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Neurophysiological correlates of purchase decision-making

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A B S T R A C T

Economic decisions are characterized by their uncertainty and the lack of explicit feedback that indicates the correctness of decisions at the time they are made. Nevertheless, very little is known about the neural mechanisms involved in this process. Our study sought to identify the neurophysiological correlates of purchase decision-making in situations where the optimal purchase time is not known. EEG was recorded in 24 healthy subjects while they were performing a new experimental paradigm that simulates real economic decisions. At the time of price presentation, we found an increase in the P3 Event-Related Potential and induced theta and alpha oscillatory activity when participants chose to buy compared to when they decided to wait for a better price. These results reflect the engagement of attention and executive function in purchase decision-making and might help in the understanding of brain mechanisms underlying economic decisions in uncertain scenarios.

1. Introduction

Most real-life decisions are made under uncertain conditions in which individuals have to rely on the history of previous decisions and learn from the consequences of their actions. Therefore, the processing of both signals providing cues about future decisions and the feedback of the performed actions are crucial, in order to adapt the behavior to the actual scenario and to be able to respond to its changes. Previous studies have delineated the brain network involved in the decision-making processing, which comprises orbitofrontal cortex, prefrontal cortex, anterior cingulate cortex, amygdala, and ventral striatum/nucleus accumbens areas, among many others (Delgado, Nystrom, Fissell, Noll, & Fiez, 2000; Delgado, 2007; Farrar, Mian, Budson, Moss, & Killiany, 2018; Si et al., 2019). In addition, EEG studies have described two main Event-Related Potentials (ERP) related to decision-making, the N2 and the P3 ERPs. The N2 is a frontocentral negative deflection that peaks between 200 and 300 ms after stimulus presentation (Dickter & Kieffaber, 2014; Luck, 2014). This component has been found to present an increased amplitude after neutral or negative cues (e.g. stimuli indicating a potential monetary loss) compared to positive ones (Novak & Foti, 2015). It has been associated with increased cognitive control and with a discrepancy between expected and real situations (template mismatch; Glazer, Kelley, Pornpattananangkul, Mittal, & Nusslock, 2018). On the other hand, the P3 component is a centroparietal ERP that appears 300–600 ms after stimuli presentation. It has been related to attentional processes (Polich & Kok, 1995; Polich, 2007), the probability and expectation of appearance of stimuli (Levi-Aharoni, Shriki, & Tishby, 2020; Luck, 2014; Polich & Margala, 1997; Sur & Sinha, 2009), the complexity of the experimental task (Polich, 2007) and relevance of contextual information (Levi-Aharoni et al., 2020). Evidence suggests that increases in P3 amplitude arise from the evaluation of new stimuli compared to the previous one stored in the working memory (Morgan, Klein, Boehm, Shapiro, & Linden, 2008), the revision and adaptation of mental models of response (Wang, Zheng, Huang, & Sun, 2015), duration of stimulus evaluation (Twomey, Murphy, Kelly, & O'Connell, 2015) and the working memory load (Wang et al., 2015).

In addition, three main oscillatory components have been associated with some key aspects of this processing. In particular, different studies have proposed a key role of the frontocentral theta oscillatory activity in the computation of the prediction error or surprise of the outcome of a decision (HajiHosseini, Rodríguez-Fornells, & Marco-Pallarés, 2012; Wang et al., 2016). In addition, theta plays an important role in cognitive control (Clayton, Yeung, & Cohen Kadosh, 2015; Cox & Witten, 2019) and is modulated by the uncertainty of the context (Cavanagh, Figueroa, Cohen, & Frank, 2012; Mas-Herrero & Marco-Pallarés, 2014). All these previous results have led to the proposal that theta oscillatory activity might act as a common adaptive control mechanism in situations with uncertainty about the outcome of responses and decisions

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(Cavanagh & Frank, 2014; Cavanagh, Figueroa et al., 2012).

A second component that has been studied in decision-making experiments is alpha oscillatory activity. Previous research has related increase in alpha power to selective inhibition (Noonan, Crittenden, Jensen, & Stokes, 2018) and alpha suppression to facilitation of attentional systems as task preparation (Glazer et al., 2018). In reward-guided tasks, higher alpha suppression has been described in feedback anticipation (Bastiaansen, Böcker, Cluitmans, & Brunia, 1999; Pornpattananangkul & Nusslock, 2016) and been related to higher motivation of participants to learn from feedbacks (Glazer et al., 2018; Pornpattananangkul & Nusslock, 2016). Finally, beta oscillations have consistently been reported in response to unexpected or highly relevant positive outcomes (Cohen, Elger, & Ranganath, 2007; Cunillera et al., 2012; Marco-Pallarés, Münte, & Rodríguez-Fornells, 2015; Mas-Herrero, Ripollés, HajiHosseini, Rodríguez-Fornells, & Marco-Pallarés, 2015). Different interpretations of this component have been proposed, including, among others, it having a possible role in maintaining the "status quo" (Engel & Fries, 2010), it being a signal driving motivational value to the reward network (Marco-Pallarés et al., 2015) or it acting as a mechanisms for the endogenous reactivation of latent cortical representation (Spitzer & Haegens, 2017).

One of the most common decisions we have to face in our daily life is to decide what to buy and when to do it. The economic decision process entails assigning values to the available options before deciding (Huettel, Stowe, Gordon, Warner, & Platt, 2006; Platt & Padoa-Schioppa, 2009; Rangel, Camerer, & Montague, 2008) and choosing the price and the moment to buy the product. This value is highly subjective and in many cases has an emotional nature, fulfilling real or perceived utilities, beliefs or satisfaction of needs which might be driven by different factors such as, e.g., the symbolic value of the product or the state of the buyer (Burnett & Lunsford, 1994). Most of the psychology literature on this topic has been devoted to explore the attitudinal (see, e.g. Denegri et al., 2012; Quintanilla & Luna-Arocas, 1999; Luna-Arocas and Fierres, 1998) and personality traits (Boyce, Czajkowski, & Hanley, 2019; Gambetti & Giusberti, 2019; Huettel et al., 2006) influencing such decisions. In addition, several studies have described the impact of multiple factors on purchasing decisions, including previous experience with the product or brand (Esch et al., 2012; Jiménez & Mendoza, 2013; Ling, Chai, & Piew, 2010), advertising image, logo and typography (Dong & Gleim, 2018; Doyle & Bottomley, 2004), and the place of purchase (virtual or traditional store; Eroglu, Machleit, & Davis, 2001). However, much less research has been devoted to studying one of the most critical factors in purchase decision-making: when to buy. Hence, in the process of deciding whether to buy a product, the actual price and its prospects of being higher or lower in the future are crucial. Nevertheless, the study of such decisions is not trivial because, although they have some similarities with the traditional paradigms used in the study of decision-making, they also present some important particularities. Therefore, in contrast to the former, in which a clear structure is presented (e.g., target-response-feedback about the consequence of the action), in purchase decision-making the feedback about the correctness of the decision is fuzzy. For example, when we decide to buy a flight ticket on an internet web page after days of checking the variation of the prices for the same flight, the feedback of the decision is ambiguous as it might be considered *good* or *bad* only on the basis of previous prices and the prospects of the future. In this situation, for example, the presentation of the price would be both a cue and, in the case of a buy, a feedback of the consequence of the action. In addition, previous non-bought prices act as the feedback for a non-performed action (Kahneman, 2009; Karimi, Papamichail, & Holland, 2015). These situations are, therefore, challenging to be translated to experimental paradigms and have been scarcely explored in the literature. In the present paper we propose a new experimental paradigm, the Purchase Decision-Making under temporal uncertainty task (PDMt) in which we simulated purchase decisions in which there was uncertainty about the correct moment to buy a product. PDMt emerges as an experimental tool for the study of consumer decisions, in order to explore the purchase decision-making process from individual variations attributable to neurophysiological markers. For this, we designed an experiment in which participants had to buy different products, where the main uncertainty was the correct time to buy, omitting other additional information to control for the effect of previous experience and information available to the participants in order to simulate what happens in purchases in virtual stores (Eroglu et al., 2001). Additionally, to achieve an appropriate simulation of said purchasing context, we generated ambiguous and uncertain price distributions, where the participants did not know the probabilities of success or failure in each decision or where the probabilities were not defined (Huettel et al., 2006), with options that might dynamically change over time (Cavanagh, Figueroa et al., 2012). These paralleled real-life situations in which the price of a product might change over time, i.e., becoming more expensive or cheaper in the future.

Previous research has revealed some interesting insights into purchase decision-making. Preference for a product over another is expressed by a reduction in the N200 event-related potential component and weaker theta band power in frontal areas (Telpaz, Webb, & Levy, 2015). Additionally, evidence suggests the existence of a left frontal asymmetry that predicts purchase decisions when the price shown is below the normal one, even when the normal one is an implicit and subjective reference (Ravaja, Somervuori, & Salminen, 2013), and it is explained by power increases in alpha band oscillations (Arieli & Berns, 2010). Braeutigam, Rose, Swithenby, and Ambler (2004), also, found that subjects' choices of consumer goods were associated with power increases in alpha and gamma bands. Importantly, most of the above-mentioned studies have focused on post-decision elements related mainly to marketing, with the main objective being improvement of sales strategies and consumers' preferences of a product over another (Arieli & Berns, 2010). However, as stated above, none of these studies have looked at one of the most common sources of uncertainty: when to buy. In the present paper, we aimed to study the neurophysiological correlates of purchase decision-making in scenarios with temporal uncertainty using the new PDMt experimental paradigm. In light of prior research, we hypothesized that the decision to buy a product or decide to wait for a new offer would lead to differences in the ERPs components elicited during price presentation. We also expected an increase in induced oscillatory activity in theta, alpha and beta frequency bands when participants decided to buy a product compared with when the decision was to wait for another offer.

2. Materials and methods

2.1. Participants

Twenty-four healthy young adults participated in the experiment (8 men, mean age 22.13 ± 4.23 (S.D)) for monetary compensation. Subjects received €25 for their participation plus a bonus depending on their performance in the task (€1 for every 50 coins saved; see above). Written consent was obtained prior to the experiment. The local ethical committee approved the experiment.

2.2. Design

We used a new experimental paradigm, the Purchase Decision-Making task (PDMt), where participants had to buy three unknown products, in 20 series, with a maximum of 10 offers (10 days in the cover of the experiment) to decide. Participants were told that they had to assume the position of a maintenance manager of a boat company in Alaska where they had to buy the three necessary products (spare parts, oil, and tools) to keep the company running. In each series, participants had a maximum budget of 1,000 coins to buy the three products required, with the instruction: "try to save as much as possible in each sequence", as a way to standardize the levels of motivation and final goal of the task.

Each trial consisted of the purchase of the three products, shown sequentially in the same order. First, the participant saw the picture of the first product and the number of the trial (1–20). Then, the information about the day (e.g., Day 1) and the price appeared on the screen. Participants could decide to buy at that price or to not buy and wait for the next price by pressing a corresponding button. If they decided to wait, the next day (e.g., Day 2) another price appeared on the screen and the participant had to decide again. In case of purchase, the image of the next product and the number of trials appeared on the screen and the procedure continued with Day 1 and the price for the product. If the participant waited until the last day (10), the product was bought at the price indicated on this day and the new product appeared. When all three products were bought, the total final price was shown, and the next trial started with the first product *(see* Fig. 1A*)*.

Unknown to the participants, each product had a particular price distribution which was defined a priori (Huettel et al., 2006). The first product had a mean fixed value every day; the second product presented two minima on days 3 and 9 and a maximum on day 6. Finally, the third product had a minimum on day 5. In addition, each day had an SD that increased linearly, from 10 coins on the first day, to 55 on the last day (*see* Fig. 1B). The different distributions allowed the creation of different uncertainty scenarios for the different products. Given the difficulty of the task, and in order to facilitate the learning of the hidden distribution of the prices, the products were presented in the same order throughout the experiment.

2.3. Electrophysiological recording

EEG was recorded from the scalp (0.01 Hz high-pass filter with a notch filter at 50 Hz; 250 Hz sampling rate) using a BrainAmp amplifier with tin electrodes mounted on an Easycap (Brain Products©), at 32 standard positions (Fp1/2, AFz (Gnd), Fz, F3/4, F7/8, FCz, FC1/2, FC5/6, Cz, C3/4, T7/8, CP1/2, CP5/6, Pz, P3/4, P7/8, L/R Mastoids, O1/2). The mean of the activity of the two mastoid (L/R) processes was used as re-reference of biosignals (off-line). Additionally, vertical eye movements were monitored with an electrode at the infraorbital ridge of the right eye. All electrode impedances were kept below 5kΩ.

2.4. Data analysis

Behavioral results were analyzed using repeated measures ANOVA analyses. First, to identify possible differences in participants' choices throughout the task, a repeated-measures ANOVA was computed for two within factors: product (distribution 1, 2, 3), and purchase block (block 1: from purchase 1–10; block 2: from purchase 11–20). The offer of the purchase decision was considered a dependent variable. The second analysis was focused on measuring the possible differences in the response time of each decision during the experiment. For that, a repeated-measures ANOVA was computed for three within factors: product (distribution 1, 2, 3), purchase block (from purchase 1–10; from purchase 11–20), and type of decision (wait or buy). The JASP software

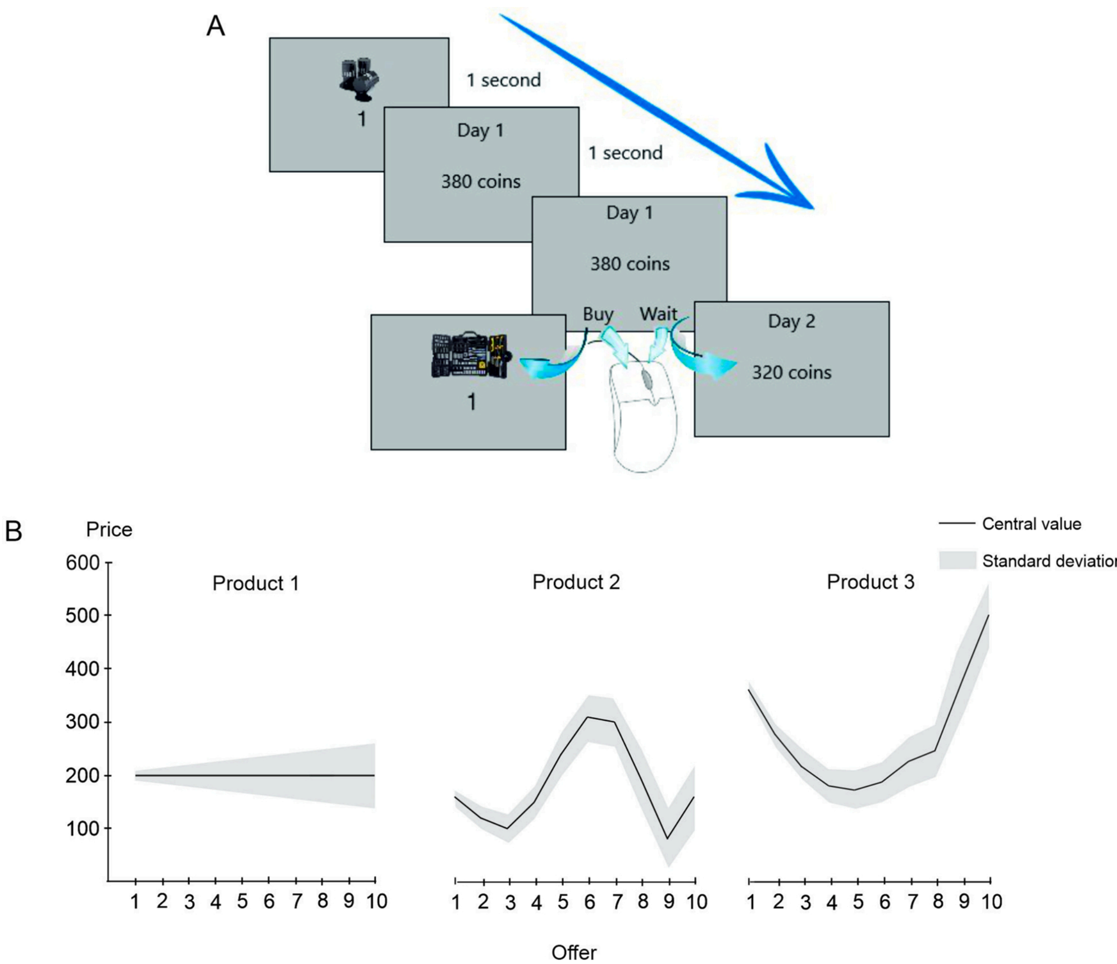

Fig. 1. A. Task structure of the Purchase Decision-Making Task. Participants had to buy three different products in each trial. Each product could be bought on 10 "days". Each day a price was presented, and participants had to decide whether to buy the product at this price or to wait for the next day and price. If the participant waited, a new day and price appeared, for a maximum of 10 days, upon which the product was acquired at the price on the last day. When the product was bought, the new product appeared, and the procedure started again until the three products were acquired. **B.** Distribution of prices for the three products with the different "days" (offer). Note the increase in the SD of the price with the offer.

was used for the statistical analysis (JASP Team, 2020).

2.4.1. Event-related brain potentials

EEG was low-pass filtered at 40 Hz offline using EEGLab 2019 under MATLAB (MathWorks, 2019). Epochs were extracted from -2000 ms before the stimuli to 2000 ms after it. Two conditions were studied: the stimuli showing the price at which the participant bought the product (buy condition), and the previous offer in which participant did not buy (wait condition). In addition, in order to have the same number of stimuli for the two conditions, we did not analyze those offers in which participants bought in the first day. Therefore, the number of trials used for the two conditions was the same for each participant (51.5 ± 7.2 trials).

Independent Component Analysis (ICA) was applied to the data and those components reflecting artifacts were removed from the data (Bell & Sejnowski, 1995; Delorme, Palmer, Onton, Oostenveld, & Makeig, 2012; Lee, Girolami, & Sejnowski, 1999). Epochs exceeding ±100 μV were also rejected from further analysis.

Event-Related Potentials were extracted from -200 ms (baseline) to 1000 ms after the presentation of the price for each epoch. A 20 Hz low-pass filter was applied and then a cluster-based spatiotemporal permutation test on full sensor data was performed between the conditions (Gramfort et al., 2013; Maris & Oostenveld, 2007) using the MNE package (Gramfort et al., 2014) under Python (Dayley, 2006) in the Spyder environment (Raybaut, 2017), in order to control the possible effect of the multiple comparisons (Gramfort et al., 2014, 2013; Maris & Oostenveld, 2007) and obtain the time range in which the two conditions were significantly different. The threshold used for the cluster formation was automatically computed based on the F-distribution of the dataset (Maris & Oostenveld, 2007); the number of permutations was 1000. In addition, repeated-measures ANOVA was computed for three within factors: condition (wait or buy), laterality (left, middle, right) and anterior-posterior (frontal, central, and parietal) in the N2 and P3 ERPs time ranges.

2.4.2. Time-frequency analysis

In order to find the induced time-frequency activity, we first subtracted the ERP for each condition from each single trial for each condition from −2000 ms to 2000 ms and then we convoluted them using a complex Morlet wavelet (Herrmann, Senkowski, & Röttger, 2004; Tallon-Baudry, Bertrand, Delpuech, & Pernier, 1997) from 1 Hz to 30 Hz at 1 Hz steps. The mean change of power respect baseline was obtained for different electrodes (Fz, F3/4, Cz, C3/4, Pz, P3/4) and a repeated-measures ANOVA was computed for three within factors: condition (wait or buy), laterality (left, middle, right) and anterior-posterior (frontal, central, and parietal).

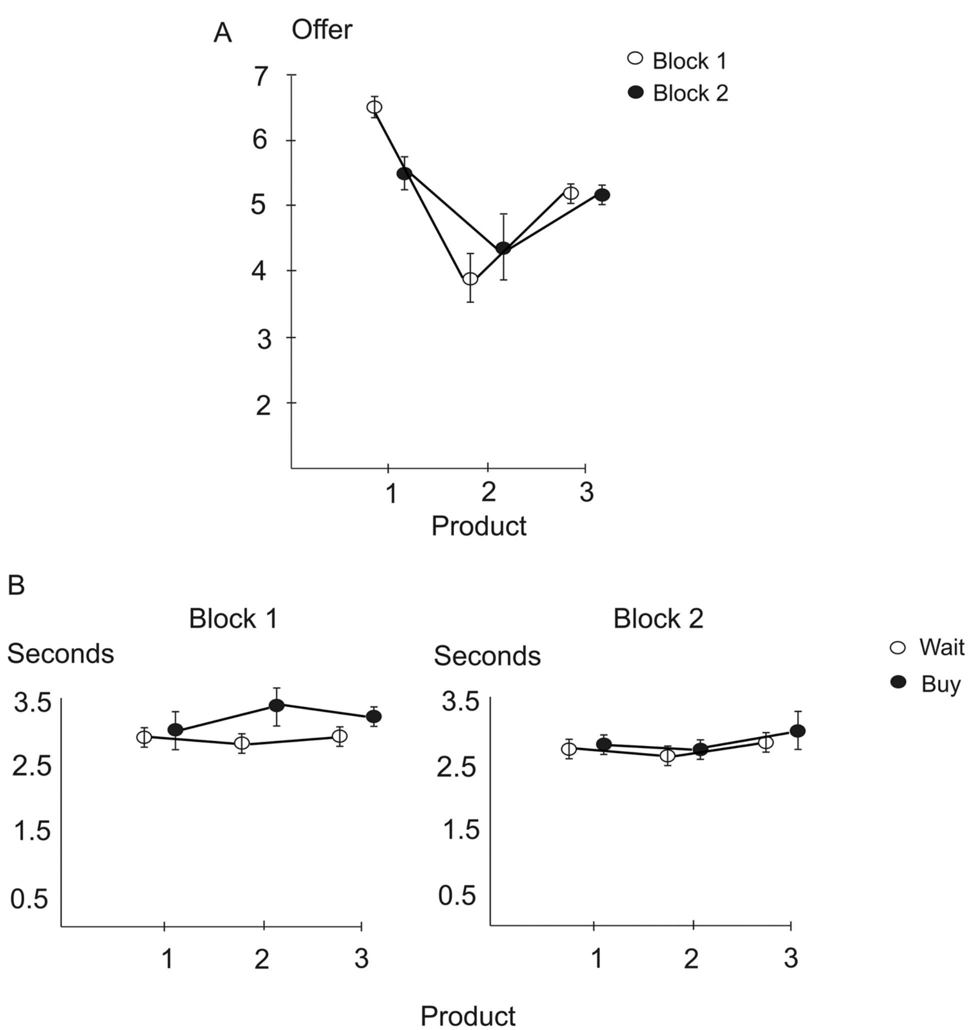

Fig. 2. **A.** Average of offer of purchase for each product and purchase block. Error bars indicate the standard error of the mean **B.** Average of response time in each product and purchase block during the task.

3. Results

3.1. Behavioral results

The general results revealed that 3.14 % of purchase decisions were made when the price variation was 0, 12.06 % were made when prices increased (49 % of them corresponded to forced purchases in trial 10), and 84.80 % of purchases were made when prices decreased. Fig. 2A shows the mean of the offer when participants decided to purchase the products in each distribution, in the first (purchase 1–10) and second (purchase 11–20) half of the experimental paradigm. Repeated measures ANOVA revealed the existence of significant differences among products ($F(2,44) = 15.784$, $p < 0.001$, $\eta_p^2 = 0.418$) and interaction between product and block of purchases ($F(2,44) = 8.983$, $p < 0.001$, $\eta_p^2 = 0.290$), but no significant effect of purchase block ($F(1,22) = 0.828$, $p = 0.373$, $\eta_p^2 = 0.036$). Therefore, the decisions of participants were dependent on the different price distributions and consistent throughout the experiment. Post-hoc analysis using Bonferroni correction showed that purchases of product 2 were made 1.793 ± 0.320 (SE) offers before product 1 ($t(20) = 5.604$, $p_{bonf} < 0.001$) and 1.011 ± 0.320 offers before product 3 ($t(20) = 3.158$, $p_{bonf} = 0.009$). In addition, purchases in the first block of product 1 were bought 0.952 ± 0.260 offers later than in the last block ($t(17) = 3.660$, $p_{bonf} = 0.008$).

Fig. 2B shows the mean of the reaction time in each decision, product, and purchase block of the experimental paradigm. The rmANOVA of response time revealed the existence of significant differences in the type of decision (wait or buy, $F(1,17) = 16.384$; $p < 0.001$; $\eta_p^2 = 0.491$). Post-hoc tests showed that the decision to wait was made 0.232 ± 0.057 s faster than the decision to buy ($t(21) = 4.048$; $p_{bonf} < 0.001$). In addition, purchase block factor was also significant ($F(1,17) = 19.320$; $p < 0.001$; $\eta_p^2 = 0.562$), with the first block being 0.248 ± 0.056 faster than the last one ($t(21) = 4.395$; $p_{bonf} < 0.001$). In addition, results showed a significant interaction between purchase block and type of decision ($F(1,17) = 6.489$; $p = 0.021$; $\eta_p^2 = 0.276$), with significant post-hoc effect for the first block in the wait condition, which was 0.349 ± 0.074 s faster than the decision to buy the product ($t(19) = 4.752$; $p_{bonf} <$ 0.001), and significant faster decision in buy condition in the second block (0.365 ± 0.073) compared to the first one ($t(19) = 5.016$; $p_{bonf} <$ 0.001).

A significant interaction between product and purchase block was also found ($F(2,34) = 3.306$; $p = 0.049$; $\eta_p^2 = 0.163$) with the first block being 0.418 ± 0.087 slower than the second block in product 2 ($t(17) = 4.799$; $p_{bonf} < 0.001$). Finally, the significant interaction of product by purchase block and type of decision ($F(2,34) = 3.695$; $p = 0.035$; $\eta_p^2 = 0.179$) was driven by product 2, with the buy decision in first block being 0.630 ± 0.119 slower than the decision to wait ($t(11) = 5.278$; $p_{bonf} < 0.001$).

3.2. Event-related brain potentials

Results of the ERP analyses showed significant differences in the amplitude of the ERP components for both conditions from 256 to 1000 ms after stimuli presentation, according to the cluster permutation analysis (Fig. 3A).

In addition, we also analyzed the two main ERPs showing significant differences between the buy and wait conditions. Therefore, Fig. 3B shows that the difference between conditions at the N2 component (200–300 ms) was higher in frontocentral electrodes, while in the P3 component (300–600 ms) difference between conditions was maximal at centro-parietal electrodes *(*Fig. 3B*)*.

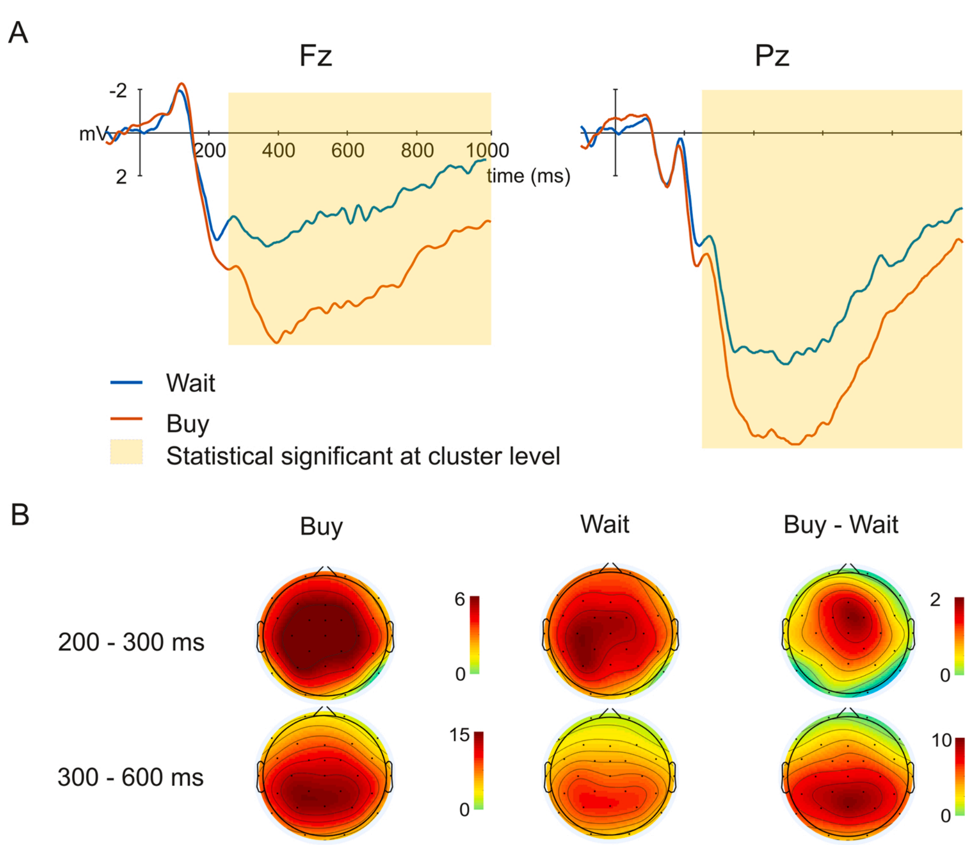

Fig. 3. **A.** ERP for Fz and Pz electrodes for the 2 conditions: buy (buy the product at price showed; line in red) and wait (wait for another offer; line in blue), including temporal range where differences are statically significant at cluster level; **B.** Topographical representation by condition and difference in N2 (200 to 300 ms) and P3 (300 to 600 ms) components.

Repeated measures ANOVA in the N2 component (200–300 ms), revealed significant effect of condition ($F(1,23) = 20.057$; $p < 0.001$; $\eta_p^2 = 0.466$) and laterality. In addition, rm-ANOVA also revealed significant interaction between condition and anterior-posterior factor ($F(2,46) = 5.308$; $p = 0.008$; $\eta_p^2 = 0.187$), and interaction between condition and laterality factor ($F(2,46) = 6.460$; $p = 0.003$; $\eta_p^2 = 0.219$). Post-hoc test showed that N2 amplitude increased 1.322 ± 0.295 in buy condition compared to the wait decision ($t(22) = 4.479$; $p_{bonf} < 0.001$), in particular, in frontal (1.560 ± 0.328) and central (1.549 ± 0.328) areas ($t(18) > 4.72$; $p_{bonf} < 0.001$).

In the P3 component (300–600 ms), rm-ANOVA revealed significant effects of condition ($F(1,23) = 70.317$; $p < 0.001$; $\eta_p^2 = 0.754$), anterior-posterior ($F(2,46) = 50.711$; $p < 0.001$; $\eta_p^2 = 0.688$) and laterality ($F(2,46) = 7.607$; $p = 0.001$; $\eta_p^2 = 0.754$) factors. In addition, significant interaction between condition and anterior-posterior factor ($F(2,46) = 5.641$; $p = 0.006$; $\eta_p^2 = 0.197$), and condition and laterality factor ($F(2,46) = 1.112$; $p < 0.001$; $\eta_p^2 = 0.363$) were found. Post-hoc analyses revealed that the amplitude of the buy condition increased 3.619 ± 0.432 compared to wait condition ($t(22) = 8.386$; $p_{bonf} < 0.001$). Activity increase in the buy condition was significantly higher in central (4.236 ± 0.556; $t(18) = 7.480$; $p_{bonf} < 0.001$) and parietal (5.095 ± 0.552; $t(18) = 7.996$; $p_{bonf} < 0.001$) areas compared to the frontal ones.

3.3. Time-frequency analysis

Fig. 4 shows the induced power analyses for frequencies 1 Hz to 30 Hz for the two conditions and their differences. Results showed that the wait condition presented an increase in the theta band around 200 ms and a decrease of induced beta power in a time range between 200 and 500 ms. The buy condition showed a power increase in the theta and alpha bands around 200 ms, and a decrease in power induced in the beta band after 400 ms. Difference between these two conditions revealed three main differences located at the theta (4 Hz–8 Hz), low alpha (8 Hz–10 Hz), and beta bands (16 Hz–26 Hz).

rmANOVA in the theta band (4–8 Hz, 300–500 ms), revealed a significant condition effect (0.119 ± 0.056 (SEM); $F(1,23) = 4.472$; $p = 0.046$; $\eta_p^2 = 0.163$), and no significant interaction between condition and position factors ($F < 1.3$; $p > 0.05$; $\eta_p^2 < 0.050$). Post-hoc tests showed that the oscillatory activity in theta band increased 0.119 ± 0.056 in buy condition than in decision to wait ($t(21) = 2.115$; $p_{bonf} = 0.046$).

In the alpha band (8–10 Hz, 200–400 ms), a significant condition effect ($F(1,23) = 6.202$; $p = 0.020$; $\eta_p^2 = 0.212$) and an interaction between condition and anterior-posterior factor ($F(2,46) = 5.423$; $p = 0.008$; $\eta_p^2 = 0.191$). Post hoc test revealed a higher induced power in the buy compared to wait condition (0.094 ± 0.038; $t(21) = 2.490$; $p_{bonf} = 0.020$), in particular, in frontal areas (0.171 ± 0.045; $t(17) = 3.828$; $p_{bonf} = 0.006$).

Finally, beta band analysis showed no significant condition effect ($F(1,23) = 0.959$; $p > 0.05$; $\eta_p^2 = 0.040$), nor significant interaction between condition and the position factors ($F < 1.2$; $p > 0.05$; $\eta_p^2 < 0.049$).

4. Discussion

The goal of the present study was to identify the neurophysiological markers of purchase decision-making in humans. To this end, we analyzed the differences in ERPs components and response-induced

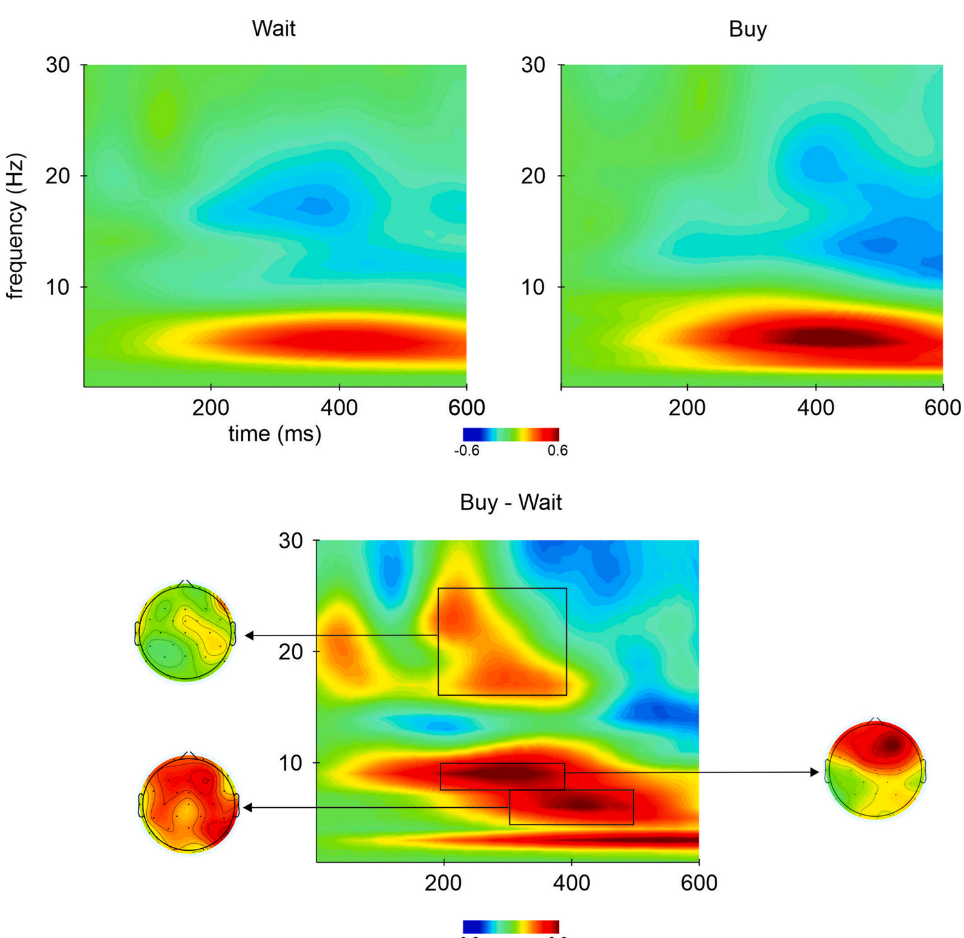

Fig. 4. Time-frequency induced power analyses for both conditions. In the upper-left, graphical representation of induced power for wait condition (wait for another offer), upper-right figure for buy condition (buy the product at price showed). The bottom figures represent differences between buy and wait conditions in induced oscillatory activity (buy – wait conditions) and the topographical representation for the difference between conditions in the time-frequency ranges indicated by the rectangular figures.

oscillation activity between two possible conditions when people were making purchasing decisions (buy or wait for next offer) using a new experimental paradigm designed for this study, the Purchase Decision-Making task (PDMt).

Our results showed significant differences between the buy and wait conditions both in the N2 and P3 ERPs. In the case of N2, buy conditions showed a reduction in the N2 component, with the difference between the two conditions presenting a clear frontocentral topography. This component has been consistently described in cues indicating a future potential reward of punishment, being larger in negative and neutral conditions compared to positive ones (Glazer et al., 2018). Traditionally, the frontocentral N2 has been associated with increased cognitive control, being larger, for example, in incongruent trials in flanker tasks (Bartholow et al., 2005) or in no-go conditions compared to go trials in go/no-go (Bruin & Wijers, 2002) and stop signals (Band, Ridderinkhof, & van der Molen, 2003) tasks. Given that in the present experiment the goal of the participants was to buy at the best price, the increase in the N2 ERP would indicate higher conflict in the wait trials compared to the buy ones, even when the number of trials of the former was higher than the latter.

We found that both decisions substantially increased the amplitude of the P3 component in the pre-decision time but also that different conditions led to different amplitudes of this component and in the posterior time of the event-related potential. In this sense, our findings reaffirm the idea that the P3 component plays a key role in the decision-making process (Rohrbaugh, Donchin, & Eriksen, 1974), where differences in amplitude of P3 for both conditions can be understood as consequence of the different cognitive process involved after those decisions. Previous studies suggest that increases in P3 amplitudes arise from the evaluation of new stimuli compared to the previous one stored in the working memory (Morgan et al., 2008), and the revision and adaptation of mental models of response (Wang et al., 2015). According to some authors, the amplitude of this component would also reflect the duration of stimulus evaluation processes (Twomey et al., 2015). Indeed, buy decisions took a longer time than wait decisions, and this could be reflected in higher amplitude in the P3 ERP. Importantly, one of the main consistent results of the P3 component is its sensitivity to probability. Previous studies have consistently reported increased P3 amplitude when the probability of the target stimuli is smaller in oddball paradigms (Duncan-Johnson & Donchin, 1977; Picton, 1992). In the present experiment, wait decisions were more frequent than buy ones. Therefore, the increased P3 amplitude in buy condition compared to wait ones could also be related to the relative low probability of buy conditions compared to wait ones. Additionally, it has also been proposed that P3 shows higher amplitude for those trials presenting higher motivational significance (Nieuwenhuis, Aston-Jones, & Cohen, 2005). Consequently, the increased P3 for buy trials could also be associated to the higher significance and utility of these trials as the goal of the task was to buy at the best possible price and, therefore, those prices at which people bought would have greater utility and emotional impact than the most frequent wait trials (Nieuwenhuis et al., 2005).

Another important result of the current experiment is the increase in the theta and alpha oscillatory activities in the buy condition compared to the wait one. Evidence suggests that theta band is modulated by levels of uncertainty in decision-making contexts (Jocham, Neumann, Klein, Danielmeier, & Ullsperger, 2009; Mas-Herrero & Marco-Pallarés, 2014; Mas-Herrero, Sescousse, Cools, & Marco-Pallarés, 2019), as well as in conflict detection and resolution (Akam & Kullmann, 2012; Clayton et al., 2015; Cohen & Donner, 2013; Cunillera et al., 2012; Donner & Siegel, 2011). In our experiment, buy trials presented a greater conflict than wait trials as they supposed the end of the decision process with no option to prospect for future and better prices. This result was also reflected by the larger RT in the buy condition compared to the wait one. In addition, it is important to note that, as stated above, in our experimental design participants chose the wait option more often than the buy one. Therefore, waiting could be considered as the habitual response and buying a novel response requiring a switch. Previous studies have indeed described increased theta activation to switching (Cooper et al., 2019) and novel events (Marco-Pallarés et al., 2010; Cavanagh, Zambrano-Vazquez, & Allen, 2012).

In addition, we also found that the decision to buy significantly increased the oscillatory activity in the alpha band, which is consistent with results reported by Ravaja et al. (2013) and Braeutigam et al. (2004), who proposed that prices and product preferences was expressed by increases in alpha activity. Previous studies have shown that highly complex trials during economic decision-making experiments (which would correspond to the buy condition in the current experiment) present increases in the alpha band (Rappel et al., 2020), suggesting a relation between alpha oscillations and impulse control and valence processing (Rossi, Gunduz, & Okun, 2015). However, contrary to our hypothesis, we did not find differences in the beta band in the buy compared to the wait condition. This oscillatory activity has been previously shown to be associated with unexpected or highly relevant positive information (Cunillera et al., 2012; HajiHosseini et al., 2012; Marco-Pallarés et al., 2015) and related to the activity of the ventral striatum and hippocampus (Andreou et al., 2017; Mas-Herrero et al., 2015).

One of the strengths of the current study is the proposal of a new experimental approach to study the purchase decision process. Previous studies have described such decisions as a multifactorial cognitive process that involve several cortical and subcortical networks, which stand out as the most important structures related to the value-related process of goods and the preferences of the prefrontal cortex and some of its substructures (Arieli & Berns, 2010; Kable & Glimcher, 2009; Pearson, Watson, & Platt, 2014; Telpaz et al., 2015). Additionally, studies have shown that the purchase decision-making process has important features that differentiate it from traditional decision-making paradigms (Kahneman, 2009; Karimi et al., 2015). It can be characterized as a decision process in which the feedback on the accuracy of a decision is neither clear nor explicit, but it is the consequences and information derived from previous decisions that can act as feedback. Based on this, our experimental paradigm included different products and price distributions associated with offers, in order to detect possible differences in the decisions in different scenarios; in other words, the differences in the subjective values given by the participants (Hayden, 2018; Kahneman & Tversky, 1984; Kahneman, 2009). However, it is well known that there exists high variability in the purchase decision-making process that is explained by individual differences in personality traits (Boyce et al., 2019; Gambetti & Giusberti, 2019; Huettel et al., 2006) and attitudes towards consumption (Denegri et al., 2012; Luna -Arocas, 2002; Quintanilla & Luna-Arocas, 1999), among many others. In addition, there might exist interactions between individual differences and different price distributions. Therefore, new designs including other price distributions and/or groups of participants with different consumer profiles might help in better understanding the neural correlates of purchase decision-making. In addition, future studies could also explore the possibility of predicting buying or non-buying decisions using single trial analysis of the studied neurophysiological components using mixed models or hierarchical lineal models.

Importantly, a limitation of the present study is that some critical aspects when making an economic decision are not controlled in the present experiment. Indeed, the current experimental paradigm allows the description of the basic decision of buying or waiting, but does not control for other important elements such as risk, uncertainty or expected value among others, which has shown to play a role in purchase decision-making (Huettel et al., 2006; Volz, Schubotz, & Von Cramon, 2005). Future studies controlling these parameters are needed to determine how these different factors modulate the described neurophysiological responses associated with purchase decision-making.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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