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Neural investigation of default effects on decision-making under uncertainty

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Abstract

Default options have increasingly become a common tool for policymakers in guiding individuals' behaviors. However, the neural mechanisms of default effects on decision-making, particularly in uncertain situations, remain unclear. In the present study, participants were asked to decide whether to stick with the default options in a gambling task, and their scalp potentials were recorded. The behavioral results indicated that the default effects did exist, given that participants demonstrated a significantly higher likelihood of selecting uncertain payoffs when these were presented as default options, as opposed to when certain payoffs were designated as defaults. The electroencephalography (EEG) data revealed that the assessment of default setting, comparing default uncertain options with default certain options, was reflected not only in early ERP components (such as P200 and MFN) but also in increased activity within the theta frequency band. Certain payoffs elicited larger P200 and MFN amplitudes compared to uncertain payoffs under default settings, and time-frequency analysis revealed greater theta power when the default options involved payoffs (rather than uncertain payoffs). Additionally, ambiguity aversion manifested not only in behavioral tendencies but also in distinct neural signatures, reflected across multiple ERP components associated with early evaluation (such as P200, MFN) and later motivational processing (such as P300, LPP). To further capture how these neural responses relate to behavior, we applied representational similarity analysis (RSA), which revealed that choice patterns were systematically associated with frontal neural activity during an early evaluative stage. Moreover, regression analyses indicated that later-stage neural responses, particularly the LPP, were predictive of individuals' subsequent uncertainty choices, suggesting that both early evaluation processes and later motivational evaluations contribute to shaping behavior under uncertainty and defaults.

Keywords: nudge; default effects; risk; ambiguity; ERP

1. Introduction

When considering two projects, one of which has a guaranteed return and the other has a higher return but with some risk, the question arises as to which project should be chosen. Additionally, there is a question as to whether the choice is influenced by a higher return that is associated with unknown probabilistic outcomes. Furthermore, there is a question as to whether the default option would be changed if an individual had defaulted in advance to the risky but high-reward project.

Decision-making under uncertainty is a very common occurrence in daily life. In some cases, the probability of an event occurring is foreseen. However, as most situations are associated with uncertainty, the probability cannot be estimated in advance. Economic studies have differentiated uncertainty into risk and ambiguity [1, 2]. Risk involves a set of outcomes with known probability distributions, and risk aversion is defined as an individual's tendency to avoid such outcomes. According to the definition proposed by O'Donoghue and Somerville [3], a commonly observed scenario of risk aversion is that, for any lottery, an individual prefers a certain amount that is equal to the lottery's expected value compared to experiencing the lottery. Conversely, ambiguity aversion is an additional form of aversion and appears to be a common characteristic of economic behavior. As Barham et al. [4] have indicated, this concept reflects an individual's aversion to being unsure about the probabilities of outcomes. Despite these small differences, people possess different attitudes towards risk and ambiguity [1, 2]. This distinction was first illustrated by the Ellsberg paradox, which serves as a classic example of ambiguity aversion. In the experiment performed by Ellsberg [5], the majority of participants demonstrated a preference for avoiding the ambiguous urn, even though it offered a higher reward compared to the risky one. Moreover, individuals are often willing to spend significant amounts of money to avoid ambiguous processes in favor of normatively equivalent risky processes [6-8].

Research indicates that the processing of uncertainty is highly contingent upon the specific situation and context in which it occurs. Furthermore, choices that are made under uncertain conditions are subject to the influence of a wide range of situational and contextual factors [9]. This scenario leads to an important question as to what occurs when there is a suggested option or a default option. A substantial and expanding body of research indicates that individuals are more likely to select options that are presented as defaults than they would under other circumstances, even when they make crucial decisions that seemingly demand careful deliberation [10-12]. This phenomenon is commonly referred to as the default effect [13]. Defaults have been demonstrated as exerting effects on a wide variety of activities, such as health decisions [11], savings and investment plans [14], charitable donations [15], and consumption [16]. Particularly, in recent research, Giuliani [17] suggested that particular attention should be given to the specific features of defaults. Specifically, under certain circumstances, individuals may not be readily nudged towards certainty; rather, they may be nudged towards risk. However, there is a notable lack of research exploring the role of default options in decision-making under uncertainty, which is a surprising observation given their potential impacts on individual and collective outcomes.

Event-related potentials (ERPs) provide researchers with excellent temporal resolution for investigating the cognitive processes that occur during decision-making under uncertainty. To date, a considerable amount of research has been performed regarding decision-making under uncertainty [18-20]. Early components of the ERP, including the P200 and the medial frontal negativity (MFN), along with the mid-latency P300 component and the late positive potential (LPP), have been extensively investigated in relation to decision-making under uncertainty [21, 22].

The P200 is an early positive wave with a peak latency of approximately 200 ms over frontal areas [23]. Previous studies have demonstrated that the P200 reflects early dedication of attentional resources to stimulus evaluation and/or serves as an index of early perceptual processing [23, 24]. In addition, the P200 component reflects early attentional processing in a nudging context, thus suggesting that nudging through natural sounds can enhance attentional congruency and facilitate the automatic evaluation of green products, thereby resulting in more intuitive sustainable choices [25]. The MFN is a negative deflection occurring at frontocentral scalp sites, which peaks approximately 250–350 ms following the onset of stimuli [26, 27]. Although MFN/FRN is commonly applied to feedback-locked negativities, prior research has shown that a morphologically similar frontocentral negativity can also be elicited by stimulus information. For example, the MFN is understood to reflect expectancy violation or the evaluation of whether upcoming events conform to one’s predictions [22, 26, 28]. Moreover, stimulus-locked MFN activity has been linked to reward-related neural activity, including sensitivity to reward probability and monetary magnitude during risk evaluation [22]. The P300, which is a positive deflection observed between 300–600 ms following stimulus onset, is typically sensitive to many factors of decision-making, such as the magnitude and valence of the reward, as well as interpersonal relationships in reward processing [18, 29]. This component is involved in decision-making under uncertainty, and a larger amplitude is observed in risk conditions than in ambiguity conditions [29]. The LPP, which is a centro-parietal slow positive deflection following the P300, is predominantly associated with affective and emotional processing [30, 31]. Studies focusing on decision-making under uncertainty indicate that the LPP reflects probability weighting [22]. An examination of the differences in the modulation of these components may help to determine whether the propensity for decision-making under uncertainty can be predicted by the magnitude of these ERP effects.

Although ERPs are informative and provide valuable insights into our understanding of the development of psychological phenomena, they do not fully capture the rich information embedded within the EEG signal. Given that neuronal oscillations are a fundamental property of the brain [32], time-frequency analyses allow for a more precise characterization of the temporal dynamics of these oscillations. Consequently, these analyses can offer more direct information regarding the neurophysiological mechanisms underlying the processes identified via the EEG data [33]. In the present study, we specifically focused on theta-band oscillations because a growing body of literature indicates that theta-band activity (4–7 Hz) is involved in the processes underlying decision-making, such as conflict monitoring, cognitive control, attention allocation, and value evaluation [34-36]. Previous findings have indicated that theta oscillations are associated with working memory and tend to increase in amplitude during tasks that require cognitive control [34, 36, 37]. Specifically, the theta band has been demonstrated to be related to unexpectedness updating and uncertainty-driven exploration [38]. Although increased theta power is frequently linked to processing uncertainty and active decision conflict, there is relatively limited knowledge regarding how theta dynamics respond to default options that vary in terms of payoff certainty.

To provide a more in-depth understanding of the relationship between brain activity and behavior, we also conducted a representational similarity analysis (RSA), which quantitatively associates behavioral patterns with neural patterns. Although RSA has been extensively used to reveal the neural representation of cognitive processes, such as memory, facial processing, and object recognition in the human brain [39-42], its application in revealing the neural representations of decision-making under uncertainty has rarely been reported. The results of the RSA may offer a novel perspective and new insights into the relationship between decision-making under uncertainty and brain activity. Decision-making under uncertainty may be sensitive to brain regions involved in the integration of emotional and cognitive inputs, the reaction to emotional information, and the prediction of rewards. The activation of brain areas, including the amygdala, orbitofrontal cortex (OFC), and striatal system, has been reported to be correlated with the degree of ambiguity in choices [2]. Another study using transcranial direct current stimulation (tDCS) to separately modulate the activity of the dorsolateral prefrontal cortex (DLPFC) and the OFC suggested that decision-making processes under risk and ambiguity may be encoded in two distinct circuits in our brains, with the DLPFC primarily impacting decisions under risk and the OFC affecting decisions involving ambiguity [43]. Another functional near-infrared spectroscopy (fNIRS) study also revealed that the mPFC is involved in decision-making under ambiguity and risk in the Iowa Gambling Task [44]. Although the brain regions involved are slightly different due to variability in experimental tasks and focus of attention, the frontal area is a region that is primarily focused on. Therefore, the region of interest was set to the frontal area based on previous neuropsychological research.

The current study aimed to address the impact of default effects on decision-making under uncertainty. We employed a binary choice task in both the ambiguity and risk conditions, wherein participants were required to choose between certain payoffs and bets on card decks. One option was set as the default, whereas the other option served as an alternative. In this study, participants were asked to decide whether to maintain the default option or to switch to an alternative, and the EEG response was recorded. We hypothesized that notable behavioral and neural differences would be observed in relation to the default effects and uncertainty. Behaviorally, we predicted that participants would exhibit a greater likelihood of selecting the default options. Moreover, we predicted that they would be more inclined to select uncertainty under risk conditions than under ambiguity conditions. From a neural perspective, we expected to observe modulations in ERPs, including the P200, the MFN, P300, and LPP, due to the fact that the P200 and the MFN are associated with stimulus evaluation and quick assessment [22, 24], whereas the P300 and LPP are linked to reward-related neural activity, as well as affective and emotional processing [18, 29, 30]. Given that the LPP reflects an integrative role in decision-making [45, 46], we hypothesize that its amplitude will track the option that carries greater subjective relevance, thereby predicting the direction of choice. Additionally, in addition to the ERP results, we expected these modulations to be reflected in the electrophysiological signature of frontal midline theta oscillations, due to the fact that this type of oscillation is associated with cognitive processing and may complement the existing findings from ERPs [47, 48]. Furthermore, we also expected to observe the representational similarity between the brain patterns in the frontal area and the behavioral choices. If these predictions can be confirmed, then the results will provide insights into the cognitive processing involved in default effects during decision-making under uncertainty.

2. Materials and Methods

2.1 Participants

Forty-four healthy Chinese volunteers (24 males; mean age 26.02 years, ranging from 22 to 29 years) participated in this study. Participants were recruited via school advertisements. According to self-report, all participants were right-handed. Moreover, they had normal or corrected-to-normal vision and reported no history of psychiatric or neurological disorders. None of the participants were aware of the study's purpose. Written informed consent was obtained before participation. The experiment lasted for approximately one hour. This study was performed in accordance with relevant guidelines and regulations and received approval from the Ethics Committee of Dongbei University of Finance and Economics.

2.2 Stimuli and task

The task was adapted from Hsu et al. [2] with the objective of distinguishing between participants' risk and ambiguity preferences and evaluating the effect of default options on decision-making under uncertainty. Drawing on earlier studies on neural correlations of decision-making [49-51], we assigned the participants a two-option forced decision-making task. In this task, they were required to choose between certain payoffs and bets on card decks. If a participant chose certain payoffs in a given round, he/she could receive that gain. Conversely, if he/she chose to bet, then the cards would be drawn automatically by the computer. If a red card was selected, the participant would be eligible for the higher associated payoffs; otherwise, he/she would receive nothing. In half of the choices, the composition of the cards was disclosed to the participants, meaning that they knew the probability of drawing a red card, which represented the risky choices. For example, in the risky choice depicted in Figure 1(A), if a participant chose to bet, the computer would randomly select a card from a pool consisting of 9 red cards and 1 blue card. This provided them with a 9/10 chance of winning 27 Chinese yuan (CNY) and a 1/10 chance of winning 0 CNY. In the rest of the choices, the composition of the cards was not disclosed, representing ambiguous choices. In the ambiguous choice shown in Figure 1(A), if a participant chose to bet, the computer would randomly select a card from a total of 7 cards. Depending on the outcome, the participant would receive 28 CNY or nothing, and the probability was unknown to him/her. Each decision involved a conflict between potential payoffs and uncertainty. To put it another way, each game allowed participants the opportunity to increase their earnings by taking on uncertainty, either in the form of risk or ambiguity. Additionally, the default options could either be the certain payoffs or the bets. The detailed experimental stimuli are provided in Table S1.

2.3 Procedure

Electroencephalography (EEG) recordings were carried out in a room that was both sound - attenuated and electrically shielded to minimize external interferences. The experimental rules were explained in detail by the experimenter prior to the experiment. The formal experiment did not begin until the participants fully understood the experiment and successfully answered the comprehension test questions.

The task comprised of four practice trials followed by ninety-six formal trials. The timeline of a single trial is depicted in Figure 1(B). At the beginning of each trial, a fixation cross would appear at the center of the screen for a duration ranging from 1500 to 3000 ms. After this period, the choice screen, which presented two options, would be displayed. Participants made their decisions by pressing either the ‘F’ or ‘J’ key on a standard keyboard within 5000 ms. If no selection was made within the time limit, the default option would be selected as the outcome of this trial. The presentation of certain rewards and bets was counterbalanced across the left and right visual fields of the screen. To avoid interfering with subsequent trials, the earnings from each trial would not be displayed following the selection. Before the task began, participants were informed that their final payment would be determined by five randomly selected trials from the experiment. This payment scheme was explained during the instructions to ensure that participants treated each trial independently and remained motivated throughout the task.

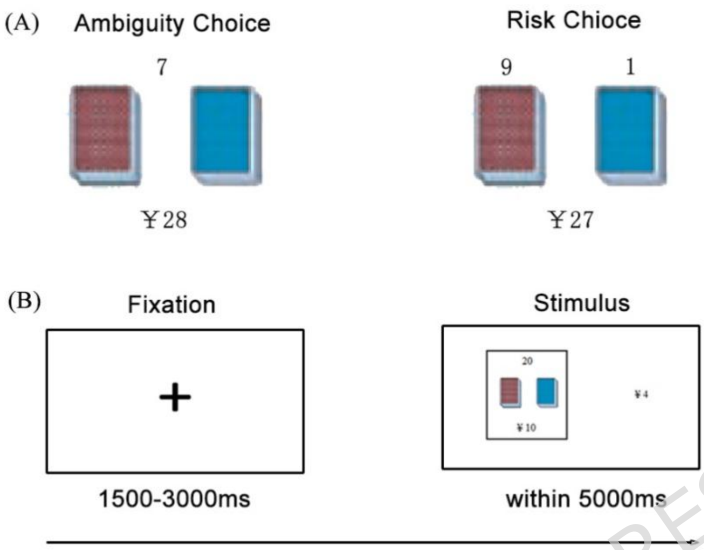

Figure 1. Schematic diagram of the experiment. (A) Card decks with ambiguity and with risk. (B) The timeline of a single trial. Each trial began with a central fixation cross displayed for 1500–3000 ms, followed by a choice screen presenting two options. Participants were required to make their decisions in 5000 ms. If no selection was made within the time limit, the default option (which was indicated by a square frame and represented the ambiguous option in this example) would be automatically selected. To compute ERPs, continuous EEG data were segmented into 1200 ms epochs time-locked to the onset of the choice screen (also referred to as the Stimulus screen), including a 200 ms pre-stimulus baseline and 1000 ms post-stimulus period.

2.4 Electroencephalography Acquisition and Data Analysis

The EEG data was acquired using a 64-channel ANT Neuro EEGO amplifier, with electrodes mounted in a cap following the international 10/20 system.

The CPz electrode, located at the central-parietal region of the scalp, served as the reference, while the AFz electrode, positioned at the anterior-frontal area, functioned as the ground channel. During the entire electroencephalography recording session, electrode impedances were maintained at levels below 5 kΩ. The EEG signals sampled at 500 Hz were intended for subsequent off-line analysis.

EEG preprocessing and analysis were conducted utilizing EEGLAB 14.1.1 tool [52], which was implemented within MATLAB 2017a environment. The data were re-referenced to the average of the bilateral mastoids (M1 and M2). Then, filtering was performed on the data, employing a 50 Hz notch infinite impulse response (IIR) filter for power-line interference removal, along with a 0.1 Hz high-pass and 30 Hz low-pass IIR filter to eliminate low-frequency drift and high-frequency noise, respectively. Independent component analysis (ICA), as introduced by Makeig et al. [53], was conducted to eliminate eye movement and blink artifacts. Relevant components were then identified and manually rejected to obtain clean data. ERPs were calculated from continuous EEG data. The EEG data were segmented into 1200 ms epochs that were time-locked to the onset of the choice screen (i.e., the stimulus screen shown in Figure 1B). These epochs ranged from 200 ms prior to stimulus onset to 1000 ms after it. Baseline correction was applied using the 200 ms pre-stimulus interval (-200 to 0 ms). Trials that contained ocular artifacts as well as other types of artifacts (where the peak - to - peak deflection of the signal exceeded the threshold of ±100 μV) were excluded from the averaging process. This exclusion procedure led to the rejection of 1.40% of the total trials.

Statistical analyses were conducted on ERP mean amplitudes, with the method selection informed by prior literature insights and visual inspection results of topographical maps. Since our task did not include outcome feedback, all ERP analyses were focused on stimulus-locked responses, thereby capturing cognitive processing during option evaluation. Previous research indicates that the P200 component is present in the fronto-central brain area and commonly peaks at midline scalp electrodes [54]. The MFN reaches its peak amplitude at the midline electrodes of the scalp within the time window of 250-350 milliseconds post-stimulus. Moreover, it is partially generated in the anterior cingulate cortex (ACC), as supported by previous research [22, 26, 55]. Additionally, the MFN amplitude is maximal at frontal-central midline sites [21, 55]. Drawing on findings from previous studies, the average amplitudes of the P200 and MFN were measured at six electrode sites (F1, Fz, F2, FC1, FCz, FC2) in the time windows of 150–270 ms (P200) and 270–320 ms (MFN). The P300 represents a prominent positive component that emerges at temporo-parietal sites and typically reaches its maximum amplitude in the centro-parietal area [55]. The LPP is an ERP component characterized by a central-parietal, midline distribution, and it typically exhibits its maximum amplitude at posterior and parietal electrode sites [56]. In order to investigate the effects of the P300 and LPP within the current experimental paradigm, the mean amplitudes were analyzed across six electrode sites: CP1, CPz, CP2, P1, Pz, and P2. The P300 component was determined within the time window spanning from 300 ms to 450 ms, while the LPP component was determined within the time window spanning from 450 ms to 650 ms. For each ERP component, two-way repeated measures ANOVAs were conducted, incorporating the factors of Uncertainty (with two levels: risk and ambiguity) and Default (with two levels: default uncertain options and default certain options).

A fast wavelet transform was applied to conduct time-frequency analysis of ERP data. Specifically, the continuous wavelet transform, which balanced time and frequency resolution, was applied to the averaged waveforms to capture evoked oscillatory activity [57]. In the present study, the mother wavelet was defined such that both its bandwidth and center frequency were set to 1, enabling it to cover the frequency range from 1 Hz to 30 Hz. Event-related oscillations were identified by employing the rectangle method [58, 59]. As illustrated in Figure 4, theta oscillations within the frequency range of 4 - 7 Hz were clearly discernible within the time window spanning from 150 ms to 250 ms. In order to investigate the impacts of ambiguity and the disparity in default conditions on neural responses within the theta band, the theta band activity was systematically isolated and extracted from six precisely located electrode sites, namely F1, F2, Fz, FC1, FC2, and FCz.

2.5 Representational Similarity Analysis

RSA was employed to pinpoint the specific time intervals during which the neural response patterns were indicative of behavioral choices made under conditions of uncertainty. The steps to construct representation dissimilarity matrix (RDM) and to compute RSA results primarily followed the methodology outlined by Liu et al. [60]. Specifically, for every participant, the behavioral variables and EEG variables (amplitudes of EEG responses in the ROI at each specific time interval) were averaged across multiple trials, separately for each of the four experimental conditions. The selection of the ROI with six electrode sites (F1, Fz, F2, FC1, FCz, and FC2) was based on the established EEG literature and tDCS literature [21, 43]. Next, we conducted Spearman correlation analyses for each variable between every pair of conditions using data from all participants. To enhance the reliability of the representational estimates, the RDMs were computed at the group level. This is a common approach in EEG-based RSA when trial numbers are limited, as group-averaged RDMs provide more stable and reliable representational estimates than noisier single-subject RDMs [61]. We used the correlation distance (1 - correlation coefficient) to create a 4 × 4 representation dissimilarity matrix (RDM). This RDM was intended to capture the differences in behavioral or EEG activity patterns. Finally, to perform the Spearman correlation analysis between the behavioral and EEG RDMs, we utilized the values extracted from the upper triangle (or, equivalently, the lower triangle) of the matrices. This analysis ultimately generated the results of RSA.

To examine the temporal dynamics of the neural–behavioral representational correspondence, RSA was performed in a time-resolved manner using a sliding-window approach. Specifically, a 5 ms analysis window was moved across the entire epoch, and all time segments showing significant correlations were recorded.

2.6 Statistical Analysis

All statistical analyses were conducted using IBM SPSS Statistics 26 and R (version 4.4.0) for mixed-effects modelling. For behavioral data, ERP mean amplitudes, and theta-band power, repeated-measures ANOVAs were conducted with Uncertainty (risk, ambiguity) and Default (default uncertain options, default certain options) as within-subject factors. When necessary, Bonferroni-adjusted pairwise comparisons were employed. Partial eta-squared was reported as an index of effect size.

Specifically, neural-behavioral association analyses were performed using linear mixed-effects regression models implemented in R. For each participant and condition, we calculated the proportion of uncertain choices and extracted neural measures averaged across trials within each condition (including P200, MFN, P300, LPP amplitudes, and theta-band power). These measures were then entered into separate mixed-effects models to test whether neural activity could predict individual differences in uncertainty choice behavior.

For RSA, statistical significance was assessed using a permutation-based correlation approach. Specifically, the behavioral and EEG RDMs were first vectorized by extracting their upper-triangle elements, and the observed RSA effect was quantified using a Spearman rank correlation between these vectors. Permutation testing was then performed by randomly shuffling the ordering of the EEG RDM vector across permutations while keeping the behavioral RDM vector unchanged, thereby breaking the correspondence between neural and behavioral representational structures. For each permutation, the Spearman correlation was recomputed to generate an empirical null distribution. A total of 5,000 permutations were performed, and statistical significance was evaluated using a one-tailed test (right-sided), with the significance level set at $p < 0.05$.

3. Results

3.1 Behavioral Data

In the experiment, participants made binary decisions involving risk and ambiguity. They were required to make a choice between certain payoffs and bets on card decks. Each decision involved a conflict between certain payoffs and uncertainty. In other words, each game offered participants the opportunity to increase their earnings by taking on uncertainty. A greater proportion of selections involving uncertain payoffs generally indicates a stronger preference for risk and ambiguity. Throughout the experiment, all participants responded within the decision window on every trial; consequently, no timeout occurred and no trial was assigned the default option automatically. Figure 2 illustrates the average percentage of choosing uncertain payoffs across different treatments.

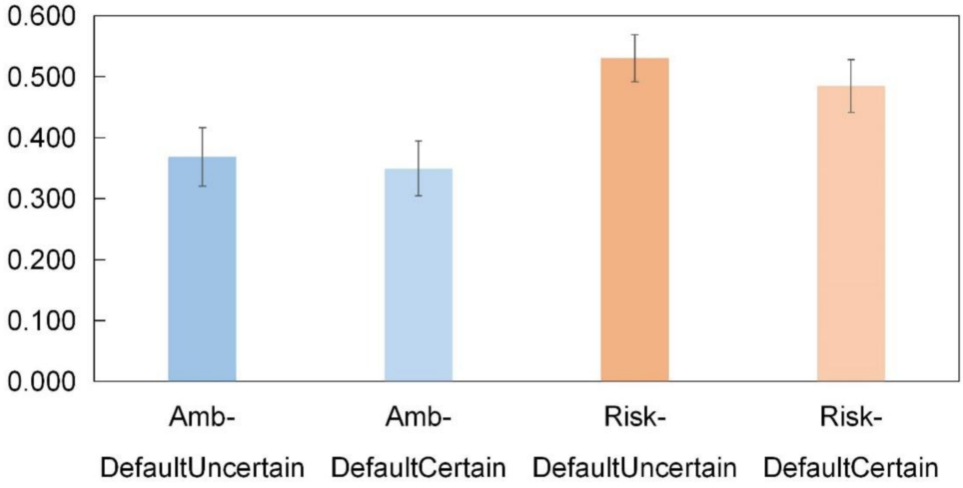

Figure 2. The average percentage of choosing uncertain payoffs across different treatments. Bars represent standard errors. “Amb“ denotes decision-making under ambiguity conditions, and “Risk“ denotes decision-making under risk conditions. “DefaultUncertain“ denotes that the uncertain payoff is the default option, and “DefaultCertain “ denotes that the certain payoff is the default option.

The ANOVA showed a significant main effect of uncertainty ($F(1,43) = 8.442$, $p = 0.006$, $\eta_p^2 = 0.164$), with the uncertain payoffs were more likely to be chosen under risk conditions than ambiguity conditions. The main effect of default was also significant ($F(1,43) = 4.664$, $p = 0.036$, $\eta_p^2 = 0.098$). Compared to certain payoffs as default, the uncertain payoffs were chosen more frequently when they were the default options. However, the interaction between uncertainty and default was insignificant ($F(1,43) = 2.151$, $p = 0.150$, $\eta_p^2 = 0.048$). A trial-level Bayesian mixed-effects analysis is reported in Supplementary Section S2, confirming the consistency of the observed choice patterns.

3.2 Time-Domain Results

P200

In the frontal area, P200 amplitudes showed a significant main effect of uncertainty type ($F(1,43) = 4.311$, $p = 0.044$, $\eta_p^2 = 0.091$), with risk conditions eliciting larger P200 responses than ambiguous options. A significant main effect of default was also observed ($F(1,43) = 6.165$, $p = 0.017$, $\eta_p^2 = 0.125$). Under default settings, larger P200 deflection was observed for certain payoffs than that for uncertain payoffs. No significant interaction between uncertainty and default emerged ($F(1,43) = 0.478$, $p = 0.493$, $\eta_p^2 = 0.011$). The grand average ERP waveforms at Fz and FCz electrodes are depicted in Figure 3 (A).

MFN

The results of the frontal MFN amplitudes yielded a significant main effect for uncertainty ($F(1,43) = 5.945$, $p = 0.019$, $\eta_p^2 = 0.121$). Results revealed that the MFN amplitudes elicited by the ambiguity conditions were larger than the risk conditions. The significant main effect of default ($F(1,43) = 12.468$, $p = 0.001$, $\eta_p^2 = 0.225$) was also found for MFN amplitudes. In the default condition, certain payoffs elicited a more negative-going deflection compared to uncertain payoffs. The interaction between uncertainty and default ($F(1,43) = 0.191$, $p = 0.664$, $\eta_p^2 = 0.004$) was insignificant.

P300

In the parietal area, a significant main effect of P300 amplitudes was found for uncertainty ($F(1,43) = 4.981$, $p = 0.031$, $\eta_p^2 = 0.104$). The risk conditions elicited larger P300 deflection compared to the ambiguity conditions. There was neither significant main effect of default ($F(1,43) = 0.052$, $p = 0.821$, $\eta_p^2 = 0.001$) nor interaction between uncertainty and default ($F(1,43) = 0.199$, $p = 0.658$, $\eta_p^2 = 0.005$). The grand average ERP waveforms at Pz and CPz electrodes were depicted in Figure 3 (B).

LPP

A significant main effect for parietal LPP amplitudes was found for uncertainty ($F(1,43) = 28.464$, $p < 0.001$, $\eta_p^2 = 0.398$). Post hoc tests revealed that the LPP amplitudes elicited by the risk conditions were larger than ambiguity conditions. There was no significant effect of default ($F(1,43) = 0.086$, $p = 0.771$, $\eta_p^2 = 0.002$) or significant interaction between uncertainty and default ($F(1,43) = 0.291$, $p = 0.592$, $\eta_p^2 = 0.007$) on LPP amplitudes.

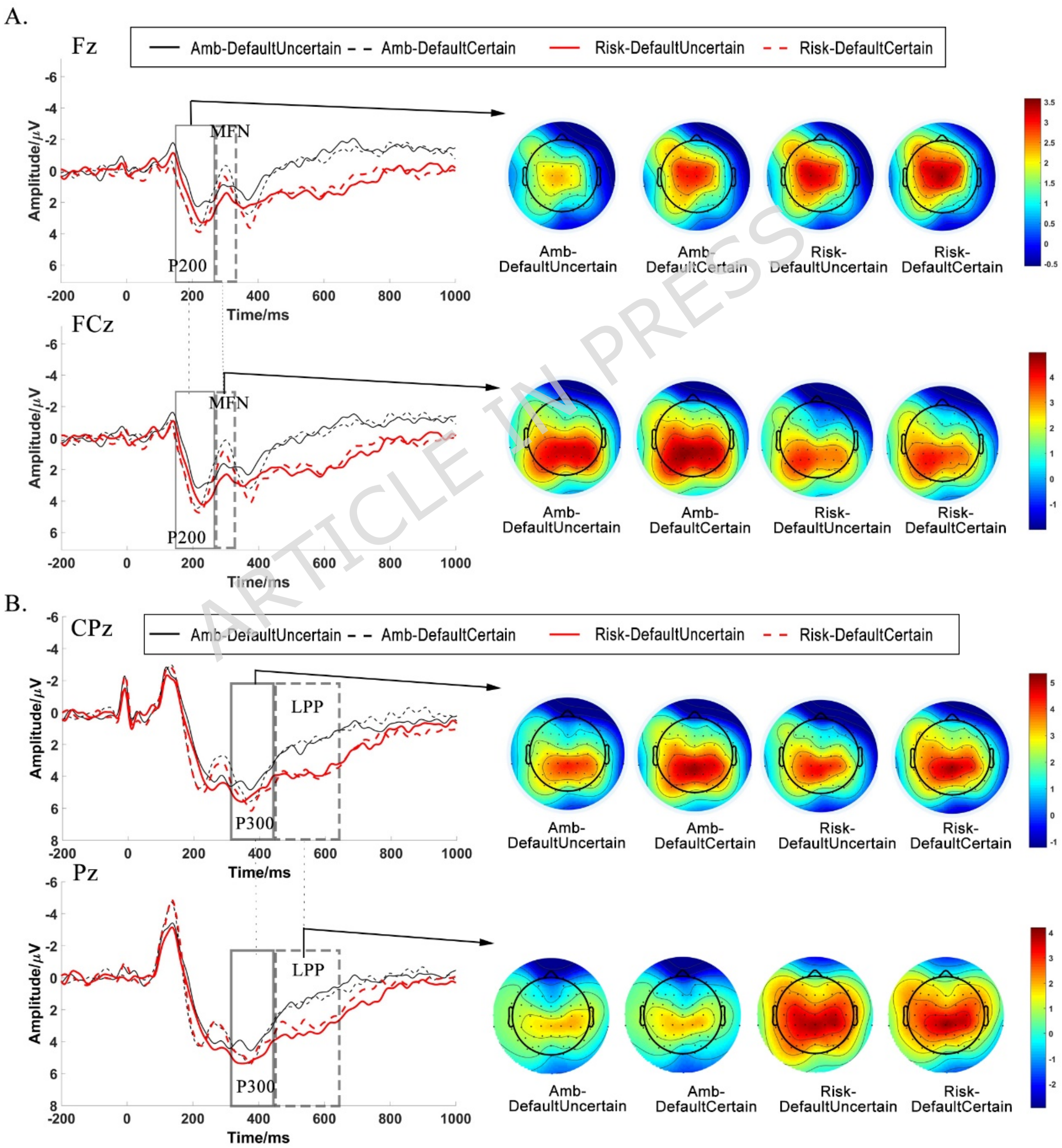

Figure 3. Grand averaged ERP waveforms and Topographical maps. (A) ERP waveforms at electrode sites Fz, FCz. And topographical maps for

P200 and MFN, respectively. (B) ERP waveforms at electrode sites CPz, Pz. And topographical maps for P300 and LPP, respectively. “Amb” denotes decision-making under ambiguity conditions, and “Risk“ denotes decision-making under risk conditions. “DefaultUncertain” denotes that the uncertain payoff is the default option, and “DefaultCertain” denotes that the certain payoff is the default option.

3.3 Time-Frequency Results

Theta Frequency band

The ANOVA revealed a significant main effect of default on theta responses ($F(1,43) = 18.255$, $p < 0.01$, $\eta_p^2 = 0.298$), with post hoc tests indicating greater theta power when the default options involved certain payoffs rather than uncertain payoffs. There was neither significant main effect of uncertainty ($F(1,43) = 0.387$, $p = 0.537$, $\eta p2 = 0.009$) nor significant interaction between uncertainty and default ($F(1,43) = 3.444$, $p = 0.070$, $\eta p2 = 0.074$). The theta oscillation at FCz electrode was depicted in Figure 4. Additional trial-level time-frequency results were provided in Supplementary Section S3, which showed the same pattern as the condition-averaged findings.

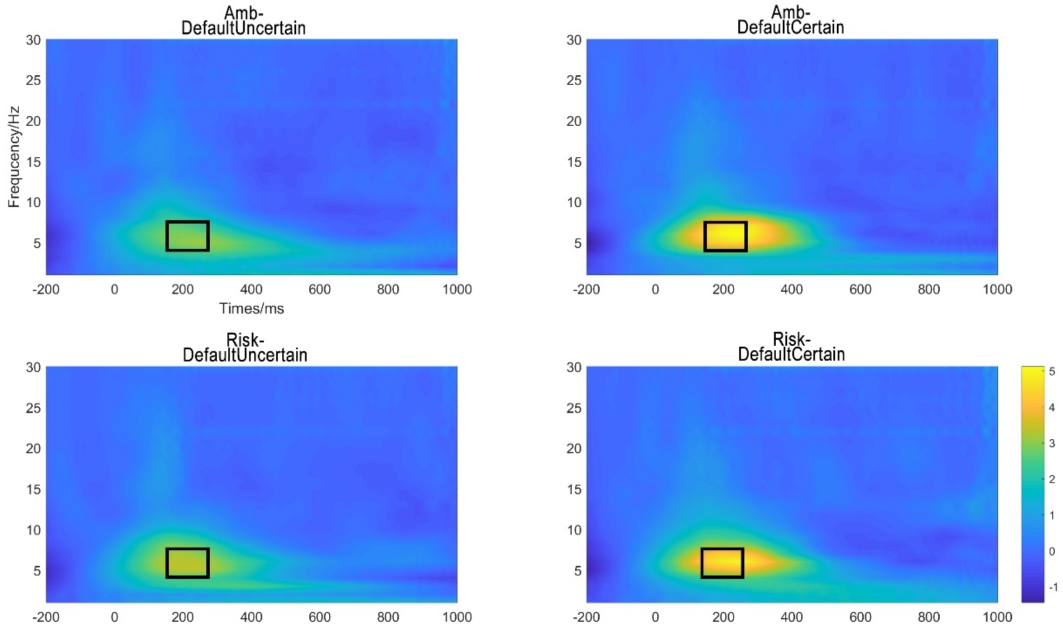

Figure 4. Time-frequency representation of ERP signals at the electrodes FCz for theta activity (4–7 Hz). Dark rectangles marked the time/frequency window used in the statistical analysis. "Amb" denotes decision-making under ambiguity conditions, and "Risk" denotes decision-making under risk conditions. "DefaultUncertain" denotes that the uncertain payoff is the default option, and "DefaultCertain" denotes that the certain payoff is the default option.

3.4 Neural–behavioral association analysis

To examine whether neural responses predicted individual differences in uncertainty choice behavior, we fitted separate mixed-effects regression models for each ERP/theta index. For each participant and condition, we computed the proportion of uncertain choices and extracted neural measures averaged across trials within each condition, including ERP amplitudes (P200, MFN, P300, LPP) and theta-band power. Each neural index was then entered separately as a predictor of behavior in a mixed-effects model with random intercepts for participants. Figure 5 presents the regression coefficients and 95% confidence intervals for each neural predictor.

Early components showed no meaningful associations. Neither P200 nor MFN amplitudes predicted behavioral tendencies (ps = 0.73 and 0.58, respectively). P300 amplitudes exhibited a positive but non-significant trend ($p = 0.21$). LPP amplitudes robustly and positively predicted uncertainty choice ($\beta = 0.022$, $p = 0.001$), indicating that individuals showing stronger sustained evaluative processing were more likely to choose uncertain options. Theta-band power did not predict behavior ($p = 0.65$).

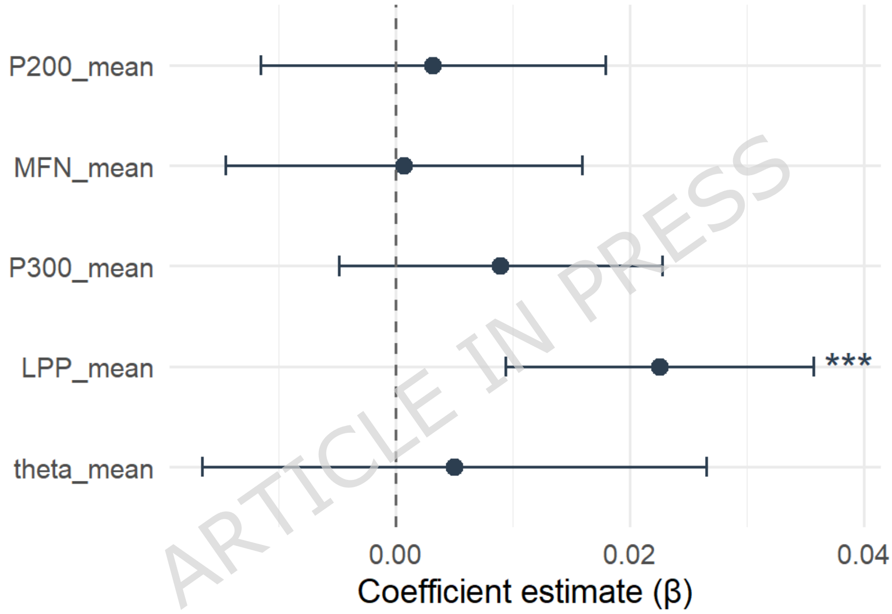

Figure 5. Single-predictor linear mixed-effects models examining neural correlates of uncertain choices. Coefficient estimates (β) and 95% confidence intervals are shown for each neural index. Significance levels are denoted as $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

3.5 RSA

To compare the behavioral results with ERP results, the non-diagonal half of the symmetrical behavioral RDM was then correlated with the neural RDM in the ROI. We found that representational similarity in the frontal area in the time window of 270–300 ms was correlated to the behavioral choices (Spearman r = 0.829, p = 0.017, Figure 6).

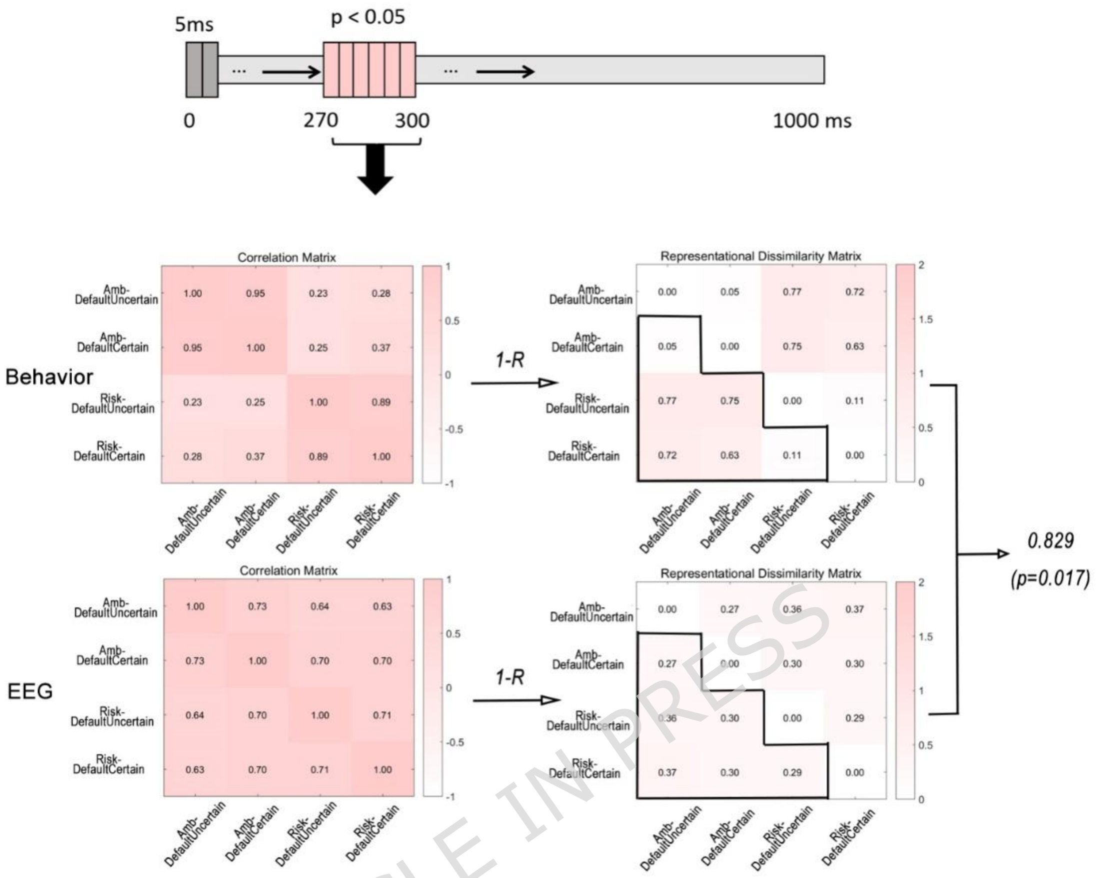

Figure 6. RSA. For each participant, we averaged the behavioral variables or EEG variables (amplitudes of EEG responses in the ROI at each time point) across trials for four conditions, respectively. Then Spearman correlation analyses were performed on each variable between each pair of conditions across all participants. Correlation distance (1 - correlation coefficient) was calculated to create the representation dissimilarity matrix, which contains a 4 * 4 cell reflecting the dissimilarity between the behavioral patterns or between the EEG activity patterns associated with each pair of conditions. Finally, numbers in the upper (or equivalently the lower) triangle of the matrices were used to perform the Spearman correlation analysis between the behavioral RDM and EEG RDM. “Amb” denotes decision-making under ambiguity conditions, and “Risk” denotes decision-making under risk conditions. “DefaultUncertain” denotes that

the uncertain payoff is the default option, and “DefaultCertain” denotes that the certain payoff is the default option.

4. Discussion

An understanding of how the brain manages uncertainty is among the key topics in the emerging field of neuroeconomics [62]. In this study, we assessed the default effects in decision-making under uncertainty and explored the neural dynamics involved in the early stage by using the ERP technique. Through behavioral analysis, we observed that participants' decision-making was influenced by the default options. The evaluation of the default setting, comparing default uncertain options with default certain options, reflected not only in the early ERP components (including the P200 and the MFN) but also in the increased activity within the theta frequency band. Additionally, individuals harbour different attitudes towards risk and ambiguity. These differences were evident not only at the behavioral level but also in ERP components such as the MFN, P300, and LPP. The results of the RSA revealed that the subsequent choices were closely aligned with the brain patterns observed in the frontal area during the early time window of 270 to 300 ms. Our research enhances the understanding of the decision-making process under uncertainty, particularly in relation to default options.

Behaviorally, we observed significant ambiguity aversion and default effects. Participants were more willing to choose to bet in risk conditions compared to ambiguity conditions, which is consistent with previous findings [1, 5]. These findings suggest that people harbour different attitudes towards risk and ambiguity, with a greater aversion to ambiguity being reported compared to risk. We speculated that this aversion stems from a fear of the unknown probabilities associated with ambiguous options, thus leading individuals to be reluctant to take chances on these options. In addition, their choices were influenced by preselected default options. A vast and growing body of research has demonstrated that people tend to choose whichever option is set as the default option, which is known as the default effect [10, 57, 63]. The role of default effects in decision-making under uncertainty may be due to reference-dependent mechanisms [12, 17]. The default option may represent a reference point that colours the evaluation of other options as gains or losses [16]. In our experiment, the payoffs associated with risky or ambiguous options were uncertain; thus, the costs of giving up the default options could not be predetermined. However, this cost could psychologically be perceived as a potential loss, which may cause reluctance to opt out.

ERPs offer better temporal resolutions for us to investigate how a cognitive process is occurring during the assessment of the options associated with conditions of uncertainty. The assessment of default setting, comparing default uncertain options with default certain options, was reflected in the early ERP components, including the P200 and the MFN. The frontal P200 revealed a significant main effect of default, with certain payoffs eliciting larger P200 amplitudes compared to uncertain payoffs under default settings. Previous studies have demonstrated that the P200 component may reflect the early dedication of attentional resources to stimulus evaluation, thus likely facilitating quick assessment [22, 24]. The default option may serve as a reference point, which facilitates rapid and intuitive judgments [12, 17, 64]. Consequently, its characteristics may be represented by the P200 component. Previous study has confirmed that the early P200 component primarily reflects the process of probability weights, with greater amplitudes elicited by high-probability reward than low-probability reward [22]. These findings align with our observation that certain payoffs elicited larger P200 amplitudes compared to uncertain payoffs under default settings. In addition, the MFN component also demonstrated a significant main effect of default, and a more negative deflection was elicited by certain payoffs compared to uncertain payoffs under default settings. There is evidence indicating that the MFN may be sensitive to processes associated with money magnitude. Specifically, when probability weights remain the same, a small money magnitude elicits a more pronounced MFN than a large one [22]. Aligning with these findings, the uncertain default, which consistently involved a larger monetary amount, resulted in a reduced MFN amplitude. These findings contribute to the understanding of the temporal dynamics of uncertain option assessment in default-based decision-making.

The differences between risk and ambiguity were reflected not only in behavior, but also in the ERPs, including early ERP components such as the P200, the MFN, the mid-latency P300 component, and the late LPP component. The amplitude of the P200 component elicited in the risky condition was significantly greater than that observed under the ambiguous condition. This finding is in accordance with previous research on decision-making under uncertainty, which has demonstrated that smaller amplitudes of the frontocentral P200 in the ambiguous condition are indicative of a rapid characteristic of the detection processes that are engaged in processing the ambiguity context [65, 66]. For the MFN, our results demonstrated that ambiguous options evoked a more negative MFN compared to risky options. Specifically, it has been suggested that the MFN response elicited by unfavorable outcomes is significantly greater than that elicited by favorable outcomes [67, 68]. Thus, our results provide evidence for ambiguous aversion at the neural level, which was also consistent with subsequent behavioral-level data. In addition, the risk conditions elicited larger P300 and LPP amplitudes compared to ambiguity conditions. The P300, which is among the most frequently studied components of ERPs, has conventionally been considered to be a valuable metric for assessing cognitive functions, processing capacity, and mental workload [69]. The present results were compatible with previous findings demonstrating that the P300 reflects the processes of attention allocation and the motivational/emotional salience of outcomes; for instance, P300 amplitudes have been observed to be greater for gains than for losses [54], as well as being greater for larger outcomes compared to smaller outcomes [70]. The late positive potential (LPP), which is a P300-like ERP, has been observed to be associated with the cognitive resources required during later processing and motivational significance attributed to affect [30]. Our results regarding the P300 and LPP components may reveal that people demonstrated much greater aversion in the ambiguity conditions than in the risk conditions. Decision-making under ambiguity may be associated with negative emotional processes, due to the fact that people may experience negative feelings (such as being worried, anxious, and hesitant) regarding unknown outcomes [29, 71].

Moreover, single-predictor regression analyses revealed that among all of the examined neural indices, the LPP amplitudes reliably predicted uncertainty choices in subsequent behavioral-level data. Specifically, we observed that individuals with larger LPP amplitudes across conditions were more inclined to select uncertain options. This result suggests that greater engagement in motivation and the subsequent allocation of attention may facilitate approaching (rather than avoiding) uncertainty, given that the LPP is generally considered to be associated with relevant motivational stimuli and the subsequent sustained allocation of attention [72-74]. This finding aligns with the interpretation that the LPP emphasises utility, thereby indicating its possible integrative role in decision-making [45, 46]. Similarly, previous research has revealed that the LPP was able to differentiate levels of ambiguity, which was specifically linked to behavioral judgments regarding ambiguous choices [75]. These results imply that decisions under uncertainty primarily rely on later-stage motivation and subsequent allocation of attention rather than early perceptual or conflict-driven responses, thus highlighting the LPP as a crucial neural correlate of uncertainty engagement.

Notably, the default effect and the distinguishing between different types of uncertainty seem to be independent additive effects in decision-making under uncertainty. This observation is interesting because it suggests that these processes may rely on different mechanisms or mental processes. As suggested by neuroimaging studies, the neural processing of risk and ambiguity in personal decision-making engages neural activities in the OFC, amygdala, and DMPFC [2], whereas the default effect is mediated by the insula and striatum [76]. Our results provide further evidence for the independent effects of defaults and uncertainty types based on temporal dynamics. The evaluation of default setting was exclusively observed in the early ERP components (specifically involving the P200 and MFN). In contrast, the distinction between risk and ambiguity was evident in the P200, MFN, P300, and LPP components. The distinct ERP components associated with defaults versus uncertainty types indicate that these processes reflect separable aspects of decision-making under uncertainty.

In addition, the findings of the present study revealed that the frontal theta band was greater when the default option involved certain payoffs than when uncertain payoffs were involved. Prefrontal theta activity likely originates in the ACC, which is an area that has been related to conflict monitoring between competing responses [77], prediction error [78] and linking reward information to action [79, 80]. One plausible explanation for our results is that certain payoffs (due to their reduced risk and higher subjective attractiveness) serve as stronger cognitive anchors during the decision process. The overriding of such a safe and salient default to select an uncertain alternative is likely to trigger greater engagement of control systems, which is reflected in elevated frontal theta activity. This finding is consistent with behavioral findings demonstrating that defaults exert a powerful anchoring effect [11, 16]. Alternatively, it is possible that greater theta activity may arise from internal motivational conflicts. Although individuals are generally biased towards certainty, the demands of maximizing payoffs may simultaneously encourage exploration of uncertain alternatives, thereby producing tension between safety and exploration. This interpretation is consistent with prior research demonstrating that theta oscillations from the frontal cortex increase in response to conflict detection, attention, and task difficulty [80-82]. Taken together, these findings suggest that frontal theta activity may represent a broader neural index combining cognitive control, motivational conflict, and evaluative processes engaged by defaults in decision-making.

RSA has been previously employed in EEG research to detect the emergence of neural activity patterns related to the encoding of specific stimulus features [60, 83-85]. Here, we adapted this method to assess the relationship between brain activity and subsequent behavior-level data. The use of RSA provides a novel perspective and offers new information on the relationship between brain activity and behavioral choices under uncertainty. The results of the RSA revealed that the subsequent choices were closely associated with the brain patterns in the frontal area in the time window of 270–300 ms. This finding aligns with our time-domain analysis, as the time window closely overlaps with the MFN component (270–320 ms), which indicates a significant main effect for both uncertainty types and defaults. These findings are also consistent with findings indicating that the MFN component is often linked to performance monitoring and outcome evaluation [86, 87]. Due to the fact that the MFN component has been suggested as a marker signaling unexpected defection and can predict subsequent belief updating [88], as well as rejection behavior in the Ultimatum Game [89], the observed neural similarity patterns further suggest that early-stage ERP components may contribute to shaping decision biases. This finding supports the notion that the brain may engage in rapid evaluation processes that guide subsequent choices [90, 91]. Specifically, Gehring and Willoughby [86] suggested a correspondence between risk-taking behavior and the outcome processing reflected by the MFN, thus further supporting the role of this component in decision-making under uncertainty. Furthermore, default effects in decision-making have been observed to be associated with early neural responses that bias attention and evaluation processes [57]. Our findings advance this line of research by presenting novel evidence indicating that brain activity in the frontal region during the 270–300 ms time period plays a crucial role in decision-making under uncertainty when default options are available. The observed neural similarity patterns further suggest that early-stage ERP components contribute to shaping decision biases, supporting that the brain might engage in rapid evaluation processes that guide subsequent choices [90, 91]. These results highlight the importance of early neural mechanisms in mediating the influence of defaults on decision-making under uncertainty.

More broadly, our results potentially provide information on the cognitive and neural mechanisms underlying the default effects on decision-making under uncertainty. Using the ERP technique, our findings contribute to a growing understanding of how default options shape the decision-making processes of individuals. Furthermore, our findings extend prior research on ambiguity aversion by demonstrating that it not only manifests behaviorally but also involve distinct neural responses, as indicated by enhanced MFN, P300, and LPP signals in risk conditions compared with those in ambiguity conditions. Importantly, these findings have practical implications, particularly in the realm of public policy. Organizations, managers, or policymakers can strategically formulate default options to guide individuals towards socially advantageous choices, such as savings or investment plans, especially in situations where uncertainty may otherwise deter action.

The current study is a preliminary investigation into the neural mechanism underlying the influence of default options on decision-making under uncertainty. However, this study has several limitations. First, in this study, the default and alternative options were presented simultaneously, which precludes a clear dissociation of neural responses uniquely elicited by the default option. Consequently, the default-related ERP effects observed here are interpreted as reflecting relative processing biases toward the default option during simultaneous choice evaluation. Future work employing alternative presentation formats may further clarify the neural mechanisms specific to the default option. Second, the experimental design employed laboratory-based decision-making tasks, which may not fully capture the complexities of real-world decision-making under uncertainty. Real-world scenarios frequently involve additional factors, such as social interactions, experience, and long-term consequences, which were not considered in this study. In addition, to eliminate the potential impact of feedback on subsequent choices, we adopted an experimental procedure without feedback. However, this approach fails to account for learning effects that may influence individuals' responses to default options and uncertain environments over time, which warrants future research.

5. Conclusion

The present study investigated the effects of neural responses to default effects on decision-making in uncertain situations. Our study revealed that neural responses were modulated by whether the certain or uncertain option was designated as the default option. This modulation was evident in the P200, MFN, and theta oscillations, indicating the rapid engagement of attentional, cognitive control, and evaluative processes. In contrast, the processing of uncertainty in risk and ambiguity contexts recruited a broader temporal sequence of neural activity. Effects were observed not only in early components (P200, MFN) but also in later evaluative stages (P300, LPP), reflecting increased cognitive demands, conflict monitoring, and motivational salience. Importantly, regression analyses revealed that LPP amplitudes reliably predicted subsequent uncertainty choices, suggesting that later-stage evaluative processes contribute to shaping behavioral preferences. Moreover, the RSA results revealed that the subsequent choices were closely aligned with the frontal brain patterns during an early time window. Together, these findings refine neurocognitive accounts of decision-making under uncertainty by demonstrating that the default effects and ambiguity aversion operate through partly distinct neurocognitive mechanisms. Our study may provide novel insights into understanding of the neural substrates underlying the influence of default effects on decision-making under uncertainty.

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Data availability statement

The datasets generated for this study are available on request to the corresponding author.

Competing interests

The authors declare no competing interests.