Visual Working Memory Filtering Efficiency

Authors: Zhang Zhao, Zhang Liwei, Gong Ran, Zhang Liwei

Date: 2020-11-05T00:00:00+00:00

Abstract

Filtering efficiency reflects the interference suppression function of visual working memory, which researchers can measure based on storage capacity or representational precision. Its neural processing primarily involves detecting distractor items, initiating filtering, and implementing filtering or storage, engaging the coordinated interaction of the prefrontal cortex, basal ganglia, and posterior parietal cortex. The direction of change in filtering efficiency is influenced by factors such as age, special disorders, emotion, and cognitive characteristics. Issues that future research still needs to address include clarifying the relationship between filtering efficiency and working memory capacity, delineating the psychological implementation process of filtering efficiency, exploring the brain mechanisms of filtering efficiency across different populations varying in age, special disorders, and occupations, and enhancing the ecological validity of basic research paradigms.

Full Text

The Filtering Efficiency of Visual Working Memory

Zhang Zhao[1,2], Zhang Liwei[1], Gong Ran[1,3]

[1]School of Psychology, Beijing Sport University, Beijing 100084, China
[2]Physical Education and Training Department III, Chengdu Sport University, Chengdu 610041, China
[3]College of Cabin Attendant, Civil Aviation University of China, Tianjin 300300, China

Abstract: Filtering efficiency reflects the interference suppression function of visual working memory and can be measured based on storage capacity or representation precision. Its neural processing involves three main stages: detecting distractors, initiating filtering, and implementing filtering or storage, which are orchestrated through coordinated activity of the prefrontal cortex, basal ganglia, and posterior parietal cortex. The direction of change in filtering efficiency is influenced by factors such as age, special disorders, emotion, and cognitive characteristics. Future research should address several unresolved issues, including clarifying the relationship between filtering efficiency and working memory capacity, identifying the psychological implementation process of filtering efficiency, exploring the brain mechanisms of filtering efficiency across different age groups, special populations, and professions, and improving the ecological validity of basic research paradigms.

Keywords: filtering efficiency, visual working memory, neural mechanism, changing features
Classification Code: B842

According to World Health Organization (WHO) data, approximately 1.35 million people die each year worldwide due to road traffic accidents, with an additional 20 to 50 million suffering non-fatal injuries, many resulting in disability (World Health Organization, 2018). Subjective factors among motor vehicle drivers constitute the primary cause of traffic accidents, including cognitive, reaction, and judgment factors (Zhang Ningning, 2012), with dangerous driving behaviors closely related to the higher cognitive function of working memory (Ge et al., 2020). Evidently, working memory is crucial for daily life, even matters of life and death.

Working memory (WM) temporarily stores and manipulates external information to enable goal-directed behavior (Kui Yixuan, 2019). However, limited working memory capacity (WMC) necessitates efficient information selection mechanisms that incorporate highly task-relevant information while avoiding capacity waste from irrelevant interference. Researchers (Vogel et al., 2005) term this information selection ability "filtering efficiency" (FE, also referred to as filtering ability in some studies)—the capacity to select task-relevant target information while filtering out task-irrelevant distractors. This represents an interference suppression mechanism during information storage in visual working memory (VWM), primarily manifested in the processing stage of visual information storage. Cowan et al. (2006) propose that FE essentially reflects the selective function of attentional control within VWM.

Overall, WMC and FE are closely related but represent distinct aspects of VWM: information storage capacity versus processing capacity for irrelevant information. Research indicates that individual WMC reflects cognitive level, while FE positively predicts WMC (Luck & Vogel, 2013; McNab & Klingberg, 2008). Consequently, some argue that FE may more significantly contribute to working memory performance than WMC. However, while numerous studies have focused on WMC, discussion of FE remains exploratory. We believe a systematic review of relevant literature is necessary to provide new directions for advancing this field. Specifically, this paper first introduces the mechanisms underlying FE, then examines its neural mechanisms based on processing stages and relevant brain regions, analyzes the changing characteristics of FE and their influencing factors, and finally proposes research directions for unresolved issues.

1.1 Working Memory Storage Capacity and Representation Precision

Unlike long-term memory with its nearly unlimited capacity, working memory storage capacity is extremely limited, evolving from the classic 7$±$2 (Miller, 1956) to approximately 4 items (Cowan, 2001). This limited capacity constrains information processing abilities. Since storage capacity correlates closely with fluid intelligence and general cognitive performance (Johnson et al., 2013), VWM capacity and its storage mechanisms have remained central research topics.

Beyond storage capacity, researchers have recently focused on representation precision, measured through color recall tasks (CRT) (Zhang & Luck, 2008), which assesses the accuracy with which object features are represented in working memory. Due to limited working memory resources, representation precision for each item is also constrained (Ma et al., 2014). By comparing the difference between participants' recalled color and the actual color, researchers can calculate representation precision. Currently, representation precision serves as a new VWM evaluation metric, complementing storage capacity to provide more accurate and comprehensive assessment from both "quality" and "quantity" perspectives.

Regarding how limited working memory resources are allocated between storage capacity and representation precision, researchers have proposed the "slot" model, flexible resource model, and integrated slot-resource model (He Xu & Guo Chunyan, 2013). The slot model posits fixed storage capacity (3-4 items); when information quantity exceeds this limit, WM can only precisely represent a few objects while ignoring others. The flexible resource model suggests resources can be flexibly allocated: individuals can store either a few high-precision representations or numerous low-precision representations. Both models have experimental support. Recently, two groups (Fougnie et al., 2012; van den Berg et al., 2012) almost simultaneously proposed the variable precision resource model (VP model), which posits that mental resources may vary across trials and be randomly allocated to stimulus items, resulting in different representation precisions. Studies support this model (Pratte et al., 2017; van den Berg et al., 2014), suggesting it provides the best fit for behavioral results.

Debate continues regarding which model best captures storage capacity and representation precision (Kui Yixuan, 2019). Consequently, researchers measure FE from both capacity and precision perspectives to understand its underlying mechanisms, which may theoretically resolve existing model controversies while providing evidence and guidance for improving VWM filtering ability through cognitive training.

1.2 Filtering Efficiency Based on Storage Capacity

Vogel et al. (2005) first used a change detection task (CDT) containing distractors to measure FE. The procedure is as follows: a central fixation cross appears, followed by a cue (typically a left/right arrow indicating attention direction) for 200ms; then a memory array presents equal numbers of stimuli on both sides of fixation while participants maintain central fixation and memorize only the cued side' s stimuli for 100-200ms; after a 900ms retention interval (blank screen with fixation), a test array appears requiring participants to judge whether a probe stimulus changed from the memory array (color, orientation, or position) via yes/no response, completing the ~1200ms trial. Stimuli include targets (T) and distractors (D) as geometric shapes (triangles, rectangles, circles). Experimental conditions typically comprise three or more levels based on stimulus type and quantity combinations: (1) n targets, no distractors; (2) 2n targets, no distractors; (3) n targets and n distractors. For example, a three-level combination might be 2T/4T/2T2D.

Researchers indirectly measure and evaluate FE by comparing storage capacity across these conditions at both behavioral and neurophysiological levels.

1.2.1 Behavioral Measurement Researchers typically use filtering efficiency scores to evaluate FE, calculated in two steps:

First, calculate WMC using either formula $K = S * (H - F)$ (Cowan, 2001) or formula $K = N * (H - F)$ (Pashler, 1988), where K represents WMC, S or N represents target quantity, H is hit rate, and F is false alarm rate. Both formulas calculate WMC in CDT tasks: the first for single-probe test arrays, the second for whole-display probes (Rouder et al., 2011).

Second, compare K values with and without distractors (Stout & Rokke, 2010); the resulting ratio is the filtering efficiency score. The logic: if WMC in 3T3D and 3T conditions is identical (score = 1), individuals successfully filter all distractors, indicating good FE; conversely, scores approaching 0 indicate poor FE. Higher scores (range 0-1) reflect better FE.

Building on this, some researchers use filtering cost and filtering benefit to evaluate FE. Filtering cost is the accuracy difference between 3T and 3T3D conditions (scores near 0 indicate good FE); filtering benefit is the accuracy difference between 3T3D and 6T conditions (higher scores indicate better FE) (Hadar et al., 2019a; Sternberg et al., 2018; Stout et al., 2015; Ward et al., 2019).

These three metrics share the core concept of comparing working memory performance with and without distractors but differ in application. The filtering efficiency score simultaneously considers target quantity, hit rate, and false alarm rate, offering greater accuracy but more complex calculation. Filtering cost and benefit directly use accuracy differences from CDT, providing simpler, faster calculation. All three are common FE metrics in the field, with the latter two developing from the first. Regardless of metric, the underlying concept remains consistent.

However, behavioral measurement only evaluates FE through task outcomes, revealing neither processing stages nor deeper neural mechanisms, necessitating more accurate and effective indicators to observe FE' s occurrence.

1.2.2 Neurophysiological Measurement Vogel and Machizawa (2004) introduced event-related potentials (ERP) to FE research, discovering a milestone indicator—contralateral delay activity (CDA). Using a contralateral control method with stimuli presented in left/right visual fields, visual stimulation in one field strongly activates the contralateral hemisphere after optic chiasm transmission, reflecting task-related neural activity, while the ipsilateral hemisphere shows activity from irrelevant factors. Subtracting ipsilateral from contralateral ERP eliminates irrelevant influences, yielding CDA. This reflects VWM encoding and maintenance, with amplitude increasing with stored stimulus quantity until reaching WMC limits (typically 4 items) (Gao Zaifeng et al., 2012).

Vogel et al. (2005) used CDA's sensitivity to object quantity to directly measure distractor storage in VWM. The logic: if CDA amplitude in 2T2D versus 2T conditions shows no significant difference, distractors failed to enter VWM—successful filtering; conversely, if 2T2D versus 4T CDA amplitudes are equivalent, distractors were fully stored—filtering failure. However, CDA amplitude comparison alone cannot directly reflect FE level, as filtering is not all-or-nothing. A scenario where 2T2D CDA differs significantly from both 2T and 4T suggests partial distractor filtering, yet lacks a specific numerical FE value, hindering inter-individual comparisons and research precision.

Accordingly, Vogel et al. (2005) provided a CDA-based FE calculation formula: $\alpha = \frac{D-T}{F-T}$, where α represents FE score, and F, D, T represent CDA amplitudes in 4T, 2T2D, and 2T conditions respectively . α ranges from 0-1; as D approaches T, α nears 1 (good FE); as D approaches F, α nears 0 (poor FE). Different studies adjust target quantities based on participant characteristics or research purposes, so F, D, T may not always correspond to these exact conditions (Jost et al., 2011).

In summary, while behavioral metrics are more convenient, CDA cross-validation is essential. Since CDA' s introduction, researchers have commonly used both measurement approaches (Allon & Luria, 2019; Jia et al., 2014; Jost et al., 2011; Jost & Mayr, 2016; Owens et al., 2013; Qi et al., 2014; Spronk et al., 2013; Stout et al., 2015; Xu et al., 2018; Ye et al., 2018). Some studies use alternative EEG indicators like N270 (Zhou et al., 2011) or Pd waves (Feldmann-Wüstefeld & Vogel, 2018), but the underlying logic remains measuring working memory performance affected by distractors to evaluate FE.

1.3 Filtering Efficiency Based on Representation Precision

Since CDT only requires judging whether targets changed with/without distractors, FE evaluation is limited to comparing WMC across conditions, precluding representation precision-based calculations. To address this, Liang Yiwen (2016) incorporated distractors into color recall tasks to examine FE. The procedure: a central fixation cross appears for 300-400ms, followed by a directional cue (200ms), then a memory array presenting equal stimuli on both sides; participants maintain central fixation and memorize only the cued side' s items for 100-200ms; after a 900ms blank interval, a probe interface appears with black frames at all target locations, one bolded, alongside a color wheel with 180 RGB values. Participants recall the specific color from the bolded frame location using a mouse click.

After all trials, angular error between selected and original colors is calculated and modeled to obtain VWM representation precision with/without distractors. Precision values are entered into the formula $DEp = \frac{P1-P2}{P1}$ to calculate the distractor effect (filtering efficiency) (Liu Zhiying & Kui Yixuan, 2017), where $P1$ is PrecisionTnD0 and $P2$ is PrecisionTnD2. In TnD0 and TnD2, Tn represents target quantity at different levels, while D0 and D2 represent no distractor and two-distractor conditions respectively. Higher DEp scores indicate worse FE.

Recently, CRT has gained popularity for simultaneously dissociating VWM storage capacity and representation precision. Adding distractors to this task enables measurement of representation precision-based FE, warranting further attention compared to storage capacity-based FE.

2 Neural Mechanisms of Filtering Efficiency

Beyond psychological mechanisms, researchers have explored FE' s neural underpinnings, revealing multiple time windows and brain region activations. This section introduces FE' s neural mechanisms from processing stages and relevant brain regions.

2.1 Processing Stages of Filtering Efficiency

Distractor filtering is a continuous, multi-region coordinated process. While CDA reflects VWM filtering function, the underlying mechanism remained unclear (Awh & Vogel, 2008; McNab & Klingberg, 2008; Vogel et al., 2005). Researchers then used high-temporal-resolution EEG to explore filtering' s temporal dynamics in VWM tasks. Current findings suggest FE comprises three cognitive stages: distractor detection, filtering initiation, and filtering implementation/storage.

Using CDT memory array onset as a reference point, EEG analysis reveals (Liesefeld et al., 2014): (1) During stimulus presentation (174-284ms), posterior regions show two overlapping components—initial scanning of targets with amplitude peaking at 4 items, indicating target detection; subsequently (201-289ms), amplitude increases with distractor quantity, termed the posterior detection component, signaling distractor detection. (2) At 245-288ms, prefrontal cortex (PFC) emits bias signals, indicating filtering initiation (Astle et al., 2014; Vogel et al., 2005). (3) During 290-715ms, parietal delay activity emerges, marking storage and filtering of targets and distractors. Before 355ms, trials with distractors (e.g., 2T3D) show equivalent amplitude to equal-quantity target trials (e.g., 5T), after which amplitude significantly decreases, indicating successful filtering. Incomplete filtering results in distractor storage in load-sensitive posterior parietal cortex (PPC), termed unnecessary storage, which occupies target storage space and negatively correlates with WMC. Unnecessary storage thus reflects individual differences in WMC from another perspective.

This study (Liesefeld et al., 2014) first documented these three stages' temporal progression during filtering implementation, integrating previous findings into a chained causal model: initial stimulus scanning detects distractors, triggering bias signals that initiate filtering, thereby implementing distractor filtering. Low filtering efficiency leads to distractor storage, whereas efficient filtering reduces unnecessary storage, alleviating VWM storage burden. This suggests earlier and faster distractor detection with stronger bias signals yields more powerful distractor inhibition and higher filtering efficiency. However, Cisler and Koster (2010) found anxious individuals show attentional bias toward threat information, with high-anxiety individuals prioritizing threat stimuli. Stout et al. (2013) also found anxiety symptoms correlate with processing bias for fearful faces, making threat distractors difficult to filter. Yet filtering stage studies (Liesefeld et al., 2014; McNab & Klingberg, 2008; Vogel et al., 2005; Wang Sisi, 2019) have not examined anxiety as a factor. Therefore, the above 推论 currently applies only to non-anxious contexts; future research should investigate cognitive-neural characteristics of filtering stages in high trait-anxiety individuals.

Beyond understanding basic processing stages and their relationships, research has substantial room for expansion, such as exploring factors influencing distractor detection. For instance, examining relationships between oscillatory synchronizations and the three processing stages may help—Engel (2012) found oscillatory synchronizations may reflect mechanisms for identifying distractors, potentially expanding current understanding of FE processing stages.

2.2 Brain Regions Related to Filtering Efficiency

To identify brain regions involved in distractor filtering, researchers have used high-spatial-resolution fMRI. Current findings suggest filtering-related brain regions can be broadly divided into filtering-related and storage-related areas: (1) During pre-distractor preparation, PFC and basal ganglia (BG) are primarily involved; (2) Post-distractor filtering stages show different activation patterns between young and older adults; (3) Distractor storage mainly involves PPC. We propose that FE relies on coordinated PFC-PPC function, reflecting aspects of the visual search fronto-parietal network (Wei Ping & Kang Guanlan, 2012).

2.2.1 Before Distractor Appearance Rainer et al. (1998) found PFC in primates is involved in selecting and maintaining targets. Vogel et al. (2005) hypothesized PFC initiates FE via bias signals when encountering distractors. McNab and Klingberg (2008) supported this using a visual-spatial working memory task with distractors: (1) Recording brain activation from distractor cue onset to memory stimulus presentation revealed enhanced MFG and BG activity, suggesting involvement in filtering set activity. BG is known to provide transient inhibitory/non-inhibitory signals to PFC, forming a dynamic gating mechanism for working memory (Hazy et al., 2007). (2) During memory-to-probe intervals, PPC activation indicated distractor encoding and storage. After measuring WMC separately, PFC, BG, and globus pallidus (GP) activity positively correlated with WMC, suggesting higher activation stores more targets. Conversely, GP activity negatively correlated with PPC activity, indicating stronger GP activity reduces distractor storage—a relationship supported in subsequent studies (Liesefeld et al., 2014), though no PFC-PPC relationship was found.

McNab and Klingberg (2008) received support from: (1) Peverill et al. (2016) found GP activation in adolescents versus adults primarily prepares for filtering initiation; (2) Sleep deprivation studies showed total sleep deprivation impaired PFC, reducing FE (Drummond et al., 2012), yet WMC remained intact, contradicting FE-induced WMC differences. We speculate this discrepancy may arise because the filtering task had three difficulty levels while the working memory task had only one, with FE impairment detected only at the highest filtering difficulty. (3) Parkinson' s disease patients with BG damage showed worse FE than age-matched controls (Lee et al., 2010). (4) fMRI comparisons of filtering training versus memory training revealed enhanced middle frontal gyrus and cuneus activity after 5 days of filtering training, with cuneus enhancement reflecting PFC' s top-down control over occipital visual areas for optimized visual perception (Ress et al., 2000; Sandrini et al., 2008).

Awh and Vogel (2008) integrated these findings into the "bouncer in the brain" hypothesis, proposing that WMC individual differences stem not from slot number but filtering efficiency (He Xu & Guo Chunyan, 2013). Analogizing PPC' s limited visual representation to a capacity-limited banquet hall (adapted from "nightclub" for cultural relevance), two solutions ensure adequate space: expanding the hall (increasing WMC) or restricting entry to invited guests only (targets). The latter is more feasible, making the bouncer crucial—PFC and BG serve this role. Before the banquet, the bouncer prepares by judging guest invitations and applying all-or-none entry decisions. Liesefeld et al. (2014) later identified posterior distractor-detection components as the bouncer' s "eyes and hands," crucial for execution. Emrich and Busseri (2015) reanalyzed McNab and Klingberg (2008), finding BG activity predicts both distractor encoding and VWM performance, supporting the bouncer hypothesis. Recently, Dube et al. (2017) discovered the bouncer' s role is more nuanced, prioritizing stimuli based on VWM importance before resource reallocation, suggesting untapped higher-order cognitive functions.

Overall, PFC-BG distractor filtering represents part of VWM's broader cognitive network, reflecting PFC's role in top-down control systems (D'Esposito & Postle, 2015). According to Duncan and Fuster, top-down control signals originate in PFC regions related to abstract cognition like rules and goals, influencing other cortical and subcortical areas (Duncan, 2001; Fuster, 2001).

2.2.2 After Distractor Appearance Vellage et al. (2016) used fMRI in a visual-spatial working memory task with high/low load conditions (both containing distractors) to compare young and older adults' filtering and storage networks. fMRI revealed young adults' filtering-related regions included bilateral insulae, right occipital cortex (OCC), brainstem, and cerebellum—insulae relate to stimulus-driven attentional orienting (Corbetta & Shulman, 2002); OCC reflects attention-driven visual enhancement (Ruff, 2013); cerebellar activation aligns with Baier et al.' s (2014) finding that cerebellar damage impairs filtering, though more research is needed. Older adults activated bilateral insulae, ventromedial PFC (VMPFC), and precuneus during filtering. VMPFC uniquely participated in both filtering and storage, potentially serving as a junction between these processes (Corbetta & Shulman, 2002; Pessoa et al., 2003), while precuneus relates to information inhibition.

PPC (intraparietal and occipital sulci) is consistently identified as a critical neural site for extremely limited mental representations of the visual world (He Xu & Guo Chunyan, 2013). Vellage et al. (2016) found young adults' storage involved PPC, VMPFC, and precuneus, while older adults showed more distributed network activation including bilateral middle/inferior temporal gyri, right superior temporal gyrus, left cingulum, and bilateral parahippocampal gyri.

2.2.3 Causal Roles of Brain Regions in Filtering Efficiency Recently, researchers have used transcranial Direct Current Stimulation (tDCS) to stimulate PFC and PPC separately, investigating their causal roles in interference filtering versus stimulus storage. tDCS is a non-invasive technique that modulates cortical excitability via weak (0.5-2 mA), sustained (15-30 min) current, affecting cognitive functions related to the targeted region (Nitsche & Paulus, 2000). Li et al. (2017) found PFC stimulation improved VWM performance in CDT with distractors, while PPC stimulation improved performance in CDT without distractors, suggesting enhanced PFC filtering and PPC storage capacities respectively. However, Robison et al. (2017) found no significant effects from PFC or PPC stimulation despite similar methodology. They analyzed potential causes (equipment, control, stimulus quantity, statistical power) without fully convincing explanations. We propose: (1) Task difficulty differed—Li et al. used 361 possible distractor orientations (0-360°) versus Robison' s 4 orientations (horizontal/vertical/$±$45°). Greater orientation variability demands finer distractor discrimination, increasing task difficulty. Jones and Berryhill (2012) found task difficulty moderates tDCS effects on PPC: high difficulty yields greater benefits, while simple tasks may produce ceiling effects. Similar difficulty moderation appears in visual attention and spatial working memory tasks (Pope et al., 2015; Wu et al., 2014). (2) Individual differences—PPC stimulation benefits may be limited to specific groups: low WMC individuals (Hsu et al., 2014; Tseng et al., 2012), low WMC older adults (Arciniega et al., 2018), and high-extrinsic-motivation individuals (Jones et al., 2015). This suggests PPC' s causal role in VWM storage may be modulated by age, WMC, and situational factors.

Overall, most tDCS studies find PPC stimulation enhances WMC (Di Rosa et al., 2019; Heimrath et al., 2012; Hsu et al., 2014; Li et al., 2017; Tseng et al., 2012; Wang et al., 2019), supporting PPC's role in stimulus representation. PFC stimulation studies for FE enhancement are fewer and inconsistent, necessitating deeper analysis using high-definition tDCS for better spatial resolution (Guo Heng et al., 2016) combined with neuroimaging data (Wang Sisi & Kui Yixuan, 2018) to explore FE' s neural substrates and mechanisms.

In summary, FE brain region analysis has yielded preliminary results forming the "bouncer in the brain" hypothesis: PFC and BG filter distractors while PPC stores stimuli. Recent research continues refining this hypothesis, with future directions including: (1) Comparing developmental trajectories of the "bouncer" between children and adults, examining cerebellar support for filtering maturation; (2) Clarifying how filtering-related brain regions connect to jointly implement filtering—Wang Sisi' s tDCS stimulation of PPC simultaneously affected PFC filtering components and PPC storage components, offering a promising direction; (3) Understanding how posterior regions activate PFC to generate bias signals.

3 Changing Characteristics of Filtering Efficiency

Understanding FE' s psychological and neural mechanisms necessitates systematic review of its dynamic changes and influencing factors. We summarize FE' s developmental trajectory and categorize influencing factors into: (1) normal developmental trends (age effects); (2) impairment and weakening (special disorders and emotions); (3) improvement and enhancement (cognitive characteristics).

3.1 Lifespan Development—Normal Trends

Researchers have compared FE across age groups to examine age-related dynamic changes. First, Spronk et al. (2012) compared adolescents (12-16 years) and adults (20-45 years), with behavioral and CDA results showing significantly weaker FE in adolescents. Plebanek and Sloutsky (2019) with children (4 and 7 years) and adults, and Peverill et al. (2016) with adolescents (mean age 16.74) provided converging evidence, suggesting adolescent FE is still developing and requires cultivation.

Second, the inhibitory deficit hypothesis (Hasher & Zacks, 1988, cited in Jost et al., 2011) proposes that age-related declines in inhibiting irrelevant information partially explain WM deterioration. Gazzaley et al. (2008) found older adults show selective deficits in suppressing irrelevant VWM information, but only during early visual processing stages, indicating partial rather than complete inhibition decline. Following this, Jost et al. (2011) hypothesized that if selection deficits occur during early encoding, FE deficits would emerge early in the retention interval. This was supported: young adults (mean 24.5 years) filtered during early retention (375-400ms) through mid-stage (550ms), while older adults (mean 72.8 years) began filtering irrelevant information only in mid-late stages (600-625ms). Further analysis showed age-related processing speed differences concentrated at 350-550ms, with no subsequent differences, indicating delayed filtering initiation in older adults, suggesting different neural mechanisms. Vellage et al. (2016) provided a possible explanation: young (mean 25.7 years) and older (mean 65.8 years) adults showed no behavioral FE differences, but fMRI revealed different brain regions, with older adults activating VMPFC during high-load tasks. This suggests older adults recruit additional prefrontal resources to match young adults' performance, consistent with Payer et al.' s (2006) proposal that prefrontal activation correlates with task difficulty. Current research allows the inference that both groups achieve similar FE levels but differ in processing duration—young adults filter efficiently and rapidly, while older adults require more time and broader brain activation.

These results partially support the inhibitory deficit hypothesis, requiring further evidence and meta-analysis. We hypothesize FE' s lifespan trajectory approximates an inverted U-curve: rapid development during adolescence, peaking in early adulthood, then gradual decline without sharp drops. This shares similarities and differences with fluid intelligence' s age-related decline: both decline post-peak, but FE declines more slowly. Future research should test this hypothesis through longitudinal studies (e.g., tracking older adults) or full age-range comparisons, and examine FE' s role in age-cognition relationships.

3.2 Impairment and Weakening

Researchers have examined how trait (special disorders) and state (emotion) factors impair and weaken FE.

3.2.1 Filtering Efficiency Impairment from Special Disorders Studies investigating FE in psychiatric/neurological disorders (Parkinson' s disease, trait anxiety, depression, ADHD, ASD, schizophrenia) illuminate impairment characteristics and pathological mechanisms.

Lee et al. (2010) found Parkinson's patients (mean 66.71 years) performed worse than age-matched controls (mean 68.57 years) on CDT with distractors, with behavioral and EEG indices indicating impaired filtering due to BG damage, supporting FE' s neural substrate research.

Stout and Rokke (2010) were among the first to examine trait anxiety' s impact on FE, finding state anxiety, rumination, and depression impair FE, with WMC potentially moderating this effect only in low-capacity individuals. Moriya and Sugiura (2012) found high trait and social anxiety impair FE regardless of WMC, as they didn' t include a low-anxiety group. Qi et al. (2014) found high trait anxiety impairs FE, with WMC moderation only in low-anxiety individuals, supported by two other studies (Stout et al., 2013, 2015). Moran' s (2016) meta-analysis of these five studies revealed a medium-large effect size for trait anxiety impairing FE ($g = -0.700$, $k = 5$, $N = 229$, $p < .001$). Notably, high trait anxiety groups show filtering deficits for both threatening (Stout et al., 2013, 2015) and neutral distractors (Moriya & Sugiura, 2012; Qi et al., 2014). In summary, high trait anxiety impairs FE, likely by disrupting attentional inhibitory control, allowing distractors to occupy VWM capacity and impair performance. As a risk factor for anxiety disorders, depression, and other conditions, examining trait anxiety' s relationship with working memory illuminates how anxiety-related cognitive processes affect behavior (Thiruchselvam et al., 2012).

Owens et al. (2012) used ERP to show dysphoria impairs FE through deficient inhibition, though cognitive training can improve it (Owens et al., 2013).

Spronk et al. (2013) found no FE differences between ADHD and control groups across adolescence and adulthood, suggesting developmental lag theories of ADHD may not apply to FE. These theories propose ADHD cognitive functions follow normal trajectories but with delayed onset (Doehnert et al., 2010), yet Spronk et al. found no FE developmental lag, though without explanatory analysis—future longitudinal studies should verify this and explore underlying neural mechanisms.

Bodner et al. (2019) found adult ASD groups matched controls in FE, while child ASD groups showed deficits that diminished by adolescence. ASD research shows selective inhibition impairment while other functions remain intact (Christ et al., 2011), suggesting long-term, stable training during development can normalize filtering function (Koshino et al., 2007).

Schizophrenia patients show intact CDT performance (Gold et al., 2006). Ran Xuemei (2017) using CRT found schizophrenia patients' FE was unimpaired and possibly superior, likely due to hyperfocusing—maintaining minimal internal representations and concentrating limited resources on few targets. While hyperfocusing doesn' t impair FE, it severely damages overall VWM, as both storage capacity and precision are reduced compared to controls, providing important evidence for understanding schizophrenia' s higher-order cognitive deficits.

3.2.2 Emotion-Related Filtering Efficiency Weakening Multiple studies show social exclusion impairs working memory performance (Buelow et al., 2015; Hawes et al., 2012; O' luanaigh et al., 2012). Xu et al. (2018) found socially excluded individuals showed worse FE than accepted individuals, possibly because exclusion increases attention to social information (e.g., smiling faces) for reacceptance or consumes self-control resources suppressing negative affect, both limiting attentional resources for cognitive control and impairing working memory.

Long Fangfang (2018) examined negative emotion effects on high/low WMC groups' FE, finding negative emotion improved low WMC group' s FE while leaving high WMC group' s FE unaffected, suggesting an enhancement effect from negative emotion in low WMC individuals. Conversely, Ye et al. (2018) found low WMC groups filtered happy faces better than high WMC groups but struggled with neutral and angry faces, suggesting negative emotion impairs low WMC individuals' FE. These inconsistent results may stem from: (1) Long' s study induced negative emotion with low intensity (PANAS negative affect mean 18, below median 30) without reporting effect sizes, suggesting only low-intensity negative emotion may enhance performance—a dosage effect warranting future investigation; (2) Ye et al. interpreted results via emotional face processing bias without direct emotion measurement.

3.3 Improvement and Enhancement

Research shows cognitive characteristics influence FE. Specifically, independent cognitive style, abstract mindset, and high representation precision benefit FE. Additionally, adding cues and targeted training can effectively improve FE.

Jia et al. (2014) demonstrated cognitive style effects: field-independent (FI) groups outperformed field-dependent (FD) groups on CDT with distractors in both behavior (accuracy) and neurophysiology (CDA), suggesting FI style' s internal information reliance enhances FE. The likely mechanism is that during storage, FI groups can maintain cognition using internal information without cues, whereas FD groups relying on external stimuli may encode distractors without cue support.

Mindset also affects FE (Hadar et al., 2019b). Researchers noted FE' s similarity to construal-level theory (CLT), which posits mental representations vary along a concrete-abstract continuum, dichotomizing mindset into abstract versus concrete (Liberman & Trope, 2008, 2014). Abstract mindset preserves essential information attributes while ignoring modifiers (e.g., "garlic sprout twice-cooked pork" becomes "food"). Similarly, filtering tasks require grasping target essence (e.g., triangle) while filtering irrelevant features (e.g., red). Laboratory-induced abstract versus concrete mindsets showed abstract mindset improved FE, suggesting higher construal levels facilitate successful irrelevant information filtering.

Liu Zhiying and Kui Yixuan (2017) found cognitive load, perceptual representation precision, and FE are interrelated. Generally, high perceptual precision groups showed better FE than low precision groups on CRT with distractors. Specifically, under high cognitive load, perceptual precision positively predicted FE, suggesting VWM representation quality constrains subsequent cognitive processing, possibly by affecting different VWM processing stages.

Adding cue information effectively enhances FE. Allon et al. (2019) applied

Gestalt principles as grouping cues, organizing targets and distractors via (1) illusory object organization (Kanizsa triangle) or (2) proximity principles, comparing filtering performance to random distributions. Five experiments showed principle (1) improved FE only when applied to targets, while principle (2) improved FE when applied to either, indicating Gestalt grouping cues facilitate VWM filtering. Allon and Luria (2017) noted early cue effects are short-lived, requiring reactivation to maintain filtering ability (Allon & Luria, 2019). Their study added cues to both memory and test arrays, with ERP showing early cues reduce distractor attention and improve FE. The neural mechanism involves target-directed neural activity in visual and prefrontal regions during preparation, with both exogenous and endogenous attention utilizing cues to enhance FE.

Targeted training also improves FE. Schmicker et al. (2016) compared filtering training (FT: selecting targets without memorizing) and memory training (MT: memorizing targets without distractors) over 5 days (1 hour/day, increasing difficulty). Both groups improved across four CDT subtasks post-training, but FT showed superior accuracy on subtasks requiring both memory and filtering, indicating FT more effectively improves FE. Owens et al. (2013) used dual n-back training (8 days) in dysphoric individuals, finding experimental groups showed significantly improved WMC and FE compared to controls, suggesting training produces generalized cognitive changes (Shipstead et al., 2010).

Finally, despite inconsistent tDCS results for PFC stimulation enhancing FE, only two such studies exist, warranting continued exploration.

4 Unresolved Issues in Filtering Efficiency Research

This review summarizes over a decade of emerging FE research: (1) FE measurement relies on VWM storage capacity or representation precision via CDT or CRT; (2) Neural mechanisms involve PFC-BG and PPC across three cognitive stages (detection, initiation, filtering/storage); (3) FE changes follow three patterns: normal development, impairment/weakening, and improvement/enhancement, influenced by age, disorders, emotion, and cognitive characteristics.

Since Vogel et al. (2005) introduced CDA, FE research has progressed steadily, yet several issues remain. We discuss future directions regarding FE-WMC relationships, psychological implementation, brain mechanisms across populations, and ecological validity.

4.1 Relationship Between Filtering Efficiency and Working Memory Capacity

Luria et al.' s (2016) meta-analysis of 7 FE-WMC studies found a medium positive correlation ($r = 0.478$, $p < .001$, 95% CI [0.356, 0.585]). Subsequent research supports this (Spronk et al., 2012; Ye et al., 2018): low WMC groups struggle more with threatening information. Recent developmental studies (Manza et al., 2014; Peverill et al., 2016; Plebanek & Sloutsky, 2019; Spronk et al., 2013) show FE develops until adulthood, suggesting third variables like age should be considered.

Current behavioral FE measurement relies on WMC, obscuring causal relationships. However, some propose FE as the key factor underlying WMC individual differences (Luck & Vogel, 2013; McNab & Klingberg, 2008), providing direction for causal exploration. The bouncer hypothesis suggests FE may better reflect VWM function than WMC. Therefore, direct FE measurement is needed, such as using eye-tracking fixation duration (Mall et al., 2014), though accuracy should be combined for comprehensive evaluation. Single-subject designs may also clarify their relationship and explore VWM' s core components.

4.2 Psychological Implementation Process of Filtering Efficiency

FE is considered the ability to select task-relevant information into VWM while blocking irrelevant information, belonging to top-down control systems. Since CDA only reflects storage outcomes, not filtering implementation, a key question remains: how is filtering implemented—through enhanced target attention, distractor inhibition, or both?

Ye et al. (2017) proposed a two-phase model of VWM resource allocation, suggesting passive then active allocation phases. Initial passive allocation, driven by external stimuli, distributes resources to all items (bottom-up). Subsequent active allocation, a top-down process, reallocates resources based on task demands. From a quantity-precision tradeoff perspective, the former emphasizes quantity with low precision (short retention, high load), while the latter emphasizes precision with high resource allocation per item (long retention, low load). Though focusing on distractor-free conditions, this model aligns with VWM distractor filtering: initial passive allocation to all items (Allen et al., 2014; Liesefeld et al., 2014), followed by active top-down reallocation to targets. Recent research (Ye et al., 2019) found high WMC individuals show superior resource allocation ability when allowed top-down control, supporting the two-phase model and consistent with WMC' s influence on FE (Vogel et al., 2005).

Feldmann-Wüstefeld and Vogel (2018) first discovered the Pd wave during distractor filtering, representing inhibition with amplitude increasing with distractor quantity/complexity and positively correlating with WMC ($r = 0.43$, $p < .001$, 95% CI [0.25, 0.58]), where high WMC indicates better FE (Gaspar et al., 2016; Vogel et al., 2005). This suggests distractor inhibition may enhance FE. Additionally, posterior parietal alpha power suppression increases with distractor quantity, supporting attentional functions for current processing (Wang Sisi, 2019). Contrary to two-phase model predictions, these studies suggest FE is achieved through distractor inhibition.

Future research should test the two-phase model' s predictions for FE to further elucidate its psychological implementation.

4.3 Brain Mechanism Studies of Filtering Efficiency Across Age, Special Populations, and Professions

First, as noted in Section 3.1, older and young adults show similar behavioral FE but different neural processes, with older adults recruiting broader brain regions, suggesting different neural mechanisms. Similarly, adolescent filtering regions differ from adults'(Section 2.2.2), indicating age-related differences worth further investigation, such as testing whether older adults compensate for FE through broader brain recruitment.

Second, examining special populations (e.g., ADHD patients' intact FE) helps understand pathological mechanisms and may inspire improvement interventions.

Finally, different professions (e.g., drivers, athletes) warrant attention, as FE may relate closely to professional performance. Brain mechanism and intervention studies could develop targeted measures to improve FE, generating applied value.

4.4 Improving Ecological Validity of Basic Research Paradigms

Storage capacity-based FE research primarily uses CDT and visual-spatial working memory tasks—the former in behavioral/ERP studies, the latter in fMRI studies. They differ in cue function: CDT cues only attention direction (Vogel et al., 2005), while the latter directly cues distractor presence to elicit top-down processing (McNab & Klingberg, 2008). Representation precision-based CRT also measures FE (Zhang & Luck, 2008). Paradigm selection should match research purposes, but current cueing differs from real life where distractor timing/location cannot be predicted. Virtual reality (VR) could simulate real-life scenarios, such as driving simulations for driver FE research.

Basic FE paradigms use abstract geometric patterns with $ $3 distractors. With diverse populations, stimulus properties, distractor quantities, or time windows should be adjusted to avoid ceiling/floor effects. For instance, Plebanek and Sloutsky (2019) used cartoon animals for children (500ms presentation) and geometric patterns for adults (100ms), respecting developmental differences and improving ecological validity. Similarly, basketball players' FE research could use basketballs, players, or spectator faces as stimuli.

References

Gao Zaifeng, Yu Wenjun, Xu Xiaotian, Yin Jun, Shui Rende, & Shen Mowei. (2012). Contralateral delay activity: An ERP index of visual working memory storage. *Chinese Science Bulletin*, 57(30), 2806–2814. https://doi.org/10.1360/972012-728

Guo Heng, He Li, & Zhou Renlai. (2016). Transcranial direct current stimulation improves memory function. *Advances in Psychological Science*, 24(3), 356–

366. https://doi.org/10.3724/sp.j.1042.2016.00356

He Xu & Guo Chunyan. (2013). Capacity and resource allocation in visual working memory. *Advances in Psychological Science*, 21(10), 1741–1748. https://doi.org/10.3724/sp.j.1042.2013.01741

Kui Yixuan. (2019). Cognitive and neural mechanisms of working memory. *Acta Physiologica Sinica*, 71(1), 173–185. https://doi.org/10.13294/j.aps.2019.0004

Liang Yiwen. (2016). *Neural mechanisms of interference inhibition in working memory processing* (Master' s thesis). East China Normal University, Shanghai.

Liu Zhiying & Kui Yixuan. (2017). The influence of perceptual representation precision on interference inhibition ability in working memory. *Acta Psychologica Sinica*, 49(10), 1247–1255.

Long Fangfang. (2018). *Effects of negative emotional states on visual working memory resource allocation and filtering efficiency* (Master' s thesis). Liaoning Normal University.

Ran Xuemei. (2017). *Visual working memory impairment in schizophrenia: Behavioral and EEG evidence* (Master' s thesis). East China Normal University, Shanghai.

World Health Organization. (2018). *Road traffic injuries.* Retrieved December 7, 2018, from https://www.who.int/zh/news-room/fact-sheets/detail/road-traffic-injuries

Wang Sisi. (2019). *Neural mechanisms of storage and interference inhibition in visual working memory* (Doctoral dissertation). East China Normal University, Shanghai.

Wang Sisi & Kui Yixuan. (2018). Causal role of right dorsolateral prefrontal cortex in visual working memory. *Acta Psychologica Sinica*, 50(7), 727–738. https://doi.org/10.3724/sp.j.1041.2018.00727

Wei Ping & Kang Guanlan. (2012). Neural mechanisms of reward cue initiation and regulation of visual search frontoparietal networks. *Advances in Psychological Science*, 20(6),

Zhang Ningning. (2012). *Research on human-vehicle interaction issues based on neuroergonomics* (Doctoral dissertation). Northeastern University, Shenyang.

English references remain as originally cited in the manuscript.

Note: Figure translations are in progress. See original paper for figures.