separate individual differences assessment (1 h). Only the memory tasks included EEG and pupillometry measurements. The memory tasks—design, goal states and common object pictures—were adapted from previous research²² in which the behavioural and neural impacts of goal-state cuing on encoding and retrieval were described. The individual differences assessment included questionnaires and a task-based sustained attention assay that were also adapted for present purposes^{23,24,31–35}. The present set of hypotheses relate to attention, goal states and episodic retrieval; encoding-related hypotheses and data will be reported elsewhere.

Goal-directed encoding and retrieval task

All tasks were run using the Psychophysics Toolbox in MATLAB³⁶. For each trial, the background screen was white, and the fixation, goal cue or object appeared centrally. All fixations, goal cues and objects were luminance- and chrominance-controlled and matched using the SHINE toolbox in MATLAB to ensure that low-level visual properties did not affect oscillatory or pupillary assays³⁷.

Encoding. Participants viewed 168 objects twice across 6 incidental encoding runs (8 min 11 s per run) of 56 trials each (once in runs 1–3 and once in runs 4–6). On each trial, a goal cue (that is, pleasant or unpleasant; bigger or smaller) appeared for 1.60 s, followed by a 0.10-s interstimulus interval, followed by an object for 2.80 s, followed by a 4-s intertrial interval. Participants performed object classification, based on a conceptual goal (is the object semantically pleasant or unpleasant) or a perceptual goal (is the object bigger or smaller in size on the screen, irrespective of real-world size), responding as quickly and as accurately as possible. Participants made each judgment with one of two button presses (pleasant or unpleasant; bigger or smaller) using their right index or middle finger (button-press mappings were counterbalanced across participants). There were eight practice trials to ensure comprehension.

In each encoding run, 28 objects were classified on the conceptual goal dimension (pleasant or unpleasant) and 28 on the perceptual dimension (bigger or smaller), yielding 84 conceptual object trials and 84 perceptual trials across runs. Before the experiment, each object was rated by 100 Amazon Mechanical Turk employees as being either more semantically pleasant or unpleasant; in the experiment, each object appeared either bigger (450 × 450 pixels) or smaller (150 × 150 pixels) in size on the screen (counterbalanced across participants). Thus, objects were crossed in a 2 × 2 design, with 14 objects from each goal crossing (pleasant and bigger, pleasant and smaller, unpleasant and bigger, and unpleasant and smaller) appearing in a random order per run (with the constraint that a particular goal—for example, pleasant or unpleasant—could not appear more than four times consecutively). Each participant received a random assignment of goal–object pairings.

Retrieval. After a 10 min delay, participants performed the critical retrieval phase. At retrieval, they viewed 252 objects—168 studied and 84 new—across 12 goal-directed retrieval runs (7 min 15 s per run) of 21 trials each. On each trial, participants made a yes or no memory judgment on an individual medium-sized object (300 × 300 pixels) after viewing one of three retrieval goal cues (pleasant or unpleasant before, bigger or smaller before, or new item). Participants were instructed that some of the objects would be old and some new. The retrieval goal cue was preceded by an 8-s intertrial interval and then appeared for 2 s, followed by an 8-s interstimulus interval, followed by an object for 2 s. An epoch of 8 s was adopted for each intertrial interval and interstimulus interval based on previous work that showed that attention lapses are more likely to be induced through 8-s than 2-s fixed intervals³⁸. Participants made each retrieval judgment as quickly and as accurately as possible, making one of two button presses (yes or no) with their right index or middle finger (button-press mapping was counterbalanced). There were eight practice trials to ensure comprehension.

In each retrieval run, 7 objects were tested for the conceptual goal (pleasant or unpleasant before), 7 for the perceptual goal (bigger or smaller before) and 7 for novelty-detection (new item) analyses, yielding 84 unique conceptual-judgment trials, 84 unique perceptual trials and 84 unique novelty trials across runs. To ensure adequate trial numbers: (1) for each of the source retrieval goals (conceptual and perceptual), 32 objects had been encoded for pleasant or unpleasant orienting, 32 had been encoded for bigger or smaller orienting and 20 were new; and (2) for novelty detection, 20 objects had been encoded for pleasant or unpleasant, 20 for bigger or smaller and 44 were new. Assignment of old and new objects to the three retrieval conditions was random for each participant. The goal–object pairings were presented in a random order per run (with the additional constraint that a particular retrieval goal could not appear more than three times consecutively). Each participant received a random assortment of goal–object pairings.

Behaviourally, accuracy on the two source memory judgments requires object recognition and recollection of how the object was processed at encoding—so as to differentiate conceptually versus perceptually encoded objects, and to respond 'yes' or 'no' as a function of the cued goal; accurate novelty detection can be based on weak item memory strength and/or the absence of recollection.

Individual differences battery

After the encoding and retrieval task, participants filled out nine self-report questionnaires (self-paced) with paper-and-pencil assessment and the Qualtrics Survey platform and performed the gradCPT in the following order.

Media multitasking inventory. The Media Multitasking Inventory (MMI) was modified from a previous study²⁴ and yields an estimate of the number of media with which the individual engaged in a typical media consumption hour; a higher score denotes heavier MMT. Part 1 assesses the number of hours per week typically spent doing each

of nine activities: reading, homework (other than reading), watching videos, movies or TV, listening to music, radio, audiobooks or other audio, playing video games, browsing the internet, texting or using social media or instant messaging, talking on the phone or video chatting and other computer activities. In part 2, participants indicate for each activity how often they simultaneously engage in each of the other activities on a four-point Likert scale. In this modified MMI, participants rate each media pairing once.

Adult ADHD self-report scale. A six-item questionnaire³¹ (part A) was used to assess ADHD symptoms.

Barratt Impulsiveness Scale-11. The Barratt Impulsiveness Scale-11 (BIS-11)³² is a questionnaire with three 11-item subcomponents that assessed non-planning, motor impulsivity and attentional impulsivity.

Video-game usage. Video-game usage was analysed using a questionnaire³³ that assessed the extent of playing five types of video games in the past 12 months.

Attentional control distractibility and shifting. An assay of everyday attentional control (or inattention)³⁴, with two four-item subsections that assessed distractibility and shifting.

Deliberate and spontaneous mind wandering. A four-item questionnaire for each subtype³⁴ that assessed everyday mind wandering.

Attention-related cognitive error scale. A 12-item questionnaire³⁵ that assessed the frequency of cognitive errors in everyday situations that are attributed to attention lapsing.

Memory failure scale. A 12-item questionnaire³⁵ that assessed the frequency of minor memory lapses in everyday situations.

Mindful attention awareness scale-lapses only. A 12-item questionnaire³⁵ that assessed everyday attention lapsing.

gradCPT. In this 10-min task-based assay of sustained attention²³, participants viewed a stream of city (90% of trials) and mountain (10% of trials) scene images (497 trials total), and were asked to press the space bar when viewing a city and withhold responding when viewing a mountain. The scenes were round, greyscale images of 10 cities and 10 mountains that repeated across the task. Images appeared individually and centrally on a computer screen, gradually onset over 0.80 s, paused for 0.40 s when fully coherent (thus, each trial was 1.20 s) and then offset. The task used linear pixel-by-pixel interpolation with a non-repeating scene rule (that is, the same scene could not successively repeat). Participants were instructed to respond as accurately as possible; a response deadline was implicit in the task but not explicitly referenced.

EEG and pupillometry data acquisition

During encoding and retrieval, EEG and pupillary data were recorded concurrently in an electric- and sound-proof chamber to minimize artefacts. Real-time EEG, eye-tracking and behavioural data, and stimulus display were monitored from an outside bay. EEG data were recorded with a 128-channel HydroCell Sensor Net (Electrical Geodesics) at a sampling rate of 1,000 Hz through a Netstation 300 amplifier with 24-bit resolution per sample and Netstation 5.4 software. Impedance was set to <50 kV and checked approximately every 20 min. Pupillary data from the right eye were recorded using an Eyelink 1000 Eye Tracker system (SR Research) at a sampling rate of 1,000 Hz. Participants were seated 60 cm from the eye-tracking and stimulus monitor with a chin mount in the chamber. Eye-tracking calibration and validation steps were completed every approximately 20 min with impedance checks. Trial-level

EEG, pupillary and behavioural data (response and response time) were synced using a custom MATLAB code with event message tags.

Data analyses

The R environment (v.3.3.3) and SPSS (v.26) were used for data pre-processing, statistics and visualization. The following R packages were primarily used with in-house scripts: openxlsx, tidyverse, dplyr, lme4, lmerTest, multilevel, mediation, lavaan, ggplot2, ggpubr and eyetrackingR. The exception was EEG data preprocessing, for which MATLAB with an EEGLAB interface³⁹ was used with in-house scripts.

Memory behavioural data analyses. Behavioural analyses focused on metrics of memory retrieval accuracy at the trial and trait levels. For trial-level retrieval, each 'yes' or 'no' response was classified as a hit, miss, correct rejection to old or new item, or false alarm to old or new item, depending on the retrieval goal condition. In conceptual goal cuing, responding 'yes' to an old pleasant- or unpleasant-encoded object was classified as a hit ('no' was a miss), whereas responding 'no' to an old bigger- or smaller-encoded object was classified as a correct rejection to old item ('yes' was a false alarm to old item), and responding 'no' to a new object was classified as a correct rejection to new item ('yes' was false alarm to new item). The same logic applies for perceptual goal cuing. In novelty detection, responding 'yes' to a new object was classified as a hit ('no' was a miss), whereas responding 'no' to an old pleasant or unpleasant or bigger or smaller object was classified as a correct rejection to old item ('yes' was a false alarm to old item). For trait-level retrieval, we adopted classic signal-detection functions⁴⁰ to compute the d' statistic ($Z_{\text{hit}} - Z_{\text{falsealarm}}$) for each goal-state condition; source false alarms and novelty false alarms were included when computing the conceptual- and perceptual-condition d' statistics (see Extended Data Table 1 for false alarm rates by memory type), and novelty false alarms were included when computing the novelty-detection condition d' .

A repeated-measures ANOVA was run to examine differences in memory performance as a function of retrieval goal condition with the dependent variable being d' . Significance was set to $P < 0.05$.

Trial-level EEG and pupillometry data analyses. A number of preprocessing steps were implemented on raw EEG and pupillary data for the analyses targeting moment-to-moment lapsing. For EEG, the 1,000-Hz data were decimated to 100 Hz, and band-pass-filtered to 0.1–30 Hz using zero-phase Hanning windows. We then used the BLINKER automated method⁴¹ to identify blink artefacts, and visually inspected each trial of each participant's data to identify bad electrode channels also due to artefacts (for example, ocular). Data were average referenced and filtered for alpha power (8–12 Hz) using Hilbert transform. To assay trial-level spontaneous tonic lapses pre-goal and pre-retrieval, epochs were a priori set at 1 s pre-goal to 0 s goal, and 1 s pre-retrieval probe to 0 s probe. Mean alpha power from each epoch was extracted and computed from an a priori posterior cluster of electrodes (channels 62, 67, 71, 72 and 75–77; Extended Data Fig. 1b) that has previously been associated⁷ with lapsing. For pupil diameter, the 1,000-Hz data were decimated to 100 Hz. Note that real-time Eye Linker functions during acquisition remove blinks, off-centre fixations and eye-tracker malfunctions from the data output, minimizing preprocessing. Additional preprocessing was done for saccades over 10 degrees. Again, to assay trial-level spontaneous tonic lapses pre-goal and pre-retrieval, epochs were a priori set at 1 s pre-goal to 0 s goal, and 1 s pre-retrieval probe to 0 s probe. Mean pupil diameter was computed from each epoch, given previous evidence that this metric captures tonic lapsing trial-to-trial^{10,11,21}. Rather than applying linear interpolation, we removed from analyses those epochs that did not have full data (for example, data missing from blinks) to ensure perceptual encoding of stimuli on a trial-to-trial basis. Noisy trial-level epochs were then removed within run (± 3.5 s.d. from mean alpha power or pupil diameter), and

the remaining trial-level epochs were z-scored within a run, rather than across runs, to account for time-on-task effects.

A number of preprocessing steps were also implemented on raw EEG data to assay goal coding at the trial level. After implementing the above described sampling rate, band-pass-filter and artefact-identification and -rejection methods, we average referenced and filtered the data for ERP signal. Epochs were set at -0.20 s pre-goal to 2 s post-goal onset to assay goal coding during the goal cuing window. Mean ERPs from these epochs were extracted from an a priori midfrontal cluster of electrodes (numbered 5–7, 11–13, 106 and 112; Extended Data Fig. 1b) that has previously been associated with goal processing^{26,27}. Only epochs with full data were analysed to ensure perceptual encoding of stimuli. Baseline correction was implemented at the trial level by subtracting the 0.20 -s tonic mean from the 2 -s phasic-goal cue-locked mean. Noisy trial-level epochs were removed within each run (± 3.5 s.d. from the mean ERP), and the remaining trial-level epochs were z-scored within each run.

After preprocessing, trial-wise logistic mixed-effects models, with a restricted maximum likelihood (REML) approach, quantified the relationship between moment-to-moment lapsing and memory accuracy. Two main logistic models quantified pre-goal lapsing on hits versus misses: one model with a continuous fixed effect of pre-goal alpha power and a categorical fixed effect of hit (1) or miss (0), and another model with a continuous fixed effect of pre-goal pupil diameter. In addition, two linear mixed-effects models quantified the relationship between pre-goal lapsing and the ERP goal coding metric at the trial level: one model with a continuous fixed effect of pre-goal alpha power and a continuous fixed effect of goal coding, and another with a continuous fixed effect of pre-goal pupil diameter. Finally, logistic mixed-effects models quantified the relationship between goal coding and memory accuracy at the trial level: one model with a continuous fixed effect of goal coding and a categorical fixed effect of hit (1) or miss (0) for the alpha analysis and another for the pupil analysis. In all cases, each model included a random effect for participant, and an interaction term with retrieval goal (conceptual, perceptual or novelty goal cuing); the linear mixed-effects models were restricted to hit and miss trials to match the other models. Significance was tested using the P value of each individual beta for each effect in the respective model ($P < 0.05$).

Given significant paths between pre-goal lapsing and memory accuracy, pre-goal lapsing and goal coding, and goal coding and memory, two formal trial-wise mediation models were implemented, one with the alpha power assay of lapsing and one with the pupil diameter assay of lapsing. The indirect path from pre-goal lapsing to goal coding (a) and goal coding to memory (b) was computed, as was the direct path from pre-goal lapsing to memory (c'). The indirect path or mediation was computed as the product of $a \times b$, with a resulting 95% confidence interval for each indirect path from 10,000 bootstrapped samples. The total, direct and indirect effects were also tested for significance at $P < 0.05$.

Although these primary analyses addressed our first core question, we repeated the same approach but replaced pre-goal lapsing with pre-retrieval probe lapsing, and hit or miss memory with correct rejection or false alarm memory. As reported in the Supplementary Information, there were no significant results that stemmed from these analyses.

Trial-level Parietal Old/New and FN400 ERP data analyses. A number of preprocessing steps were implemented on raw EEG data for the analyses targeting trial-level canonical neural signals of recollection (Parietal Old/New) and familiarity-based (FN400) memory. After implementing the sampling rate, band-pass-filter and artefact-identification and -removal steps (see 'Trial-level EEG and pupillometry data analyses'), we average referenced and filtered the data for ERP signal. Epochs were set to -0.20 s pre-retrieval probe to 1 s post-probe onset. For the Parietal Old/New component, mean ERPs from these epochs were extracted and computed from an a priori left posterior cluster

of electrodes (numbered 42, 47, 52–54 and 61; note that 52 is P3; Extended Data Fig. 1b) that canonically demonstrates a recollection-based memory signal²⁸. For the FN400 component, mean ERPs from these epochs were extracted and computed from an a priori left midfrontal cluster of electrodes (numbered 19, 20, 23, 24, 27, 28, 33 and 34; note that 24 is F3; Extended Data Fig. 1b) that canonically demonstrates familiarity-based memory signal²⁸. Only epochs with full data were analysed to ensure perceptual encoding of stimuli. Data were segmented into 0.10 s (100-ms) bins based on previously published research²⁸ noting that a Parietal Old/New component typically onsets at around 400 ms, peaks at about 500 ms, and offsets at approximately 800 ms (all post-probe), and a FN400 component typically onsets at around 300 ms, peaks at about 400 ms, and offsets at approximately 500 ms (all post-probe). Baseline correction was implemented at the trial level by subtracting the 0.20 -s tonic mean from each of the ten 0.10 -s mean phasic-stimulus-locked bins. Noisy trial-level epochs were removed within run (± 3.5 s.d. from the mean ERP for Parietal Old/New or FN400), and the remaining trial-level epochs were z-scored within a run (by component).

Analyses first focused on replicating canonical signals of recollection- and familiarity-based memory in the three goal-state conditions, irrespective of lapsing. For Parietal Old/New in the left posterior cluster, we contrasted ERP signal on (1) source hits to old pleasant or unpleasant, or bigger or smaller objects relative to (2) correct rejections to new objects in conceptual- and perceptual-retrieval tasks, respectively. For FN400 in the left midfrontal cluster, we contrasted ERP signal on (1) correct rejections to old pleasant or unpleasant, or bigger or smaller objects relative to (2) hits to new objects in novelty detection (note: the terminology here is in relation to the retrieval task goal, such that new items called 'new' are termed hits). Following previous research²⁸, a series of repeated-measures ANOVAs and post hoc F -tests were adopted. For Parietal Old/New, a 2 (retrieval type: source hit versus correct rejection to new object) by 2 (retrieval goal: conceptual versus perceptual goal cuing) by 10 (time bin: for example, 0 – 0.10 s) model was used for which the dependent variable was the ERP signal. For FN400, a 2 (retrieval type: correct rejection to old object versus hit to new object) by 10 (time bin: for example, 0 – 0.10 s) model was used in the novelty-detection task in which the dependent variable was the ERP signal. Significance was set to $P < 0.05$ for the ANOVAs and post hoc tests. Because z-scoring the ERP signal within run and time-binning in 100 -ms intervals can smooth the data, reducing smaller temporal effects often observed in grand-average ERPs, for completeness we also plot these ERPs using 10 -ms time-bin intervals (Extended Data Fig. 4). As a complementary analysis to ensure the specificity of our findings²⁸, we extracted the ERP signal from right posterior (numbered 78, 79, 86, 92, 93 and 98; Extended Data Fig. 1b) and right midfrontal (numbered 3, 4, 116–118 and 122–124; Extended Data Fig. 1b) clusters using the same preprocessing and analytic steps. We then included lateralization (left versus right) as an additional factor in the repeated-measures ANOVAs for Parietal Old/New and FN400. Significance was set to $P < 0.05$ for the ANOVAs and post hoc tests, and the interaction results by lateralization are reported in the Supplementary Information.

Next, trial-wise linear mixed-effects models, with an REML approach, quantified the relationship between moment-to-moment lapsing and these canonical neural memory signals. We focused on hit versus miss memory in conceptual and perceptual goal cuing and novelty detection given the relationships observed between trial-to-trial lapsing, goal coding and memory accuracy in response to these types of trials. For Parietal Old/New, two main models assessed the relationship between pre-goal lapsing and ERP signal during the 500 – 600 -ms post-probe window for remembered compared with forgotten trials in conceptual- and perceptual-retrieval tasks: one model with a continuous fixed effect of pre-goal alpha power and a continuous fixed effect of ERP signal, and another model with a continuous fixed effect of pre-goal pupil diameter. For FN400, two main models assessed the relationship between

pre-goal lapsing and ERP signal during the 400–500-ms post-probe window for correctly endorsed new items (hits) compared with miss trials in novelty detection: one model with a continuous fixed effect of pre-goal alpha power and a continuous fixed effect of ERP signal, and another model with a continuous fixed effect of pre-goal pupil diameter. Each model included a random effect for participant, and an interaction term with retrieval accuracy (hit versus miss). The Parietal Old/New models included an additional interaction term with retrieval goal (conceptual versus perceptual cuing). The post-probe windows were selected based on previously reported signal peaks for the Parietal Old/New and FN400 effects²⁸. Significance was tested using the *P* value of each individual beta for each effect in the respective model ($P < 0.05$). As a complementary analysis²⁸, we also included an interaction term for lateralization (left versus right) in each model, and the interaction results by lateralization are reported in the Supplementary Information.

Trial-level phasic pupil old/new analysis. Although we addressed our second core question regarding relationships between trial-to-trial lapsing and neural signals of remembering from canonical ERP components, we also leveraged previously published findings^{42–44} that have documented differences in phasic pupillary signal post-retrieval probe as a function of memory to provide a secondary internal check on memory performance. Akin to an FN400 effect, higher peak pupil diameter is typically exhibited for correctly identified old versus new items post-retrieval probe in old/new recognition memory, a phenomenon referred to as a ‘pupil old/new effect’^{42–44}. We focused on phasic pupillary signal post-retrieval probe in correctly rejected old objects versus hits to new objects (that is, old versus new) in the novelty-detection retrieval condition to examine evidence of a pupil old/new effect. We did not examine tonic lapses on phasic pupil diameter post-retrieval probe given research that demonstrated strong anti-correlations between tonic and phasic pupil diameter that could lead to the over-interpretation of findings⁴⁵.

After implementing the eye-tracking preprocessing steps (see ‘Trial-level EEG and pupillometry data analyses’), phasic pupil diameter was extracted for each trial using a -0.2 -s pre-retrieval probe to 1-s post-probe epoch. Only epochs with full data were analysed, and data were segmented into 0.10-s time bins. As is typical in phasic pupillary work^{42–45}, we then extracted a peak (that is, maximum) pupil diameter value from each of the 10 post-probe time bins for each trial. Baseline correction was implemented at the trial level by subtracting the 0.20-s tonic mean from each of the ten 0.10-s peak phasic-stimulus-locked bins. Noisy trial-level epochs were then removed within each run (± 3.5 s.d. from phasic pupil), and the remaining trial-level epochs were z-scored within each run to account for time-on-task effects.

To examine evidence of a pupil old/new effect (Extended Data Fig. 6), we ran a repeated-measures ANOVA with a 2 (retrieval type: correct rejection to old object versus hit to new object) by 10 (time bin: for example, 0–0.10 s) model within novelty-detection cuing, in which the dependent variable was phasic pupillary signal. Significance was set to $P < 0.05$ for the ANOVAs and post hoc tests.

Trait-level analyses. To answer our third core question, we first examined the relationship between trait-level lapsing and d' on the memory tasks. Previous research^{7,10} suggests that trait-level increases in tonic alpha power and variability in tonic pupil diameter are correlated with trait-level inattention. An increase in mean alpha power in the absence of external distraction is thought to reflect reduced suppression (that is, release from inhibition), and an increase in pupil variability is correlated with increases in mind wandering and decrements in psychomotor vigilance^{7,10}. To quantify these trait-level metrics, we computed each participant’s mean alpha power and pupil diameter variability across the 1-s pre-goal epochs during memory retrieval. Only full epochs were used. For pupil variability, we computed a coefficient of variation: s.d. across each participant’s pre-goal epochs divided by

the mean across the epochs, multiplied by 100. To standardize the key metrics, we z-scored the mean alpha power, pupil variability and d' in each retrieval goal condition across participants. We then ran one-tailed Pearson correlations between mean alpha power and each d' , as well as pupil variability and each d' , setting significance to $P < 0.05$. One-tailed correlations were used for all trait-level analytics given our a priori hypotheses about directionality between lapsing and memory, and lapsing, MMT and memory.

To more directly assess relationships between trait-level lapsing and memory, we also used assays of lapsing from a canonical sustained attention task, the gradCPT^{23,46}. We computed two assays of lapsing from the task: (1) CER, the proportion of responses to ‘no-go’ mountain trials over the total number of ‘no-go’ mountain trials; and (2) RTV, for responses to ‘go’ city trials, using a coefficient of variation metric (s.d. of the reaction time on city trials divided by the mean reaction time, multiplied by 100). Following previous work with the gradCPT^{23,46}, we also computed canonical assays of vigilance (mean reaction time over five 2 min windows) and omission error rate (proportion of no responses on ‘go’ city trials divided by the total number of ‘go’ trials), which we report in the Supplementary Information. We z-scored all gradCPT metrics across participants and ran one-tailed Pearson correlations: (1) between mean alpha power or pupil variability from the memory task and CER or RTV from the gradCPT, and (2) between the d' from each retrieval task and CER or RTV from the gradCPT.

Given significant paths between lapsing and memory, lapsing and CER on the gradCPT and CER on the gradCPT and memory, two formal participant-level mediation models were implemented on the z-scored metrics to examine whether the relationship between lapsing and memory on the memory task was partially explained by trait-level differences in sustained attention, as indexed by the gradCPT. Note that we computed a common metric of memory by averaging across the d' values from the three retrieval goal conditions; the same findings were obtained with each d' metric separately. One mediation model examined the indirect path from lapsing (mean alpha power) to gradCPT (*a*) and gradCPT to memory (*b*), as well as the direct path from lapsing to memory (*c'*). The other model examined the same paths but replaced mean alpha power with pupil variability. Each indirect path or mediation was computed as the product of $a \times b$, with a resulting 95% confidence interval for each indirect path from 10,000 bootstrapped samples. The total, direct and indirect effects were also tested for significance at $P < 0.05$ (Fig. 2d).

As a final step, a confirmatory factor analysis tested for a trait-level relationship between sustained attention and memory. The ‘attention’ latent variable consisted of z-scored pre-goal lapsing from the memory task (mean alpha power and pupil variability) along with z-scored lapsing from the gradCPT (CER and RTV). The ‘memory’ latent variable consisted of z-scored d' for each retrieval goal condition from the memory task (conceptual, perceptual and novelty detection). Model fit and the covariance between components were tested for significance at $P < 0.05$. We treat this result as preliminary given that a higher sample size is sometimes recommended for confirmatory factor analysis.

To answer our fourth core question about trait-level cognitive differences correlated with MMT, we first assessed the relationship between MMT and memory. We computed a MMI score for each participant, using the standard formula²⁴, and then z-scored across participants for standardization. For the main continuous approach, Pearson correlations quantified the relationship between MMT and each d' from the memory tasks. Given previous research¹⁸, we also incorporated an extreme groups approach in which participants with the lowest 25% of MMI scores were treated as light media multitaskers and those with the top 25% of MMI scores were treated as heavy media multitaskers (Extended Data Fig. 7); we note that this analysis was treated as secondary given the sample size (20 per group). A 2 (MMT: light versus heavy) by 3 (retrieval goal: conceptual versus perceptual versus novelty) mixed-factorial ANOVA was run with d' as

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the dependent variable, and significance was set to $P < 0.05$ (Extended Data Fig. 7a).

We then adopted the same continuous and extreme groups approaches to assess the relationship between MMT and attention (Extended Data Fig. 7b, c). In terms of attention, we examined z-scored gradCPT performance (CER and RTV) and lapsing on the memory task (mean alpha power and pupil variability).

On the basis of significant paths between MMT and memory, MMT and lapsing and lapsing and memory, we leveraged four participant-level mediation models to examine whether the relationship between MMT and memory is partially explained by trait-level differences in sustained attention. An average d' across the three retrieval measures was used; again, the same findings were found when examining each d' separately. The mediation models tested the indirect path from MMT to each gradCPT and attention lapsing metric (CER, RTV, mean alpha power or pupil variability (a)), and from each gradCPT and lapsing metric to memory (b), as well as the direct path from MMT to memory (c'). Each indirect path or mediation was computed as the product of $a \times b$, with a resulting 95% confidence interval for each indirect path from 10,000 bootstrapped samples. The total, direct and indirect effects were also tested for significance at $P < 0.05$.

The primary analyses described above addressed our fourth core question. We also took three additional steps for completeness. First, we used canonical formulas to compute a trait-level score for each self-report questionnaire and implemented an exploratory factor analysis to quantify how MMT relates to these other constructs. The mean across items was used for ADHD, attentional control distractibility and shifting and deliberate and spontaneous mind wandering, and the sum across items was used for BIS-11 subcomponents (which included reverse-scoring of appropriate items), the attention-related cognitive error scale, memory failure scale and mindful attention awareness scale-lapses only questionnaires. Each questionnaire was z-scored across participants. A categorical frequency of video game playing (more than 5 h per week of action video games) was used for video-game usage; note that we did not perform further analyses on this questionnaire because under 10% of the sample endorsed video-game playing. For the exploratory factor analysis, we implemented a principal component analysis that extracted latent factors from the questionnaire scores and maximized the loading of each score on one factor and minimized its loading on the other factors. To account for collinearity and sampling distribution adequacy, we qualitatively examined correlations among questionnaire scores and quantitatively assessed the determinant, Kaiser–Meyer–Olkin value and Bartlett test statistics and the communality of each questionnaire score. We then examined factor output with a Scree plot before and after extraction, and after varimax rotation, and selected a three-factor model given that three factors showed eigenvalues of >1.0 . We then assessed which questionnaire scores with a communality above 0.5 loaded on each of the three extracted factors. Although we adopted typical steps and parameters for the exploratory factor analysis (that is, the principal component analysis), our analysis should be treated as preliminary given the sample size. Subsequently, Pearson correlations between the other questionnaire scores and the gradCPT and memory metrics were examined to assess whether additional variance not captured by MMT could explain task-based attention and memory assays. Significance was set to $P < 0.05$. As a final step, we verified that the same findings for trait-level analytics were found when we computed lapsing assays from our memory task that incorporated mean alpha power and pupil variability across (1) pre-retrieval probe epochs alone, and (2) both pre-goal and pre-retrieval probe epochs.

Data and analytic code are publicly available^{47,48}.

Reporting summary

Further information on research design is available in the Nature Research Reporting Summary linked to this paper.

Data availability

Data that support the findings of this study are publicly available via the Open Science Framework⁴⁷ with identifier zj7tb (<https://osf.io/zj7tb>). Data used in the preparation of this manuscript are also publicly available from the National Institute of Mental Health (NIMH) Data Archive (NDA) (<https://doi.org/10.15154/1519022>)⁴⁸. The source data underlying all figures are provided as a Source Data file. Source data are provided with this paper.

Code availability

Analytic code that support the findings of this study are publicly available via Open Science Framework⁴⁷ with identifier zj7tb (<https://osf.io/zj7tb>).

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Acknowledgements We thank A. Gonzalez and J. Qi for assistance with various aspects of the study. This research was supported by the National Institute of Mental Health (R56MH111672 to A.D.W.) and the National Institute on Aging (R01AG065255 to A.D.W.; F32AG059341 to K.P.M.). The content is solely the views of the authors and does not necessarily represent the official views of the National Institutes of Health.

Author contributions K.P.M., A.M.K., M.R.U., A.M.N. and A.D.W. developed the study concept and contributed to study design; K.P.M. and C.W.B. collected data under supervision of A.M.N. and A.D.W.; K.P.M., A.M.K., C.W.B. and J.J. analysed data under supervision of A.M.N. and A.D.W.; K.P.M. and A.D.W. wrote the manuscript, and all authors provided critical revisions.

Competing interests The authors declare no competing interests.

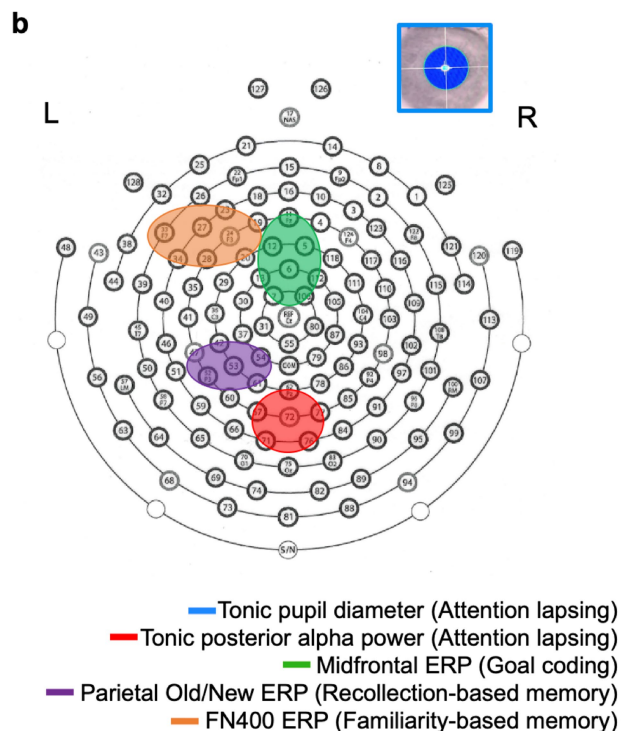
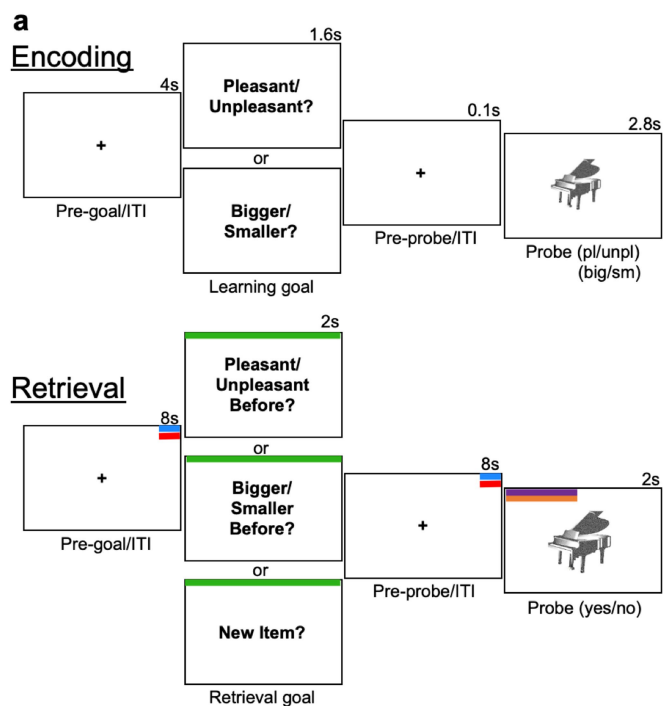
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Supplementary information is available for this paper at <https://doi.org/10.1038/s41586-020-2870-z>.

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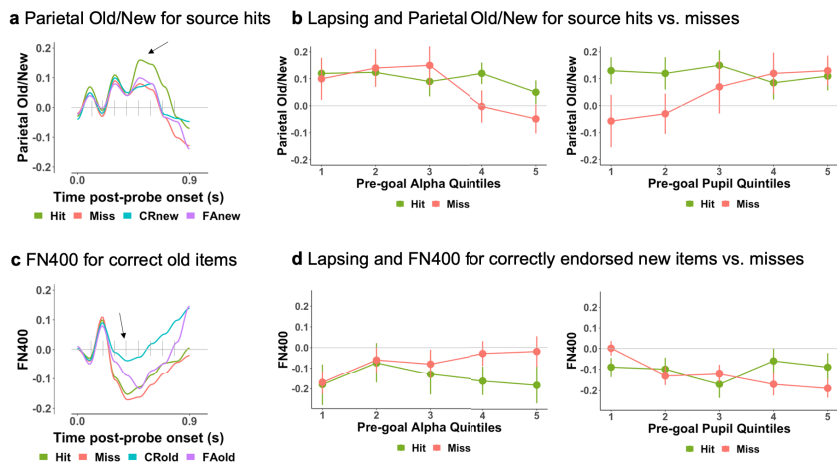
Peer review information Nature thanks Edward K. Vogel and the other, anonymous, reviewer(s) for their contribution to the peer review of this work.

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Extended Data Fig.1 | Experimental design. a, Schematic of the goal-directed memory task with EEG and pupillometry measurements. **b**, Schematic of electrode clusters from which alpha or ERP signals were extracted for the

respective analyses; electrode clusters are illustrated on a 128-channel net. Pupil diameter from the right eye (top right) was recorded concurrently using an eye-tracking system. L, left; R, right.

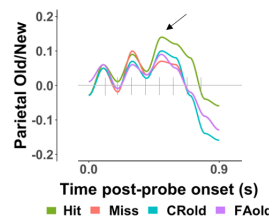


Extended Data Fig. 2 | Pre-goal attention lapses relate to canonical neural signals of recollection- and familiarity-based memory as assayed by grand-average left-lateralized Parietal Old/New and FN400 ERP effects, respectively. **a**, Evidence of a peak Parietal Old/New signal (indicated by the black arrow) in the 500–600-ms post-probe window as a function of memory outcome in conceptual and perceptual source-retrieval trials. **b**, Trial-level interaction between pre-goal attention lapses and the Parietal Old/New signal during remembered (source hit) and forgotten (miss) trials. **c**, Evidence of a peak FN400 signal (indicated by the black arrow) in the 400–500-ms post-probe window as a function of memory outcome in novelty-detection trials. **d**, Trial-level interaction between pre-goal attention lapses and FN400 signal on correctly endorsed new items (hits) compared with misses. For

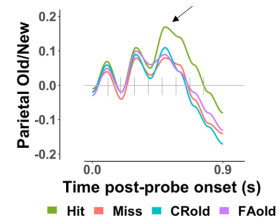
visualization, quintiles are shown for the relationship between pre-goal lapsing and ERP signal; statistics included an interaction term for retrieval goal state (for Parietal Old/New) and treated pre-goal lapsing and the ERP signals continuously in trial-level mixed models. y-axis units are z-scores. Data are mean $\pm$ s.e.m. Note that z-scoring within run and time-binning in 0.1-s (100-ms) intervals reduces smaller temporal effects that are sometimes exhibited in grand-average ERP plots (for visualization of grand-average ERP plots downsampled to 0.01-s intervals (10-ms), see Extended Data Fig. 4). CRold, correct rejection of old item; CRnew, correct rejection of new item; FAold, false alarm to old item; FAnew, false alarm to new item. $n = 75$ participants from a single independent experiment.

Parietal Old/New for old items via:

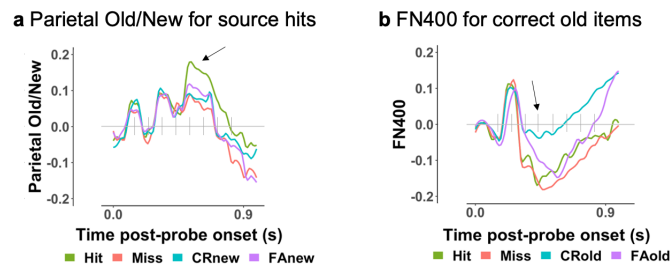
a conceptual cuing



b perceptual cuing



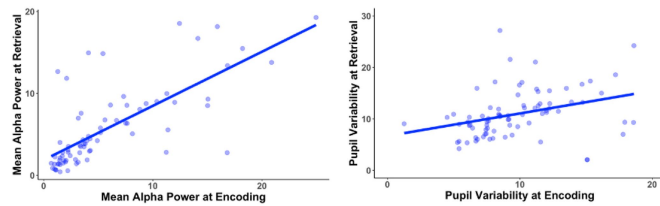
Extended Data Fig. 3 | Evidence of mean peak Parietal Old/New signal in the 500–600-ms post-probe window as a function of memory outcome in source retrieval trials. The mean peak Parietal Old/New signal is indicated by the black arrow. **a, b**, Data are split by conceptual (**a**) and perceptual (**b**) source trials. CRold, correct rejection of old item; FAold, false alarm to old item. For conceptual cuing, hits and misses are for conceptually studied items, and correct rejections and false alarms are for perceptually studied items. For perceptual cuing, hits and misses are for perceptually studied items, and correct rejections and false alarms are for conceptually studied items. $n = 75$ participants from a single independent experiment.



Extended Data Fig. 4 | Grand-average left-lateralized ERPs revealing recollection-based Parietal Old/New and familiarity-based FN400 memory effects. Data were down-sampled to 10-ms time-bin intervals.

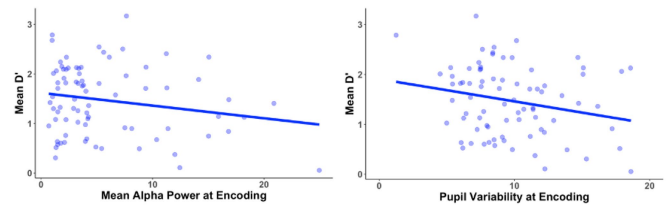
a, b, The same profile of findings is observed as with the 100-ms time-bins (see main text), such that evidence of a peak Parietal Old/New signal (indicated by the black arrow) is exhibited 500–600-ms post-probe onset as a function of memory outcome in conceptual and perceptual source-retrieval trials (**a**) and evidence of a peak FN400 signal (indicated by the black arrow) is exhibited 400–500-ms post-probe onset as a function of memory outcome in novelty-detection trials (**b**). y-axis units are within-run z-scores. $n = 75$ participants from a single independent experiment.

a Attention lapsing (alpha and pupil) at encoding relates to lapsing (alpha and pupil) at retrieval

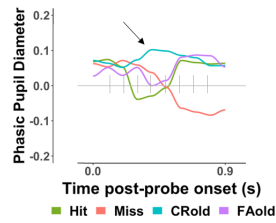


Extended Data Fig. 5 | Trait-level differences in sustained attention at encoding help to explain why individuals are more prone to remembering or forgetting. a, b, Greater pre-goal attention lapsing at encoding is correlated with greater pre-goal attention lapsing at retrieval (**a**) and lower d' on the memory task (**b**). For visualization, raw scores are plotted; statistics included

b Attention lapsing (alpha and pupil) at encoding relates to memory

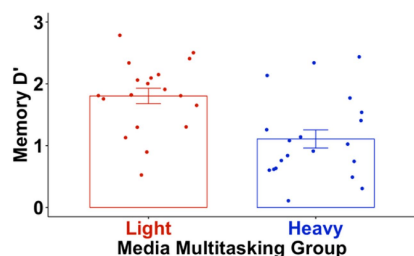


z-scored assays with Pearson correlations. $n = 75$ participants for alpha retrieval data and $n = 80$ participants for all other data from a single independent experiment. These trait differences in attention at encoding do not fully explain the relationship between the trait differences in attention at retrieval and memory ability (Supplementary Information).

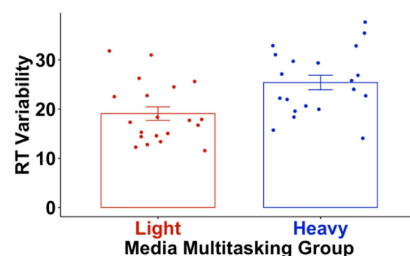
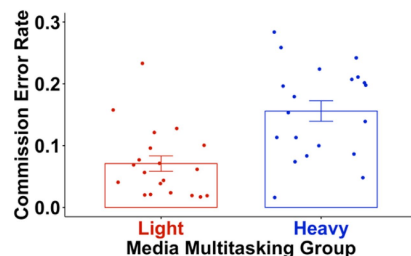


Extended Data Fig. 6 | Phasic pupil and memory effects. Evidence of a phasic pupil old/new effect in novelty-detection trials 300–500 ms post-probe, particularly between correctly rejected old objects versus hits to new objects. The mean peak difference is at 400 ms post-probe (indicated by the black arrow). *x*-axis units are 100-ms time-bin intervals; *y*-axis units are within-run *z*-scores. *n* = 75 participants from a single independent experiment.

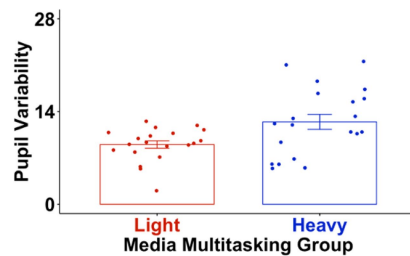
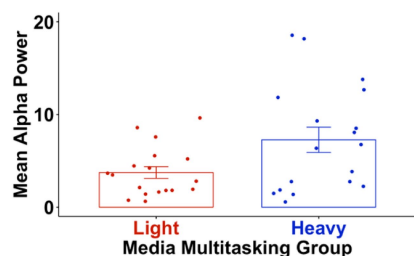
a LMMs vs. HMMs: memory



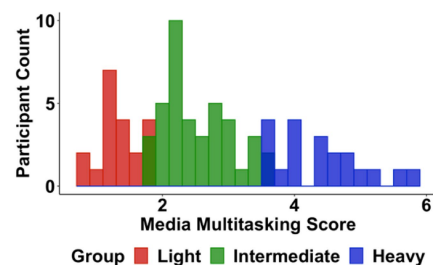
b LMMs vs. HMMs: lapsing on sustained attention task (gradCPT)



c LMMs vs. HMMs: lapsing (alpha and pupil) on memory task



d Distribution of MMT scores



Extended Data Fig. 7 | Key results from extreme group analyses of multitasking, memory and sustained attention for light and heavy media multitaskers. **a–c.** Heavy media multitaskers exhibited lower d' on the memory tasks (**a**), more attention lapses on the gradCPT (**b**) and more evidence of attention lapsing (assayed by mean alpha power and pupil variability) on the memory task (**c**), relative to light media multitaskers. Data are mean $\pm$ s.e.m.

from a single independent experiment. $n = 18$ light and $n = 18$ heavy media multitaskers for alpha data; $n = 20$ light and $n = 20$ heavy media multitaskers for all other data. **d.** Histogram of scores ($n = 80$) on the MMI, illustrated by the bottom 25% of scores (light media multitaskers), the middle 50% of scores (intermediate media multitaskers) and the top 25% of scores (heavy media multitaskers). LMM, light media multitasker; HMM, heavy media multitasker.

Extended Data Table 1 | Mnemonic rates as a function of retrieval goal

	Conceptual cuing	Perceptual cuing	Novelty cuing
Hit rate	0.63 (0.02)	0.60 (0.02)	0.69 (0.02)
CR _{old} rate	0.77 (0.02)	0.80 (0.02)	0.80 (0.02)
CR _{new} rate	0.88 (0.02)	0.91 (0.01)	-

Data are mean ± s.e.m. for each type (that is, rate) of memory outcome for each goal cue condition at retrieval. Note that the miss rate for each condition is the complement of hit rate (1 – hit rate); and the false alarm rate to old items or new items is the complement of the respective correct rejection rate (1 – correct rejection rate). All analyses in the manuscript were computed over *d'* values (main text and Supplementary Information), rather than mnemonic outcome rates, because the *d'* metric accounts for response bias.

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Software and code

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Data collection

All tasks were run using the Psychophysics Toolbox (version 3; Brainard, 1997) in MATLAB (version 2019a 9.6). In-house code was implemented to tag metrics related to EEG, pupil, memory, and sustained attention with Netstation software (version 5.4). Self-report questionnaires were completed paper-and-pencil and on the Qualtrics Survey platform (Qualtrics, Provo, Utah, USA) with in-house design.

Data analysis

The R environment (version 3.3.3) and SPSS (version 26) were leveraged for data preprocessing, statistics, and visualization. The following R packages were primarily utilized with in-house scripts: openxlsx, tidyverse, dplyr, lme4, lmerTest, mediation, lavaan, ggplot2, ggpubr, and eyetrackingR. Various toolboxes in MATLAB were also leveraged with in-house scripts for various reasons: the SHINE toolbox (version 1; Willenbockel et al., 2010) to luminance- and chrominance-control stimuli, the BLINKER toolbox (version 1.1.1; Kleifges et al., 2017) to identify blink artifacts in EEG data, and the EEGLAB toolbox (version 14.1.1b; Delorme & Makeig, 2004) to preprocess EEG data. Analytic code is publicly available and archived via Open Science Framework: <https://osf.io/zj7tb>. Identifier is zj7tb.

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Behavioural & social sciences study design

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Study description	Data are quantitative from EEG, pupil, behavioral, and questionnaire-based measures. We tracked and measured spontaneous fluctuations in attention and relationships to goal coding strength, as well as behavioral and neural signals of different types of remembering. A within-subject experimental manipulation of goal coding was included at encoding and at retrieval, so that we could assess how spontaneous fluctuations in attention predicted coding of goals and different types of memory.
Research sample	Eighty young adults enrolled in the study (49 female; Mean age = 21.70 years, SD = 1.48, range = 18-26). They were members of Stanford University or from the surrounding community. The sample was representative of demographics at Stanford University. This sample was chosen because our research questions involved interactions between attention, memory, and media multitasking in young adults.
Sampling strategy	Random sampling was implemented. A sample size of 80 participants was chosen based on prior work documenting this number was adequate for a reliable individual differences approach (Gignac & Szodorai, 2016). Because trial-level analyses were completed within subject, the sample size was focused on trait-level robustness. Data saturation was not applicable.
Data collection	During encoding and retrieval, EEG and pupillary data were recorded concurrently in an electric- and sound-proof chamber to minimize artifacts. The participant completed encoding and retrieval in the chamber alone, and real-time EEG, eyetracking, behavioral data, and stimulus display were monitored from an outside bay by the experimenter. EEG data were recorded with a 128-channel HydroCell Sensor Net (Electrical Geodesics, Eugene, Oregon, USA) at a sampling rate of 1000Hz through a Netstation 300 amplifier with 24-bit resolution/sample and Netstation 5.4 software. Impedance was set at <50 kV and checked approximately every 20m. Pupillary data from the right eye were recorded via an EYELINK 1000 Eye Tracker System (SR Research, Ottawa, Canada) at a sampling rate of 1000Hz. Participants were seated 60cm from the eyetracker and stimulus monitor with a chin mount in the chamber. Eyetracking calibration and validation steps were completed every ~20m with impedance checks. Participants made task responses with a keyboard. After the memory tasks, participants completed 9 self-report questionnaires by hand and on the computer, and the sustained attention task (gradCPT) on the computer, in the chamber. Only the participant and experimenter were present. Each participant completed the study alone in a sound- and electric-proof chamber, so experimenter was not blind to study hypothesis during data collection.
Timing	April 9, 2018 (start) - November 12, 2018 (stop)
Data exclusions	Exclusion criteria were pre-established. <10 hits or <10 misses in each retrieval condition for trial-level analyses, blinking/other visual artifacts from EEG and pupillometry for trial-level and trait-level analyses, and failing to complete all tasks and questionnaires in the study for trial-level and trait-level analyses. Five participants (of 80) were excluded from trial-level analyses involving EEG assays due to retrieval outcomes and technical artifacts. Five participants (of 80) were excluded from trait-level analyses involving EEG assays due to technical artifacts. No participants were excluded for failing to complete the study.
Non-participation	No participants dropped out or declined participation.
Randomization	Participants were not allocated into between-subject experimental groups.

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Methods

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Population characteristics

See above.

Recruitment

Participants were recruited from online advertisements at Stanford University and the surrounding community, were right-handed, and had normal or corrected-to-normal vision, no history of neurological or psychological impairment, and no current medication. There was no self-selection bias in recruitment.

Ethics oversight

Stanford University Research Compliance Office (Human Subjects Research and IRB)

Note that full information on the approval of the study protocol must also be provided in the manuscript.