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Computational cognitive mechanisms of visual working memory in major depressive disorder and sex differences

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Abstract

This study examined the computational cognitive mechanisms of visual working memory (VWM) in MDD, focusing on memory precision while exploring potential sex differences. 159 Major Depressive Disorder (MDD) patients and 67 healthy controls (HC) completed the color delay estimation task to measure their VWM. The mainstream models of VWM were compared, and the variable-precision (VP) model was the best fit for our data. The Bayesian ANCOVA was used to compare the differences between groups (MDD & HC) and sexes (male & female). Results revealed that MDD had worse memory precision than HC (BF_{10} = 103.872, decisive evidence for H_1). Specifically, they had larger resource allocation variability (BF_{10} = 19.421, strong evidence for H_1), indicating that they distributed memory resources more unevenly across different items than HC. In addition, females had better memory precision than males (BF_{10} = 10.548, strong evidence for H_1). More specifically, they had more initial resources during the color delay estimation task (BF_{10} = 6.003, substantial evidence for H_1) than males. These findings highlight the critical role of diminished precision, specifically, larger resource allocation variability, in impaired VWM in MDD. Meanwhile, these findings highlight sex differences in memory precision and initial resources of VWM.

Keywords Visual working memory, MDD, Cognitive mechanism, Computational modeling, Sex differences

Introduction

Major depressive disorder (MDD), a common mental disorder, is the leading cause of mental health-related disease burden [1]. Patients with MDD are usually accompanied by a series of cognitive dysfunctions, among which a working memory deficit is considered as one of the core manifestations [2–5]. As a capacity-limited cognitive system used to hold and process information related to ongoing cognitive tasks, working memory is proved to be a core cognitive function closely related to a wide range of other cognitive functions. Visual working memory (VWM) is a vital sensory channel for studying working memory [6, 7]. Dysfunction of VWM may cause a wide spectrum of negative consequences [8, 9], such as attentional deficits [10], decision-making biases [11], and

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a decline in learning ability [12]. Figuring out the VWM deficits in MDD patients may have important implications for the improvement of psychosocial functioning in this population.

When studying VWM, VWM capacity is an acknowledged important measure. Previous studies have evaluated the VWM deficits in patients with MDD, focusing on the indicator of capacity and found a reduction in their VWM capacity. For example, previous studies usually employed the n-back tasks and the digit span tasks, along with measures of reaction time and accuracy, to assess the VWM performance of MDD. The studies found that on the digit span tasks, the maximum number of digits that MDD participants could remember was less than that of HC [13, 14]. In the n-back tasks, the accuracy of MDD was lower than that of HC [15]. Certainly, capacity is a key indicator for VWM performance, which can reflect the maximum number of items related to the current cognitive task that an individual can process.

However, as the understanding of VWM deepens, researchers have found that capacity is not the only indicator of VWM, and relying solely on capacity cannot fully reflect the cognitive mechanism of VWM. An increasing number of theoretical models have introduced the concept of VWM precision [16, 17]. VWM precision refers to the degree of accuracy with which an individual can recall visual features, such as color, orientation, or location, after briefly viewing them. Precision depends on the amount of memory resources allocated to individual items. Items allocated a greater amount of memory resources tend to exhibit higher levels of precision [17]. The initial memory resources may be different between individuals. Also, the precision largely depends on the individual's memory-allocated strategies. For example, memory resources can be flexibly allocated among different items. They can be allocated to a small number of items, resulting in high-precision memory representations, or distributed across multiple items, leading to low-precision memory representations. Thus, precision may reflect other important aspects of VWM, which is something that capacity, the index focused on in previous studies, cannot achieve. Therefore, previous studies that attributed VWM deficits in MDD only to the decreased memory capacity may be unilateral. The VWM deficit, such as VWM precision as well as the related cognitive mechanism of VWM in MDD, needs further investigation.

For cognitive tasks, traditional behavioral indicators are important indicators of performance. However, they may fail to decompose cognitive processes and, thus, are unable to explore the cognitive mechanism behind the performance. In recent years, researchers have begun using computational cognitive modeling to refine the understanding of the mechanisms underlying cognitive processes. Computational cognitive modeling is also a commonly used method in measuring VWM precision [18, 19]. It can help decompose complex VWM tasks into smaller quantifiable cognitive components, such as initial resources and resource allocation variability, to facilitate analysis and thereby reveal the specific underlying mechanisms, helping us gain a deeper understanding of the mechanisms of these processes.

In addition, when investigating the VWM, sex is also a factor that should be considered. Previous researchers have found sex differences during the VWM processing. Specifically, studies found that males responded more quickly, while females responded more accurately, which indicated that females focused more on the details of objects [20–22]. The differences in VWM between sexes may be related to the different functions of sex hormones on brain structure and function [23, 24], as well as different sex roles and expectations, education, and training [25, 26]. Besides the sex differences in VWM, there were also sex differences in the symptom presentation and cognitive processing of MDD [27, 28]. However, due to the insufficient evidence to suggest an interaction between sex and MDD in VWM, we only hypothesized that females had higher memory precision compared to males, regardless of MDD and HC.

In summary, by focusing on memory precision, this study was designed to investigate the computational cognitive mechanism of VWM in MDD. The color delay estimation task was used to measure the VWM performance. The mainstream models of VWM were evaluated and compared to find the best-fitting model. The effect of memory precision and other factors, such as initial resources and resource allocation variability, on the VWM of MDD, as well as the sex differences, were explored. The study helps reveal the internal processing mechanism of VWM in MDD and provides an empirical basis for further proposing targeted intervention measures.

Methods

Participants

A total of 159 patients with MDD (male = 63, female = 96), aged between 16 and 45 (21.35±4.566), were recruited through advertisements from the outpatient clinic of the Medical Psychological Center at the Second Xiangya Hospital and enrolled in this study. They were diagnosed with MDD by a psychiatrist at or above the attending physician level. The inclusion criteria were: (1) Meeting the diagnostic criteria for MDD as defined by the DSM-5; (2) Drug-free; (3) Have completed nine years of compulsory education; (4) Normal or corrected-to-normal vision; (5) No color blindness or color weakness. The exclusion criteria included: (1) Presence of comorbid

psychiatric disorders or major physical illnesses; (2) Organic brain dysfunction.

Sixty-seven age- and sex-matched healthy participants (male = 29, female = 38), aged between 16 and 45 (22.25±3.975), were recruited through advertisements from universities and communities in Changsha City and enrolled in this study as healthy control (HC). The inclusion criteria were: (1) No history of or current psychiatric disorders; (2) Have completed nine years of compulsory education; (3) Normal or corrected-to-normal vision; (4) No color blindness or color weakness. The exclusion criteria included organic brain dysfunction.

Participants with MDD did not receive financial compensation but were provided with free follow-up assessments. HC were compensated with 300 RMB (Chinese Yuan) for their participation. The required sample size was calculated using G*Power software [29], which suggested 36 participants were needed for each group. To increase the statistical power, we ultimately enrolled 159 MDD and 67 HC to account for potential attrition.

The study was approved by the ethics committee of the Second Xiangya Hospital, Central South University, and was carried out following the provisions of the World Medical Association Declaration of Helsinki. Written informed consent was obtained from all participants.

Measurements

The Beck Depression Inventory (BDI) developed by Beck and others [30], was used for individuals to self-assess their depression level. It consists of 21 items, with a 4-point rating scale ranging from 0 to 3. The higher the score on the scale, the more severe the depression.

A simplified version of the Wechsler Adult Intelligence Scale (WAIS) [31], which includes the knowledge test, calculation test, verbal similarity test, and digit span test, was used to assess the verbal intelligence of the participants.

Stimuli and procedures

All subjects performed the color delay estimation task to evaluate the performance of VWM. All the stimuli were generated and programmed by Matlab and Psychtoolbox. The experiment was conducted using a 14-inch Huawei MateBook monitor, and the resolution was set to 1920*1080p with a refresh rate of 60 Hz. The participants sat 60 cm away from the computer screen in a quiet environment to perform it.

The color delay estimation task is depicted in Fig. 1. On each trial, a fixation cross was first presented in the center of the screen and maintained throughout the experiment [32]. After a duration randomly chosen from a sequence of 400, 450, 500, 550, or 600 milliseconds, a set of colored squares (set size = 1,2,4 or 6) were shown for a duration of 500 ms in the sample array. The order of set sizes was randomized between blocks. The probe array appeared after a delay of 1000 ms and consisted of a randomly rotated color wheel and an equal number of outlined squares located at the same positions as items in the sample array, with one of the outlined squares bolded as the probe. Participants were asked to use a computer mouse to click on a color on the color wheel to select the remembered color of the probe as accurately as possible, with no time limit on their response. Each square was 1.5° × 1.5° of visual angle. The colors of the squares were randomly chosen from a selection of 360 colors equally distributed around the wheel, representing the CIE L*a*b color space, centered at L = 70, a = 20, b = 38, with a radius of 60 in the color space [32]. The color wheel had a width of 2.1° of visual angle, with inner and outer radii of 7.8° and 9.8° of visual angle, respectively. Before the formal

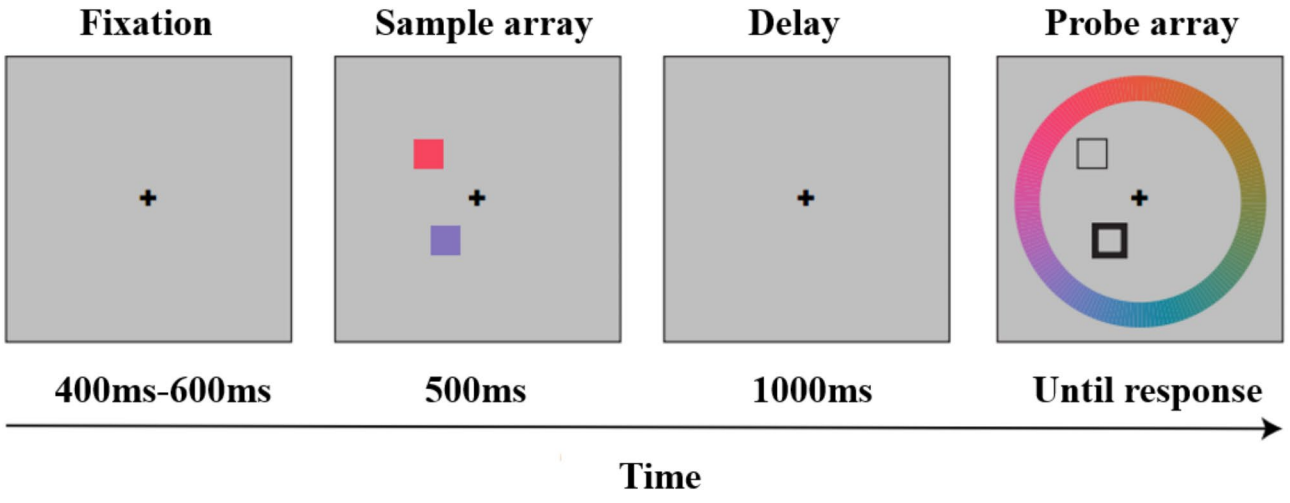

Fig. 1 The color delay estimation task process. Participants were asked to remember the colors of all squares on the screen (i.e., set size = 2 in this example trial), and select the color of the probe square (the bold one in the lower visual field in this example) on the color wheel after a delay of 1000 milliseconds

test, participants completed 5 practice trials to familiarize themselves with the task requirements. These practice trials were identical in structure to the experimental trials but were excluded from the final analysis. For the formal task, the participants completed 4 blocks for the set sizes 1, 2, 4, and 6, respectively, and each block included 51 trials. The order of the blocks was randomized across different participants.

For each trial, the angular difference between the color chosen by the participant and the true color of the target was defined as the response error. The standard deviation of the response error on the circle (circular standard deviation, CSD) for each experimental condition was adopted as one of the main indicators to assess the visual working memory (VWM), with larger CSD indicating poorer working memory performance [19, 32, 33].

Before the commencement of the formal experiment, each participant was required to complete a color perception task to evaluate their color perception abilities. The color perception task is depicted in Fig. 2. The task procedure was similar to the color delay estimation task, but each time, only one colored square was presented. The participants were asked to select the corresponding color on a color wheel and to complete one block, which included 24 trials. Similarly, CSD was used to reflect the participants' color perception ability (represented by base CSD in this study).

Computational modeling and comparison

The original data were modeled using the BADS Toolbox in MATLAB software. Specifically, the maximum likelihood estimation algorithm was applied in conjunction with five mainstream models of VWM to fit the angular differences between each participant's responses and the correct answers. The five mainstream models included: (1) The item-limit (IL) model, according to which, working memory can retain only a fixed number of items with a fixed response variability across set size levels. All the items can be perfectly recalled, meaning that there is no uncertainty during the sensory encoding stage [34, 35]. However, choice variability arises between sensory measurements and participants' color reports, consequently requiring the IL model to estimate two distinct parameters: choice variability (k_r) and memory capacity (K). (2) The slots-plus-averaging (SA) model, acknowledges the presence of noise during the sensory encoding stage, but it insists that memory resources manifest as discrete chunks, and these chunks can be flexibly allocated to multiple memory items [36]. The SA model estimates two key parameters: memory capacity (K) and unit resource (J_s); the J_s specifies the resource allocation per representational chunk in the memory system. (3) The mixture (MIX) model. It assumes that the memory capacity of each participant is fixed, but their response changes with the size of the set [37]. The MIX model postulates uncertainty in the transformation from sensory input to participants' color reports, whereby this uncertainty

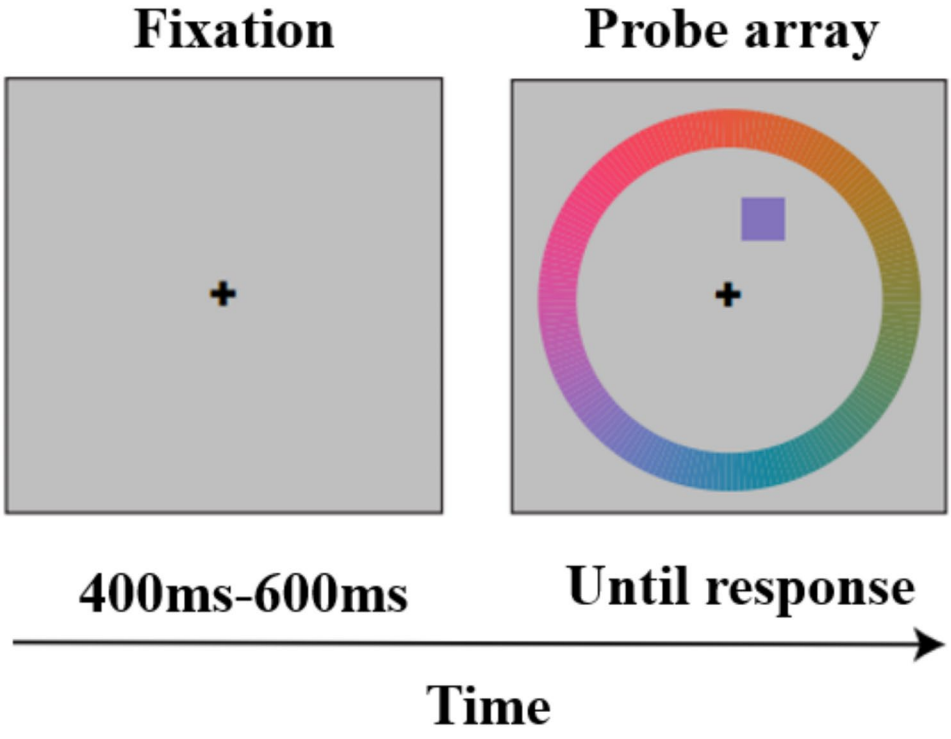

Fig. 2 The color perception task process. Participants were asked to select the corresponding color on a color wheel

arises from both sensory processing noise and choice variability, with its magnitude parametrically modulated by set size. The MIX model generates three parameters: k_1, k_3, and memory capacity K, where k_1 and k_3 represent the uncertainty factors when the set sizes are 1 and 3, respectively. (4) The equal-precision (EP) model. Memory resources are assumed to be continuous and evenly distributed across all items [38]. The EP model generates three parameters: initial resources ($\bar{J}_1$), decaying exponent (α), and choice variability (k_r). $\bar{J}_1$ represents the memory resources when the memory load is one, and α represents the degree to which the average memory resources decrease as the set size increases. The k_r represents the uncertainty between sensory measurements and participants' color reports. (5) The variable-precision (VP) model. It is similar to the EP model but it proposes that the allocation of memory resources across different items is variable [39]. The VP model, based on the EP model parameters, adds a parameter called resource allocation variability (τ). The larger this value, the more imbalanced the allocation of memory resources is between trials and items, meaning that some items in certain trials occupy more memory resources, while others occupy fewer resources.

The IL, SA, and MIX models are based on the discrete slot theory. The EP and VP models are based on the continuous resource theory. The discrete slot theory posits that VWM is constrained by a fixed number of capacity limitations, with memory resources existing as discrete chunks. In contrast, the continuous resource theory proposes a memory system operating under finite resource constraints, where memory resources can be flexibly allocated among different items.

We compared which of the five models demonstrated the best fit for our data using both the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) [40–42]. The two criteria differ in their focus: AIC prioritizes predictive accuracy, aiming to select models that generalize well to future data, whereas BIC emphasizes goodness of fit, seeking the model that best explains the observed data. By combining these two criteria, a more comprehensive evaluation of the models can be achieved.

Table 1 Evidence categories for bayesian factor BF_{10} [45, 48]

Bayesian factor	Interpretation
> 100	Decisive evidence for H_1
30–100	Very strong evidence for H_1
10–30	Strong evidence for H_1
3–10	Substantial evidence for H_1
1–3	Anecdotal evidence for H_1
1	No evidence
0.33-1	Anecdotal evidence for H_0
0.1–0.33	Substantial evidence for H_0
0.033 – 0.1	Strong evidence for H_0
0.01–0.033	Very strong evidence for H_0
< 0.01	Decisive evidence for H_0

Statistical analysis

The one-way analysis of variance (ANOVAs), two sample t-tests, and chi-square tests were used to evaluate the demographic and clinical differences among different groups.

To evaluate the group and sex differences on standard behavioral indicator (CSD) of the VWM and the VP model parameters (Initial resources, Decaying exponent, Resource allocation variability, and Choice variability), we performed the Bayesian ANCOVA in JASP software [43–45]. The Bayesian ANOVA is a method used in Bayesian statistics for model comparison and hypothesis testing [45, 46]. BF_{10} represents the relative support of the alternative hypothesis over the null hypothesis under specific data conditions. In the Bayesian ANOVA, the evidence in favor of an effect was expressed as the "inclusion Bayesian Factor" (BF_{inclu}), which measures the likelihood of the data in models that include the factor compared to in models that exclude the factor [45]. The evidence categories for Bayesian factors are shown in Table 1.

There are several advantages of Bayesian ANOVA. Firstly, the computation of Bayesian factors simultaneously considers both the null hypothesis (H_0) and alternative hypothesis (H_1) and updates the prior probabilities of H_0 and H_1 being true based on all existing data [47, 48]. Secondly, the calculation of Bayesian factors relies on the principle of likelihood and does not require preconceived assumptions about the data analysis [49–51]. Meanwhile, the Bayesian ANOVA can provide the posterior distribution of parameters [52]. Moreover, the Bayesian ANOVA inherently accounts for uncertainty in the data by providing a complete posterior distribution, which eliminates the need for multiple comparison corrections [53]. Most importantly, the Bayesian ANOVA allows differences in variance between groups, which is more suitable for our data than the traditional AVOVA.

The Pearson correlation coefficients were calculated to represent the relationship between the abnormal model parameters and the BDI scores in MDD patients.

Results

Demographic and clinical variable results

The descriptive results of demographic variables and their group differences are shown in Table 2. The four groups (male MDD, female MDD, male HC, female HC) were matched in age ($F = 1.258$, $p = .290$, $\eta^2_p = 0.017$). MDD and HC were matched in sex ($\chi^2 = 0.262$, $p = .609$, $Phi = 0.034$). There were significant group differences in

Table 2 Demographic variables for all participants

	MDD(*N* = 159)		HC(*N* = 67)			
	Male(*N* = 63)	Female(*N* = 96)	Male(*N* = 29)	Female(*N* = 38)	*F*	*p*
Age	21.87 ± 5.12	21.01 ± 4.15	21.90 ± 4.49	22.53 ± 3.57	1.258	0.290
IQ	49.68 ± 7.71	48.20 ± 7.51	52.93 ± 4.85	52.76 ± 7.68	5.337	0.001
BDI score	29.56 ± 8.64	31.25 ± 8.13	6.55 ± 4.34	5.39 ± 4.18	176.615	< 0.001
Base CSD	0.33 ± 0.18	0.28 ± 0.20	0.28 ± 0.13	0.24 ± 0.13	2.171	0.092

Base CSD: The circular standard deviation in the color perception task reflects the participants' color perception ability

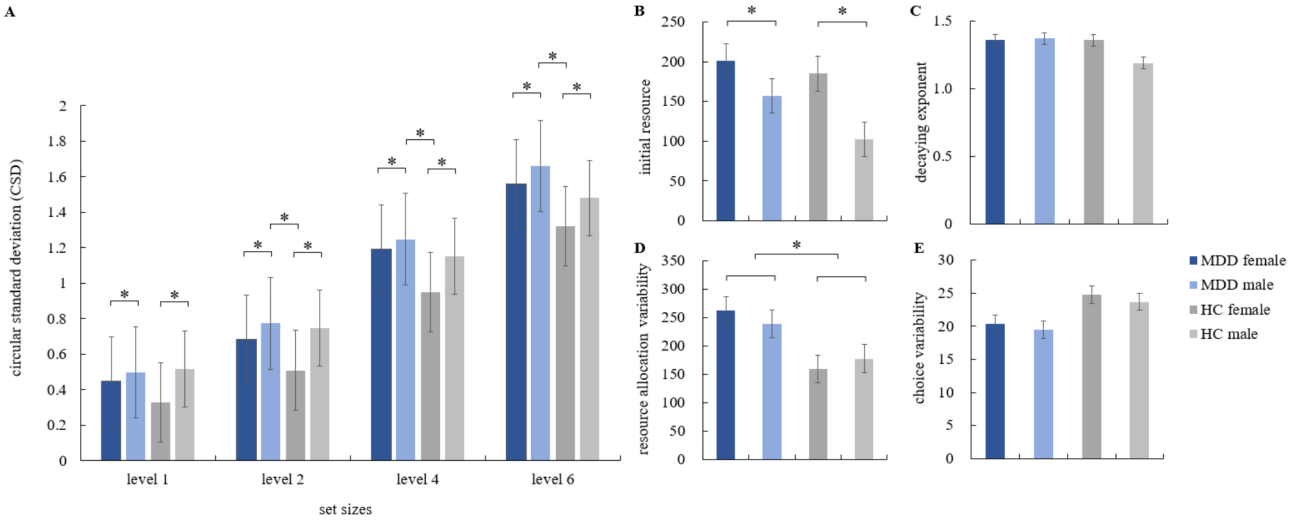

Fig. 3 Group and sex differences on the circular standard deviation (CSD) in several set sizes and on the VP model parameters. The CSD represents the visual memory precision of the subjects, and the larger the CSD, the worse the memory precision. Males showed higher CSD than females at all levels of set size, and MDD showed higher CSD than HC at set size 2, 4, and 6 but not at set size 1 (**A**). Females have more initial resources than males (**B**). MDD has larger resource allocation variability than HC (**D**). No significant group differences or sex differences in decaying exponent and choice variability(**C** & **E**). Note: ∗ represents significant differences between the groups or sexes, and the error bars represent the error deviations

IQ ($F = 5.337$, $p = .001$, $\eta^2_p = 0.067$) and BDI ($F = 176.615$, $p < .001$, $\eta^2_p = 0.705$). The post-hoc tests indicated that IQ in male HC was higher than in male MDD ($p = .049$, *Cohen's* $d = 2.797$), in female HC was higher than in female MDD($p = .001$, *Cohen's* $d = 4.603$), in female HC was higher than in male MDD($p = .042$, *Cohen's* $d = 2.898$) and in male HC was higher than in female MDD($p = .003$, *Cohen's* $d = 4.316$) The post-hoc tests also indicated that male HC had lower BDI score than male MDD ($p < .001$, *Cohen's* $d = 19.647$), female HC had lower BDI score than female MDD ($p < .001$, *Cohen's* $d = 25.856$), female HC had lower BDI score than male MDD ($p < .001$, *Cohen's* $d = 22.541$), and male HC had lower BDI score than female MDD ($p < .001$, *Cohen's* $d = 22.343$). We included IQ and age as covariates in the subsequent analysis.

Standard outcome measures in the behavioral task

Results of the one-way ANOVA showed that there was no significant difference in base CSD among the four groups, indicating that there was no significant difference in their color perception ability. We included base CSD as a covariate in the subsequent analysis to exclude the influence of color perception ability.

The group and sex differences in the CSD in different set sizes are depicted in Fig. 3. The Bayesian three-way mixed ANCOVA, with group and sex as between-subjects factors and set size as a within-subjects factor, was conducted to compare the CSD in different set sizes.

The results provided decisive evidence for the main effects of group (BF_{inclu}=140.095), sex (BF_{inclu}=1776.799), and set size (BF_{inclu}=∞) separately. The post-hoc tests indicated that CSD under a larger set size was larger than that under a smaller set size (BF_{10} in the supplementary materials Table S1, decisive evidence for H_1), meaning that the participants' VWM precision was worse with increasing set size levels. The CSD of MDD was larger than that of HC ($BF_{10} = 103.872$, decisive evidence for H_1), indicating that the VWM precision of MDD was worse than HC, and the CSD for males was larger than that for females ($BF_{10} = 10.548$, strong evidence for H_1), meaning that the VWM precision of males was worse than females. Also, very strong evidence for the alternative hypothesis of an interaction effect between set size and group (BF_{inclu}=43.446) in the results of the Bayesian ANCOVA was revealed. The post-hoc tests indicated that when the set size was one, the evidence supporting

the difference between MDD and HC was anecdotal (BF_{10} = 1.355). Here, we did not have enough confidence to say that there was a difference in CSD between MDD and HC. When the set size was two, the evidence was strong (BF_{10} = 12.855), and when the set sizes were four and six, the evidence was decisive (BF_{10} = 1146.476, BF_{10} = 1253.215). Under these three conditions, we had enough confidence to believe that the CSD of MDD was larger than that of HC, meaning that the VWM precision of MDD was worse than HC. The Bayesian ANCOVA yielded anecdotal evidence for no interaction effect between group and sex (BF_{inclu}= 0.993), very strong evidence for no interaction effect between set size and sex (BF_{inclu}= 0.020), as well as strong evidence for no interaction effect among set size, sex, and group (BF_{inclu}= 0.048). The results provided anecdotal evidence for the covariate effect of the base CSD (refers to the color perception ability, BF_{inclu}=1.015), which had no significant impact on our research results.

Results for model comparison

Based on the results, we discovered that the VP model was the best-fitting model for over 97% of the participants in the HC and the MDD groups. This result suggested that the VP model was the best-fitting model, and MDD and HC adopted the same processing procedure when performing the working memory task. The details of the model comparison were described in the supplementary materials. All of the data and the code are available via OSF. (https://osf.io/qc6ua/?view_only=563b892b875843c1975e7f7b94a64fcc)

Results from the VP model

The group and sex differences on the VP model parameters are depicted in Fig. 3. The Bayesian two-way ANCOVA, with group and sex as between-subject variables, was conducted to compare the parameters in the VP model.

The results provided anecdotal evidence for no main effect of the group on the initial resources ($\bar{J}_1$, BF_{inclu}= 0.477), the choice variability (k_r, BF_{inclu}= 0.608), and the decaying exponent (α, BF_{inclu}= 0.744). This can be explained as MDD and HC had a similar amount of memory resources, with a similar amount of noise generated between sensory measurement and color reporting, and the average memory resources decreased by a similar rate as set size increased. However, it provided substantial evidence supporting the main effect of the group on resource allocation variability (BF_{inclu}=3.976). The post-hoc tests indicated that resource allocation variability was larger in MDD compared to HC (BF_{10} = 19.421, strong evidence for H_1). This finding suggested that the memory resources of MDD were allocated less evenly across different items, with more memory resources allocated to some items and fewer to others. In contrast, HC allocated memory resources more evenly across all the items. This can be understood as a difference in memory strategies.

For the effect of sex, the analyses yield substantial evidence on the initial resources ($\bar{J}_1$, BF_{inclu}=5.104), the post-hoc tests showed that females had more initial resources than males (BF_{10} = 6.003, substantial evidence for H_1), indicating that females had more memory resources than males in the color delay estimation task. The sex differences in initial resources seem to be more innate and inherent. However, there was substantial evidence for no main effect of sex on the decaying exponent (α, BF_{inclu}= 0.175), the choice variability (k_r, BF_{inclu}= 0.157), and the resource allocation variability (τ, BF_{inclu}= 0.155), which indicated that the VWM processing strategy may be similar between females and males.

No main effects of interaction between group and sex were suggested on the initial resources (BF_{inclu}= 0.279, substantial evidence), the resource allocation variability (BF_{inclu}= 0.275, substantial evidence), the choice variability (BF_{inclu}= 0.212, substantial evidence), and the decaying exponent (BF_{inclu}= 0.723, anecdotal evidence). For the covariate effect of the base CSD (refers to the color perception ability), there was anecdotal evidence for no effect on the initial resources ($\bar{J}_1$, BF_{inclu}= 0.353) and substantial evidence for no effect on the resource allocation variability (τ, BF_{inclu}= 0.319), anecdotal evidence for an effect on the choice variability (k_r, BF_{inclu}=1.290), and very strong evidence for an effect on the decaying exponent (α, BF_{inclu}=55.964), which had no significant impact on our research results. More results regarding the effects of covariates were listed in the supplementary materials.

Correlations with the symptom severity

The correlation plot of resource allocation variability and BDI scores is shown in Fig. 4. The correlation analysis revealed a significant positive relationship between resource allocation variability and BDI scores (r =.167, p =.035, uncorrected) in MDD. In other words, the higher the BDI scores of MDD, the more unevenly memory resources were allocated across different items. No other significant correlations between measures in the tasks and the symptom severity were detected.

Discussion

This study aimed to explore the computational cognitive mechanism of VWM, focusing on precision in MDD and sex differences. We found that the VWM precision of MDD was worse than HC, and the VWM precision of females was better than males, which corresponded to our previous hypotheses. Further, we evaluated and

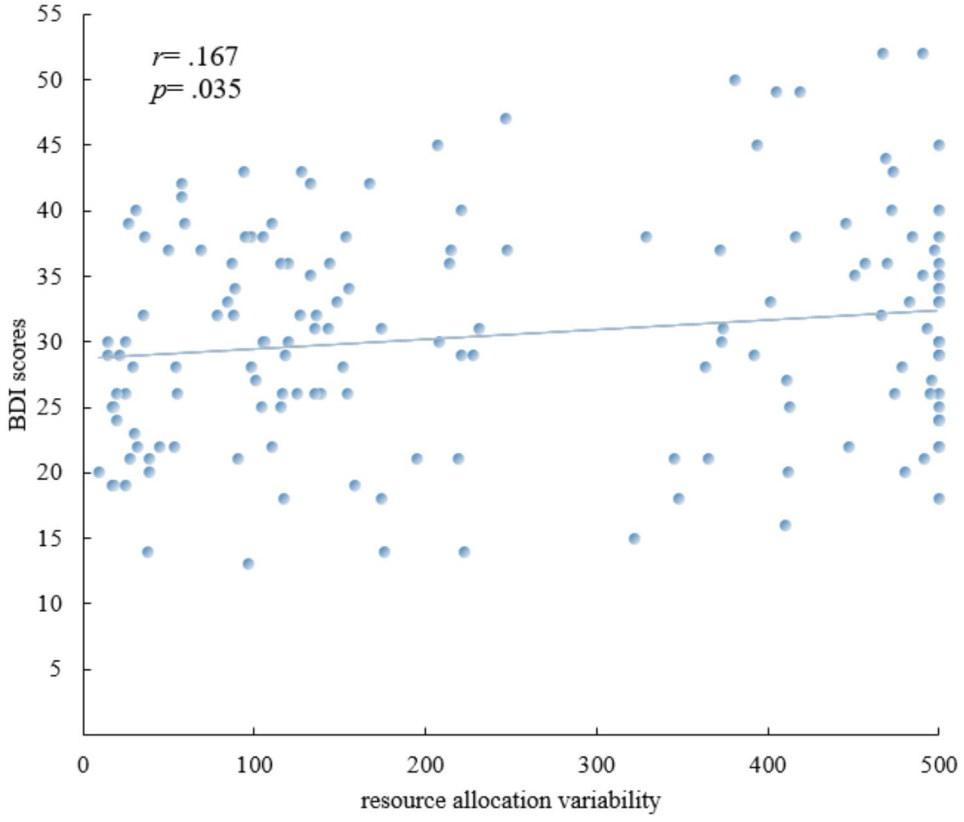

Fig. 4 A significant positive relationship between resource allocation variability and BDI scores in MDD

compared the parameters of the VP model among all groups and discovered that MDD had larger resource allocation variability, while females had more initial resources. The resource allocation variability was significantly correlated with the BDI scores in MDD. These findings revealed the computational processing mechanism of VWM in MDD, proposed a new perspective into the working memory deficit in MDD and provided an empirical basis for further proposing targeted intervention measures.

Our findings indicated that larger resource allocation variability was a key factor contributing to impaired VWM precision in MDD. The resource allocation variability was one of the parameters of the VP model and referred to the heterogeneity of memory resource allocation across multiple color squares in the color delay estimation task. The larger the resource allocation variability, the more unevenly the memory resources were distributed among the color squares. Fluctuations in attention may be one source of resource allocation variability [19, 39]. Attention and working memory are two core components of individual cognitive function, and they are closely related [54]. Also, a large body of research has confirmed that MDD patients exhibit attention deficits [55]. Specifically, studies have found that depressed patients experience attention distraction disorders, resulting in poor performance when completing two tasks simultaneously [55, 56]. If MDD patients cannot focus on multiple items simultaneously during the memory encoding phase, it may lead to uneven allocation of resources. In addition, the poor motivation of MDD patients has been confirmed by many studies [57, 58], so they may only focus on a few items and neglect others, which leads to the allocation of resources is uneven. It may be another reason for their poor visual working memory precision. Interestingly, our research results found that there was no significant difference between MDD and HC when the memory load was one. However, as the memory load increased to two, four, and six, the performance of MDD was significantly worse than that of HC. Of course, this can also be interpreted as the complexity of the task influencing VWM precision. When there is more intense competition for memory resources (set sizes are 2, 4, 6), differences in VWM precision are more easily detected. Besides fluctuation in attention and poor motivation, neural variability may be the other source of resource allocation variability [19]. Neural variability refers to the fluctuations and inconsistencies in the activity of neurons and neural circuits over time. It is an inherent characteristic of neural systems and plays an important role in sensory processing and cognitive tasks [59, 60]. Increased neural variability in specific brain

regions has been linked to cognitive deficits in disorders like MDD [61, 62]. Recent studies indicated that variability in precision may be caused by stimulus-specific effects of neural variability [63].

The study also found that females had better visual working memory precision than males regarding diagnosis, maybe because they had more initial resources. Previous research on sex differences in visual working memory has also shown that while males respond more quickly, females respond more accurately [20, 21]. Also, females tend to pay more attention to the details of objects [22], which may make them better at recognizing the colors of color blocks. The initial resources are the memory resources when the memory load is one [18]. The sex differences in initial resources may be due to the following reasons. Firstly, substantial clinical evidence suggests that ovarian hormones, including estradiol, which can regulate hippocampal synaptic plasticity and induce plasticity from cells to circuits, play a role in working memory in females and maybe the physiological basis of sex differences in performance [64, 65]. Meanwhile, under hormone-suppression conditions, regional cerebral blood flow patterns from the prefrontal cortex are markedly reduced [66], while the prefrontal cortex is vital for working memory [67]. Additionally, females have a larger gray matter volume in the parietal lobe compared to males [68, 69], which plays an important role in working memory [70, 71]. Working memory performance is positively correlated with parietal lobe gray matter volume [71].

However, all the calculation models used in our study are designed based on the color delay estimation task. The VWM deficits of MDD may arise from different mechanisms in different project characteristics. Whether visual working memory deficits in tasks specific to other project characteristics (e.g., location and orientation) can also be explained by larger memory resource allocation needs future studies to verify.

In summary, our findings revealed that the abnormally large resource allocation variability in MDD may account for their worse VWM precision. Different from the decreased-capacity theory, these findings may shed new light on the explanation of the VWM deficit in MDD. Additionally, females had better VWM precision, probably because they had more initial resources. This study identified the best-fitting model for VWM in MDD, eliminating the need for model comparison in future research. Also, our findings may have implications for further proposing targeted intervention measures in MDD.

Abbreviations

MDD	Major depressive disorder
HC	Healthy control
IL model	Item-limit model
SA model	Slots-plus-averaging model
MIX model	Mixture model
EP model	Equal-precision model
VP model	Variable-precision model
CSD	Circular standard deviation
VWM	Visual working memory

Supplementary Information

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Supplementary Material 1

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Author contributions

Qingzu Kong: Conceptualization, Formal analysis, Methodology, Writing– original draft, Writing– review & editing. Qian Liu: Writing– review & editing. Feng Gao: Methodology. Xiang Wang: Conceptualization, Writing– review & editing. Zhiyan Wang: Methodology. Chuman Xiao: Writing– review & editing. Xinyue Zhang: Conceptualization. Qianmei Yu: Data curation. Jie Fan: Writing– review & editing, Supervision, Funding acquisition. Xiongzhao Zhu: Supervision, Funding acquisition. All authors approved the final version of the paper for submission.

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Data availability

All of the data and code are available via OSF.(https://osf.io/qc6ua/?view_only=563b892b875843c1975e7f7b94a64fcc).

Declarations

Ethics approval and consent to participate

The study was approved by the ethics committee of the Second Xiangya Hospital, Central South University, and was carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki. Written informed consent was obtained from all participants.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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