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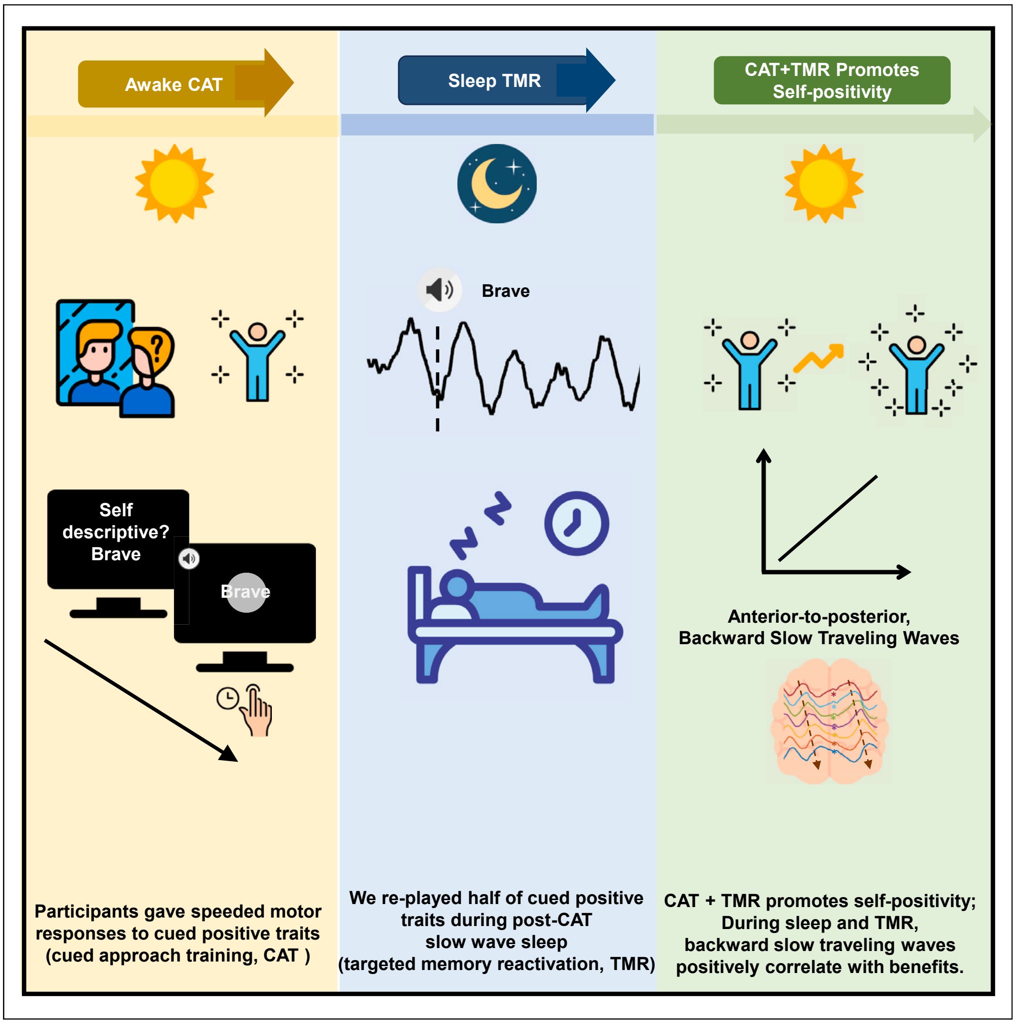

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Highlights

We tested how to promote people's positive self-referential processing

We used cued approach motor training and sleep-based targeted memory reactivation

Our integrated procedure enhanced positive self-referential processing

Enhancements were linked to anterior-posterior slow traveling wave during sleep

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Reactivating cue approached positive personality traits during sleep promotes positive self-referential processing

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SUMMARY

People preferentially endorse positive personality traits as more self-descriptive than negative ones, a positivity self-referential bias. Here, we investigated how to enhance positive self-referential processing, integrating wakeful cue-approach training task (CAT) and sleep-based targeted memory reactivation (TMR). In the CAT, participants gave speeded motor responses to cued positive personality traits. In a subsequent nap, we unobtrusively re-played half of the trained positive traits during slow-wave sleep (TMR). Upon awakening, CAT+TMR facilitated participants' speed in endorsing positive traits in immediate tests, and rendered participants endorse more positive traits as self-descriptive after one week. Notably, these enhancements were associated with the directionality of cue-related 1–4 Hz slow traveling waves (STW) that propagate across brain regions. Specifically, anterior-to-posterior backward STW was positively associated with these benefits, whereas forward STW showed negative associations. These findings demonstrate the potential benefits of integrated wakeful cue-approach training and sleep-based memory reactivation in strengthening positive self-referential processing.

INTRODUCTION

People often perceive themselves through rose-tinted lenses, exhibiting a positivity bias.[1,2] This positivity bias is evident in self-referential judgments, as people preferentially choose positive personality traits to describe themselves and have better memories for positive traits compared to negative ones.[1,3–7] A positive self-referential bias is commonly associated with lower levels of depressive symptoms (e.g., self-doubt and worthlessness) and is crucial for mental well-being, especially when facing self-threatening information.[8] While the psychological benefits of positive self-referential processing are well established,[1,9–11] a significant gap exists in understanding how to effectively enhance this process.[10,12] To address this gap, we integrated two procedures that may enhance positive self-referential processing: (1) wakeful cued-approach training (CAT, Schonberg et al.[13]) and (2) a sleep-based targeted memory reactivation procedure (TMR, Oudiette et al.[14]).

The CAT task prompts participants to give speeded motor responses to cued stimuli, ultimately increasing positive evaluations or preference toward these trained stimuli.[13,15–17] While CAT has been used to alter preferences for various stimuli, such as food, abstract patterns, and images (for a review, see Salomon et al.[15]), its impact on higher-order social-cognitive processes such as self-referential processing remains unexplored.

Complementing the wakeful CAT, the TMR aims to promote memory consolidation during post-training sleep, a phase vital for stabilizing newly acquired memories. During sleep, reactivation of prior learning experiences contributes to memory consolidation, notably during non-rapid eye movement (NREM) sleep characterized by the <4 Hz slow-wave activity.[18–22] TMR entails replaying memory-related sensory cues to sleeping participants, further strengthening episodic memories or even changing subjective preferences during NREM sleep.[23–29] (for a

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meta-analysis of TMR see Hu et al.[30]) Here, in the context of self-referential processing, we hypothesize that the integration of wakeful CAT and sleep-based TMR could change how individuals perceive and endorse positive personality traits as self-descriptive. Specifically, while CAT would increase salience of specific positive traits, TMR consolidates memories for these traits during sleep, potentially enhancing positive self-referential judgments. Therefore, we tested the joint impact of CAT and TMR on the positive self-referential processing, particularly focusing on how they influence the immediate and long-term endorsements and retention of positive personality traits.

During NREM sleep, cardinal neural oscillations such as slow oscillations (<1 Hz), delta waves (1–4 Hz) and the 12–16 Hz spindles are instrumental in mediating memory reactivation and consolidation.[19,20,22,31–34] Specifically, in TMR, research repeatedly shows that the cue-elicited delta, theta and sigma electroencephalogram (EEG) power changes predicted TMR benefits. However, how propagation of sleep EEG oscillations, particularly the slow waves, would contribute to memory consolidation remains unclear. In particular, the propagation of EEG oscillations across various brain regions, referred to as traveling waves, has garnered increasing attention for their potential in bridging neural activity with behavioral outcomes.[35–38] Notably, during sleep, slow oscillations and spindles form pronounced traveling waves, propagating across cortical regions implicated in memory processing.[35] These traveling waves are hypothesized to orchestrate neural communication across different regions during sleep, thereby may play a vital role in the reactivation and consolidation of memory traces.[39–42] Despite these insights, sleep research has predominantly focused on spontaneous traveling waves,[39] with significant gaps on the understanding of traveling waves induced by external cues and their functions in supporting sleep-mediated memory reactivation. To bridge this gap, we aim to investigate how cue-elicited sleep traveling waves may contribute to TMR benefits. Emerging research suggests that during wakefulness, cue-elicited traveling waves, depending on their direction (backward/anterior-to-posterior or forward/posterior-to-anterior), serve distinct functions in sensory processing and memory.[37,38,43] This bolsters the possibility that during TMR, cue-elicited sleep traveling waves might also support TMR benefits.

Here, we employed an adapted version of the well-established self-referential encoding task (SRET) to quantify participants' self-referential processing.[6,7,44,45] (for procedure and tasks, see Figure 1). In addition to this SRET, we assessed participants' recall of self-referential traits from the SRET in a free recall task and self-referential endorsement preference in a probe task. To examine the immediate and possible long-term effects of TMR, we measured participants' self-referential processing both immediately after the TMR and one-week later. Our findings revealed that the integration of CAT and TMR facilitated the endorsement speed of positive personality traits immediately after TMR and enhanced positive self-referential endorsements one week later. Moreover, analysis of cue-elicited EEG showed that the strength of 1–4 Hz backward traveling waves predicted the endorsement speed of positive traits during immediate test and the endorsement of positive traits one-week later.

RESULTS

Awake CAT promoted self-referential preferences

First, to examine whether CAT promoted the preferences of positive Go traits, we analyzed the proportion of trials in which participants preferred Go over NoGo traits as better self-descriptive in the probe task (Figure 1D), using a generalized linear mixed model with participant factor as a random effect (GLMM, see STAR Methods for specific model). In each Go/NoGo pair, both traits had comparable initial endorsement level based on the baseline SRET rating phase. Consistent with previous CAT research,[15] we found that participants were more likely to choose Go over NoGo traits despite their comparable baseline endorsement level: mean proportion = 53.3% (vs. chance level 50%), odds ratio (OR) = 1.14, 95% confidence of interval (CI) [1.04, 1.25], $p = 0.006$. This result suggested that the CAT specifically increased participants' self-referential choice of the Go traits in the probe task.

Awake CAT + sleep TMR enhanced positive self-referential endorsements and speed

Having established that the CAT enhanced preferences of positive Go traits, we next examined how CAT+TMR impacts positive self-referential processing. Specifically, we analyzed two outcome variables from the SRET task, including binary endorsements (self-descriptive or not), and reaction times (RTs) when endorsing positive traits. We employed Bayesian generalized linear mixed model (BGLMM) to analyze binary outcomes including SRET endorsement choices (self-descriptive or not) and recall outcome (recalled vs. not recalled). We employed Bayesian linear mixed model (BLMM) to analyze continuous outcomes, specifically the reaction times associated with SRET endorsement of positive traits.

Specifically, to examine changes in binary endorsements (self-descriptive or not), we ran a Bayesian generalized linear mixed model (BGLMM) using pre-TMR baseline endorsement and ratings as covariates, conditions (Go-cued, Go-uncued, and NoGo-uncued) and time (post-TMR and delay) as fixed effects, and participant as a random effect (including both random intercept and slope) to predict endorsement of positive traits (self-descriptive or not). Our results revealed a significant interaction between CAT+TMR conditions and time such that after one week delay, participants endorsed more Go-cued traits as self-descriptive than NoGo-uncued traits (median $_{diff}$ = 0.46, 95% (high density interval (HDI) [0.03, 0.91], Figure 2A). No differences were found between other comparison contrasts (Go-uncued versus NoGo-uncued, Go-cued versus Go-uncued traits, Table S1).

Given that endorsement RT could indicate preferences,[46] we analyzed item-level RTs when participants endorsed positive traits via a Bayesian linear mixed model (BLMM) using baseline endorsement RT and rating as covariates, with the same fixed and random factors as in SRET endorsement model. The results showed a significant interaction between CAT+TMR and time such that in the post-TMR, participants were significantly faster in endorsing Go-cued traits than NoGo-uncued traits (median $_{diff}$ = −0.05, 95% HDI [-0.08, −0.01], Figure 2B). Other comparisons were not significant (Table S2). Taken together, these results suggest that the CAT+TMR jointly facilitated endorsement speed for Go-cued positive traits compared to NoGo-uncued positive traits.

To investigate observed endorsements and RT differences might be solely due to CAT or the joint CAT + TMR effect, we analyzed data from two additional groups of participants: an active-CAT group and a passive-CAT group. Both groups underwent the SRET and

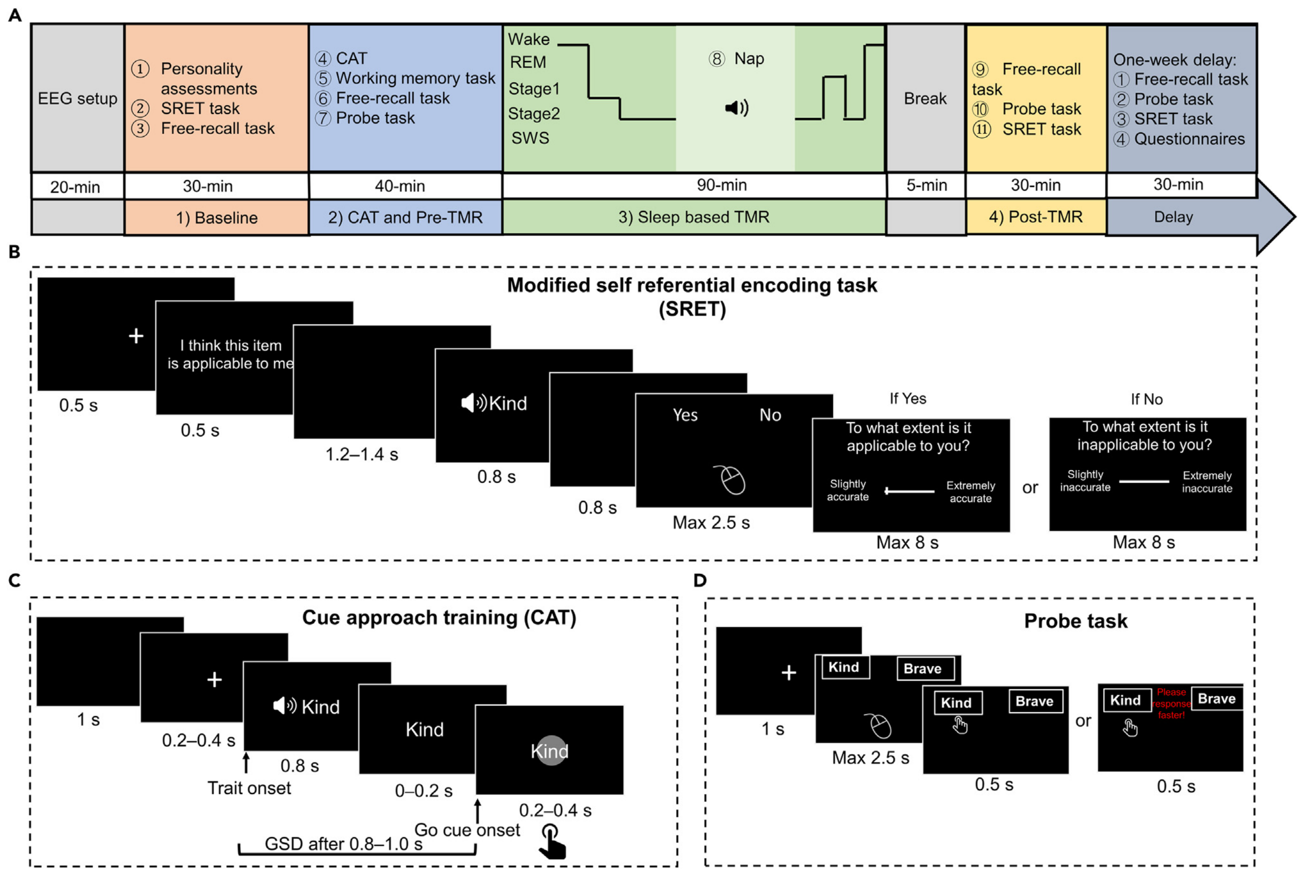

Figure 1. An overview of experimental design and main tasks

(A) The task flow illustrates the baseline tests (phase 1), CAT and post-CAT tests (phase 2), sleep-based TMR (phase 3), and post-TMR tests (phase 4), followed by a delayed tests phase after one week (n = 35).

(B) Modified SRET, in which participants made speeded binary endorsement task to determine whether a personality trait was descriptive of oneself, followed by rating the accuracy of specific traits in describing themselves within the same trial (i.e., endorsement level). After completing the baseline SRET, participants performed a 3-min self-referential free recall task during which they would recall and type out only traits they deemed self-descriptive. In both the post-TMR and the one-week delay phases, participants completed the self-referential free recall task and the SRET with binary endorsements while omitting ratings.

(C) An exemplar trial of CAT, in which participants either passively viewed positive traits presented visually and aurally (i.e., NoGo trials) or pressed a button when they saw a semi-transparent white dot (Go-cue) appear immediately after the positive trait onset (i.e., Go trials). The GSD (go-signal-delay, the delay between trait onset and Go-cue onset) varied between 0.8 and 1 s.

(D) Probe test, participants were presented with pairs of positive Go and NoGo traits and were asked to select which trait was more self-descriptive. Note that Go and NoGo traits in each pair were matched on baseline self-descriptive ratings (see STAR Methods for a full description of the procedure and experimental tasks).

self-referential free recall tasks at baseline, immediately and one-week delay tests, yet without the TMR session. Further details on these groups are available in the supplementary online material (SOM). More specifically, participants in the active-CAT group would respond to visual Go cues with prompt button presses in the same way as in the CAT + TMR group. In contrast, participants in the passive-CAT group would view the same traits without motor responses, while their attention was maintained through intermittent catch trials that required button presses. Including this passive-CAT group was essential for disentangling the effects of mere exposure to positive traits from active motor responses to the positive traits as in the active-CAT group. In this analysis, we included CAT conditions (Go vs. NoGo), time (post-CAT, and delay), and group (active vs. passive) as fixed effects, with baseline performance as covariate, and participants as random effects, focusing on endorsements and RTs, separately in two models. This analysis revealed no significant effects associated with CAT conditions, as evidenced by the 95% HDI encompassing zero across all contrasts between Go and NoGo conditions (Tables S3 and S4). These findings, therefore, suggest that it is the joint CAT+TMR effect, rather than CAT alone or solely repetition of positive trait words, that promotes positive self-referential processing.

Overall enhancement of positive self-referential long-term memory following CAT and TMR

We next investigated whether CAT+TMR would improve the memory of positive traits in the self-referential free recall tests. We used a BGLMM including TMR (Go-cued, Go-uncued, and NoGo-uncued) and time (post-TMR, delay) as fixed effects, baseline and post-CAT recall

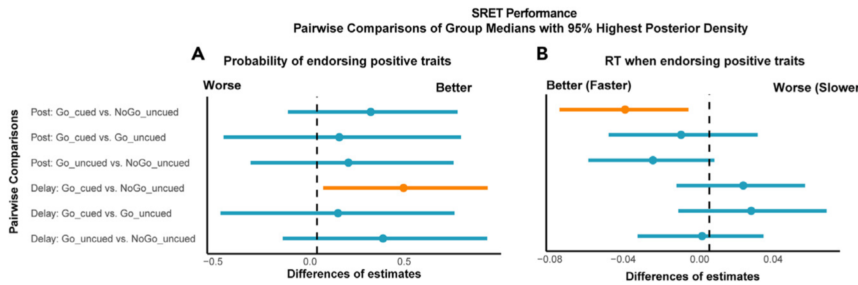

Figure 2. Behavioral results across time in the SRET tasks

(A) The probability of endorsing positive traits with group medians and 95% highest density interval (HDI) intervals, with positive differences indicating higher endorsements.

(B) RT when endorsing positive traits, with negative differences indicating faster responses endorsing positive traits. Dots indicate the median of the posterior samples and their 95% HDI for each contrast. We considered an effect as significant if the 95% HDI estimated from the posterior distribution did not include zero. Orange horizontal lines represent significant differences (the 95% HDI does not include 0), whereas the blue horizontal lines indicate non-significant comparisons.

and baseline endorsement rating as covariates, and participant factor as a random effect to predict recall outcomes (recalled vs. not recalled). Results revealed no significant differences between Go-cue vs. NoGo-uncued or other contrasts in post-TMR or delay sessions (Table S5).

Despite of the non-significant results of CAT+TMR, when examining the main effect of time, we found that in the one-week delayed test, participants recalled significantly more positive traits compared to baseline (median $_{diff}$ = 0.31, 95% HDI [0.04, 0.59], all contrasts presented in Table S6). To further ascertain whether this enhanced recall of positive self-referential traits would be attributable to CAT+TMR or CAT alone, we ran two additional analyses. Given these control analyses aimed to confirm the time effect (delayed vs. baseline), we included all positive traits irrespective of CAT+TMR conditions in the following analyses.

First, we examined whether the same enhancement would be evident in the active-CAT and the passive-CAT groups. We ran a BGLMM using recall as dependent variable, group as the fixed effect, time as covariate (i.e., baseline, post-CAT, delay), and participant as random effect. The analyses revealed no significant time effect on delayed recall in either the active or passive CAT groups, as evidenced by 95% HDI that encompassed zero in comparisons between baseline and delayed recall (Table S7).

Second, we compared the CAT+TMR group with the active- and passive-CAT groups. We ran a BGLMM using delayed recall as dependent variable, group as the fixed effect, both baseline endorsement level and preceding recall as covariates and participant as random effect. This analysis showed that participants in the CAT+TMR group exhibited superior recall of positive traits compared to the passive-CAT group (median $_{diff}$ = 0.50, 95% HDI [0.17, 0.82]) but not higher than the active-CAT group (median $_{diff}$ = 0.30, 95% HDI [-0.02, 0.62]). No significant difference was found between the active and passive CAT groups (median $_{diff}$ = 0.19, 95% HDI [-0.15, 0.51]). This result highlights that the sleep TMR contributed to the long-lasting impact in facilitating self-referential recall of positive traits.

These behavioral findings demonstrated that CAT first shifted preferences toward positive traits. When combining CAT and subsequent sleep TMR, CAT+TMR induced faster RTs when endorsing positive traits and promoted positive self-referential endorsements relative to NoGo-uncued traits. Moreover, compared to a passive-CAT group, the CAT+TMR increased the recall of self-referential positive traits. Together, these data suggest that CAT and TMR jointed enhanced positive self-referential processing.

Auditory processing of positive traits during sleep TMR

To first validate the neural responses to spoken positive traits during sleep, we quantified cue-elicited event-related potentials (ERPs) and time-frequency-resolved EEG power changes during the TMR. Consistent with prior TMR research,[29,47,48–51,52–54] cue-elicited ERPs showed two positive clusters over frontal-central electrodes (F1/2, FC1/2, C1/C2, Fz, and Cz) from 0.3 to 0.52 s and from 1.05 to 1.33 s (two-tailed t test, cluster-based permutation-corrected $p < 0.001$). In addition, the time-frequency analysis also identified two significant positive clusters over frontal-central electrodes: the delta-theta-alpha band (1–12 Hz, 0–2.3 s), and the sigma-beta band (10–30 Hz, 0.3–1.64 s, two-tailed t test, cluster-based permutation-corrected $p < 0.001$, Figures 3A and 3B). We next examined whether EEG power changes within these clusters may be associated with changes in RTs and choices during the positive self-referential processing. We used B(G)LMM with power from these identified significant clusters as a fixed effect, alongside the number of trait repetitions during TMR and baseline endorsement ratings as covariates, and participant as a random effect, to predict post-TMR endorsements and RTs when endorsing positive traits for delta-theta-alpha and sigma-beta clusters, respectively. However, we did not find significant associations (Table S8).

Cue-elicited slow traveling waves predicted post-TMR positive traits endorsement speed

Next, we investigated how traveling waves during TMR might influence post-TMR positive self-referential processing. Following traveling wave analyses in previous research,[43] we first analyzed the strength of directionality of both forward (from posterior to anterior brain regions) and backward (from anterior to posterior brain regions) traveling waves. Specifically, we used 1–4 Hz SWS from midline electrodes (POz, Pz, CPz, Cz, FCz, Fz, and FPz) within the first 2s post-cue, a significant time window identified in the aforementioned time-frequency analyses. (Figure 4A–C, see STAR Methods). After obtaining the strength of forward and backward traveling waves, we first examined during TMR

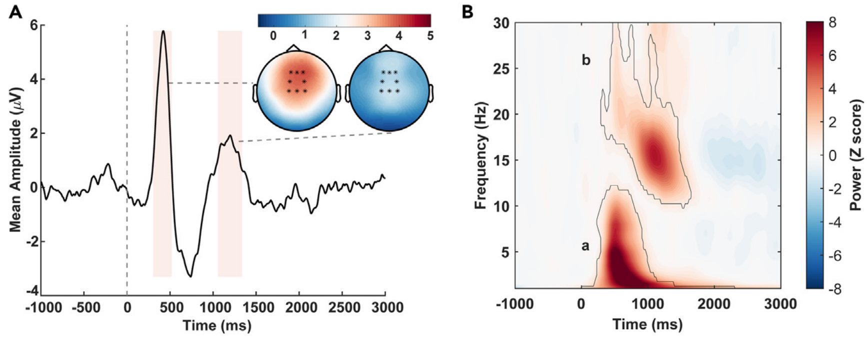

Figure 3. Cue-elicited power changes did not predict post-TMR endorsements or positive endorsement speed

(A) Grand averaged ERPs across frontal-central electrodes (Fz/1/2, Cz/1/2, and FC1/2). Shaded area indicates significant time point when comparing ERPs against zero. Top right panel presents group average scalp topography of ERPs in response to TMR cues in corresponding to the two positive clusters; with black circles highlighting the electrodes used in the ERP analysis.

(B) Contour plot depicting the temporal and spectral characteristics of the significant clusters. Cluster a represents the low-frequency delta-theta-alpha band (1–12 Hz), and cluster b represents the sigma-beta band (10–30 Hz), with both clusters showing significant changes across the TMR time course (cluster-based permutation-corrected $p < 0.001$).

cueing, whether backward or forward slow traveling waves would be more pronounced; second, we used these directional strength indicators to predict item-level binary endorsements and RTs for endorsing positive traits, across immediate and delayed tests.

Firstly, we ran a BLMM with traveling wave direction (backward vs. forward) as fixed effect, repetition number as covariate, and participant as random effect to compare the forward and backward traveling waves strength during TMR cueing. Consistent with previous research,[39] our findings indicated that the anterior-to-posterior backward traveling waves were more pronounced than posterior-to-anterior forward traveling waves (median $_{diff}$ = 0.12, 95% HDI [0.03, 0.21]).

We next examined how cue-elicited backward and forward traveling waves might be associated with post-TMR behavioral performance. To do this, we used B(G)LMM with strength of traveling waves as a fixed effect, alongside the number of trait repetitions during TMR and baseline endorsement ratings as covariates, and participant as a random effect, to predict post-TMR endorsements and RTs when endorsing positive traits on item level. Results revealed that during the post-TMR test, no significant predictions were found for binary endorsements in the immediate session using either forward ($\beta = 0.28$, 95% CI = [-0.70, 1.26], Figure 5A) or backward traveling waves ($\beta = -0.56$, 95% CI = [-1.48, 0.36], Figure 5B). Notably, during the immediate tests, we found that forward traveling waves predicted longer RTs ($\beta = 0.11$, 95% CI = [0.03, 0.18], Figure 5C), and backward traveling waves predicted faster RTs in endorsing positive traits ($\beta = -0.07$, 95% CI = [-0.14, −0.00], Figure 5D).

Interestingly, after one week delay, forward traveling waves negatively predicted ($\beta = -1.31$, 95% CI = [-2.51 -0.17], Figure 5E), while backward traveling waves positively predicted the endorsement of positive traits ($\beta = 1.15$, 95% CI = [0.12, 2.26], Figure 5F). However, during this delayed test, we did not find any significant predictions from forward ($\beta = 0.02$, 95% CI = [-0.06, 0.10], Figure 5G) or backward traveling waves ($\beta = -0.03$, 95% CI = [-0.10, 0.05], Figure 5H) on positive endorsement RTs. Together, our results showed that during sleep and TMR, the cue-elicited slow traveling waves patterns were associated with post-TMR positive self-referential processing.

DISCUSSION

By combining wakeful cue-approach training (CAT) and sleep-based targeted memory reactivation (TMR), we found that this integrated procedure effectively enhanced participants' positive self-referential processing. We first used CAT to heighten participants' preferences for specific "Go" positive traits, extending existing CAT research. During a subsequent nap, TMR was employed to re-play a subset of these Go traits, further enhancing their accessibility and thus promoting positive self-referential processing post-TMR. Specifically, CAT+TMR expedited endorsement of these Go-cued positive traits immediately after sleep TMR and increased endorsements of positive traits in the delayed test. Additionally, the presence of 1–4 Hz backward slow traveling waves during TMR was associated with enhanced positive self-referential processing, indicating an important role of cross-regional backward neural communications in driving behavioral benefits. These new findings contributed to our understanding of how to modulate and enhance positive self-referential processing.

We first found that the CAT successfully increased participants' likelihood to choose Go over NoGo traits as self-descriptive in the probe task, demonstrating CAT's efficacy in influencing self-referential choices. This finding extends the known effects of CAT on consumables such as snacks,[15,16] revealing its capability to shape high-level self-referential processing.

Following the CAT phase, we re-played a subset of the trained positive traits during sleep to examine the cumulative impact of CAT and TMR on self-referential processing. Behaviorally, we found that CAT+TMR induced higher positive endorsements and faster endorsement speed for these Go-cued traits, compared to untrained traits (NoGo-uncued). The lack of significant differences between other contrasts (e.g., Go-cued vs. Go-uncued and Go-uncued vs. NoGo-uncued) suggests that the benefits were likely due to the joint effect of CAT and TMR. Apart from positive endorsement speed, we also observed that participants endorsed more Go-cued positive traits than NoGo-uncued traits as self-descriptive after one week delay. Previous CAT research suggests that the CAT enhanced stimulus salience.[13,16] TMR during

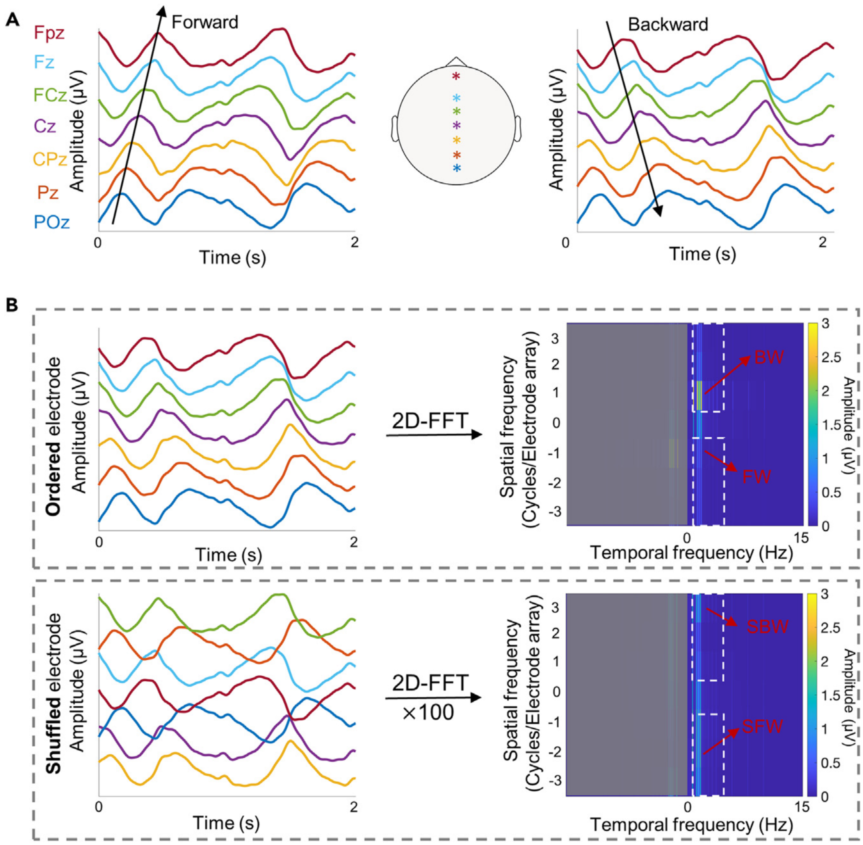

Figure 4. Slow traveling waves analysis after TMR cue onset

(A) The left panel displays simulated EEG waveforms over seven electrodes from POz to Fpz positions, representing forward wave propagation over a 2-s time frame. The central illustration denotes the scalp with electrode placements; each star's color corresponds to the EEG waveforms' color coding, denoting the anterior-posterior direction of wave travel. The right panel illustrates the simulated EEG waveforms for backward wave propagation across the same time frame, with wave amplitude (in microvolts, μV) modulating over time (in seconds, s).

(B) The upper panel exhibits the 2D fast fourier transform (2D-FFT) analysis of the original, ordered EEG waveforms. It showcases the temporal frequency domain from 0 to 15 Hz, specifically emphasizing the delta waves' analysis due to their relevance to the study's focus. The spatial frequency is displayed from −3 to 3 cycles/electrode array. Intuitively, the spatial frequency is a measure of how many cycles occur over the span of the entire electrode array (i.e., POz, Pz, CPz, Cz, FCz, Fz, and FPz). The strength of the forward (FW) and backward (BW) waves are indicated by peak values in the delta band (1–4 Hz) within the designated quadrants (denoted by the white dashed squares). The lower panel presents the 2D-FFT analysis of surrogate EEG waveforms derived from shuffled electrode arrangements. Each shuffle iteration yields surrogate forward (SFW) and backward (SBW) wave strengths, calculated analogously to the process for ordered electrodes. The shuffling process was repeated a hundred times per trial to establish baselines. The actual values for forward and backward traveling waves (FTW and BTW) were computed by contrasting the FW/BW strength against their respective baselines (detailed methodology provided in the STAR Methods section).

post-CAT sleep, on the other hand, may further promote memory reactivation and consolidation, improving the accessibility of the cued stimuli.[22,28,30,54–56] Together, our CAT+TMR procedural likely augments the salience and the accessibility of the trained positive traits, thereby improving positive self-referential processing.

Behavioral benefits in self-referential positive processing can be partially explained by neural activity during sleep and TMR. In contrast to power spectral analysis that often examines regional EEG activity, the concept of traveling waves encompasses a wider array of neural characteristics. These include both spatial propagation and frequency property, offering a more comprehensive view of the spatial-temporal dynamics of brain activity during sleep.[35,36,39,57] Consistent with previous research, our study similarly reveals more dominant backward over forward slow traveling waves.[39] Intriguingly, we found significant associations between both backward and forward traveling waves and positive self-referential processing, including post-TMR endorsement speed of positive traits and endorsements after a one-week interval. This novel insight posits that dominant backward slow traveling waves play a crucial role that may facilitate cue-elicited memory reactivation during sleep.

Recent research in traveling wave dynamics has demonstrated that during wakefulness, posterior-to-anterior forward traveling waves likely facilitate memory encoding, whereas anterior-to-posterior backward waves contribute to memory recall.[37] During TMR, the replay of spoken

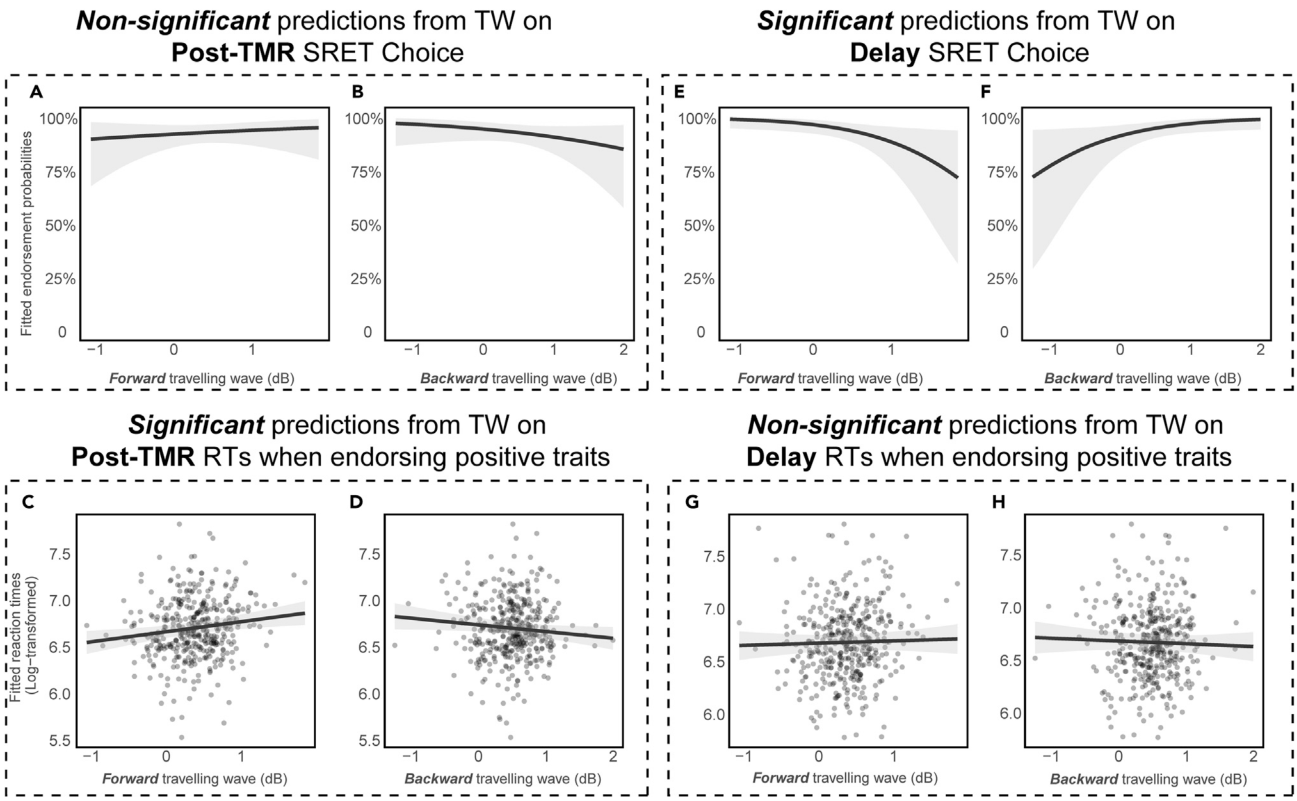

Figure 5. Slow traveling waves predicted behavioral benefits in post-TMR and delay phases of the SRET task

(A, B, E, and F) Predictions from forward and backward traveling waves on positivity endorsement probabilities in post-TMR phase (A and B) and in delay phase (E and F).

(C, D, G, and H) Predictions from forward and backward traveling waves on positivity endorsement RTs in post-TMR phase (C and D) and in delay phase (G and H). In panels (C), (D), (G), and (H), each data point corresponds to the fitted value from a single trial within the BLMM. Where data points overlap, they present a darker shade. Shaded area indicates 95% confidence interval (CI). Panels C, D, E, and F showed significant predictions, as the 95% CIs do not include 0. SRET: self-referential encoding task.

positive traits during sleep may reactivate memories for previously encoded positive traits, mirroring the cued retrieval processes observed during wakefulness.[37] Similarly, we found that the directional strength of backward anterior-to-posterior traveling waves was positively correlated with the behavioral benefits, such as positivity endorsement RTs and positivity endorsement. These results suggest that in addition to wakefulness, backward anterior-to-posterior traveling waves may support memory even during sleep and during cue-triggered memory reactivation processing.

When evaluating participants' self-referential memories using a free recall task, we did not find significant main effects of CAT+TMR. This result may stem from the experimental design, where participants engaged in the free recall task twice prior to sleep. Repeated recall may induce fast memory consolidation that makes the self-referential memories less susceptible to TMR.[32,49] Notably, a week later, participants showed an overall enhanced memories for positive traits compared to the baseline, regardless of CAT+TMR conditions. We found that this non-selective, general memory enhancement was only observed in the CAT+TMR group but not in the other two groups without TMR (active CAT or passive CAT). These findings suggest that the post-CAT sleep and TMR may have a generalization effect in improving positive self-referential memories. Indeed, previous TMR research suggested that memory reactivation during sleep may have generalized benefits: in addition to enhancing cue-specific memories, TMR also strengthened uncued memories that shared the same context as the cued memories, leading to overall benefits of both cued and uncued memories.[50] (see also Oudiette et al.[14] for TMR generalization effects).

In conclusion, our study presents a novel approach in enhancing positive self-referential processing by combining wakeful motor training and sleep-based memory reactivation. In addition to behavioral benefits, our findings underscore the importance of cue-related backward slow traveling waves in supporting positive self-referential processing during sleep. By reinforcing positive self-referential processing through CAT+TMR, it is possible to alter maladaptive cognitive biases or restore self-esteem, thereby improving mental health outcomes.

Limitations of the study

Future directions and limitations shall be discussed. First, our study follows most prior research in administering the TMR during the NREM sleep, given the established link between NREM sleep and TMR benefits (see Lewis et al.[28] and Hu et al.[30]). However, research also pinpoints the role of REM sleep in modulating emotional memory and vocabulary learning.[58,59] Future research could investigate how TMR during REM sleep, and how the REM-related neural activity may impact the consolidation of self-referential memories. Second, while positive self-referential processing is linked with mental wellness,[7,60,61] our study did not examine how our procedure may impact outcomes that bear direct clinical relevance such as depression-related symptoms. Future research is warranted to investigate whether enhancing positive self-referential processing may directly alleviate depressive symptoms.[10,62] Third, while our research question concerns self-referential processing, we did not include non-personal traits as a control condition. Future studies could consider including such a control condition to disentangle non-self-referential from self-referential processing during CAT and sleep TMR. Fourth, our findings underscore that the joint benefits of CAT and TMR in enhancing positive self-referential trait memories, as compared to the passive-CAT control group. However, given that the TMR was administered during a 90-min nap, whether sleep alone may also contribute to this observed delayed benefit remains unknown. Future investigations are warranted to ascertain if post-CAT sleep alone suffices to foster positive self-referential processing. Finally, it is imperative to acknowledge that our traveling waves analyses were exploratory. As such, the robustness of these observations requires further validation. Given recent findings establishing the link between traveling waves and memory encoding/retrieval,[37] we urge future research to examine the pivotal role of traveling waves in memory reactivation and consolidation during sleep.

STAR★METHODS

Detailed methods are provided in the online version of this paper and include the following:

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.isci.2024.110341.

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AUTHOR CONTRIBUTIONS

Z.Y.: conceptualization, data curation, formal analysis, investigation, methodology, project administration, writing – original draft, and writing – review and editing. T.X.: formal analysis, visualization, and writing – review and editing. J.W.: formal analysis, visualization, and writing – review and editing. Z.Z.: writing – review and editing. X.L.: writing – review and editing. D.Z.: writing – review and editing. P.Q.: writing – review and editing. Y.M.: funding acquisition, writing – original draft, and writing – review and editing. X.H.: conceptualization, methodology, funding acquisition, resources, supervision, writing – original draft, and writing – review and editing.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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STAR★METHODS

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Deposited data		
Behavioral and EEG data	This paper (is available)	https://osf.io/rztdh/
Custom code	This paper (is available)	https://osf.io/rztdh/
Software and algorithms		
MATLAB 2022b	http://www.mathworks.com/products/matlab/	RRID:SCR_001622
R Studio 2022.02.2 Build 485	https://www.rstudio.com/	RRID: SCR_000432
R (4.2.0)	https://www.r-project.org/	RRID:SCR_001905
R package **'lme4'** (v1.1-29)	https://github.com/lme4/lme4/	RRID:SCR_015654
R package **'lmerTest'** (v3.1-3)	https://github.com/runehaubo/lmerTestR	RRID:SCR_015656
R package **'brms'** (v3.1-3)	https://paul-buerkner.github.io/brms/	RRID:SCR_023862
Python 3.7	https://www.python.org/	RRID:SCR_008394
Python package **'MNE-Python'** (v 1.1.1)	https://mne.tools/stable/index.html	RRID:SCR_005972
Python package **'Numpy'** (v 1.19.2)	https://numpy.org/	RRID:SCR_008633
Python package **'YASA'** (v 0.6.2)	https://raphaelvallat.com/yasa/build/html/index.html	N/a
Python package **'pandas'** (v 1.1.3)	https://pandas.pydata.org/	RRID:SCR_018214
Python package **'seaborn** (v 0.11.2)	https://seaborn.pydata.org/index.html	RRID:SCR_018132

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the lead contact, Xiaoqing Hu (xiaoqinghu@hku.hk).

Materials availability

This study did not generate new unique materials.

Data and code availability

- Data: All the behavioral data and the EEG data have been deposited at the Open Science Framework repository (https://osf.io/rztdh/) and is publicly available. DOIs are listed in the key resources table.
- Code: All original code has been deposited at the Open Science Framework repository (https://osf.io/rztdh/) and is publicly available. DOIs are listed in the key resources table.
- Additional information: Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

Ethics statement

Human Research Ethics Committee of the University of Hong Kong approved the study (HREC Reference Number: EA1808012). All participants provided written consent prior to the experiment.

Study participant details from main TMR study

Our final sample included 35 participants with valid behavioral and EEG data (8 males, $M_{age} \pm SD = 20.83 \pm 2.20$ years), which is comparable to recent TMR studies (e.g., Schechtman et al.[50]). Nine additional participants had inadequate number of cues (<= 3 rounds) due to relatively short slow-wave sleep (SWS). Because low numbers of trials per cue would significantly increase the noise, compromise the data quality and the analysis' reliability,[63,64] we excluded these nine participants in subsequent analyses. An additional participant was excluded because he or she reported hearing the cues during sleep. To facilitate sleep in the lab, we asked participants to wake up 1 h earlier than their usual waking time and to avoid consuming caffeinated drinks on the day prior to – and of – the experiment. Participants were pre-screened regarding any current or history of sleep, psychiatric, or neurological disorders and had normal or corrected-to-normal vision. Participants received monetary compensation for their time (250 RMB, ~36 USD).

Study participant details from behavioral study

In this behavioral study, we recruited 74 participants who received monetary compensation at a rate of 50 RMB per hour (~7.8 USD). Participants were randomly assigned to either the active- or passive-CAT group. The active CAT was similar like in the CAT in the main study. The only difference between the active- and passive-CAT group is that participants in the passive-CAT group were only instructed to look at the words presented on the screen and were not required to press a button when the white cue was displayed. We excluded four participants (two from each group) based on their self-reported lack of attention during the CAT. Additionally, three of these participants withdrew their data consent and did not attend the scheduled delay test, leaving 34 participants in each group for analysis (active-CAT group: 17 Males, Mage $\pm$SD = 22.57 $\pm$ 2.25; passive-CAT group, 18 Males, Mage $\pm$SD = 22.71 $\pm$ 1.60). We only included participants with normal or corrected-to-normal vision, no history of mental illness or neurological disorder, and no current or history of sleeping disorders. Only data from self-referential encoding task were analyzed in this paper.

METHOD DETAILS

Materials

All experimental procedures were implemented in E-Prime 3.0 (Psychology Software Tools, Inc., Sharpsburg, Pennsylvania, USA). A pilot group of 20 participants rated personality traits (two characters trait words) on a scale from 1 (extremely negative) to 9 (extremely positive). We selected 60 positive personality trait adjectives (e.g., 'clever', M $\pm$ SD = 6.92 $\pm$ 0.44) and 60 negative personality trait adjectives (e.g., 'lazy', M $\pm$ SD = 3.00 $\pm$ 0.44). Each spoken trait lasted around 1 s (range: 0.72–1.08s, M $\pm$ SD = 0.91 $\pm$ 0.08s). During the TMR phase, we used a neutral trait (valence rating: 4.9) as a control word.

In the experiment, the stimuli were presented in Mandarin. The original versions of the trait adjectives are provided in the Table S10. The translated version of the document is available as supplementary material on our OSF repository: https://osf.io/rztdh/.

Task overview

Participants attended two lab sessions, scheduled approximately one week apart. In the first session, participants arrived at the lab at approximately 12:00 pm (exact arrival times ranged between 11:30 am to12:30 pm), where they read and signed consent forms and were set up with EEGs. Subsequently, a series of four task phases began in which participants completed a number of tests, beginning with baseline tests in the first phase, followed by CAT and post-CAT tests in the second phase, sleep-based TMR in the third phase, and post-TMR tests in the fourth phase. In the preliminary baseline phase, participants completed computer-based personality questionnaires, serving as a cover story for the personality trait words (hereafter, traits) presented to them in the following SRET. During the SRET, participants rated the extent to which specific traits described themselves. Participants then completed a self-referential free recall test. In the second phase, participants manually responded to positive traits (i.e., Go traits), prompted by visual and aural cues presented on screen and from a nearby loudspeaker (CAT). Participants then completed a free recall test and a probe test, in which they were presented with Go and NoGo trait word pairs and asked to select the trait word that was more self-descriptive. In the third phase, half of the positive traits were aurally re-played to sleeping participants during slow-wave sleep (SWS). Then, in the fourth phase, participants completed the same free recall test, probe test, and SRET. In the second lab visit (~7 days later), participants completed the same free recall test, probe test and SRET as previously completed in the final phase of the first visit to examine the possible long-term CAT+TMR effects. Thus, they completed four self-referential free recall tests (baseline, post-CAT, post-TMR, delay), three SRETs (baseline, post-TMR, delay), and three probe tasks (post-CAT, post- TMR, delay).

Baseline tasks

Participants completed preliminary computer-based personality questionnaires, including the Rosenberg Self-Esteem Scale (RSES),[65] Narcissistic Personality Inventory (NPI),[66] Big Five Inventory (BFI),[67] Beck Depression Inventory-II (BDI-II),[68] State-Trait Anxiety Inventory (STAI state and STAI trait),[69] and Barratt Impulsiveness Scale (BIS-11).[70] Completing these questionnaires served as a cover story for the subsequent self-referential encoding task (SRET): participants were told that the personality traits that would be presented in the SRET were from their questionnaire data (for descriptives, see Table S11).

In the SRET (see Figure 1B), a cross symbol was presented on a computer screen at the beginning of each trial for 0.5 s, followed by the presentation of the sentence 'I think this word is applicable to me' in the center of the screen for another 0.5 s. After 1.2 to 1.4 s, participants were presented with a random word, given visually in written form and aurally from a speaker, from a selection of 120 adjectives for 0.8 s. After, participants were shown a blank screen for another 0.8 s and then were prompted to select if a trait word applied to them within 2.5 s by moving the mouse cursor continuously. The spatial location of 'Yes' and 'No' responses were counterbalanced (upper left/upper right or upper right/upper left). Following a 'Yes' response, participants were asked to rate the extent to which a trait word applied to them on a scale ranging from 'slightly accurate' to 'extremely accurate', covertly equating to values from 1 to 50; following a 'No' response, participants were asked to rate the extent to which a trait word did not apply to them on a scale ranging from 'slightly inaccurate' to 'extremely inaccurate', covertly equating to values from -50 to -1.

Following the SRET, participants completed a 3-min self-referential free recall task. Unlike previous free recall tasks wherein participants wrote down as many traits as possible, we asked participants to write down only the traits they had endorsed (i.e., 'yes' response) during the previous SRET. Participants typed each recalled trait on a computer one at a time. Therefore, recalled traits would reflect self-referential memories.

Traits selection in the probe task

For each participant, we ranked all 60 positive traits in ascending order based on their baseline endorsement ratings (from 1, being the lowest rating and least self-descriptive, to 60, being the highest rating and most self-descriptive). We next equally divided these 60 traits into 'Go' and 'NoGo' trials, forming 30 Go-NoGo pairs for each participant. We chose traits for each pair based on each trait rating's rank orders (i.e., from 1 to 60), to ensure that the Go and NoGo traits had comparable baseline ratings ($p = 0.64$, for details, see Figure S1A). For the post-TMR probe task, these Go/NoGo pairs were further categorized into cued (Go-cued) and uncued (Go-uncued) conditions, with each condition having 15 trait pairs (Figure S1F). Full details for the trait allocations in the CAT and the probe task are provided in Figure S1.

CAT and post-CAT probe tests from main study

Following baseline assessments, participants completed a cue-approach training (CAT) task (see Figure 1C). For each CAT trial, a positive trait was presented visually and aurally for 1.2 s. For Go trials, a delayed Go cue, manifested as a semi-transparent white dot, was introduced at least 0.8 s following the onset of the trait word presentation. The appearance of this cue signified that participants were required to press a button as quickly as possible before the trait's offset. To maintain participants' attention, we used an adaptive response window. Specifically, the go-signal-delay (GSD, the delay between trait onset and Go-cue onset) was approximately 0.9 s. If the participants gave a timely response (i.e., button press before the offset of the trait), the GSD was increased by 17 ms to increase task difficulty. If participants failed to make a button press before the offset of the trial, the GSD was reduced by 50 ms to reduce task difficulty.[13,15] Conversely, for NoGo trials, participants merely viewed and listened to the traits without any behavioral responses. All 60 positive traits were presented randomly in each of the five blocks during the CAT, resulting in a total of 300 trials. Participants could take a 0.5-1-min break between blocks. While previous CAT research adopts over 10 blocks of training,[15] we chose to only include 5 blocks so as to avoid ceiling effect in subsequent memory recall. This CAT task was followed by a 5-min working memory task, serving as distractions.

Following the working memory task, participants proceeded to a 3-min post-CAT self-referential free recall task, which was identical to the baseline task. Subsequently, a post-CAT probe task was administered to evaluate the impact of CAT.

In the probe task (see Figure 1D), participants were presented with Go and NoGo traits in pairs and were asked to choose which trait would be more self-descriptive. Within each trial, the Go and NoGo traits were matched on baseline endorsement ratings, so that preferential choices of Go traits would indicate the CAT training effects. The positions of the Go/NoGo traits per pair were randomly assigned to the upper-left/right or upper-right/left sides of the monitor in the first block, and were swapped in the second block. Each trial started with a fixation cross (1 s), followed by the side-by-side presentation of two traits. Participants selected the trait that would best describe them by clicking a push button below the trait within 2.5 s. The chosen trait was then highlighted by a button-press shaped image for 0.5 s. If participants exceeded the 4-s response time, a prompt would appear during the confirmation phase, urging them to respond quickly. We excluded trials with response times exceeding 3 s, accounting for potential mouse delays.

CAT and post-CAT probe task from behavioral study

Based on the previous design,[13] we first created a sorted-item list based on initial ratings from 1 (lowest value) to 60 (highest value). In contrast to the CAT in the CAT+TMR Experiment, we selected half of the words as Go and the other half as NoGo to increase the number of comparison pairs. The specific Go and NoGo words were assigned based on the sorted rating order (see Figure S1A). All 60 positive traits were presented randomly for each participant and each block during the CAT. To avoid a ceiling effect during the recall test, we opted for five blocks of training, with blocks separated by a 1-min break and participants being able to skip after a 30-s break. Participants were randomly assigned to either the active- or passive-CAT group.

Active-CAT Group. In the active-CAT group, 30 words (across the entire list of words) were associated with a visual Go cue that required participants to press a button as quickly as possible before the current trial's offset. The trait words were presented visually for 1.2 s, starting with spoken words (<0.8 s) followed by Go cues. We used an adaptive response window to keep participants attentive to Go cues. Specifically, the first Go cues were presented with GSD (the delay between trait-word onset and Go-cue onset) $\sim$0.9 s. If the participants successfully pressed a button before the offset of the trial, the GSD was increased by 17 ms to increase task difficulty. If they failed to make a button press before the offset of the trial, the GSD was reduced by 50 ms to reduce the task's difficulty. See Figure S2 for the schematic representation of the modified CAT.

Passive-CAT Group. The only difference between the active- and passive-CAT group is that participants in the passive-CAT group were only instructed to look at the words presented on the screen and were not required to press a button when the white cue was displayed. To ensure that the participants remained engaged throughout the task, we randomly added six catch trials to each block, during which participants were presented with a button-press image and directed to click the button within 1.2 s (the same duration as the presentation of the visual word) to continue the task.

Nap targeted memory reactivation (TMR)

Participants took a 90-min nap in a quiet, darkened sleep chamber. Background white noise (at ∼38 dB) was played to participants throughout the duration of the nap via a loudspeaker placed near the bed. Participants' brain and physiological activities were continuously monitored during the map. Upon participants entered SWS for at least 2 min, we presented spoken positive traits (the same spoken traits presented during the SRET and CAT tasks) at approximately 40 dB. Note that the spoken traits (∼40 dB) were played against the background white noise (∼38 dB), yet remained subtle to avoid arousal and waking participants up.

The TMR began with playing a neutral trait (∼0.6 s) for three times, ensuring that the auditory stimulation would not wake participants up. We started playing the spoken traits if participants did not show signs of arousal or changes in NREM sleep stage. During each round of the TMR, half of the positive Go traits (i.e., 15 traits) were played together with the neutral trait as a control word. Each trait last for about 1 s, with a randomized interstimulus interval of 5–6 s. TMR continued as participants remained in the SWS, with a minimal repetition of three rounds of stimulation, resulting in at least $3 \times 16 = 48$ trials for TMR-related EEG analyses.

Specifically, participants were exposed to spoken traits once they entered a sustained SWS period lasting at least 2 min. The TMR procedure was discontinued after 30 min, or earlier if EEG recordings indicated micro-arousal or full awakening. If no SWS was detected within the first 40 min, the presentation of spoken traits commenced during the N2 sleep stage. After a total sleep session of 90 min, participants were awakened if they were in the N1 or N2 sleep stages, or we waited until they transitioned to these stages before awakening them. A brief 5-min break was provided upon awakening to mitigate the effects of sleep inertia.

Post-TMR tests

Participants completed the self-referential free call task, probe task, and SRET task. Here, the probe task instructions were identical to the post-CAT probe task, but with randomized 'Go' and 'NoGo' trait positions. The SRET was similar to the baseline SRET except that participants only made a Yes/No binary response to each trait, omitting the rating part.

One-week delayed tests

Participants returned to the lab about one week later to complete the delayed tests in the following order: (1) a 3-min self-referential free call task; (2) a probe task; (3) an SRET task. The tasks were identical to the tasks in the post-TMR. Participants were not informed of the delayed tasks ahead of the time. Upon completing all tasks, participants were debriefed and paid.

EEG data pre-processing

Continuous EEGs were recorded using a 63-channel customized cap with passive Ag/AgCl electrodes via a BrainAmp amplifier with a 1000 Hz sampling rate (Brain Products, Gilching, Germany). Electrodes were positioned according to the International 10–10 system. The ground electrode was located at AFz, with FCz as the on-line reference electrode. Impedances were kept below 20 kΩ. We placed one electro-oculography (EOG) electrode under participants' left eyes and bipolar electromyography (EMG) electrodes on their chins to monitor eye movements and muscle activity during sleep.

EEG data were pre-processed using custom-written scripts and the MATLAB Toolbox EEGLAB.[71] First, nap EEG data were down-sampled to 250 Hz, notch-filtered at 50 Hz, and then re-referenced to the averaged mastoids. Second, EEG data were band-pass filtered at 0.5 to 40 Hz. While EOG and EMG data were used for sleep staging, these data were not used in the time-frequency analysis.

Offline sleep stage scoring

Sleep stages, including N1, N2, Slow-Wave Sleep (SWS), and Rapid Eye Movement (REM), were scored using EEG (Channel C4), EOG, and EMG patterns. This process employed algorithms from the YASA open-source Python Toolbox.[72] Consistent with YASA guidelines, the EEG data were initially re-referenced to FPz before conducting the staging analysis. Table S9 presents the sleep staging results and cueing number within each stage for 34 participants (One participants only reserved 28 min EEG data including TMR stage).

QUANTIFICATION AND STATISTICAL ANALYSIS

Behavioral data analysis

Statistical analyses were carried out using R (Version 4.2.1., R Core Team (2020).[73] For the choice from probe task (Figure 1D), we performed a generalized linear mixed model (GLMM) fitted via '*glmer*' function of the '*lme4*' R package (Bates et al. 2014 June 23)[74] to analyze self-referential endorsement preferences. The significance threshold (alpha level) was set at 0.05. For SRET performance and self-referential free recall performance, we performed Bayesian (generalized) linear mixed models (B[G]LMMs) via '*brm*' functions of the '*brms*' R package[75] and the Stan modeling language.[76] Using the default non-information priors, each model was fitted using four chains with 5000 iterations each with 1000 warmup iterations, thereby yielding 16000 samples for each parameter tuple. The observed Gelman-Rubin diagnostic (Rhat) was consistently below 1.1 across all models and parameters, indicating satisfactory convergence and mixing of chains.[75] We considered an effect as significant if the 95% highest density interval (HDI) estimated from the posterior distribution did not include zero.

Self-referential preference choices in the probe task

We ran a paired sample t test analysis on baseline endorsement ratings for Go and NoGo traits. Result confirmed that there was no significant rating difference between Go and NoGo traits (t (34) = 0.55, p = 0.586).

Following previous CAT research,[13,15,77] we ran generalized linear mixed model (GLMM) to compare the odds of choosing Go traits against the chance level (50%, log odds = 0; odds ratio = 1) during post-CAT phase. Given the alternation of Go/NoGo positions (left and right) in two blocks, we included Go position as a covariate in our model. The GLMM was defined as:

$$\text{Preference Choice (Go/NoGo)} \sim 1 + \text{Position} + (1|\text{Subject ID})$$

Self-referential endorsement in the SRET

We employed a Bayesian generalized linear mixed model (BGLMM) to examine how CAT+TMR conditions (Go-cued, Go-uncued, and NoGo-uncued) influenced participants' endorsement for positive traits across time (post-TMR and delay). We used baseline endorsement rating, and baseline performance as a covariate and participant as random effect. The model was defined as:

Endorsement choice (Yes/No) ~ 1 + Baseline endorsement rating + Baseline Endorsement Choice + Time × TMR Condition + (1+ Time × TMR Condition |Subject ID)

Subsequently, we employed a Bayesian linear mixed model (BLMM), incorporating the same factors as used in the preceding GLMM for binary choice outcomes to analyze RTs when endorsing positive traits:

RTs (via log-transformed) ~ 1 + Baseline Endorsement RT + Baseline endorsement rating + Time × TMR Condition + (1 + Time × TMR Condition |Subject ID)

Lastly, in order to assess whether CAT alone influenced the endorsement for positive traits and response speed during the endorsement of positive traits, we employed another BLMM in two additional behavioral samples. These samples comprised one group that underwent only CAT training (referred to as the 'active' group) and another group that received no CAT training (referred to as the 'passive' group). Detailed information on these two behavioral samples can be found in the Supplementary Online Material (SOM). The BLMM incorporated several fixed effects: group (active vs. passive), time (post-CAT, delay), and CAT (Go vs. NoGo). Additionally, the baseline endorsement rating and baseline endorsement choices/endorsement RT for positive traits was included as a covariate. The model also accounted for random effects at the participant level:

Endorsement choice (Yes/No) ~ 1 + Baseline endorsement rating + Baseline Endorsement Choice + Group × Time × CAT Condition + (1 + Time × CAT Condition |Subject ID)

RTs (via log-transformed) ~ 1 + Baseline endorsement rating + Baseline Endorsement RT + Group × Time × CAT Condition + (1 + Time × CAT Condition |Subject ID)

Self-referential memories in the free recall task

To understand how TMR affect self-referential memories across time, we ran a BGLMM using TMR (Go-cued, Go-uncued, and NoGo-uncued), and time (post-CAT, post-TMR, and delay) as fixed effects, baseline recall and endorsement rating as covariate, participant as random effect. The model was defined as follows:

Recall outcome (Yes/No) ~ 1 + Baseline Recall outcome + Baseline endorsement rating + Time × TMR Condition + (1 + Time × TMR Condition | Subject ID)

Additionally, a BGLMM was applied to analyze overall changes of positive traits, using time as a fixed effect:

Recall outcome (Yes/No) ~ 1 + Baseline endorsement rating + Time + (1 + Time | Subject ID)

Finally, incorporating data from two additional samples — one with only CAT training and another with no training (see SOM for details regarding behavioral samples)— we expanded our analysis to encompass three distinct groups. To assess delayed recall across these groups, we employed a BGLMM on delayed recall performance with baseline and post-CAT recall as covariate, training groups (i.e., CAT+TMR, active-CAT, passive-CAT) as fixed effect:

Recall outcome (Yes/No) ~ 1 + Baseline recall + Post-CAT recall + Baseline endorsement rating + Group + (1 | Subject ID)

EEG data analysis

Event related potentials (ERPs) and time-frequency analysis

Before analyzing cue-elicited ERPs and time-frequency EEG power changes, the cue-elicited EEG data were epoched into −1.5 to 5.5 s segments, relative to the onset of each cued trait word. This long epoch ensured that we had enough edge artifact-free segments for each clean epoch to assess TMR benefits (−1 to 3 s). Epochs with artifacts were visually inspected and removed.

Time-frequency decomposition was performed in the Fieldtrip open-source MATLAB toolbox.[78] We used 3 to 10 cycles in a step of 0.5 Hz Morlet wavelet and baseline corrected using z-transformation of all trials from −1 to −0.1 s relative to the cue onset. Following previous sleep and TMR studies,[51,79–81] we calculated the mean EEG power over frontal-central channel (F1/2, FC1/2, C1/2, Fz, Cz) to ensure the robustness of results. The calculated time-frequency decompositions were then down-sampled to 50 Hz. To investigate cue-elicited EEG activity, we employed the rigorous cluster-based one-sample permutation t test[82] to identify the significant cluster against zero across all participants in both the time domain (ERPs, cluster-thresholding p at 0.05) and the time-frequency domain (cluster-thresholding p at 0.001).

Traveling wave analysis

We employed a traveling wave analysis approach similar to that used by Alamia et al.[43] To investigate the cue-elicited traveling waves, we first used EEG data from the interval after cue onset [0, 2000] ms during NREM stage 3 (based on YASA staging result) spanning from posterior to anterior scalp midline regions (POz, Pz, CPz, Cz, FCz, Fz, FPz) to create time-electrode EEG representations (illustrated by Figure 4A). Note that FCz was interpolated using *speherical* method in EEGLAB toolbox to ensure the symmetry of the 2D-FFT spectrum, which would require an odd number of electrodes (e.g., 7). The time window [0, 2000] ms was chosen given significant ERP and ERSP responses (Figure 3). Subsequently, we quantified traveling wave propagation (illustrated by Figure 4A) using the 2D Fast Fourier Transform (2D-FFT) on time-electrode EEG signals. The 2D-FFT segregated signals into temporal and spatial frequency components. For temporal frequency, it conveys the same meaning as spectral frequency in the analysis of the power spectrum of EEG time series. For spatial frequency, it measures how many cycles occur over the span of the selected electrode array. In the 2D-FFT spectrum, the power within the upper and lower right quadrants of the 2D-FFT spectrum indicated the original strength of backward (BW) and forward waves (FW), respectively (Figure 4B upper right panel). The spatial frequency of 0 indicating a neutral point with neither FW nor BW. Subsequent to the analysis of the ordered electrode sequence, we randomly shuffled the order of electrodes for 100 times. This shuffling served as a control by disrupting the spatial pattern, thus helped distinguish genuine, directional traveling waves from traveling patterns that could occur due to the spatial structure of electrode placement. For each shuffle, surrogate forward and backward waves (SFW and SBW) were computed using the same method applied to the data from ordered electrode sequence (Figure 4B lower panel). The mean of the surrogate values served as the baseline against which actual traveling waves were measured. The resultant amount of backward and forward traveling waves (BTW and FTW) in decibels [dB] was quantified as follows:

$$FTW = 10 \times \log_{10} FW / \mathrm{mean}(SFW); \; BTW = 10 \times \log_{10} BW / \mathrm{mean}(SBW) \qquad \text{(Equation 1)}$$

Given previous studies showed that slow traveling waves are dominantly backward during sleep,[39] we used BLMM to compare the difference of backward and forward traveling waves. We ran this analysis on each TMR trial and then averaged trials within each cue to obtain single-item forward and backward traveling waves values. The BLMM included the type of traveling waves (i.e., backward vs. forward) as fixed effect, number of trial repetition as covariate, participants as the random factor.

The model was defined as:

Traveling wave strength∼ 1 + Type + Repetition + (1 + Type | Subject ID).

Brain-behavior association analysis

To establish a direct link between TMR-induced behavioral changes and TMR-elicited EEG activity, we extracted the averaged power within the identified significant positive clusters, and also calculated mean traveling waves averaged across repetitions of each cue to obtain item level data. Then we performed a series of B(G)LMMs using EEG power and traveling waves to predict post-TMR SRET performance metrics at the item level, including endorsement choices and positive endorsement RTs. All EEG metrics were centered before being included as fixed effects. We used BGLMM to predict endorsement choice (Yes/No) and BLMMs to predict RTs for endorsing positive traits. We considered an effect as significant if the 95% confidence interval (CI) estimated from the posterior distribution did not include zero.The models were defined as.

(1) Post-TMR endorsement choice (Yes/No) ∼ 1 + Positive delta-theta-alpha cluster/Positive sigma-beta cluster/Forward traveling wave/Backward traveling wave + Baseline Choice + Repetition + (1|Subject ID).
(2) Delay endorsement choice (Yes/No) ∼ 1 + Positive delta-theta-alpha cluster/Positive sigma-beta cluster/Forward traveling wave/Backward traveling wave + Baseline Choice + Post-TMR choice + Repetition + (1|Subject ID).
(3) Post-TMR RTs for endorsing positive traits ∼1 Positive delta-theta-alpha cluster/Positive sigma-beta cluster/Forward traveling wave/Backward traveling wave + Baseline RTs + Repetition + (1|Subject ID).
(4) Delay RTs for endorsing positive traits ∼1 + Positive delta-theta-alpha cluster/Positive sigma-beta cluster/Forward traveling wave/Backward traveling wave + Baseline RTs + Post-TMR RTs + Repetition + (1|Subject ID).