Choice overload interferes early processing and necessitates late compensation: evidence from electroencephalogram

Xinye Hu[1], Zong Meng[2], and Qinghua He[1]

[1]Southwest University
[2]Beijing Normal University

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Abstract

Having a multitude of choices can be advantageous, yet an abundance of options can be detrimental to the decision-making process. Based on existing research, the present study combined electroencephalogram and self-reported methodologies to investigate the neural mechanisms underlying the phenomenon of choice overload. Behavioral data suggested that an increase in the number of options led to negative evaluations and avoidance of choice tendencies, even in the absence of time pressure. Event-related potential results indicated that the large choice set interfered with the early visual process, as evidenced by the small P1 amplitude, and failed to attract more attentional resources in the early stage, as evidenced by the small amplitude of P2 and N2. However, the LPC amplitude was increased in the late stage, suggesting greater investment of attentional resources and higher emotional arousal. Multivariate pattern analysis revealed that the difference between small and large choice set began at around 120ms and the early and late stages were characterized by opposite activation patterns. This suggested that too many options interfered with early processing and necessitate continued processing at a later stage. In summary, both behavioral and ERP results confirm the choice overload effect, and it was observed that individuals tend to subjectively exaggerate the choice overload effect.

Introduction

Advances in science and technology, combined with globalization, have drastically changed the way humans conduct economic activities, giving consumers a wide range of options (Lee & Lee, 2004; Lurie, 2004) even when making simple decisions such as what to eat for breakfast. While it may not be consequential to make the wrong choice for a daily decision, it is a different story when it comes to lifetime decisions such as selecting a healthcare plan or making a retirement investment, where one has to make the best choice from dozens or even hundreds of options (Gourville & Soman, 2005). It is thus essential that individuals, as well as corporations, governments, and state agencies, make informed decisions among the numerous options available to them, as the cost of making the wrong decision or delaying it can be quite significant (Sagi & Friedland, 2007).

Theories in economics, marketing, and psychology suggest that having more choices increases the sense of freedom and self-determination (Warren & Lupinek, 2019), and is more attractive to merchants as it can satisfy a wider range of consumer preferences (Buturak & Evren, 2017). However, large choice sets can lead to an increase in the cost of decision-making, such as the fear of mistakenly passing up the ideal choice, making trade-offs, and being hesitant in decision-making (Diehl & Poynor, 2010; Lee et al., 2021; Reed et al., 2011). This can result in decreased satisfaction with choices, alteration of the initial choice, or even postponement of the choice, all of which are unfavorable outcomes (Diehl & Poynor, 2010; Wan et al., 2009). Evidence of this phenomenon (i.e., choice overload) (D'Angelo & Toma, 2017; Iyengar & Lepper, 2000).is seen in the financial investment field, where fewer types of pension plans are offered and more employees are willing to join pension plans (Soroya et al., 2021).

Research has attempted to identify the optimal number of options for consumers, and it has been found that a choice set between 8-15 options is preferred (Chernev et al., 2015; Sharma & Nair, 2017). Large choice sets may initially be appealing, however, if cognitive load is present, the motivation to make a selection is reduced (Basili & Vannucci, 2015). Studies conducted in the areas of charitable giving and travel souvenirs indicated that choice overload did not occur (Lindkvist & Luke, 2022; Sthapit, 2018). A meta-analysis revealed that the effects of choice overload are moderated by boundary conditions (Scheibehenne et al., 2009; Spassova & Isen, 2013) such as the difficulty of the decision task (e.g. time pressure; (Basso et al., 2019)), the complexity of the choice set (e.g. option attributes and dominant options; (Townsend & Kahn, 2014; Wan et al., 2009)), preference uncertainty (e.g. expertise; (Hadar & Sood, 2014)), individual differences (e.g. trait anxiety, (Hu et al., 2023)), and the decision goal (e.g. decision focus; (Wang & Shukla, 2013)).

The cognitive load theory (Sweller, 1988) argued that the decision-making process required a substantial amount of cognitive resources. When the amount of cognitive resources required to make a decision exceed the individual's available resources, they experience cognitive overload. Compared to a small choice set, individuals must process more information when presented with a larger choice set, which can exceed their cognitive capacity (McShane & Bockenholt, 2018). This can lead to decreased satisfaction, increased negative experiences, and even delays or abandonment of choices (Gerasimou, 2018; Hills et al., 2013). Previous researchers have primarily evaluated cognitive load through self-report methods, such as subjective evaluations of task difficulty and negative emotions (Gerasimou & Papi, 2018; Li, 2017; Saltsman et al., 2019; Song et al., 2019; Sthapit et al., 2017; Turri & Watson, 2022). Current explanatory models of choice overload have been largely derived from behavioral experiments or self-reports, with only one study combining eye-tracking and functional magnetic resonance imaging to investigate choice overload. This study found that the cost of choosing from a large choice set can be reflected in the activity of task-relevant areas of visual and sensorimotor processing, saccade frequency, and average saccade amplitudes (Reutskaja et al., 2018). Additionally, some researchers have used electroencephalogram (EEG) to explore the effects of information overload on decision-making (Kim et al., 2018). It has been found that information overload may impair the decision-making process, as evidenced by a decrease in P2 and P3 amplitudes, as well as an increase in LPC. However, it is important to note that choice overload is distinct from information overload, and it is possible for consumers to experience choice overload without experiencing information overload (Kuan et al., 2014; Wan et al., 2009).

This study utilizes EEG to investigate the neural foundations of choice overload and to evaluate the cognitive load theory. As per the Cognitive Load Theory, larger choice sets necessitate more attentional resources, resulting in the choice overload effect. However, it is still unclear when and how choice overload affects attentional engagement. Based on prior research, the early component P1 reflects attention-based early visual perceptual processing and allocation of attention to stimuli (Grand et al., 2004; Mangun, 1995; Mangun & Buck, 1998). The magnitude of P2 is related to the allocation of attentional resources and the ability to sustain perceptual processing (Ferreira-Santos et al., 2012; Huang & Luo, 2006; Mercado et al., 2006; Schupp et al., 2003). P3 is a positive component related to the allocation of attentional resources allocation (Folstein et al., 2008; Polich, 1987), and is also associated with task difficulty and decision confidence (Nieuwenhuis et al., 2005; Qin & Han, 2009). LPC is a widely used physiological measure that reflects emotional responses and the allocation of attentional resources during cognitive processes (Alomari et al., 2015; Cuthbert et al., 2000; Ferrari et al., 2011; Hajcak & Foti, 2020). In summary, P1 and P2 were selected as markers of attention during the initial processing stage, while P3 was used to measure attention during the intermediate processing stage. Additionally, LPC was employed as an indicator of attention during the final processing stage.

We additionally conducted multivariate pattern analysis (MVPA) to capture the differences in processing patterns between different choice set sizes. This method has become increasingly popular in cognitive neuroscience due to its increased sensitivity compared to traditional univariate analysis (Carlson et al., 2019; Meng et al., 2023). By combining MVPA analysis with event-related potential (ERP) analysis, we can gain a more comprehensive understanding of the neural mechanisms of choice overload and develop a more accurate model for it.

Materials and methods

Participants

A total of 30 right-handed individuals with no history of psychiatric or neurological disorders and normal vision (or vision corrected to normal) were recruited for the study. After providing written informed consent, each participant was compensated with ¥75. Ultimately, 28 participants (18 female, mean age = 21.6 years, SD = 1.5 years) were included in the sample, as two participants were excluded due to excessive EEG artifacts. This study was approved by the local Human Ethics Committee for Human Research, and it was conducted in accordance with the guidelines of the Declaration of Helsinki and its subsequent amendments.

Stimuli, apparatus, andprocedure

Participant completed the experiment in a quiet and soundproof laboratory, individually. They were asked to select pictures in four different choice set sizes, and then fill out a choice overload questionnaire to evaluate their experience (**Fig. 1A**). The experiment was managed by E-Prime 2.0 (Psychology Software Tools, Inc., Pittsburgh, PA), which controlled the presentation and timing of the stimuli.

In the choice task, each trial consisted of three main stages: fixation (1s), image presentation stage (10s + 0.5s mask) and response (3s) (**Fig. 1B**). During the image presentation stage, participants were shown sets of natural landscape images and were asked to select the one they preferred. The sets size varied, containing 4, 8, 12, or 16 clear images, while non-target images were mosaicked (**Fig. 1C and D**). The 10-second duration of the image presentation period was determined based on a pilot experiment, allowing participants enough time to make decisions without feeling rushed, and to make use of the period for information processing. The mask was used to reduce the after effect of image presentation. All pictures were obtained from the free image material website (*https://www.pexels.com/zh-cn/*) with a total of 800 pictures. These images were standardized to 236 × 177 pixels. Each image was only presented once in the same condition. During the response stage, participants used the mouse to select their preferred image from the current selection set. Each condition contained 50 trials, resulting a total of 200 trials. The order of the four conditions was counterbalanced across participants.

Upon the completion of each condition in the choice task, participants were asked to rate the difficulty of selection on a 7-point scale, together with their positive (including satisfaction with the final choice, pleasure, and satisfaction with the selection process) and negative emotions (including regret, hesitation, and frustration), as well as their inclination to avoid making a choice (for example, delaying or abandoning the choice). Additionally, they were prompted to assess whether the choice sets contained the "right amount of options" on a 7-point scale.

EEG recording and preprocessing

EEG data was acquired using a standard 64-channel Ag/AgCl electrode cap (Brain Products) in accordance with the extended international 10–20 system. Vertical and horizontal electrooculograms were simultaneously recorded, with electrodes placed below the left eye and on the outer canthus of the right eye. The EEG signals were referenced to the FCz electrode and sampled at 1000 Hz, and were online filtered using a 0.1-100 Hz bandpass filter. The impedance of all electrodes was kept below 10 kΩ during the recording.

EEG data was preprocessed offline using EEGLAB (Delorme & Makeig, 2004) and custom scripts in MATLAB (MathWorks). A zero-phase high-pass filter at 0.3 Hz was used to eliminate slow drifts, followed by*Zapline-plus* (Klug & Kloosterman, 2022) and *CleanLine*(Mullen 2012) to remove line noise. Bad channels were identified and removed by *Clean_rawdata* , and the data was downsampled to 250 Hz to conserve computation time. Independent component analysis was conducted with *ICLabel* (Pion-Tonachini et al., 2019) to recognize and eliminate components associated with eye blink, vertical eye movement, muscle motor, and channel noise. The EEG data was then segmented from -300 to 1500 ms with epochs locked on the onset of the stimuli, and baseline correction was conducted using an interval from -300 to 0 ms. Artifact rejection was used to mark and exclude epochs with voltage values exceeding ± 100 μV at any time point. Bad channels were interpolated, and the data was re-referenced to the common average. Our preprocessing process was based on some recent standardized EEG processing pipelines (Bailey et al., 2023; Monachino et al., 2022; Pedroni et al., 2019).

Two participants had more than 40% of their trials identified as artifacts, and were thus excluded from further analysis. Of the 28 participants included, 2.57% (SD = 3.84%) of the trials contained artifacts, and 1.897 (SD = 1.496) channels were deemed bad.

ERP analysis

ERPLAB (Lopez-Calderon & Luck, 2014) was utilized to calculate the amplitudes of ERP components after averaging epochs for each condition per participant. The occipital electrodes (Oz, O1, O2) were employed to calculate the amplitudes of P1 and P2, the frontal electrodes (Fz, F1, F2) to calculate the amplitudes of N2, and the parietal electrodes (Pz, P1, P2) to calculate the amplitudes of P3 and LPC. The mean amplitudes of P1, P3 and LPC were calculated over the respective intervals of 100-150 ms, 400-600 ms and 1000-1500 ms, while the mean amplitudes of P2 and N2 were calculated over the interval of 200-350 ms.

Multivariate pattern analysis

MVPA was applied to decode patterns of neural activity associated with different numbers of choices. A backward decoding classification algorithm (linear discriminant analysis) was used, with all electrodes as features. To ensure reliability and interpretability of the results, the choice set sizes of 4 and 8 were grouped together to create the small choice set condition, and 12 and 16 were grouped together to create the large choice set condition11Decoding was also conducted with four distinct choice set sizes, with results presented in the Supplementary Materials.. Before performing MVPA, the epochs were down sampled to 50 Hz to minimize computation time. A 10-fold cross-validation procedure was the applied using within-class and between-class balancing with the Amsterdam Decoding and Modeling toolbox (Fahrenfort et al., 2018). In this procedure, the trials were randomized and divided into 10 equal-sized folds. Nine folds were used for training, while the remaining fold was used for testing. This process was repeated 10 times, ensuring that each fold served as the test set once. To ensure the impartiality of the classifier training, we implemented within-class balancing by undersampling. This procedure involved the random selection of trials from conditions with a surplus of trials to harmonize the conditions with fewer trials, thereby equalizing the count of trials within each class. Additionally, between-class balancing using undersampling was employed to mitigate the potential of the classifier from developing a bias towards the overrepresented class during training, as unbalanced designs can often result in asymmetrical trial counts. The performance of the classifier was assessed using the area under the curve (AUC) (Hand & Till, 2001).

Temporal generalization analysis was conducted to assess the stability of a representation across different time points. A classifier trained on a specific time point was tested on all other time points (King & Dehaene, 2014). The resulting temporal generalization matrix was used to identify periods of stability. Additionally, the product of the classifier weights and the data covariance matrix was calculated and spatially normalized for each participant to obtain the activation patterns (Haufe et al., 2014). Cluster-based nonparametric statistical tests (two-tailed cluster-permutation, alpha $p< 0.05$, cluster alpha $p < 0.05$, N permutations = 5000) were used to evaluate the MVPA results using FieldTrip (Oostenveld et al., 2011).

Results

Manipulation Check

One-way repeated measures analysis of variance (ANOVA) showed that choice set size had a significant effect on the perception of the number of options (F (3,81) = 27.8, $p < 0.001$,$\eta^2 = 0.507$, **Fig 2A**). Post hoc tests suggested that the differences between the four different sizes of choice sets were all statistically significant, indicating that the manipulation of choice set size was successful ($ps < 0.025$).

Behavioral results

As hypothesized, choice set size had a significant effect on the perceived difficulty of choosing (F (3,81) = 11.187, $p< 0.001$, $\eta^2 = 0.293$). Post hoc tests revealed that participants experienced greater difficulty in selecting from 8, 12, and 16 options compared to 4 options (t (27) = -3.689,p = 0.001, d = -0.491; t (27) = -5.366, p< 0.001, d = -0.714; t (27) = -4.528, p< 0.001, d = -0.602). There were no significant differences observed in any other condition (ps>0.584, **Fig. 2A**). The results showed that the size of the choice set had a significant effect on the tendency to avoid certain behaviors (F (3,81) = 6.136, p < 0.001,η^2 = 0.185). Post hoc tests showed that participants were more likely to avoid making a choice when choosing from 8, 12, and 16 options compared to 4 options (t (27) = -2.162,p = 0.023, d = -0.268; t (27) = -3.047, p = 0.019, d = -0.377; t (27) = -4.128, p < 0.001, d = -0.511),with no significant differences in any other condition (ps >0.118, **Fig. 2A**).

As for the emotional experience of choice, the choice set size had a significant effect on both positive and negative emotional experiences (F (3,81) = 3.695, p = 0.015, η^2 = 0.120; F (3,81) = 11.7, p < 0.001,η^2 = 0.302). Fewer positive experiences (t (27) = 1.889, p = 0.007, d = 0.348; t (27) = 2.334, p = 0.012, d = 0.430; t (27) = 3.223,p = 0.011, d = 0.594) and more negative experiences (t (27) = -4.858, p < 0.001, d = -0.682;t (27) = -4.501, p < 0.001, d = -0.632;t (27) = -5.072, p < 0.001, d = -0.712) were observed when participants chose from 8, 12, and 16 options compared to 4 options, with no significant differences in any of the other conditions (ps > 0.290, ps> 0.558, **Fig. 2A**).

ERP results

One-way repeated measures ANOVA results showed that choice set size significantly affected the amplitudes of P1 (F (3, 81) = 4.985,p = 0.003, η^2 = 0.156, **Fig 2B ,3C, and 3D**). Post hoc tests revealed that when the number of images was reduced to 4 (t (27) = 2.506, p = 0.040,d = 0.258; t (27) = 3.336, p = 0.021, d = 0.344) or 8 (t (27) = 1.947, p = 0.007, d = 0.201;t (27) = 2.777, p < 0.001, d = 0.286), the P1 amplitudes were significantly higher than when there were 12 or 16 images . No other significant differences were observed (p s > 0.396).

The analysis of P2 amplitudes showed that choice set size significantly affected the amplitudes of P2 (F (3,81) = 8.676, p< 0.001, η^2 = 0.243, **Fig 2B ,3C and 3D**). Post hoc tests revealed that when the number of images was reduced to 4 (t (27) = 3.702, p = 0.002,d = 0.499; t (27) = 4.758, p < 0.001,d = 0.642) or 8 (t (27) = 2.777, p = 0.041, d= 0.375), the P2 amplitudes were significantly higher than when there were 12 or 16 images . No other significant differences were observed (p s > 0.396).

For the N2 component, the ANOVA results indicated that choice set size significantly affected the amplitudes of N2 (F (3,81) = 8.466,p < 0.001, η^2 = 0.239,**Fig 2B , 3A, and 3D**). Post hoc tests revealed that when the number of images was reduced to 4 (t (27) = -2.997, p = 0.022, d = -0.412; t (27) = -4.733, p < 0.001, d = -0.651) or 8 (t (27) = -3.438, p = 0.006,d = -0.473), the N2 amplitudes were significantly higher than when there were 12 or 16 images. No other significant differences were observed (ps > 0.067).

As for LPC, the results suggested that choice set size significantly affected the amplitudes of LPC (F (3,81) = 4.087, p = 0.009, η^2 = 0.131, **Fig 2B, 3B, and 3D**). Post hoc tests revealed that when the number of images was reduced to 4 (t (27) = -2.536, p = 0.013, d = -0.434) or 8 (t (27) = -3.341, p = 0.002, d = -0.572), the LPC amplitudes were significantly higher than when there were 16 images. No other significant differences were observed (p s > 0.058). In addition, the size of the choice set did not have a significant effect on the amplitude of P3 (F (3,81) = 1.449,p = 0.235, **Fig 2B and 3B**).

MVPA results

MVPA analyses showed that neural activity between the small and large choice sets began to differ 128 ms after stimulus onset and persisted until 1500 ms (p < 0.001, cluster-based correction;**Fig. 4A**). Temporal generalization matrices indicated that neural activity between the small and large choice sets during these time periods (training time = [128,1488], testing time = [108, 1488], p < 0.001; **Fig. 4B**) could be predicted from one another. As depicted in the activation maps in**Fig. 4C** , the posterior electrodes exhibited activation (p < 0.001, cluster-based corrected) while the anterior electrodes showed inhibition (p < 0.001, cluster-based corrected) in the early stage. However, in the late stage, the posterior electrodes were inhibited (p < 0.001, cluster-based corrected) and the anterior electrodes were activated (p< 0.001, cluster-based corrected). No significant cluster of electrodes was observed during the middle stage. Furthermore, the decoding outcomes for four different choice set sizes were illustrated in **Supplemental Figure 1** . The significant time clusters between the two adjacent choice sets (e.g., between 4 and 8) were relatively small; however, as the number of choices that differ between them increases, the significant time clusters become more expansive.

Discussion

This study used both self-report and EEG techniques to examine the impact of the number of options on choice overload. The findings showed that increasing the number of choices led to an increased sense of choice difficulty, which in turn caused choice overload. Specifically, choosing from a large range of options was associated with a more negative evaluation of the decision-making process and an increase in avoidance behavior in comparison to a smaller set of options. ERP results revealed that selecting from a larger set of choices resulted in smaller amplitudes of P1 and P2, and a larger amplitude of N2 and LPC, compared to a smaller set. Moreover, MVPA results indicated that there were significant differences in neural activity between large and small choice sets from 128ms to 1500ms. These results will be discussed in more detail below.

ERP results demonstrated the neurological and cognitive processes associated with option evaluation and selection. Compared to the smaller selection set, the amplitudes of P1 and P2 decreased when selecting from the larger selection set. P1 is associated with early visual processing and attention allocation, with its amplitude being enhanced when attention is directed towards a stimulus (Hillyard & Anllo-Vento, 1998; Munneke et al., 2008). P2 is related to early automatic attention allocation and visual processing (Jing et al., 2019). An increased P2 amplitude is observed when a visual stimulus requires a higher level of attentional focus (Handy et al., 2010; Mercado et al., 2006). Previous research has also found that extensive information processing leads to a lower P2 component (Peng et al., 2021). This suggests that choice overload impairs early processing by decreasing the amplitudes of P1 and P2, as individuals must allocate their attentional resources to cognitively process the stimuli and identify their needs while attempting to minimize cognitive effort.

It has been observed that when presented with a small choice set, individuals tend to allocate more attention to the target options in a particular area of the screen. This is in contrast to the large choice set, where fewer cognitive resources are invested. This is due to the fact that complex decisions often require the use of heuristic strategies in order to make decisions quickly (Besedes et al., 2012). Moreover, when faced with a limited number of options, individuals are more likely to employ compensatory strategies in order to thoroughly evaluate the options, thus investing more attentional resources (Besedes et al., 2012; Gerasimou & Papi, 2018). The increased number of choices leads to increased uncertainty and the risk of missing out on the best option. This is reflected in the increased N2 amplitude in the anterior cingulate cortex (ACC) and frontal regions of the brain (Hedgcock et al., 2012; Ma et al., 2010). Additionally, differences in the color, shape, and spatial location of the stimulus can also lead to changes in N2 amplitude (Cui et al., 2000; Tian et al., 2001). Furthermore, research in the field of risky decision-making has revealed that N2 is sensitive to risky information (Wang et al., 2016). Studies related to choice overload have also found that individuals who selected from larger choice sets exhibited cardiovascular responses consistent with high levels of stress (Saltsman et al., 2019). Therefore, it can be concluded that choice overload interferes with early processing and leads to increased cognitive conflict.

It has been suggested that individuals must invest more attentional resources when faced with a larger choice set. However, having more options can also increase the complexity of decision making and reduce an individual's confidence in their decision-making ability. Research has shown that P3 amplitude is directly correlated with the amount of attentional resources allocated (Folstein et al., 2008) and inversely proportional to the difficulty of decision-making, with a lack of confidence resulting in a smaller P3 (Polich, 1987; Qin & Han, 2009). Furthermore, studies have indicated that lower perceived load triggers larger peaks in P3 amplitude (Barnhardt et al., 2008). This discrepancy may explain the absence of a significant difference in P3.

At the late processing stage, once sufficient information has been gathered, individuals must evaluate the various options and potential outcomes. Late information processing requires more attentional resources due to the lack of initial processing of the large choice set. Thus, individuals assess and analyze options based on their personal needs and the external environment, which leads to increased attentional resource allocation(Zhao et al., 2015). Moreover, individuals tend to experience emotional arousal, such as regret, when selecting from a larger set of options due to counterfactual thinking. This is evidenced by the larger amplitude of the late positive component (LPC) induced by the large choice set compared to the small choice set (Fields, 2023; Hajcak et al., 2006). The LPC amplitude is linked to the allocation of attentional resources and the level of emotional arousal (Hajcak & Foti, 2020; Hajcak & Nieuwenhuis, 2006). Hence, the extensive selection necessitates continuous and prolonged attention, but it also leads to more negative emotional experiences.

Analyses via MVPA revealed that neural activity varied between small and large choice sets from 128ms to 1500ms post-stimulus onset. Temporal generalization analysis illustrated persistent predictive dynamics during the early, middle, and late stages, suggesting prolonged attention engagement. Activation pattern maps indicated that the contrast between the two choice sets depended on activation in the posterior electrode over the anterior electrode during the early stage. In contrast, the late stage displayed an activation pattern opposite to that of the early stage. These findings were partially confirmed by the ERP results, which showed a decrease in the amplitude of the early attention process and an increase in the amplitude of the late attention process in the large choice set condition in comparison to the small choice set condition. This implies the presence of two opposed processes during the early and late stages. Interestingly, P3 amplitude remained unchanged between the two choice set sizes in the middle phase. MVPA successfully distinguished the processing patterns between the choice set sizes with a precision greater than random chance. The activation topography during the middle stage did not demonstrate significant clustering of electrodes, demonstrating that the capacity to differentiate between large and small choice sets during this phase is not reliant on specific electrodes, but instead involves a complex spatial processing pattern. The processing in the middle stage likely involves a complex transition from the early to the late stage.

This study utilized EEG and self-report methods to investigate and refine the cognitive overload theory of choice overload. It was found that choice overload occurs during the information processing phase, not at the time of making the ultimate decision. This finding is consistent with past researches (Lee & Lee, 2004; Reutskaja et al., 2018). Without the pressure of time, individuals take the time to assess all of their options before making a decision, and decision time was not affected by the size of the choice set after a full evaluation of the options. Self-reported data showed that even without time pressure, a significant number of choices still led to negative emotions and an inclination to avoid them. It was further noted that in large choice sets, late sustained attentional processing compensates for the diminished allocation of early attentional resources. Additionally, it was found that people tend to overestimate the effects of choice overload, and there is a lack of consistency between subjective reports of decision difficulty and choice experiences and objective EEG metrics. The findings provided insight into the neurological mechanisms of choice overload, which may help people gain a greater understanding of the choice overload effect and then apply strategies to make better decisions. However, this study had limitations, such as using only landscape pictures as stimulus materials., which are not as complex as the attributes of objects people choose in real-life scenarios. Therefore, future studies should consider using more elaborate options to simulate realistic choice situations.

Conclusion

Numerous studies have explored the mechanisms of selection overload and how to address it. It has been argued that time pressure and incomplete information processing are contributors to choice overload. Nevertheless, our study found that individuals experience choice overload even when given sufficient time to carefully process the options. People initially evaluate options in the early processing stage, form criteria based on the options and their needs, and use these criteria to process the options in depth before ultimately making a choice.

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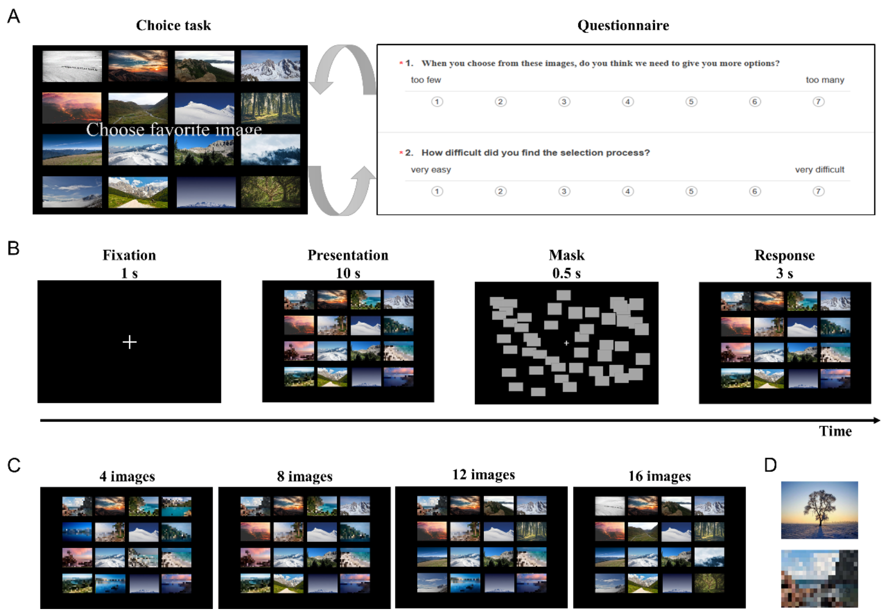


Fig 1. The experimental flowchart. Participants were asked to complete a survey evaluating their experience after completing the choice task. Each trial began with a 1 second fixation period, followed by a 10 second image presentation stage. Participants were then required to select their preferred image and respond with a mouse after a 0.5 second mask. The four choice set conditions varied in the number of clear images, with 4, 8, 12, and 16 clear images in the respective conditions, and the remainder being mosaic treatment. Examples of clear and mosaic pictures are shown in panel D.

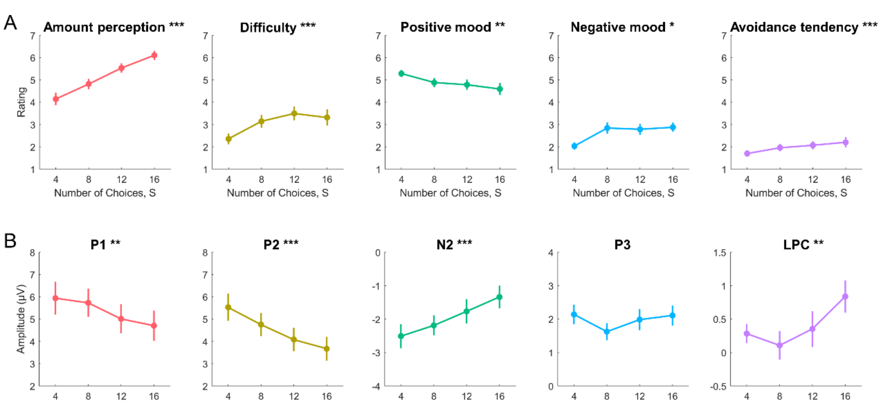


Fig 2. The number of choice sets had an effect on both behavioral measures (A) as well as the mean amplitude of ERP components (B). Error bars represented the standard error of the mean (SEM) across participants. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

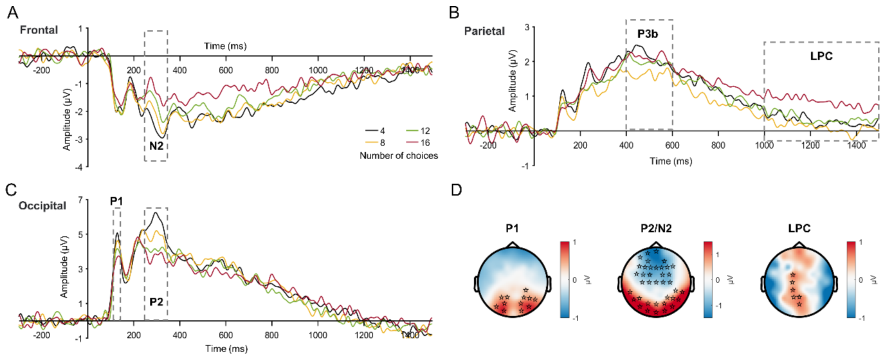


Fig 3. ERP waveform and topographic maps. Pannel A, B and C showed the ERP waveform maps on frontal (Fz, F1, F2), parietal (Pz, P1, P2) and occipital (Oz, O1, O2) electrodes, respectively. Pannel D indicated the topographic maps of the P1, P2, N2 and LPC.

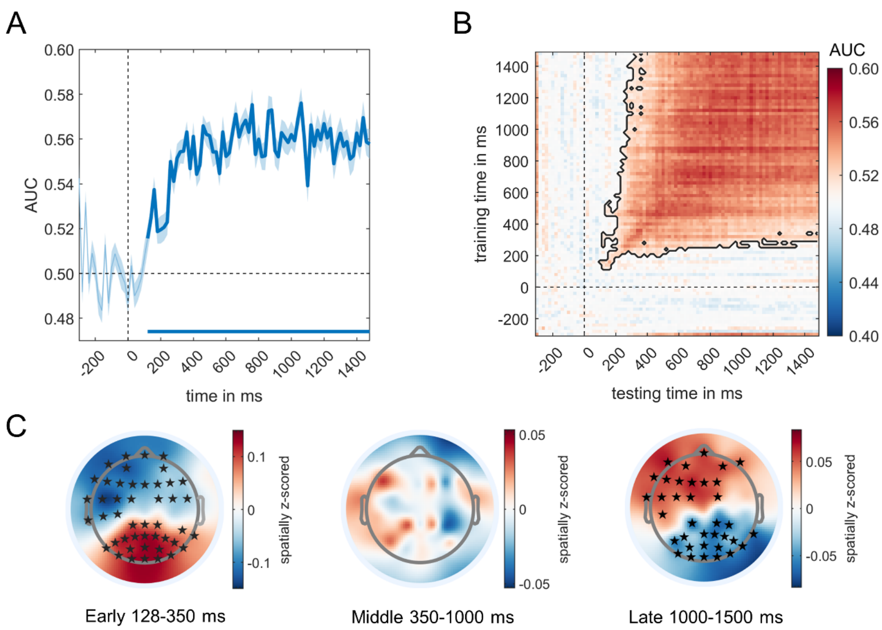
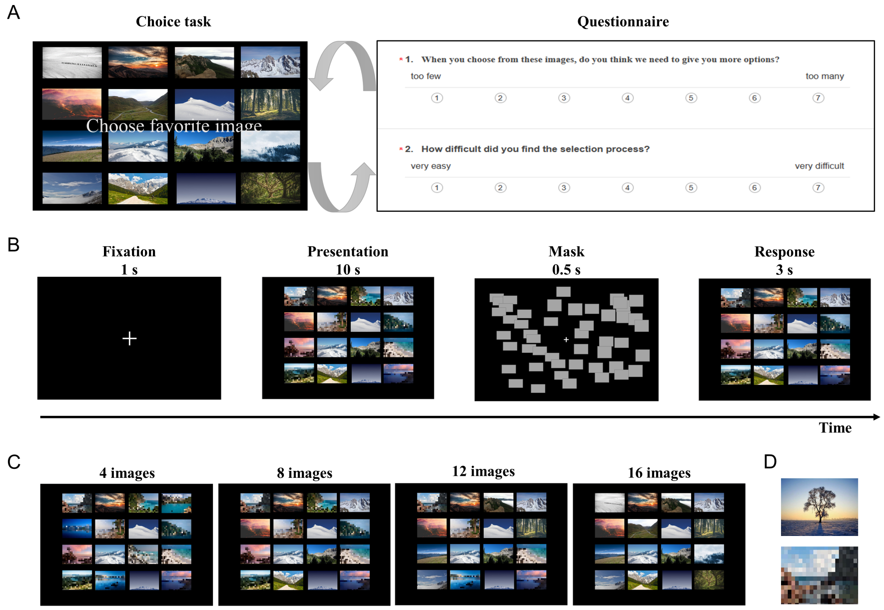
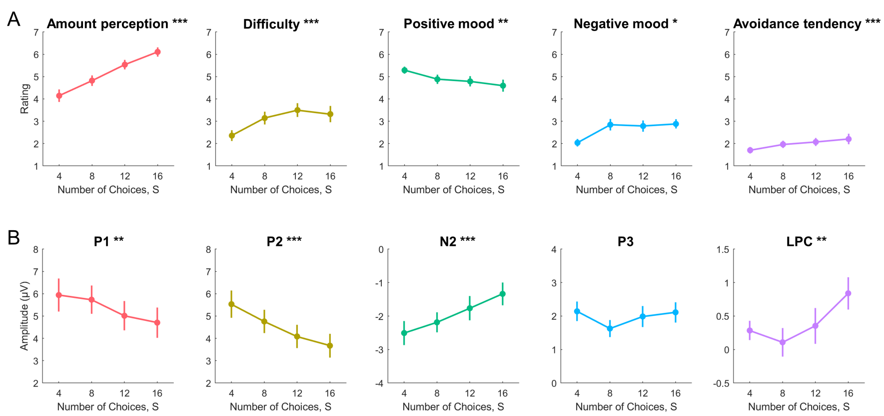
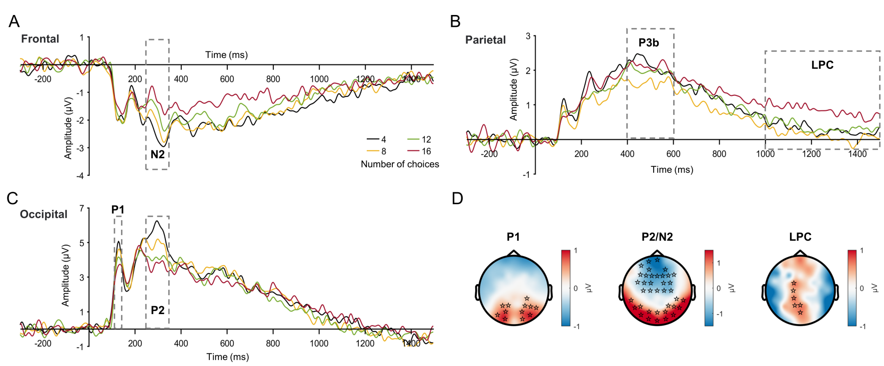


Fig 4. Results of the time-resolved decoding were displayed, with the small and large number of choices shown in (A) with shading indicating the standard error of the mean across participants at each time point. The temporal generalization matrices (B) and activation maps of the decoding result at the early, middle, and late stages (C) were also presented. Clusters that were significant in the cluster-based nonparametric test ($p < 0.001$) were highlighted with a bold line in (A), enclosed area in (B), and asterisk-marked electrodes in (C).


A
Choice task
Choose favorite image
Questionnaire
* 1. When you choose from these images, do you think we need to give you more options?
too few
too many
* 2. How difficult did you find the selection process?
very easy
very difficult
B
Fixation
1 s
Presentation
10 s
Mask
0.5 s
Response
3 s
Time
C
4 images
8 images
12 images
16 images
D


A
Amount perception ***
Difficulty ***
Positive mood **
Negative mood *
Avoidance tendency ***
Rating
Number of Choices, S
B
P1 **
P2 ***
N2 ***
P3
LPC **
Amplitude (μV)
Number of Choices, S


A
Frontal
Time (ms)
Amplitude (μV)
N2
Number of choices
B
Parietal
P3b
LPC
Amplitude (μV)
Time (ms)
C
Occipital
P1
P2
Amplitude (μV)
Time (ms)
D
P1
P2/N2
LPC
μV