A neuroeconomic model of purchase decision making

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Sometimes the simple reason of having shared plans, transform trivial things in the most important experiences in our lives.

To Nicolle.

Table of contents

List of Abbreviations

ACC	Anterior Cingulate Cortex
dCC	Dorsal Cingulate Cortex
DLPFC	Dorsolateral Prefrontal Cortex
EEG	Electroencephalography
ERN	Error-related negativity
ERPs	Event-related potentials
FRN	Feedback-related negativity
HPC	Hippocampus
Hz	Hertz
IT	Inferior-temporal
LFP	Local field potentials
mPFC	Medial Prefrontal Cortex
ms	Milliseconds
NAcc	Nucleus Accumbens
OFC	Orbitofrontal Cortex
PDMt	Purchase Decision-Making task
PF	Prefrontal
PFC	Prefrontal Cortex
PPC	Posterior Parietal Cortex
SNc	Substantia Nigra compacta
STG	Superior Temporal Gyrus
VLPFC	Ventrolateral Prefrontal Cortex
vmPFC	Ventromedial Prefrontal Cortex
VS	Ventral Striatum
VTA	Ventral Tegmental Area

Abstract

One of the most recurring decisions in our day to day is choosing what and when to buy. To do this, we use all the information we have at our disposal, in addition to our experience, preferences, and interests. Something that differentiates this type of decision from many others is the uncertainty under which we choose the best moment to buy. When we need to buy a product, we do so assuming that we don't know if it's the best time or if is better keep waiting until get a better price, therefore we rely on the limited information available to choose.

Thus, the main objective of this thesis was to propose an exploratory predictive model of the decision to buy, considering neurophysiological, attitudinal, and behavioral markers. Previous evidence suggests that these three components are the main motivators of behavior and that, therefore, would be linked to the decision-making process.

Four studies that make up this thesis were designed to respond to the general objective, each of them addressing specific objectives. In study 1, we designed a new paradigm to identify the effect of contextual and attitudinal variables on the decision to buy. To do this, we programmed a task that simulated the purchase process in a virtual store where the participants had to decide the optimal moment to buy, having predefined price distributions for three unconventional products. Behavioral results showed that, depending on the conditions of the simulated context, behavior of

participants varies and that, in addition, there are interactions between contextual and attitudinal variables that influenced the decision to buy.

In study 2 of the thesis, we studied the neurophysiological correlate of the decisions to buy or wait when an offer was presented, making use of the experimental paradigm designed in the first study. The main results showed significant differences between the two decisions at the level of evoked potentials and oscillatory activity, when measured at the pre-decision time.

Study 3 was designed with the aim of analyzing the electrophysiological activity associated with the different types of price variations, considering high and low prices' increases and decreases. Results showed that, despite the fact that the experimental paradigm does not have feedback derived from each decision, the electrophysiological activity was consistent with that reported by the evidence of traditional decision-making studies, allowing us to hypothesize about the existence of subjective feedback mechanisms during decisions in contexts of uncertainty.

Finally, study 4 was designed with the aim of generating an exploratory predictive model of the decision to buy, combining contextual, attitudinal variables and neurophysiological markers identified in previous studies. Results showed that, as established by the existing evidence, purchasing decisions are highly dependent on various factors, being influenced by attitudes, context variations, neurophysiological markers, and interactions between those variables.

Overall, results of this doctoral thesis have contributed to increase the understanding of purchasing decisions, as well as the oscillatory processes at the base of these. These will allow to deliver exploratory approaches towards the understanding of the phenomenon, but, above all, it opens new questions that will allow to continue developing the scientific study in these subjects.

Resumen

Una de las decisiones más recurrentes de nuestro día a día es escoger qué y cuando comprar. Para ello, utilizamos toda la información que tenemos a nuestro alcance, nuestra experiencia, nuestros gustos y nuestros intereses. Algo que diferencia este tipo de decisiones de otras tantas que enfrentamos cotidianamente es la incertidumbre bajo la cual escogemos el mejor momento para comprar. Cuando decidimos comprar algún producto, lo hacemos asumiendo que no sabemos si es el mejor momento o si convendría seguir esperando hasta conseguir un mejor precio, por lo tanto, nos basamos en la limitada información disponible para escoger.

Así, el objetivo principal de esta tesis es proponer un modelo predictivo exploratorio de la decisión de comprar, considerando marcadores neurofisiológicos, actitudinales y comportamentales. La evidencia previa sugiere que estos tres componentes son los principales motivadores de la conducta y que, por lo tanto, estarían vinculados con el proceso de toma de decisiones.

Los cuatro estudios que componen esta tesis se diseñaron para dar respuesta al objetivo general, abordando objetivos específicos cada uno de ellos. En el estudio 1, diseñamos un nuevo paradigma para identificar el efecto de las variables contextuales y actitudinales en la decisión de comprar. Para ello, programamos una tarea que simulaba el proceso de compra en una tienda virtual y diseñamos distribuciones de precios para tres productos poco convencionales que debían ser comprados por los

participantes del estudio. Los resultados comportamentales muestran que, dependiendo de las condiciones del contexto simulado, la conducta de los participantes varía y que, además, existen interacciones entre variables contextuales y actitudinales que tienen efecto sobre la decisión de comprar.

En el estudio 2 de la tesis estudiamos el correlato neurofisiológico de las decisiones de comprar o esperar ante una oferta, haciendo uso del paradigma experimental diseñado en el primer estudio. Los resultados principales mostraron diferencias significativas entre ambas decisiones a nivel de potenciales evocados y de actividad oscilatoria, al ser medidas en el tiempo de pre-decisión.

El estudio 3 se diseñó con el objetivo de analizar la actividad electrofisiológica asociada a los diferentes tipos de variaciones de los precios, considerando incrementos y reducciones de precio de alta y baja magnitud. Los resultados mostraron que, a pesar de que el paradigma experimental no cuenta con retroalimentación derivada de cada decisión, la actividad electrofisiológica fue coherente con lo reportado por la evidencia de estudios de toma de decisiones, permitiendo evidenciar la existencia de mecanismos subjetivos de retroalimentación de la conducta en contextos de incertidumbre.

Finalmente, el estudio 4 fue diseñado con el objetivo de generar un modelo predictivo exploratorio de la decisión de comprar, combinando variables del contextuales, actitudinales y marcadores neurofisiológicos identificados en los estudios anteriores. Los resultados mostraron que, tal como establece la evidencia existente, las decisiones de compra son altamente dependientes de diversos factores, siendo influidas por las actitudes, las variaciones del contexto, los marcadores neurofisiológicos registrados y sus interacciones.

En conjunto, los resultados de esta tesis doctoral han contribuido a incrementar la comprensión de las decisiones de compra, así como de los procesos oscilatorios a la base de estas. Estos hallazgos permiten entregar aproximaciones exploratorias hacia la comprensión del fenómeno, pero, sobre todo, abre nuevas interrogantes que permitirán continuar desarrollando el estudio científico en estas temáticas.

Chapter 1
Introduction

Chapter 1: Introduction

Trying to understand how and why people make certain decisions in economic contexts has been an area of study that has gained relevance over time, leading to its approach from different disciplinary sectors. Initially, economic science tried to answer these questions by generating universal models of behavior that would make it possible to predict human behavior. Thus, from this perspective, Mill (1844) proposed a new concept of person called "Homo economicus", where people's behavior was understood as a perfectly rational action, which maximizes the benefits obtained through the optimization of resources and, above all, accesses and uses the totality of information available before deciding (DellaVigna, 2009; Thaler, 2017). From this approach people was characterizing as calculative, selfish, with unlimited computational capacity and incapable of making systematic mistakes (Arrow, 1990; Cartwright, 2018).

Despite the fact that these postulates were initially assumed as universal models of conduct, various criticisms arose from the economic community of the mid-nineteenth and early twentieth centuries, due to the rigidity of the models and their inability to explain the variations or deviations observed in the behavior of people in their daily lives or, even, when the economic context varied substantially, as with financial crises (Wheeler, 2020). Consequently, in response to these difficulties, new postulates emerged that sought to complement and offer explanations to these complex phenomena from less generalist perspectives, such as the marginal utility theory of Jevons (1871).

For Jevons, the utility derived from an economic decision was not defined exclusively by the optimization of resources, but also considered a subjective factor that was related to the satisfaction obtained once the decision was made, which he conceptualized as total utility. In turn, he proposed the existence of an additional factor associated to the number of times a good or product was consumed in a given time interval. The satisfaction derived from its acquisition varied depending on the type of good or product consumed and the availability to obtain it again, which was called marginal utility (Arrow, 1990; Cartwright, 2018; Jevons, 1871).

Additional to this, John Maurice Clark (1918), began the path towards the development of the study of economic behavior by incorporating psychological variables, establishing for the first time the concept of desire as a reaction to stimuli. He also discussed the importance of the environment in learning financial administration, resulting in the subsequent formalization of Economic Psychology as a discipline in the 20th century (Cartwright, 2018).

Later developments increased the interest to combine subjective and contextual elements in the study of economic behavior. For instance, Knight (1921) highlighted the importance of contextual risk and its perception as a relevant element during economic decision-making (Wheeler, 2020). Samuelson (1947), furthermore, proposed that the utility derived from an economic decision was based on a preference and that, therefore, the economic behavior was based on choices rather than reasoning (Cartwright, 2018). Samuelson's conclusion caused a stir in the economic world by questioning the assumption of perfect rationality in economic behavior. This allowed the consolidation of psychology as a relevant field for the study of economic behavior (Arrow, 1990; Wheeler, 2020).

Thus, in 1950, George Katona formulated the first model of psychological analysis of economic behavior, incorporating attitudes and expectations as relevant variables for classical economic analysis (Denegri, 2010; Katona, 1951). At the same time, the development of cognitive decision-making models, with the rise of Cognitive Psychology in the 1960s, allowed, later, the integration of neurophysiological, psychological, and economical perspectives in the study of the various economic scenarios, strengthening the existing explanations on the role of risk and uncertainty in economic decisions (Arrow, 1990; Thaler, 2017; Wheeler, 2020), such as the model of Kahneman and Tversky (1979).

From then on, the study of economic behavior ceased to be an exclusive field of study for economists, becoming a multidisciplinary field called Behavioral Economics. Studies in this field have allowed to identify that the determinants of economic behavior are diverse, dynamic, and include personal, social, cultural, situational, and economic factors that stimulate or inhibit behavior (Cartwright, 2018; Denegri, 2010; Kahneman, 2009; Larsen, 2022). Consequently, to study economic behavior it is necessary to understand the relevance and complexity of the decision-making process, taking into consideration the common elements and those that are particular to certain scenarios. Therefore, the following sections of this introductory chapter will focus on reviewing the central factors of the economic decision-making process, to delve into behavioral economics and, in particular, in the advances of the study of purchasing behavior.

1. The economic decision-making

The economic decision-making process is defined as a sophisticated and vital psychological process of human behavior that consists in choosing between options or actions (Fellows, 2004; Sugrue et al., 2005), seeking to obtain the most beneficial result (Kim & Lee, 2011). This process is carried out by a complex neural network (Arieli & Berns, 2010; Broche-Pérez et al., 2016; Kable & Glimcher, 2009; Pearson et al., 2014; Telpaz et al., 2015) through which values are assigned to the available options before deciding (Green & Myerson, 2004; Huettel et al., 2006; Platt & Padoa-Schioppa, 2009). In this process, the uncertainty and the possible consequences resulting from a decision are considered (Corrado et al., 2009). The principal outcome of this decision is an action that, as result of the different elements that interact, might or might not match with the expectancies and predictions (Kahneman, 2015; Luhmann, 2009; Marco-Pallarés et al., 2008).

Studying this process is complex due to the multiplicity of relevant factors or elements to consider, since deciding implies that contextual and personal elements interact to mobilize an action or behavior (Green & Myerson, 2004). Thus, various aspects have been described in the literature as relevant to the decision process. These factors can be grouped as contextual, personal, and neurophysiological and will be reviewed in the following sections.

1.1 The role of context

The context of a decision can be described as all the elements and information available at the moment of deciding (Camerer & Weber, 1992; Gallistel, 2009). Evidence suggests that decisions made when the probabilities of succeeding or failing in a task are known are not the same as those done without knowing what to expect as a result. This condition determines the certainty or uncertainty of the decision (Samuelson & Zeckhauser, 1988; Schröder & Gilboa Freedman, 2020). On the one hand, stable economics contexts are characterized by outcomes with constant and well-known probabilities of occurrence (Huettel et al., 2006), becoming totally predictable. Stable contexts promote people to choose among alternatives in accordance with well-defined preferences, having definite outputs as possible response (Samuelson & Zeckhauser, 1988; Schröder & Gilboa Freedman, 2020; Simon, 1959). On the other hand, uncertainty economic scenarios are non-constant and vary (Samuelson & Zeckhauser, 1988; Schröder & Gilboa Freedman, 2020) along two main dimensions: risk and ambiguity (Huettel et al., 2006). These contexts are characterized by a gap between the information available and the knowledge that decision makers would need to make the best decision (Marchau et al., 2019). This gap might be driven by different factors.

Risk is determined by the presence of multiples possible outcomes with estimable or defined probabilities, that are well-known by the person that is deciding (estimable; von Neumann & Morgenstern, 1947). Ambiguity, instead, refers to existence of multiple possible outcomes with unknown or not well-defined probabilities (Camerer & Weber, 1992). Contexts with the highest levels of ambiguity are also called Knightian uncertainty contexts and are characterized by the lack of any quantifiable knowledge about the probability of occurrence of an event (Huettel et al., 2006; Marchau et al., 2019).

Previous studies have shown that context can alter the prediction of the outputs derived from decisions. Huettel et al., (2006) found that in ambiguous scenarios, participants adapted decisions in function of local and temporal values rather than a "strategy" learned across the experience, adapting response models based on information extracted from the context. In the same line, Mas-Herrero & Marco-Pallarés (2014) found that levels of certainty/uncertainty defines importantly the type of relevant information, leading to different behaviors (Berridge & Robinson, 2003). Therefore, although learning processes are on the bases of behavior in any context (Donaldson et al., 2016), in uncertain scenarios new pieces of information are more important for adapting behavior than in certainty scenarios, where the previous experience is more important than the new information (Graybiel, 2008; O'Doherty et al., 2017).

Thus, the characteristics of context become essential to understand expectancies and prediction of future feedbacks, as consequence of a decision (Karimi et al., 2015; Schultz, 2006; Vilà-Balló et al., 2017). Changes in the context in uncertain scenarios will determine the need to adapt the behavior to adjust expectancies and predictions to the actual situation (Marco-Pallarés et al., 2008; Vilà-Balló et al., 2017), while stable contexts will promote the formation of more stable models of behavior (Donaldson et al., 2016). Because of this, currently experimental paradigms usually use uncertainty contexts as they are closer to daily-life decisions (Huettel et al., 2006; Marchau et al., 2019), to offer more realistic explanations of this decision-making process (Camerer & Weber, 1992).

Additionally, authors such as Kahneman & Tversky (1979) attempted to explain the subjectivity of economic decisions using uncertainty models and proposed a theoretical model to explain the subjectivity underlying the interpretation of the context in decision-making process. They propose that decisions are influenced by various subjective, personal, and cognitive elements that "limit" or interfere in the way in which people interpret the context and the information extracted from it. This led to the development of the concept of bounded rationality (Pena Lopez, 2005). According to the American Psychological Association, bounded rationality corresponds to a phenomenon of economic decision making in which the processes used are rational but depend on restrictions or limitations of different nature, such as the individual's knowledge, cognitive limitations, and the empirical factors that derive from the complex situations of real life (VandenBos, 2015d).

Initially, the bounded rationality concept was proposed by Herbert A. Simon in opposition to the assumptions of perfect rationality, widely accepted by classical economics (Pena Lopez, 2005). Consequently, Simon (1976) proposed that rationality in economic decision-making depends on two factors that directly affect people's perception of the real world: people's knowledge and their individual capacities. Later, Kahneman and Tversky (1979) delved into the study of these "limitations of rationality" focusing their work on the study of economic decisions under risk. One of the most outstanding advances in the study of this subjectivity was the conformation of the theoretical model of cognitive heuristics, that is, problem-solving or decision-making strategies that are based on experience and whose purpose is cognitive efficiency in uncertain situations (VandenBos, 2015a), and their role in the interpretation of the decision context (Pena Lopez, 2005). Heuristics are useful for reducing the cost of information processing, but they also introduce systematic bias in decision-making (Kahneman, 2015; Kahneman & Tversky, 1979; Pena Lopez, 2005; VandenBos, 2015a). The uncertainty of the context is, therefore, interpreted using strategies that deviate from rationality.

1.2 Individual differences

The decision-making process not only depends on the context, but on the characteristics, interests and personal attributes of the person who decides or, in other words, on individual differences. According to Marsh et al. (2010), individual differences explain the majority of the variation in decision-making across subjects. Studies focusing on individual differences are typically interested in how psychological events occur (Whiteside & Lynam, 2001), considering the implicit processes that arises during the performance of a task or a particular event (Dillon & Watson, 1996; Kahneman, 2015). Evidence suggests that most relevant types of individual differences commonly studied in decision-making process are personality traits (Dalley et al., 2011; O'Doherty et al., 2017) and attitudinal components (Denegri et al., 2012; Sanbonmatsu et al., 2014). These characteristics are closely related to information processing and behavior in economic decisions (Alí Diez et al., 2021; Dillon & Watson, 1996; Santesso et al., 2008).

Personality traits, on the one hand, are defined as a relatively stable, consistent, and enduring internal characteristic that are inferred from a pattern of behaviors, attitudes, feelings, and habits in an individual (VandenBos, 2015b). Over time, traits have been widely studied as relevant variables to summarize, predict, and explain individual behaviors. However, the role of personality traits in decision-making process is controversial (Santesso et al., 2008; Whiteside & Lynam, 2001).

Some studies have proposed the existence of a close relationship between certain personality traits and the behavior of people when making decisions, proposing, for example, a relationship between neuroticism and conscientiousness levels with risky decisions (Denburg et al., 2009; Gardiner & Jackson, 2012; Hooper et al., 2008; Lauriola & Levin, 2001). However, these results have been subsequently questioned by other studies that have not found such relationship (see, for example, Buelow & Cayton, 2020; Nga & Ken Yien, 2013; Skeel et al., 2007; Soane & Chmiel, 2005). As a consequence, some authors propose that, given that personality is a complex and multifactorial construct, the personality traits that impact the decision-making are those that are exacerbated and/or are predominant in the person's profile, as, for example, impulsivity in certain disorders (Buelow & Cayton, 2020).

Thus, the study of clinical populations has allowed the identification of the existence of significant alterations in the decision-making process in different psychiatric disorders (Ernst & Paulus, 2005). Patients with schizophrenia exhibit dysfunctions during the formation of preferences, execution, and evaluation of decisions outputs (Laruelle et al., 2003; Passerieux et al., 1997; Zec, 1995), presenting difficulties to estimate the contextual risk (Cole et al., 2020; Hutton et al., 2002) and to retrieve the information from different available alternatives (Baving et al., 2001). In the case of anxiety disorders, evidence shows that patients present an attentional bias towards threats (Mogg & Bradley, 1999), which predisposes to experience negative affects during decision making (Loewenstein et al., 2001; Loewenstein &

Lerner, 2003), considered as critical determinant of hyperarousal (Dowden & Allen, 1997), affecting the error monitoring during the execution, as well as making it difficult the error detection during feedback (Liberzon et al., 2003; Ursu et al., 2003).

On the other hand, substance-dependent subjects present alterations in the perception of risk and benefits associated with decisions (Bechara & Damasio, 2002; Grant et al., 2000; Madden et al., 1999; Petry et al., 1998), being more prone to take risks (Lane & Cherek, 2000). Also, they present difficulties in estimating the probabilities and magnitude of potential outcomes (Rogers, 1999; Rogers & Robbins, 2001), decreasing their sensitivity to detect and update their decisions on the bases of the outputs derived from previous actions (Paulus et al., 2002). Finally, impulsivity, is a multidimensional construct that presents a wide range of variation in healthy population. However, people with very high values are incapable of waiting (Reynolds et al., 2006), show a tendency to act without thinking (Bevilacqua & Goldman, 2013), made fast cognitive decisions (Evenden, 1999; Patton et al., 1995), and cannot inhibit incorrect behaviors (Stanford et al., 2009). All of them are critical factors in value-based decision-making (Coffey et al., 2003; Evenden, 1999; Martínez-Loredo et al., 2015; Vasconcelos et al., 2012) and risky decision-making (Buelow & Cayton, 2020; Quilty et al., 2014; Smith et al., 2007; Whiteside & Lynam, 2001).

Taking into consideration the previously exposed antecedents, there are no doubts about the importance and usefulness of the study of personality traits in decision-making in clinical populations. However, as stated above, there are doubts about their relevance in the study of healthy population. In this sense, it seems that attitudes provide a more comprehensive approach to understand economic behavior.

Attitudes are defined as a relatively enduring general evaluation of an object, person, group, issue, or concept on a dimension ranging from negative to positive. Attitudes, provides summary evaluations of target objects and are often assumed to be derived from specific beliefs, emotions, and past behaviors associated with those objects (VandenBos, 2015c). According to Breckler (1984), attitudes are negatives, positives or neutral evaluative judgments on the specific object, fact, action or thought, and are composed by three main components: affect, cognition, and behavior. Affect is the emotional component, cognition is the belief system related to the object, and behavior is the predisposition to act in a specific and coherent way based on the other components (Denegri et al., 2012; Sanbonmatsu et al., 2005). Attitudes are strongly related to the real behavior when they refer to the same object (Alí Diez et al., 2021; Ajzen & Fishbein, 1977; Denegri et al., 2012). For example, attitudes towards racial discrimination measured through affirmations of specific racial discrimination have a strong relationship with people's real discriminatory behaviors. Based on this, attitudinal studies have become an instrument widely used by psychology (Ajzen & Fishbein, 1977), since they allow to know the affects, ideas and predisposition of people towards specific objects of study (Breckler, 1984; Castellanos et al., 2016; Denegri, 2010), offering a useful tool to understand individual differences in decision-making in non-clinical (Luna-Arocas & Tang, 2004; Quintanilla & Luna-Arocas, 1999; Sanbonmatsu et al., 2005).

1.3 Neuroanatomy of Decision-Making

The decision-making process requires the interaction of an extensive network composed by cortical and subcortical structures (Delgado, 2007; Delgado et al., 2000; Farrar et al., 2018; Rosenbloom et al., 2012; Si et al., 2019). One of the main structures related to this process is the prefrontal cortex (PFC). Three main prefrontal (PF) sub-regions play an important role in decision-making: orbitofrontal cortex (OFC), anterior cingulate cortex (ACC), and the dorsolateral prefrontal cortex (DLPFC; Domenech & Koechlin, 2015; Purves et al., 2018).

Anatomically, the OFC is composed by four cytoarchitectonic Brodmann areas: BA11, anteriorly; BA13, posteriorly; BA14, medially; and BA47/12, laterally (Rosenbloom et al., 2012). In particular, the lateral OFC (BA47/12) receive and integrate visual information form the inferior temporal cortex, auditory information form secondary and tertiary auditory areas, heteromodal inputs form the superior temporal cortex, and somatosensory information from the secondary somatosensory and parietal cortex (Premkumar et al., 2015; Rosenbloom et al., 2012; Rudebeck & Murray, 2014). Additionally, the OFC receives inputs from the hippocampus (Broche-Pérez et al., 2016) and some adjacent regions of the medial temporal lobe, majorly involved in the memory storage and retrieval information (Purves et al., 2018). Dopaminergic projections from the midbrain, amygdala, and limbic system also implicate the OFC in the reward-based behavior (Rosenbloom et al., 2012; Wallis, 2007). As consequence, the role of the OFC in decision-making is commonly associated with the estimation of the value of an option based in present and past information (Purves et al., 2018; Wallis, 2007). Thus, the relevance of this sub-region in the decision-making process is the integration of multiple sources of information to choose the best alternative (Rosenbloom et al., 2012) based on the rewards, emotions, and experiences linked with similar events (Purves et al., 2018; Rosenbloom et al., 2012; Squire et al., 1997).

The ACC is located in the medial prefrontal cortex (mPFC) and have strong cortical connections with the OFC and DLPFC, and subcortical projections to the Nucleus Accumbens (NAcc; Broche-Pérez et al., 2016). According to Purves et al. (2018) the function of the ACC in the decision-making process is principally the modulation of the others prefrontal (PF) regions, in particular the OFC and DLPFC. In this sense, the ACC is the responsible of the analysis of ambiguous or conflictive situations, in addition to the optimization of future decisions based in the previous contingencies during the options selection process (Squire et al., 1997; Ullsperger & von Cramon, 2003). In addition, the function of ACC can also be characterized as "monitoring", principally in the analysis of outcomes (Purves et al., 2018). ACC is considered the source of the error-related negativity (ERN) Event-Related potential, a brain response that appears after error commissions (Broche-Pérez et al., 2016). Consistent with this, the ACC has been implicated in the evaluation of outcomes, generation of feedbacks signals (Rosenbloom et al., 2012) and signaling prediction errors between expected and real outputs (Weiss 2018), which are used to update behavioral goals, and adopt new cognitive rules according to context (Squire et al., 1997).

One model that propose an integrative explanation of the ACC's role is the Predicted Response Outcome (PRO) Model. According to Alexander and Brown (2011), the main role of the ACC during the decision-making process is the analysis and monitoring of the predicted responses and the results obtained. In PRO model, ACC activity increases in situations where an expected output fails to occur, while signals are inhibited when predicted outcome actually occurs (Brown, 2013). This is consistent with evidence reporting increases in ACC activity in conflictive decision-making (Botvinick et al., 2004; Broche-Pérez et al., 2016; Brockett & Roesch, 2021; Feuerriegel et al., 2021; Frank et al., 2005, 2015; Kang et al., 2019; Mansouri et al., 2009; Mayr, 2004; Pochon et al., 2008; Zhang & Gläscher, 2020) and prediction error (Cavanagh et al., 2010; Hauser et al., 2014; Niv et al., 2012; Oya et al., 2005; Weiss et al., 2018).

Additionally, Broche-Pérez et al. (2016) proposes that the ACC can be regarded as complementary to the DLPFC, with ACC detecting the need of changing the behavior and the DLPFC implements these changes (Purves et al., 2018) in reward-guided decision-making (Neubert et al., 2015).

The DLPFC, in turn, is located in the lateral and superior regions of the frontal lobes where it is organized through the dorsoventral axis (Purves et al., 2018). According to Pandya & Yeterian (1996), the dorsal portion of the DLPFC plays a critical role in working memory monitoring, while the ventral region is essential in recovering information from posterior regions (Rosenbloom et al., 2012). The DLPFC has strong limbic and cortico-cortical connections, principally with temporal, parietal and occipital regions (Broche-Pérez et al., 2016). The DLPFC is specialized in the integration of multiple sources of information (Martinez-Selva et al., 2006). Additionally, the ACC and DLPFC play an important role in facilitating intellectual effort when decisions depend on working memory and reasoning (Rosenbloom et al., 2012).

1.3.1 The reward system

The results obtained from the decisions made are one of the main inputs available to optimize subsequent behavior. Therefore, feedback and the outcome of actions (either positive or negative) become of vital importance during the decision-making process since they allow incentive-based learning. In this sense, feedbacks influence behavior by promoting or discouraging certain behaviors (e.g., repeating those actions that yield to rewards or avoiding those that yield to punishments; Berridge & Kringelbach, 2015; Berridge & Robinson, 2003; Haber & Knutson, 2010; Schultz, 2015). Consequently, the association of a particular event with a reward or a punishment represents a powerful learning signal that allows humans to search for and identify signals in the environment, make predictions, and develop action plans that allow them to obtain the expected result (Berridge & Kringelbach, 2015). The accuracy of the predictions depends on the amount of information available and previous experience, having as a basic principle the search of reward maximization and punishment minimization (Schultz, 2006, 2015).

Various studies using neuroimaging techniques have oriented their work in the identification of brain structures and functions based on reward processing, being able to recognize the existence of specific areas that encode particular aspects of their processing, such as their valence, probability of occurrence and novelty, among others. The role of these brain areas and their connections is described below.

1.3.2 Reward processing brain network

The reward network can be defined as an interconnected network of cortical and subcortical brain areas of the mesocorticolimbic dopaminergic system (Berridge & Kringelbach, 2015; O'Doherty et al., 2007, 2017; and Schultz, 2015 for review). Central areas of this network are the orbitofrontal (OFC) and medial prefrontal cortex (mPFC), in addition to the ventral striatum (VS), and the dopaminergic ventral tegmental area (VTA) and substantia nigra pairs compacta (SNc) in the brainstem (Berridge & Kringelbach, 2015; Càmara et al., 2009; Haber & Knutson, 2010;

Schultz, 2015). Other areas described as involved in reward processing are sensory and motor areas, in addition to insula, amygdala, thalamus and hippocampus.

Due to the multiplicity of interconnected areas, the reward network integrates emotional, sensorial and memory information to predict outputs and optimize the decision-making process, facilitating the learning from the consequences (i.e., rewards and losses) derived from decisions (Dayan & Balleine, 2002; Dixon & Christoff, 2014).

Dopamine has been systematically identified as one of the main neurotransmitters in the reward system. Although it was initially related to motor function (Lerner et al., 2021), with impairments in patients with Parkinson's disease, later studies revealed its crucial role in motivation and learning from rewards (Schultz et al., 1997). Most of the cell bodies of dopaminergic neurons are located in the midbrain VTA and SN regions (Berridge & Kringelbach, 2015; Haber & Knutson, 2010; Schultz, 2015). Although these areas contain a relatively small number of neurons, they present an enormous number of projections and terminals of individual neurons (Lerner et al., 2021; Phillips et al., 2022). Projections from VTA to VS shape the mesolimbic pathway, but also includes other limbic regions as the hippocampus, amygdala and cortical regions (vmPFC, ACC, entorhinal cortex), conforming the mesocortical pathway (Berridge & Kringelbach, 2015; Càmara et al., 2009; Tu et al., 2020; Weiller et al., 2021). In addition, projections from the SN to the caudate nucleus and putamen form the nigrostriatal dopamine system (Hollon et al., 2021; Ikemoto, 2007; Weiller et al., 2021; Wise, 2009), that has been related to the establishment of habits and behaviors connected to addiction (Haber, 2016; Haber & Knutson, 2010; Schultz, 2006; Schultz et al., 1997).

Midbrain dopamine neurons' increased phasic (spike-dependent) activity has been linked to both receiving unexpected rewards and anticipating conditioned rewards (Schultz, 2006; Schultz et al., 1997). In addition, a reduction in dopamine cell activity occurs when a projected reward does not materialize. Therefore, the predictability of stimuli influences dopamine activity (Schultz et al., 1997). Prediction error is the discrepancy between an expected reward and its actual occurrence. It can be either positive or negative (better or worse than predicted respectively).

The VS is regarded as the primary integration site within the reward network (Yager et al., 2015). It is a component of the basal ganglia, a collection of subcortical nuclei that also includes the subthalamic nucleus, caudate nucleus, putamen, globus pallidus, and SN. The NAcc is interconnected with a number of cortical and subcortical brain areas, receiving a substantial glutamatergic innervation from the OFC, amygdala, thalamus, and hippocampus (Càmara et al., 2009; Haber & Knutson, 2010; Ikemoto, 2007), as well as a main dopaminergic input from the midbrain (Haber, 2016; Haber & Knutson, 2010).

Dopamine levels in the NAcc rise in response to primary and secondary rewards. The VS is involved in both the estimation of novel rewards and the anticipation of expected rewards (Cho et al., 2013; Gruber et al., 2014; Knutson et al., 2001; Knutson & Greer, 2008), and is activated by salient rewarding but also nonrewarding stimuli (Daniel & Pollmann, 2014; Meffert et al., 2018; Zink et al., 2003). Salience is driven by the motivational, emotional, and cognitive elements as well as the physical characteristics of the stimuli. A stimulus will capture greater attention if it is more salient (Meffert et al., 2018).

Studies on humans have also shown that the OFC is sensitive to reward magnitude and is involved in coding and anticipating the rewarding value of sensory and monetary stimuli (Gläscher et al., 2010; Niv et al., 2012; O'Doherty et al., 2017), having a crucial role in associative learning (Grabenhorst & Rolls, 2011; Holroyd & Coles, 2002; Ridderinkhof et al., 2004; Smith et al., 2009; Wallis, 2007). As stated above, the OFC is essential for prediction and decision-making when faced with a choice between several options because it provides information about the representation of the reward value, the expected value, and the subjective utility of the rewards (Farrar et al., 2018; Gallistel, 2009; Graybiel, 2008; Haber, 2016; Klein-Flügge et al., 2022; Rushworth et al., 2011).

According to Haber (2016), the integration of OFC inputs combined with emotional valence data and memory from the amygdala and hippocampus, respectively, is thought to mediate the striatal sensitivity to reward value and saliency. The amygdala, in conjunction with the VS and PFC, has been linked to emotional processing of positive and negative valences inputs, emotional decision-making, emotional memory, and emotional learning (Broche-Pérez et al., 2016; Haber & Knutson, 2010; Purves et al., 2018; Rudebeck et al., 2008).

The hippocampus, on the other hand, is sensitive to novel motivational information from rewarding and salient (new or unexpected) events through the discrepancy between new information and learned associations (Biane et al., 2023). As consequence, a strong phasic dopamine signal is produced in the VTA after this novelty signal is transmitted from the subiculum through the ventral pallidum and VS (Biane et al., 2023; Càmara et al., 2009; Farrar et al., 2018; Lisman & Grace, 2005). The hippocampus receives dopamine released in the VTA, leading to memory formation through long-term potentiation (LTP; Biane et al., 2023; Daniel & Pollmann, 2014; Haber, 2016; Lisman & Grace, 2005).

In summary, decisions are derived from a dynamic, reciprocal, and multidimensional process based on specific interaction between prefrontal (principally OFC, ACC, and DLPFC) and subcortical structures, most of them involved in reward processing (Rosenbloom et al., 2012). However, these interactions, as well as others related to other functions such as perception, memory and attention among others, occur at different sub-second time scales. To be able to study the temporal evolution of such functions a technique able to capture these fast variations is needed. The next section will focus on the electroencephalography (EEG) neuroimaging technique, that has an excellent temporal resolution in the order of milliseconds and is the method used in three studies of the present thesis. After this, the following sections will focus on purchasing decisions, which correspond to a type of economic decision, but which present particularities due to their nature and the relevance they have in the daily life of people and the frequency in which they are carried out and that are the main focus of the present dissertation.

2. The electroencephalography technique

The EEG is a technique to record the brain electrical activity (Louis & Frey, 2016), allowing the study of the brain functions by monitoring, measuring and analyzing changes in brain electrical potentials in an extra cranial way, that is to say, using electrodes located in the scalp (Dickter & Kieffaber, 2014; Luck, 2014). One of the most important characteristics of this technique is the temporal sensitivity, which allows important advances in brain evaluation of dynamic cerebral functioning (Louis & Frey, 2016; Luck, 2014). The origins of this technique were consequence of two important findings. First, Richard Caton (1842–1926) discovered the electrical properties of the brain. Using a sensitive galvanometer, he described variations in brain electrical activity during sleep, in addition to the absence of activity after dead. Following this, Hans Berger (1873-1941) recorded the first EEG in humans using scalp electrodes. Since then, the EEG technique has improved its procedures, analysis and technologies, becoming what we know today (Herreras, 2016; Louis & Frey, 2016).

Neural activity detectable by the EEG is the summation of the excitatory (action potential) and inhibitory postsynaptic potentials of relatively large groups of neurons firing synchronously (Buzsáki, 2006). When thousands of neurons geometrically aligned receive similar synaptic outputs, the electrical fields sum and become powerful enough to be measured by extracellular recordings, also called local field potential (LFP), and extracranially with EEG (Buzsáki, 2006; Cohen, 2017; Herreras, 2016; Luck, 2014). As the EEG technique involves the measurement of voltage changes, it requires the signals to be amplified and represented over time, having high temporal resolution in a scale of milliseconds and enabling to separation of brain events in real time. In contrast, some limitations of the technique are the poor spatial resolution (Herreras, 2016). Despite this, EEG technique has become widely used, due to the relevance and diversity of results reported in the literature, both at the level of electrical potentials and in the resulting power analysis for the various electrical frequency bands.

2.1 The event-related potentials

The event-related potentials (ERPs) time-locked to an external event (Luck, 2014) represent the coordinated activity from neural population in response to specific motor, cognitive or sensory events (Bressler, 2011; Peterson et al., 1995; Sur & Sinha, 2009). Each ERP consists of consecutive deflections called components, which reflect sensory and cognitive processes (Brandeis & Lehmann, 1986; Dickter & Kieffaber, 2014; Sur & Sinha, 2009). The majority of components are referred by a letter which indicate their negative (N) or positive (P) polarity, plus a number indicating either the latency in milliseconds (i.e.: 200) or the ordinal position of the component in the waveform (i.e.: 1, 2, 3; Luck, 2014). Other classifications for ERPs components are related to the scalp distribution and sensitivity to task manipulations (Sur & Sinha, 2009).

Latency is the elapsed time period from the stimulus onset to the point of maximum positive or negative amplitude in a given time-window (Dickter & Kieffaber, 2014). To compute the amplitude of a component, the difference between the mean pre-stimulus baseline voltage and the largest negative or positive peak of the ERP is estimated (Polich, 2007). Components that appear early (within the first 100 ms) are called exogenous because they reflect early sensory responses and depend on external factors of the stimulus (i.e.: physical properties; Luck, 2014). Components that appear later, are called endogenous or cognitive ERP components because they are related to task-specific-events and depend on internal factors, indicating information processing (Sur & Sinha, 2009).

2.2 ERP components in decision-making

As mentioned above, making decisions involves processing context-dependent information, comparing it with our previous experiences, and forming expectations about possible alternatives. Historically, experimental tasks that allow for the control and manipulation of various factors have been used to comprehensively examine this process, revealing its neurophysiological correlates. This previous research has identified the N2 and P3 ERPs as the main components in the decision-making process (Sur & Sinha, 2009; Zhong et al., 2019).

The N2 component is a negative deflection in electrical potential that begins around 200 ms after stimulus presentation and lasts for approximately 100 ms (Dickter & Kieffaber, 2014; Luck, 2014). Decision-making studies have identified the existence of a relation between the amplitude of frontocentral N2 component and outcome evaluation processing (Gehring & Willoughby, 2002; Miltner, Braun, & Coles, 1997). Evidence systematically reports that amplitude of this component is related to the conflict-monitoring role developed by the ACC, with greater amplitudes when conflicting or incongruent stimuli appears compared to congruent ones (Bellebaum & Daum, 2008; Clayson & Larson, 2011; Flores et al., 2015; Fong et al., 2018; Luu et al., 2003; Wendt & Luna-Rodriguez, 2009; Yeung & Sanfey, 2004).

Therefore, previous studies have found that N2 component is commonly associated with the processing of unfavorable outcomes after a decision (Bellebaum & Daum, 2008; Flores et al., 2015; Luu et al., 2003; Meadows et al., 2016; Yeung & Sanfey, 2004), presenting larger amplitudes in non-reward or neutral conditions compared to expected or positive rewards (Hajcak et al., 2005, 2006), even when its conditions are defined by cues (Novak & Foti, 2015). Studies also reported that its amplitude indexes prediction errors (Mas-Herrero & Marco-Pallarés, 2014; Meadows et al., 2016), and is sensitive to discrepancies between expected and real situations (template mismatch), with larger amplitudes as a consequence of the increase in cognitive control during decision-making (Band et al., 2003; Bartholow et al., 2005; Bruin & Wijers, 2002; Feldman & Freitas, 2019; Glazer et al., 2018).

P3 component, on the other hand, is a high amplitude positive deviation that peaks between 250-450 milliseconds after the appearance of stimuli or relevant events (Dickter & Kieffaber, 2014; Luck, 2014). Initially, it was described by Sutton, Braren, Zubin, & John (1965) as a response to unpredictable and uncertain stimuli (Luck, 2014; Sur & Sinha, 2009), but now is one of the most important and widely explored late ERPs component, commonly applied to assess different cognitive function in humans (Sutton et al., 1965).

Studies have related this component to attentional processes (Polich & Kok, 1995). In decision-making studies there is a clear consensus about the existence of a relationship of P3 component amplitude and the working memory load (Levi-Aharoni et al., 2020; Morgan et al., 2008; Wang et al., 2015), information processing (Polich, 2007), novelty of the stimulus exposed (Levi-Aharoni, Shriki, & Tishby, 2020; Polich, 2007) and the concentration and speed of mental processing (Casali et al., 2016). Increases in amplitude of this component are related to increases in stimulus information, where greater attention induced to larger P3 waves (Polich, 2007; Zhong et al., 2019). The latency of the P3 has been associated with the speed of stimulus processing and classification, with shorter latencies indicating better performance in comparison to longer ones (Polich, 2007).

Based on the topographic distribution of this component and the type of processing to which is sensitive, two different types of P3 components have been described (Polich, 2007): P3a and P3b (Volpe et al., 2007). P3a, reflects a frontocentral activation as a consequence of attentional processing of stimuli that induces changes in the working memory load (Polich, 2007; Polich & Comerchero, 2003). P3b, presents a parietal topography and is associated with a series of subsequent attentional activations that promotes memory operations (Polich, 2007; Polich & Kok, 1995), reflecting activity related to updating the contextual information and its corresponding memory storage (Brázdil et al., 2003; Polich, 2007; Sun & Wang, 2020), to review and adapt mental models of a response (Wang et al., 2015). The amplitude of this component is sensitive to the duration of stimulus evaluation process (Twomey et al., 2015), higher motivational significance (Nieuwenhuis et al., 2005), the probability and expectation of stimuli appearance (Levi-Aharoni et al., 2020; Luck, 2014; Polich, 2007; Polich & Margala, 1997; Sur & Sinha, 2009), complexity of decisions (Polich, 2007) and the relevance of contextual information for the correct resolution of the task or challenge (Levi-Aharoni et al., 2020)

2.3 Brain oscillatory responses

Event-related oscillations reflect the time-locked brain electrical activity in the frequency domain, where the EEG signal is transformed in a frequency spectrum, using a fast Fourier transform or wavelet transforms (Dickter & Kieffaber, 2014), the latter being more used in recent years (Buzsáki, 2006).

Thus, neural oscillations are a synchronized pattern of changes in voltage of a large number of neurons at certain frequency or range of frequencies (Boashash, 2016; Lopes da Silva, 2013). Oscillatory responses are generally referred to as stimulus-evoked or stimulus-induced. Stimulus-evoked oscillations are responses that are phase-locked to the stimulus onset (Dickter & Kieffaber, 2014; Luck, 2014), while, stimulus-induced oscillations are oscillatory responses that show trial-to-trial variations in latency (Chen et al., 2012; Tallon-Baudry & Bertrand, 1999). Stimulus-induced oscillations can also be conceptualized as changes in time varying energy (measured as the square of the convolution between the transformation and signal) in the frequencies of interest, respect to baseline that cannot be explained by the average power (David et al., 2006).

In the study of brain oscillatory responses, the first wave discovered was the alpha frequency band, which was labeled with the first letter of the Greek alphabet by its discoverer, Hans Berger (Dickter & Kieffaber, 2014). Subsequently discovered bands were labeled following this tradition (Buzsáki, 2006). Currently, EEG signal is mainly describe by five different signals, including delta (δ; < 4 Hz), theta (θ; 4-8 Hz), alpha (α; 9-12 Hz), beta (β; 13-30 Hz), and gamma (γ; > 30 Hz; Luck, 2014).

Evidence suggests that high frequency oscillations (fast oscillations; amplitude lower than 2 millimeters) plays an important role in local cortical processes, while slower (amplitudes bigger than 1 centimeter) might reflect the integration of distant areas in a long range (Dickter & Kieffaber, 2014; Lopes da Silva, 2013). Despite this, frequency-bands do not correspond to one unique cognitive function, but rather, one frequency can be associated with different brain functions, just like each cognitive function are related to multiple frequency bands (Buzsáki, 2006; Karakaş &

Barry, 2017). For this reason, other elements, such as topography, duration, latency, and power increases or decreases, must be considered.

2.4 Oscillatory responses in decision-making

Evidence suggests the existence of three main oscillatory bands related to the decision-making process: theta, alpha, and beta bands.

Midfrontal theta oscillatory activity plays a key role in the prediction error computation, reflecting the surprise associated with the output obtained in a decision (HajiHosseini et al., 2012; Wang et al., 2016). Increases in oscillatory power has been reported after unexpected (Mas-Herrero & Marco-Pallarés, 2014), error responses or negative feedback (Andreou et al., 2017; Cavanagh et al., 2010; Cohen et al., 2007; Cohen & Donner, 2013), as a consequence of the learning and behavioral adjustment processes required (Cavanagh et al., 2010; Christie & Tata, 2009; Ferdinand et al., 2012; Mas-Herrero & Marco-Pallarés, 2014, 2016), revealing its sensitivity to the valence and magnitude of feedback derived from the decisions. Other studies revealed that theta activity is also modulated by novelty, conflict (Cavanagh, Figueroa, et al., 2012), rules switch (Cunillera et al., 2012) and risk (Christie & Tata, 2009). 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 (Cavanagh, Figueroa, et al., 2012; Cavanagh & Frank, 2014).

The second component that has been found to be involved in decision-making is alpha oscillatory activity. Studies have identified that alpha oscillations are related to different highly relevant processes in decision making. Thus, previous research has related increase in alpha power to selective inhibition (Noonan et al., 2018), and alpha suppression to the facilitation of attentional systems as task preparation (Glazer et al., 2018; Ward, 2003). In reward-guided tasks, higher alpha suppression has been described in feedback anticipation (Bastiaansen et al., 1999; Pornpattananangkul & Nusslock, 2016) and been related to higher motivation of participants to learn from feedbacks (Glazer et al., 2018; Pornpattananangkul & Nusslock, 2016). In oddball tasks, different studies have reported the influence of cognitive targets on alpha oscillations in P3, identifying an increase in activity and greater synchronization in frontocentral fast alpha, as well as a reduction in parietal slow alpha, when compared to non-targets objects (Stampfer & Başar, 1985). Other studies have shown that increases in alpha oscillatory activity during decision-making tasks are strongly correlated with working memory demands and, possibly, with long-term memory processing (Başar & Stampfer, 1985; Kolev et al., 1999; Yordanova & Kolev, 1998). During economic decision-making experiments, Rappel et al. (2020) reported increases in alpha band in more complex trails which can be explained by the role of alpha activity in impulse control and feedback valence processing (Rossi et al., 2015).

Finally, the beta oscillations activity has also been related to decision-making processing. Different interpretations have been proposed including, among others, its possible role in maintaining the "status quo" in the cognitive and behavioral control (Engel & Fries, 2010) and its expression as a mechanism for the endogenous reactivation of latent cortical representation (Spitzer & Haegens, 2017). Despite this, beta oscillations have consistently been reported as a neural marker of reward, showing significant increases after positive feedback and wins relative to losses (Andreou et al., 2017; Cohen et al., 2007; Cunillera et al., 2012; Doñamayor et al., 2012; HajiHosseini & Holroyd, 2015; Luft et al., 2013; Marco-Pallarés et al., 2008; Van de Vijver et al., 2011) or in response to unexpected or highly relevant positive outcomes (Cohen et al., 2007; Cunillera et al., 2012; Marco-Pallarés et al., 2015; Mas-Herrero et al., 2015). Increases in frontocentral beta power has been found to be sensitive to magnitude and probability of reward, being larger for bigger compared to lower wins (Marco-Pallarés et al., 2008) and for improbable or unexpected ones (Cohen et al., 2007; HajiHosseini et al., 2012).

Using combined EEG and fMRI techniques, studies have reported a relation between beta oscillatory activity and VS, amygdala, hippocampus and PFC activity (Andreou et al., 2017; Mas-Herrero et al., 2015). The existence of the relationship between these core areas of the dopaminergic reward network, and the evidence that accounts for the sensitivity of beta to positive feedback processing, have led to propose that beta oscillatory activity can mediate communication between the different areas involved in learning form rewards (Andreou et al., 2017; Cohen et al., 2011; Luft, 2014; Marco-Pallarés et al., 2015; Van de Vijver et al., 2011), reflecting a signal of motivational value of decisions (Marco-Pallarés et al., 2015).

3. Purchase Decision-making

As has been presented, the information we obtain from the decision context is essential for the generation of response models that allow us to successfully solve the challenge of choosing between one alternative and another. Thus, various neurophysiological processes store and process information that allows us to optimize behavior based on the results obtained with previous behavior.

But... what does happen when there is no real feedback on behavior? Or when the consequences of our own behavior are the only available information we have to optimize our future behavior?

In our daily lives, we commonly face these types of decisions. We live in an uncertain environment, which means deciding with limited information about the possible future and the consequences of our behavior, so it is essential to understand how we operate to deal with this uncertainty and learn to successfully solve everyday challenges. Thus, studying how we make purchase decisions would allow us to answer these initial questions from a daily practice that is becoming more complex every day. In this section, I will delve into purchasing decisions, reviewing the main results of the studies carried out and evidencing the main gaps in this matter that support this thesis work.

The study of the elements at the basis of purchasing decisions has become important in the study of economic behavior due to the frequency in which these behaviors are carried out, as well as their impact on the well-being and quality of people's lives (Denegri et al., 2012, 2016). Even so, due to the diversity and complexity of the elements that influence this type of decision, studies have focused on explaining in a fragmented way the effect of the different variables, as the context information and the individual differences on the purchase decisions.

Studies focused on context have described that purchase decisions are made under uncertainty at different levels, as time, risk and, particularly, the absence of explicit feedback before deciding (Bland & Rosokha, 2021; Kahneman, 2009; Schröder & Gilboa Freedman, 2020; Simon, 1959). All these aspects are essentials to understand, learn, and decide correctly (Cohen et al., 2011; Luu et al., 2003; San Martín et al., 2012; Sun & Wang, 2020; Van de Vijver et al., 2011; Walsh & Anderson, 2012; Wischnewski & Schutter, 2018). When we decide whether to buy something at a specific time, we do not know what will happen the next day with the same product. Therefore, it is not possible to know if to buy it at certain price is the right one. This permanent uncertainty makes us depend on our own self-learning as the only way to adjust and improve future behaviors and actions (Kahneman, 2009; Karimi et al., 2015; Lane, 2017). The self-learning process is, in turn, highly influenced by emotional elements, beliefs and symbolic values that make up the subjective expectations of the consumer, playing an essential role in interpreting decisions as right or wrong (Bland & Rosokha, 2021; Burnett & Lunsford, 1994; Hayden, 2018; Kahneman, 2009; Kahneman & Tversky, 1984; Slovic et al., 2004).

Thus, some studies have tried to identify the neurophysiological correlates of the decision to buy in a pre-decision time, using experimental scenarios where participants must choose to purchase or not a product based on the contextual information provided by the experimental task, and using uncertainty scenarios. As result of this, it has been reported that the N2 component is significantly lower in buying condition compared to not buying (Braeutigam et al., 2004), being considered an indicative of the preference of one product over another (Telpaz et al., 2015). On the other hand, evidence supports that the decision to buy is preceded by a significant increase in the frontocentral alpha (Braeutigam et al., 2004; Horr et al., 2022) and theta activity (Horr et al., 2022). Increases in alpha activity have also been reported as a consequence of obtaining a price below normal (Arieli & Berns, 2010), even when this reference price is subjective or non-explicit (Ravaja, Somervuori, & Salminen, 2013).

Studies focused on individual differences and purchasing decisions have shown the existence of a close relationship between attitudes and behavior (Ajzen & Fishbein, 1977; Alí Diez et al., 2021; Denegri et al., 2012). Evidence proposed the existence of three attitudinal styles that coexist in each person and explain the buying behavior: rational, impulsive and compulsive style (Castellanos et al., 2016; Denegri, 2010; Denegri et al., 2012; Gebaüer et al., 2003). In this sense, the attitudinal style is determined by the positive, neutral or negative predisposition of a person towards specific behaviors or objects of a rational, impulsive and compulsive nature (Alí Diez et al., 2021; Denegri, 2010; Denegri et al., 2012; Gebaüer et al., 2003; Luna-Arocas & Tang, 2004). In addition, attitudes towards purchase can be dynamic when contexts, products or situations change (Denegri, 2010).

Although evidence allow us to suppose that both the context and the attitudes have a relevant behavioral impact and modulate the neurophysiological correlates of decision-making in different ways (Simon, 1959), there are no studies describing the interaction of all these factors with behavioral and neurophysiological measurements of purchasing decisions. In recent years, some studies have tried to combine personal and contextual elements, such as personality (Schröder & Gilboa Freedman, 2020) and characteristics of particular products and brands (Ambler et al., 2000, 2004; Komalasari et al., 2021; Kranzbühler et al., 2017; Shastry & Anupama, 2021), to describe, more accurately, segments of potential consumers of their products (Laran, 2009; Laran & Wilcox, 2011; Mackenzie & Spreng, 1992; Sanfey et al., 2003). However, there are no experimental studies explaining the interaction of these different variables (neurophysiological, attitudinal, and contextual) in general populations, using neutral experimental paradigms, to assess the purchase decision-making process.

Chapter 2

Research aims

Chapter 2: Research aims

The main objective of this thesis work is **to propose an exploratory predictive model of the purchase decision**, considering neurophysiological, attitudinal, and behavioral markers, and controlling the effect of personal preferences and interest, motivation, and previous experience in an experimental setting. To reach this goal, four studies were designed to identify the main neurophysiological, attitudinal, and behavioral markers related to the purchase decisions, in order to propose a predictive model. Specific aims for each study are detailed below.

The goal of **Study 1** was twofold. First, to **design a new experimental paradigm to identify the effects of contextual and attitudinal variables related to purchase decision making in three types of uncertainty scenarios and**, in addition, to **assess the differential role of attitudinal and contextual variables in the purchase decision making in uncertainty contexts**.

As previously described, purchase decisions are made under uncertainty at different levels (Bland & Rosokha, 2021; Kahneman, 2009; Schröder & Gilboa Freedman, 2020; Simon, 1959), where the absence of explicit feedback entails that the exclusive input to adapt and optimize future decision is the self-learning (Bland & Rosokha, 2021; Burnett & Lunsford, 1994; Hayden, 2018; Kahneman, 2009; Kahneman & Tversky, 1984; Slovic et al., 2004). As a consequence, we expected that different levels of uncertainty would lead to different behavioral outputs during the experimental scenario. In addition, evidence supports the idea that attitudes are strongly related to behavior (Ajzen & Fishbein, 1977; Alí Diez et al., 2021; Denegri et al., 2012), proving that attitudinal measures are significant predictors of consumption behaviors (Alí Diez et al., 2021). As a consequence, we also expected that different attitudinal levels would lead to differences in the purchase decisions made in the experiment.

The **Study 2**, sought to investigate the **neurophysiological correlate of purchase decision-making in scenarios with temporal uncertainty using the new experimental paradigm** designed and tested in the first study. Considering 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, as it was proposed by Braeutigam et al. (2004) and Telpaz et al. (2015). Additionally, 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 during experimentation, based on previous studies describing that theta and beta oscillatory activity plays a crucial role in decision-making process. On the one hand, theta activity is related to cognitive control (Clayton et al., 2015; Cox & Witten, 2019) and is modulated by the uncertainty presented in the context of decision (Cavanagh, Figueroa, et al., 2012; Mas-Herrero & Marco-Pallarés, 2014). On the other hand, beta oscillations have consistently been reported in response to unexpected or highly relevant positive outcomes (Cohen et al., 2007;

Cunillera et al., 2012; Marco-Pallarés et al., 2015; Mas-Herrero et al., 2015). Additionally, evidence related to purchase decisions, supports that decision to buy is preceded by a significant increase in the frontocentral alpha activity (Braeutigam et al., 2004), but also, studies have reported increases in alpha activity when participants obtain a lower price than expected (Arieli & Berns, 2010), even when this reference price is subjective or not explicit (Ravaja et al., 2013).

Based on the various studies that describe the role of valence and magnitude of the feedback received during the decision-making process, **Study 3** wanted to complement the information from Study 2 and **sought to measure the neurophysiological response associated to different types of variations between prices, while participants were deciding between buying the product or waiting for a new offer**. We hypothesized that electrophysiological activity would vary in the different price-variations in terms of valence (increase/decrease) and magnitude (low/high), at early and late stage. In particular, based on previous studies that reported that the magnitude of the P3 component is sensitive to the valence and magnitude of the feedback presented (Balconi & Crivelli, 2010b; Ferdinand et al., 2012; Palidis & Gribble, 2020; Pfabigan et al., 2014; San Martín, 2012; Wu & Zhou, 2009), we expected to find increases in early and late P3 ERP amplitudes attributable to high magnitude and negative valence (price increases).

In addition, we expected to find, on the one hand, increases in power-induced theta band attributable to high magnitude and negative valence, as a consequence of the key role of frontocentral theta activity in the computation of prediction error or unexpected outcomes derived from decisions (HajiHosseini et al., 2012; Wang et al., 2016), and cognitive control (Clayton et al., 2015; Cox & Witten, 2019).

On the other hand, we expected to find increases in power-induced activity in beta band for high magnitude and positive valence (price decreases), based on studies that have been reported as a neural marker of reward due to its sensitivity to positive feedback and wins, in comparison to losses or negative feedback (Andreou et al., 2017; Cohen et al., 2007; HajiHosseini et al., 2012; HajiHosseini & Holroyd, 2015; Marco-Pallarés et al., 2008, 2015; Mas-Herrero et al., 2015; Van de Vijver et al., 2011; Weismüller et al., 2019).

Finally, in **Study 4,** we aimed to **propose an exploratory model of the decision to buy including neurophysiological, attitudinal, and behavioral markers**, and controlling the effect of personal preferences, interests, motivation, and experiences of previous purchases of the same or similar products, **using the experimental paradigm designed** in this doctoral thesis.

We expected that different factors (types of price variations and its magnitudes, increases in ERP amplitudes and oscillatory activity, and different attitudinal styles) would predict the probability of purchase.

Chapter 3
Study 1

Chapter 3: Study 1

Modeling Purchase Decision-Making: The role of personal and contextual variables in different decision scenarios under uncertainty

Several variables associated with personality traits, attitudes, and characteristics of the context have been proposed to play a key role in purchase decision-making. However, there are no studies trying to combine personal, attitudinal, and contextual variables to predict consumer behavior in experimental settings. The goal of the present study was to identify the interaction between variables derived from the context and the individual differences of the participants. Ninety-four subjects participated in a new experimental paradigm with three different uncertainties contexts in which the participants had to decide the optimal temporal moment to buy new products.

Mixed-effects models allowed the identification of significant effects of contextual variables and personal characteristics in the decision-making. Additionally, results showed that the models were dynamic, and that the role played by personal traits and attitudes was highly dependent on the characteristics of the context. Finally, predictive capacity of the models designed met appropriate to classifying the decisions of the participants.

Results are discussed based on the importance of including the individual differences and context characteristics when we attempt to understand purchase decision-making.

1. Introduction

One of the most common decisions we have to face in our daily life is to choose which products to buy and what price to pay for them, in other words, making purchase decisions. Understanding how people make such consumption decisions has been one of the main topics in different disciplines, including psychology and economics. Although different elements might influence such decisions, most studies have focused on two different factors, mainly the elements of the context of decision and the individual differences of consumers. Studies based on the context of the decision consider that purchase decision-making is performed under uncertainty at different dimensions, and that those elements of the context are crucial to understand this behavior. Some examples of these different dimensions are the time (e.g. when is the best moment to buy a product), or the risk level of the decision (e.g. make a risky investment expecting to obtain a higher return rate vs. select a non-risky investment with a low but safe return), among many others (Green & Myerson, 2004; Wheeler, 2020). Therefore, in such uncertain environments, the main goal of the consumer would be to maximize the utility of each decision (Kahneman, 2009; Kahneman & Tversky, 1984; Simon, 1959; Wheeler, 2020). In contrast, the second main framework focuses on the study of individual differences among consumers and how do they affect purchase decisions. It is well-known that attitudes, personality traits, motivation, previous experience and goal orientation influence consumers' decisions (Martinez-Selva et al., 2006; Simon, 1959; Whiteside & Lynam, 2001). Impulsivity, for example, plays a key role in the decision to buy (Dalley et al., 2011; Dalley & Robbins, 2017). High impulsivity is related to fast decisions (Evenden, 1999; Patton et al., 1995) and a strong orientation to the present (lack of "futuring"). Impulsivity is characterized by a tendency to accept small immediate rewards in front of large delayed or uncertain rewards (Bevilacqua & Goldman, 2013; Evenden, 1999; Patton et al., 1995), a phenomenon which often studied under the delay discounting construct. Delay discounting is the decline of the value of a reward with time, and has become a widely used instrument to understand the capacity of people to wait for a larger reward (MacKillop et al., 2011), using the intertemporal choices as a measure of the delayed or expected utility of a reward (Frederick et al., 2002). In addition to these general measures, attitudes of individuals in front of the object of the decision have been frequently studied in the psychology of consumption to understand consumers' behavior (Alí Diez et al., 2021; Denegri et al., 2012; Luna-Arocas & Tang, 2004). In contrast to personality traits, which are supposed to be relevant in all situations, attitudes only have a real effect on behavior when they affect the object of interest or involve the same action as the real behavior (Ajzen & Fishbein, 1977). In this sense, the study of attitudes towards purchase has found specific styles/factors associated with this behavior (such as compulsivity, rationality or impulsivity, see, e.g., Luna-Arocas & Tang, 2004).

Although these two approaches have been independently addressed in several studies, it is reasonable to consider that personality traits and attitudes interact with the environment characteristics (e.g., uncertainty, degree of risk) in consumer behavior (Simon, 1959). Therefore, in the last years, different studies have been devoted to combine the information provided by these different frameworks (see, among many others, Laran, 2009; Laran & Wilcox, 2011; Mackenzie & Spreng, 1992; Sanfey et al., 2003). However, even when these studies provide crucial inside in the interaction between contextual and personality variables in consumer decision, it is difficult to generalize the results given the different approaches and scenarios used, often oriented to understand the behavior in front of a specific product or brand and not to understand the purchase decision making as a general phenomenon. One reason for this heterogeneity is the lack of experimental paradigms which could allow studying the different elements of purchase decision-making (including individual differences and contextual variables). Therefore, the goal of the present study was to design a new experimental paradigm, The Purchase Decision Task (PDT), which allowed the identification of the contextual and individual differences' variables associated with purchase decision making in different scenarios. PDT involved the decision of when to buy a product with the uncertainty of unknowing the optimal purchase moment, a situation which parallels several of the purchase decisions people have to face in real life (e.g., online booking of flight tickets). The task allowed the use of different products with different distributions or prices with time presenting different optimal purchase moments. With this experimental paradigm, we aimed to identify the effect of variables of the context and individual differences, commonly associated with consumers' decision in purchase decision making.

2. Method

Participants

Ninety-four healthy students participated in the experiment (fourteen men, mean age 21.6 ± 4.8 (SD)) All participants were volunteers and received an academic compensation for their participation (2 extra points in any of the subjects dictated by the Department of Basic Psychology in the same period of their participation). Written consent was obtained prior to the experiment. The local ethical committee approved the experiment.

The final sample size was obtained considering two elements: on the one hand, to control the veracity of the results, five participants were discarded because their scores in the BIS-11 were < 52 points, which may reflect a bias of social desirability or false response (Stanford et al., 2009). On the other hand, twenty-eight participants were excluded in the analyses of the second model because their responses were used to test an initial prices distribution, which was adjusted in the subsequent applications of the task.

As result of this, the final sample size was eighty-nine undergraduate students (twelve men, mean age 21.2 ± 3.8 (S.D.)) for models 1 and 3, and sixty-one undergraduate students (eight men, mean age 20.9 ± 3.2 (S.D.)) for model 2.

Experimental design

To assess the decision-making process in an experimental context, a "Purchase Decision Task" (PDT) was designed for the present study. To avoid any effect of previous experience purchasing the products, the cover of the task involved commodities that were not familiar to the participants. Participants assumed the role of a supply manager of a boat maintenance company in Alaska who had to buy a set of spare parts for boats (Distribution 1), a barrel of oil (Distribution 2), and a kit of maintenance tools (Distribution 3). For each product, participants had certain time periods (10 in total) in which they could buy each product but, as in real life, the decision about buying it or not was made without knowing the price in the future. Participants had a maximum budget of 1,000 coins to make the purchase of the three products, and they were told that the objective of the task was save as many coins as possible in each sequence of purchase.

In each trial, the number of the offer (between day 1 until day 10) and the price of this day was presented on the screen. Participants had to choose between the two alternatives presented (buy or wait). In case of selecting the "wait" option, a new price/offer pair was displayed. If participants waited until offer 10, the product was marked as purchased with the last price shown. In contrast, when participant selected the option "buy", the purchase of the product ended, feedback indicated the amount paid for this product and the image of the next product was presented. When the last of the three products was bought, feedback showed the price paid for each product, the total spent, and the amount saved. Then, a new sequence of buying of the three products started. After twenty sequences, the final feedback showed the mean of coins saved during the task.

The price of the three products followed different distributions. Average values were defined for each offer (10 days and 20 purchases of each product) following an intentional structure of prices distribution to simulate different contexts of uncertainty *(Figure 1)*.

The first distribution was designed with the same average value for each day (offers), increasing the variability of prices offer by offer, with the intention of generating a context of complete uncertainty where, over the days, prices showed greater variability between the highest and the lowest *(Figure 1, product 1)*. Distribution 2 was a double peak distribution, where there was a clear moment (offer) in which prices were the lowest, as well as offers in which they were permanently the highest. *(Figure 1, product 2)*. Finally, Distribution 3 was designed to present a sustained decrease from the initial price until t=5, where the most convenient prices were shown, followed by a rise in the price until the end *(Figure 1, product 3)*. To generate the increase of uncertainty with time, as in real situations, in all distributions the standard deviations of the values were increased by 5 in each day. Accordingly, an uncertainty formula was defined with an initial standard deviation of 10 and a slope of 5 by the days (x) following.

$$\delta = 10 + 5x$$

Equation 1. Uncertainty formula

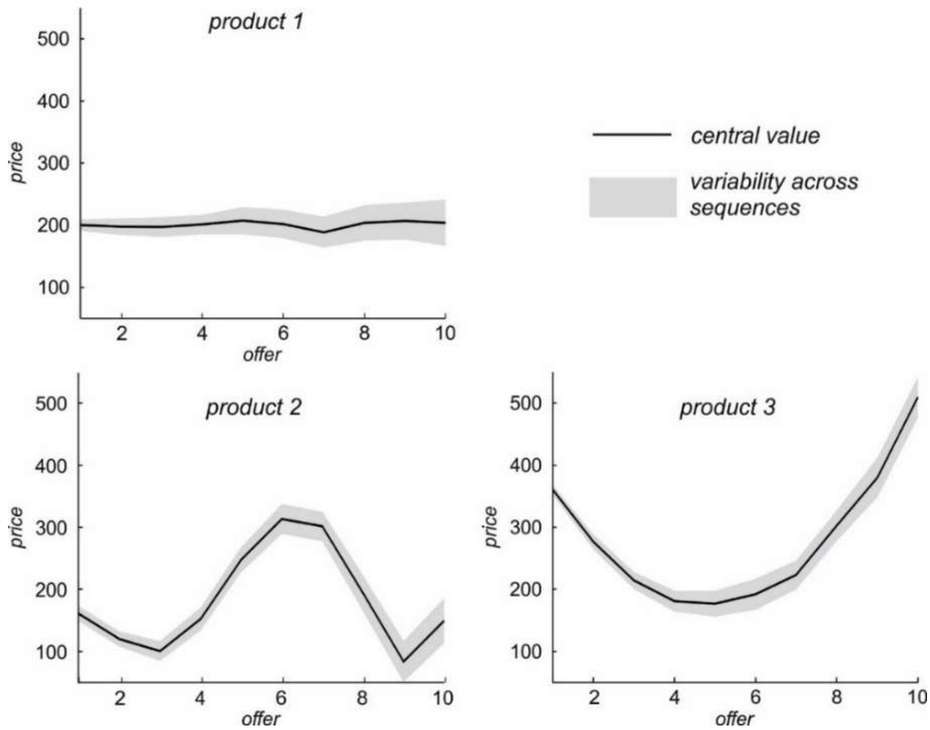

Figure 2. Price distributions designed for the task

Questionnaires

In order to determine different personality traits and attitudes, participants also completed three different questionnaires.

First, participants completed the *Attitudes Toward Purchase* questionnaire which is an adapted version of three different questionnaires to assess specific attitudinal dimensions using a check list of behaviors, emotions, and thinking's related to purchase behaviors. Habits and Consumption Behaviors Questionnaire (Denegri et al., 1999) was adapted to generate the rationality dimension; Impulsivity in Purchase Scale (Quintanilla & Luna-Arocas, 1999) to the impulsivity dimension; and Compulsive Purchase Scale (Luna-Arocas & Fierres, 1998) to the compulsivity dimension. Thus, three different attitudinal dimensions were measured: Rationality, defined as a rational consumption style, based on the analysis and reflection prior to the purchase decision; Impulsivity, defined as the absence of analysis and reflection prior the purchase decision; and Compulsivity, defined as a type of impulsivity marked by the need to buy certain product, using consumption as a regulatory element in emotional terms (Alí Diez et al., 2021; Denegri, 2010; Denegri et al., 2012; Gebaüer et al., 2003).

The second questionnaire used was the *Barratt Impulsiveness Scale Version 11 (BIS-11;* Patton et al., 1995), adapted for Spanish population (Oquendo et al., 2001), composed by 30 items Likert-type.

Finally, participants completed the *Monetary-Choice Questionnaire* (Kirby et al., 1999), where participants had to complete 27 choices between a small immediate reward or a large delayed reward. Delayed-Discounting measurement were obtained using the hyperbolic function described by Kirby & Maraković (1996):

$$V = \frac{A}{1 + kD}$$

Equation 2. Hyperbolic function of Delayed-Discounting

Where V is the present value (small immediate reward); A is the amount of the large delayed reward; D is the delay in days; and k is the free parameter of delay discounting estimation (Madden et al., 2003). Higher k-values reflect greater delay discounting and higher levels of impulsivity (Reynolds et al., 2006). Finally, the k-values were transformed using the Log(k) transformation, in order to obtain a valid parameter to include in the model's estimations (Myerson et al., 2014), using the auto-scorer spreadsheet developed by Kaplan et al. (2014) for the estimation of k-values.

Data analyses

Binary Logistic Generalized Linear Model with mixed effects (GLMM) was used to determine the relationship between the decision (wait or buy) and the studied variables using the lme4 package for R (Bates, Kliegl, et al., 2015).

In concrete, contextual variables extracted from the "Purchase Decision Task" were: decision in each trial (wait = 0 or buy = 1), coded as a binary response variable; purchase number (1 to 20); initial price showed in each purchase; block of purchase (1st block: purchases 1 to 10; 2nd block: purchases 11 to 20); and variation between each price respect the previous one. In the case of the variation, two variables were generated to be included in the models. The first was the type of variation that refers to the type of variation existing between the current price respect the previous one, encoded as a nominal variable of three levels (0 = "no variation"; 1 = "increase" ; 2 = "decrease"). The second was variation magnitude that refers to the absolute value of the variation of prices between current and the previous one.

Then, the variables extracted of the questionnaires (Rationality, Impulsivity, and Compulsivity from Attitudes Toward Purchase questionnaire, and General Impulsivity from BIS-11 scale) were transformed in order to reduce the differences of scales of measurements (Bates, Kliegl, et al., 2015; Chou et al., 1998). For this propose, the SoftMax Transformation of the DMwR2 package (Torgo, 2016) was used in order to be fitted to the Generalized Linear Model.

Generalized Binary Logistic General Models with mixed effects were generated for each type of distribution (e.g., Model 1 corresponded to product 1). Each initial model incorporated as random effects the within-subject effect and the effect of learning through purchases (purchase number). In addition, the fixed effects incorporated each variable and the interaction effect of each individual differences' variables, and contextual variables. Then we used the Backward Elimination Method and final models for each distribution were obtained.

Finally, for each final model, the optimal cut-off point was calculated for the appropriate classification of the predictions, using the Youden Index [YI] method and the balance between the Specificity and Sensitivity of the proposed model. According to this method, the level of sensitivity and specificity has to be evaluated, in addition to finding a suitable cut-off point for the classification of the responses (Fuentes, 2013).

Based on that, sensitivity (probability of the model to predict a true positive) and specificity (probability of predicting a true negative) were computed (Dreiseitl &

Ohno-Machado, 2002; Fuentes, 2013). Then YI was estimated as the balance of both sensitivity and specificity, using the formula:

$$YI = \left(\frac{sensitivity + specificity}{100}\right) - 1$$

Equation 3. Youden Index formula

Using these indicators, the optimal cutoff point was the one that presented a specificity and sensitivity greater than or equal to 62,5% (Rial & Varela, 2008), ideally ≥ 75%, and/or the highest YI that reduced the number of errors in the prediction [PE] (Fuentes, 2013), calculated by:

$$PE = \frac{False\ positive + False\ negative}{total\ observations}$$

Equation 4. Prediction error formula

All statistical analyzes were performed using R (R Core Team, 2018).

3. Results

Descriptive statistics

Participants presented a rationality of 14.61 ± 4.55 (SD; min= 4; max=24), impulsivity of 28.48 ± 6.54 (SD; min=15; max=42), and a compulsivity of 15.56 ± 7.06 (SD; min=7; max=33). General Impulsivity results showed a sample mean of

68.2 ± 8.93 (SD; min=52; max=93). In the case of Delay Discounting variable, the sample mean was of 0.0159± 0.0254 (SD), presenting a minimum of 0.00016 (k-value), and a maximum of 0.15844 (k-value). In terms of the choices in the Monetary Choice Questionnaire participants selected the Late Delayed option 40.54% ± 17.45 (SD) in the small amount condition, 49.29% ± 16.74 (SD) in the medium amount, and 54.49% ± 16.14 (SD) of times in the large amount. Overall, the proportion of Late Delayed Reward was 48.11% ± 15.67.

Figure 2 shows the moment of the purchase (offer of purchase) for the three distributions in the different decisions. Results shows that the decisions for the three distributions was relatively consistent trough the purchases.

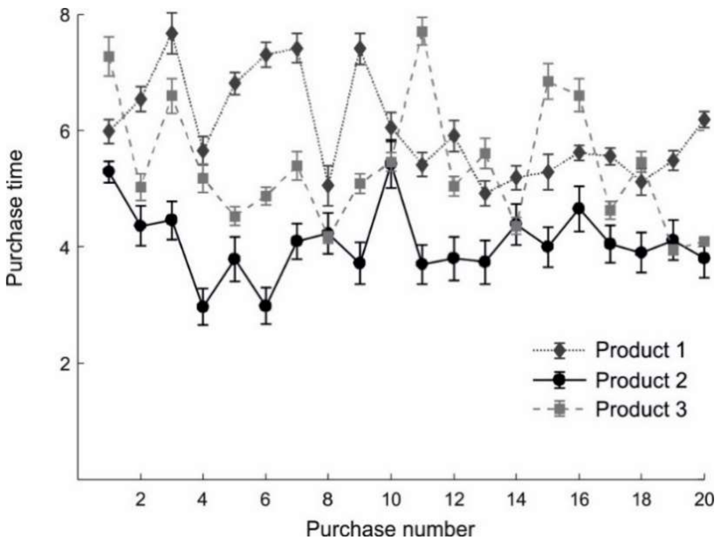

Figure 3. Offer of purchase by product and purchase number

Generalized Linear Model with mixed effects

Full Model analyses

A full GLMM was computed for each Distribution of prices. Table 1 summarize the results of each full models designed, detailing random and fixed effects tested and p-values obtained.

As shown in *Table 1*, there were differentiated effects in the three models and, in addition, some of the fixed effects were not significant. Therefore, the initial proposed model was adjusted until a reduced model showed equal or better model adjustment indicators and met the parsimony criterion (Forster & Sober, 1994), using the Backward Elimination Method.

Final model analyses

Based on the analysis performed for the three distributions, Model 1 presented no significant differences between the general adjustment parameters of the complete model and the final one (Model 1: X2(24) = 31.47; p-value = .141). In contrast, Model 2 (X2(16) = 29.69; p-value = .020) and Model 3, (X2(28) = 56.41; p-value = .001) showed significant differences between the general adjustment of the Final model compared to the Full Model. In the three cases, the Final Model was selected because it turned out to have a better fit and be more parsimonious (see *Table 2*).

Table 1
Full purchase predictive model Distribution 1, 2 and 3: random Subject effect across Purchases (*Subjects=89; 61; 89; Purchases=20*), GLMM logistic parameters estimates (Est.), standard errors (SE), and *P* values.

	Distribution 1			Distribution 2			Distribution 3		
Parameter	Est.	SE	*P* value	Est.	SE	*P* value	Est.	SE	*P* value
Intercept	-4.458	3.542	0.208	0.289	3.236	0.929	-0.224	1.036	0.031 *
Offer	0.456	0.075	< 0.001 ***	2.788	0.327	< 0.001 ***	1.023	0.187	< 0.001 ***
Initial price	0.004	0.017	0.815	-0.016	0.022	0.463	0.042	0.029	0.145
Variation magnitude	0.005	0.009	< 0.592	0.027	0.010	0.006 **	2.364E-04	4.64E-03	0.959
Variation type									
Price increase = 1	-1.392	0.796	0.081	-1.935	2.372	< 0.001 ***	-1.687	1.085	0.120
Price decrease = 2	0.280	0.706	0.692	-0.156	2.080	< 0.001 ***	2.498	0.851	0.003 **
Purchase block = 2	0.601	0.139	< 0.001 ***	-0.216	0.112	0.067	0.393	0.308	0.203
Rationality	0.712	1.977	0.719	-1.047	1.905	0.583	-3.758	4.251	0.376
Impulsivity	2.425	2.509	0.334	-2.196	2.708	0.417	1.427	5.496	0.795
Compulsivity	-2.436	2.623	0.353	1.060	2.925	0.717	3.699	5.592	0.508
General impulsivity	2.674	1.993	0.180	-0.808	1.914	0.673	1.799	4.292	0.675
Delay Discounting	1.784	1.330	0.180	-1.090	1.215	0.370	-3.884	2.771	0.161
Initial price by Rationality	-0.002	0.009	0.808	0.011	0.013	0.414	0.016	0.012	0.176
Variation magnitude by Rationality	-0.003	0.005	0.540	-3.20E-04	-5.72E-03	0.956	-0.007	0.003	0.019 *
Variation type (1) by Rationality	0.181	0.480	0.706	6.352	1.537	< 0.001 ***	1.117	0.654	0.087
Variation type (2) by Rationality	-0.169	0.421	0.689	2.506	1.305	0.055	-0.889	0.509	0.081
Offer by Rationality	-0.036	0.045	0.427	-0.499	0.206	0.016 *	-0.273	0.073	< 0.001 ***
Initial price by Impulsivity	-0.009	0.012	0.445	0.022	0.018	0.228	-0.006	0.015	0.701
Variation magnitude by Impulsivity	-0.002	0.007	0.787	0.011	0.009	0.222	0.004	0.004	0.229
Variation type (1) by Impulsivity	-1.435	0.600	0.017 *	2.733	1.718	0.112	-0.042	0.867	0.961
Variation type (2) by Impulsivity	-1.142	0.521	0.028 *	0.679	1.766	0.701	0.359	0.676	0.595

Offer by Impulsivity	0.072	0.058	0.212	-0.554	0.259	0.032 *	0.017	0.093	0.853
Initial price by Compulsivity	0.006	0.013	0.640	-0.017	0.020	0.390	-0.007	0.015	0.651
Variation magnitude by Compulsivity	0.005	0.007	0.499	-0.007	0.010	0.426	-0.002	0.004	0.536
Variation type (1) by Compulsivity	0.840	0.647	0.195	-3.995	2.134	0.061	0.392	0.891	0.660
Variation type (2) by Compulsivity	0.785	0.566	0.165	-2.313	2.009	0.250	-0.710	0.689	0.303
Offer by Compulsivity	0.045	0.059	0.446	0.893	0.305	0.003 **	-0.143	0.095	0.132
Initial price by General impulsivity	-0.011	0.010	0.251	0.006	0.013	0.625	-0.003	0.012	0.819
Variation magnitude by General impulsivity	0.016	0.005	0.004 **	0.008	0.006	0.184	-0.003	0.003	0.277
Variation type (1) by General Impulsivity	0.406	0.488	0.406	-2.233	1.328	0.092	0.272	0.641	0.672
Variation type (2) by General Impulsivity	0.562	0.428	0.190	-0.235	1.225	0.848	-0.206	0.500	0.680
Offer by General impulsivity	-0.179	0.046	< 0.001 ***	-0.157	0.190	0.407	-0.091	0.071	0.203
Initial price by Delay Discounting	-0.007	0.007	0.304	0.007	0.008	0.390	0.012	0.008	0.119
Variation magnitude by Delay Discounting	-0.009	0.004	0.013 *	4.62E-04	3.53E-03	0.896	0.002	0.002	0.415
Variation type (1) by Delay Discounting	0.324	0.326	0.320	-2.624	0.664	< 0.001 ***	0.654	0.414	0.114
Variation type (2) by Delay Discounting	0.031	0.285	0.913	-2.508	0.699	< 0.001 ***	0.053	0.315	0.866
Offer by Delay Discounting	-0.044	0.030	0.151	0.527	0.099	< 0.001 ***	-0.140	0.047	0.003 **
Intercept-Purchase covariance	0.060	0.233		6.049E-04	0.030		4.09E-01	0.639	
Purchase-Subject covariance	4.40E-07	0.001		1.171E-05	0.003		1.19E-05	0.004	
Bayesian Information Criteria [BIC]	6797.7			3687.9			6808.1		

Note: Distribution 1: n=89; Distribution 2: n=61; Distribution 3: n=89. Purchase block "1" and variation type "no variation" set to zero for identification. P values not given for covariance parameters and goodness of fit. "*" p-value < .05; "**" p-value < .01; "***" p-value < .001.

All models presented significant intercepts (Models 1, 2, and 3: p-value < .001). Additionally, random effect of intercept by purchase was identified in the three models. In brief, all model presented significant effect of some variables of the context (offer, variation magnitude and variation type). In contrast, individual differences measures were only significant in some models (general impulsivity in model 1, rationality and compulsivity in model 2, and impulsivity in models 1 and 2). Interestingly, model 2 showed some significant interactions between personality characteristics and contextual variables, such as variation type x rationality, impulsivity, compulsivity and delay discounting (the latter also significant in model 3). In addition, intercept parameter in all the models was not constant, based in the existence of a covariance between purchase number and intercept. According to this result, the intercept parameter was presented as an additional fixed parameter that varied for each purchase of each model. In that way, is possible to describe that intercept parameter was fixed between -4.245 (min) and -3.433 (max) for Model 1, -2.170 (min) and -2.062 (max) for Model 2 and, finally, between -6.902 (min) and -4.522 (max) in Model 3.

To identify possible multicollinearity problems, we analyzed the Variance Inflation Factor (VIF) of the model's predictors. Results revealed that there were no collinearity problems, being VIFs of predictors distributed between 5.32 and 7.85, and a general Kappa Index of 9.73.

Table 2
Final purchase predictive models: random Subject effect across Purchases, GLMM logistic parameters estimates (Est.), standard errors (SE), *P* values, and Exponential β (Exp(β)).

	Distribution 1			Distribution 2			Distribution 3		
Parameter	Est.	SE	*Exp(β)*	Est.	SE	*Exp(β)*	Est.	SE	*Exp(β)*
Intercept	-3.775	0.294	0.023 ***	-2.117	0.398	0.121 ***	-5.453	0.751	0.004 ***
Offer	0.529	0.030	1.698 ***	2.695	0.293	14.81 ***	0.769	0.097	2.157 ***
Variation magnitude	0.001	0.008	1.001	0.030	0.002	1.031 ***	-0.007	0.001	0.993 ***
Variation type									
Price increase = 1	-2.148	0.180	0.117 ***	-20.213	2.058	1.7E-09 ***	-0.563	0.818	0.569
Price decrease = 2	0.154	0.158	1.166	-15.639	1.478	1.6E-07 ***	1.955	0.660	0.636 **
Purchase block = 2	0.635	0.141	1.889 ***	-	-	-	-	-	-
Rationality	-	-	-	0.610	0.252	1.840 *	-	-	-
Impulsivity	-0.715	0.220	0.489 **	0.975	0.320	2.652 **	-	-	-
Compulsivity	-	-	-	-1.252	0.348	0.286 ***	-	-	-
General impulsivity	0.722	0.231	2.058 **	-	-	-	-	-	-
Delay Discounting	0.340	0.097	1.404 ***	-0.026	0.143	0.975	0.382	0.332	1.465
Variation type (1) by Rationality	-	-	-	6.314	1.371	552.08 ***	-	-	-
Variation type (2) by Rationality	-	-	-	2.906	0.898	18.828 **	-	-	-
Offer by Rationality	-	-	-	-0.595	0.189	0.552 **	-	-	-
Variation type (1) by Impulsivity	-	-	-	4.391	1.329	80.695 ***	-	-	-
Variation type (2) by Impulsivity	-	-	-	1.461	1.061	4.309	-	-	-
Offer by Impulsivity	0.080	0.038	1.083 *	-0.453	0.216	0.636 *	-	-	-

Variation type (1) by Compulsivity	-	-	-	-5.882	1.741	0.003 ***	-	-	-
Variation type (2) by Compulsivity	-	-	-	-2.283	1.213	0.102	-	-	-
Offer by Compulsivity	-	-	-	0.677	0.250	1.967 **	-	-	-
Variation magnitude by General impulsivity	0.019	0.005	1.019 ***	-	-	-	-	-	-
Offer by General impulsivity	-0.150	0.040	0.861 ***	-	-	-	-	-	-
Variation magnitude by Delay Discounting	-0.010	0.003	0.990 **	-	-	-	-	-	-
Variation type (1) by Delay Discounting	-	-	-	-2.662	0.551	0.070 ***	0.756	0.365	2.130 *
Variation type (2) by Delay Discounting	-	-	-	-2.335	0.458	0.097 ***	0.161	0.293	1.174
Offer by Delay Discounting	-	-	-	0.501	0.092	1.649 ***	-0.135	0.044	0.874 **
Intercept-Purchase covariance	0.067	0.259		0.001	0.031		0.434	0.659	
Purchase-Subject covariance	1.3E-07	0.000		0.001	0.004		6.8E-06	0.003	
Bayesian Information Criteria [BIC]	6606.3			3581.4			6607.8		

Note: Purchase block "1" and variation type "no variation" set to zero for identification. The parameters indicated with "- "were not included in the final model as result of the step back analysis. P values not given for covariance parameters and goodness of fit. "*" p-value < .05; "**" p-value < .01; "***" p-value < .001.

Table 3

Models predictive capacity based in the initial (default) cutoff point and the final selected cutoff point for classification, for Models 1, 2, and 3. PE: Prediction error; YI: Youden Index.

Default Cutoff = 0.5							Alternative Cutoff						
Predicted							Predicted						
Model	Observed	Wait = 0	Buy = 1	Correct classification	PE	YI	Cutoff	Observed	Wait = 0	Buy = 1	Correct classification	PE	YI
1	Wait = 0	8736	279	96.91%	12%	0.40	**0.23**	Wait = 0	7689	1326	85.29%	16%	0.61
	Buy = 1	1014	764	42.97%				Buy = 1	435	1343	75.53%		
2	Wait = 0	3577	178	95.26%	16%	0.45	**0.35**	Wait = 0	2976	779	79.25%	21%	0.59
	Buy = 1	615	603	49.51%				Buy = 1	243	975	80.05%		
3	Wait = 0	7403	419	94.64%	14%	0.41	**0.25**	Wait = 0	6380	1442	75.76%	19%	0.58
	Buy = 1	952	828	46.52%				Buy = 1	423	1357	76.24%		

Models' predictive capacity

The second main goal of the present manuscript was assessing the predictive capacity of the models designed. Given that the default cutoff point (cutoff = 0.5) did not meet the minimum requirements in any model due to the low sensitivity and high specificity (*Table 3*), the optimal cut-off point was identified in each model using the Youden Index (YI) analysis.

The cut-off point for Model 1 was 0.23, yielding a specificity of 85.29% and a sensitivity of 75.53% (YI=0.61). In Model 2, the optimal cut-off point was set to 0.35, with a specificity of 79.25%, sensitivity of 80.05% (YI=0.59). Finally, appropriate cut-off point for Model 3 was set to 0.25, with specificity of 75.76% and sensitivity of 76.24% (YI=0.58).

4. Discussion

The goal of the present study was to identify the effect of variables of the context (such as the initial price, variation, number of offer, among others), and individual differences variables commonly associated with consumer decisions (such as impulsivity, rationality and compulsivity) on consumer behavior. To this end, we designed and tested a new experimental paradigm to evaluate purchase decision in contexts with different uncertainty. Results showed that contextual variables (current offer and difference with previous offer) played a key role in all the models, while the contribution of individual differences and their interaction with contextual variables depended on the different contexts. Finally, results showed that it was possible to build predictive models of purchase decision making on the bases of these variables using this experimental design. This supports the idea that the task could be a useful tool to study purchase decision making in experimental settings. Indeed, the task show that different price distributions yielded to a differential contribution of participants' individual differences, revealing a potential utility for the study of other products and/or contexts, as well as its use in psychophysiological or neuroimaging studies.

The main result of the study is that, overall, variables with significant effects on the purchase decision vary in each context, and importantly, interaction between personality measures and characteristics of the environment are crucial to explain the variations in the decisions of participants. This is of pivotal importance, as shows that consumer behavior does not only depend on a fixed set of individual traits, but it is closely linked to the contextual measures. Indeed, different studies in decision making have showed that behavior of subjects is adapted in different situations as a function of the characteristics of the environment (Behrens et al., 2007; Mas-Herrero & Marco-Pallarés, 2014), showing that, to explain purchase decision making, both individual differences and contextual variables (and their interactions) are important (Whiteside & Lynam, 2001). Certainly, the models were designed to show the effect of each of these variables in decision making, but above all, to show the interrelation between context variables and individual differences in specific contexts. In other words, interaction effects can explain purchase decision making in particular situations or scenarios and might be critical in understanding different segments of consumers, as well as the variation of the decisions of the same consumers in different contexts (MacKillop et al., 2011).

The different models also revealed the role of individual differences in purchase decisions but, crucially, that classical factors used in previous studies do not influence decisions in all the scenarios in the same way. For example, the delay discounting parameter, which should be a critical factor in the present context, seems to play a different role in the three designed models. Therefore, it only showed a significant positive effect (the higher the delay discounting parameter, the higher the probability to buy earlier) in the first model, in which uncertainty increased with time and there was no optimal purchase moment. In contrast, neither model 2 nor 3 presented such effect. Importantly, in the first model an interaction of this parameter with the magnitude of the variation of the offer compared to previous one was negative (reducing the probability of buying), but in the second model the effect of this interaction was the opposite. Indeed, people with high levels of Delay Discounting tend to be more sensitive to small variations (MacKillop et al., 2011), and to choose small immediate rewards, versus larger delayed rewards (Frederick et al., 2002; Patton et al., 1995; Stanford et al., 2009). However, current results show that, rather than there being a direct relationship between personality factors and purchase decision making, there is a complex relationship highly dependent on the context of such decision. In this sense, this study also shows that to have a more realistic understanding of purchase decision making, variables cannot be considered alone, but it is crucial to analyze the interactions between contextual and personality elements as well as the direction of their effects.

In terms of the predictive capacity of the designed models, it is important to notice the need of considering and analyzing all the elements that create a useful model (Dreiseitl & Ohno-Machado, 2002; Fuentes, 2013). In the specific case of the present study, the cut-off point defined for the classification turned out to be critical when considering the usefulness of a model to predict purchase behavior, as occurred when considering the default cut-off point, versus the one calculating using the data.

Results of this study present some limitations in terms of their representativeness. In particular, all participants were university students, and therefore it is unknown to what extent results might be the same in other age segments or population groups. In addition, although in the present study the use of uncommon products was intended to avoid effects of previous knowledge, it is unknown if there could be a differential effect in contexts or purchase situations in which the participants had prior experience with the products and their distribution. Futures studies could be designed to study decision making in a more heterogeneous population and, in turn, to evaluate the possible differences in the behavior when there is knowledge about the product of purchase and when there is none.

In conclusion, present study demonstrates the importance of environmental and individual difference measures in the study consumer behavior in uncertainty context. In addition, present results suggest that each consumer scenario is explained by different variables, supporting the idea that decision making in economical settings is highly dynamic and dependent of the characteristics of the environment. Finally, from a methodological point of view, it is possible to identify the usefulness of this type of studies and the task designed to understand and predict consumer behavior in experimental settings.

Chapter 4
Study 2

This study corresponds to:

Alí Diez, Í., & Marco-Pallarés, J. (2021). Neurophysiological correlates of purchase decision-making. *Biological Psychology*, 161(February), 108060. https://doi.org/10.1016/j.biopsycho.2021.108060

Chapter 4: Study 2

Neurophysiological correlates of purchase decision-making

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, 2007; Delgado et al., 2000; Farrar et al., 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 et al., 2018). On the other hand, the P3 component is a centroparietal ERP that appears 300 to 600 ms after stimuli presentation. It has been related to attentional processes (Polich, 2007; Polich & Kok, 1995), the probability and expectation of appearance of stimuli (Levi-Aharoni et al., 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 et al., 2008), the revision and adaptation of mental models of response

(Wang et al., 2015), duration of stimulus evaluation (Twomey et al., 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 et al., 2012; Wang et al., 2016). In addition, theta plays an important role in cognitive control (Clayton et al., 2015; Cox & Witten, 2019) and is modulated by the uncertainty of the context (Cavanagh, Figueroa, et al., 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 (Cavanagh, Figueroa, et al., 2012; Cavanagh & Frank, 2014).

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 et al., 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 et al., 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 et al., 2007; Cunillera et al., 2012; Marco-Pallarés et al., 2015; Mas-Herrero et al., 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 et al., 2006; Platt & Padoa-Schioppa, 2009; Rangel et al., 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 exploring the attitudinal (see, e.g. Denegri et al., 2012; Luna-Arocas & Quintanilla, 2000; Quintanilla & Luna-Arocas, 1999) and personality traits (Boyce et al., 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 et al., 2010), advertising image, logo, and typography (Dong & Gleim, 2018; Doyle & Bottomley, 2004), and the place of purchase (virtual or traditional store; Eroglu et al., 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, 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 et al., 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 et al., 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 et al., 2013), and it is explained by power increases in alpha band oscillations (Arieli & Berns, 2010).Braeutigam et al. (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. Method

Participants

Twenty-four healthy young adults participated in the experiment (8 men, mean age 22.13 ± 4.23 (SD)) 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.

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 to 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 Figure 1A).*

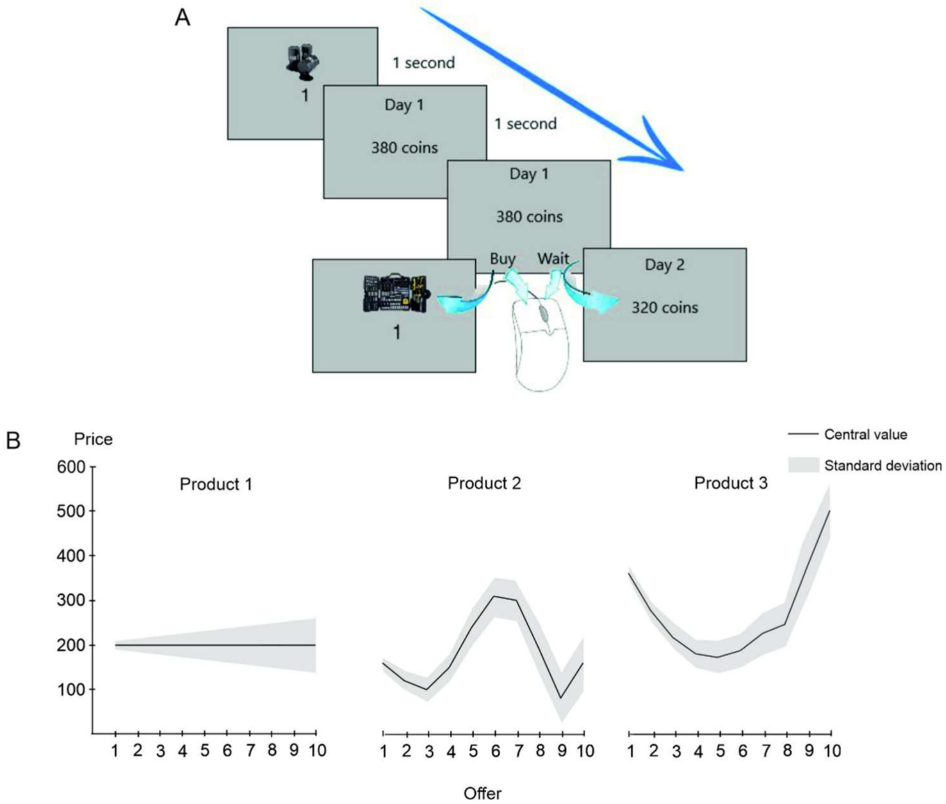

Figure 1: A. Task structure of the Purchase Decision-Making Task. Participants had to buy three different products in each trial. Each product could be bought on 10 "days". Each day a price was presented, and participants had to decide whether to buy the product at this price or to wait for the next 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.

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 Figure 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.

Electrophysiological recording

EEG was recorded from the scalp (0.01 Hz high-pass filter with a notch filter at 50Hz; 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.

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 to 10; block 2: from purchase 11 to 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 to 10; from purchase 11 to 20), and type of decision (wait or buy). The JASP software was used for the statistical analysis (JASP Team, 2020).

Event-related brain potentials

EEG was low-pass filtered at 40 Hz offline using EEGLab 2020 under MATLAB (MathWorks, 2020). 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 et al., 2012; Lee et al., 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 20Hz 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., 2013, 2014; 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.

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 et al., 2004; Tallon-Baudry et al., 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).

3. Results

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. *Figure 2A* shows the mean of the offer when participants decided to purchase the products in each distribution, in the first (purchase 1 to 10) and second (purchase 11 to 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 ($t(17) = 3.660$, $p_{bonf} = 0.008$).

Figure 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 seconds 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 seconds 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 ($t(19) = 5.016$; $p_{bonf} < 0.001$).

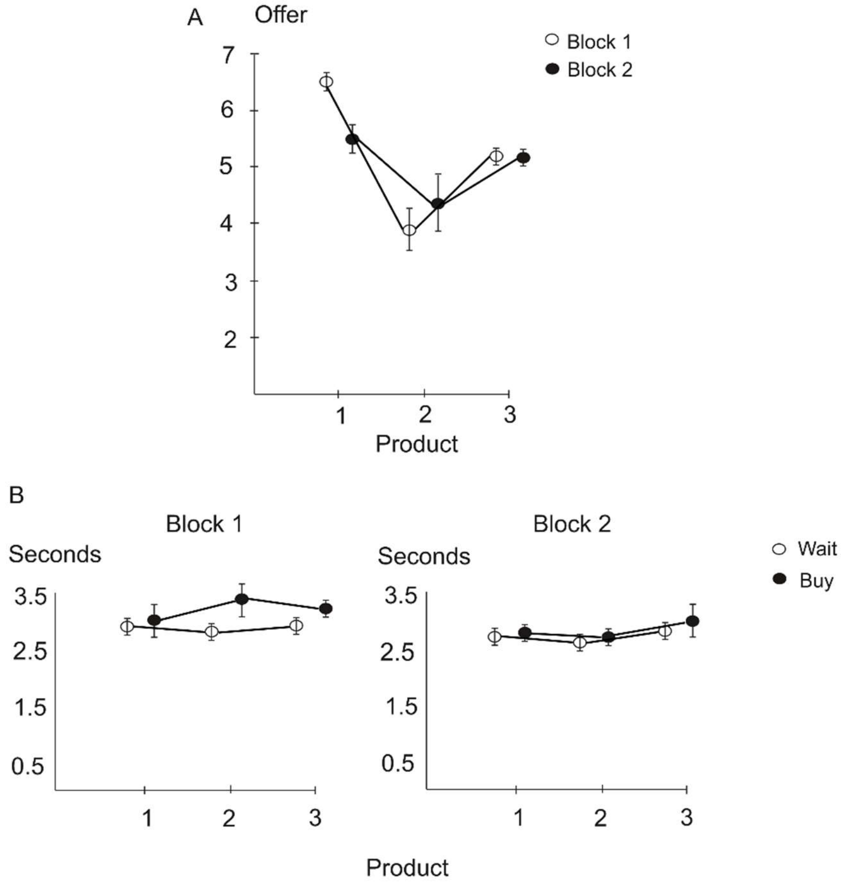

Figure 2: A. Average of offer of purchase for each product and purchase block. Error bars indicate the standard error of the mean B. Average of response time in each product and purchase block during the task.

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).

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 (Figure 3A).

In addition, we also analyzed the two main ERPs showing significant differences between the buy and wait conditions. Therefore, Figure 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 *(Figure 3B)*.

Repeated measures ANOVA in the N2 component (200-300ms), 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 ($t(18) > 4.72$; $p_{bonf} < 0.001$).

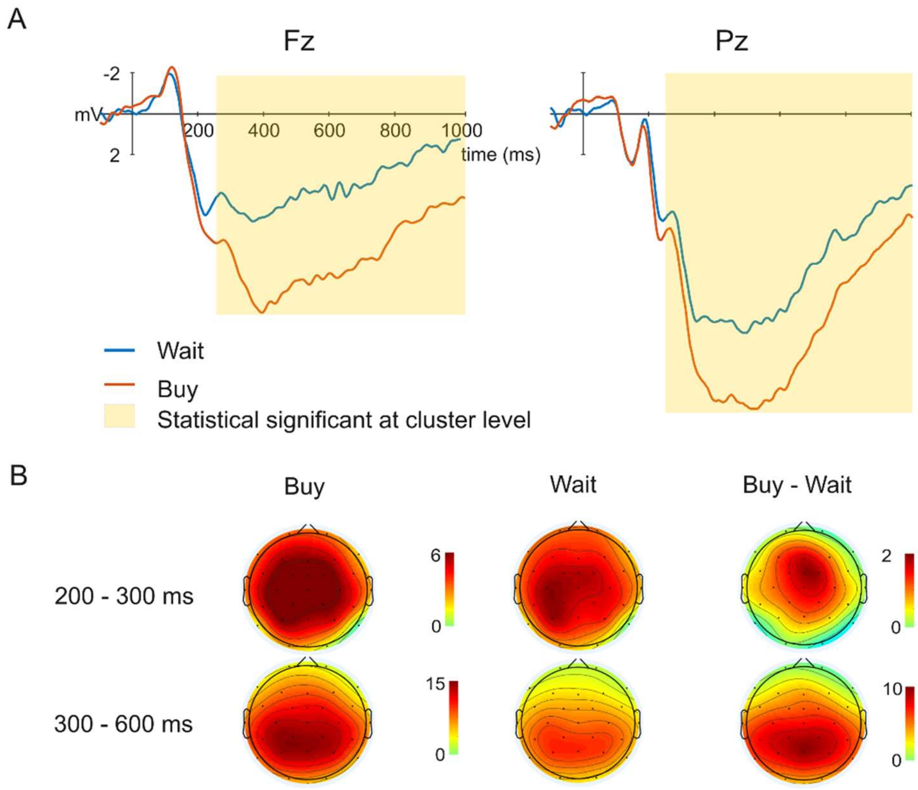

Figure 3: A. ERP for Fz and Pz electrodes for the 2 conditions: buy (buy the product at price showed; line in red) and wait (wait for another offer; line in blue), including temporal range where differences are statically significant at cluster level; B. Topographical representation by condition and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

In the P3 component (300-600ms), 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.

Time-frequency analysis

Figure 4 shows the induced power analyses for frequencies 1Hz to 30Hz 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 500ms. The buy condition showed a power increase in the theta and alpha bands around 200ms, 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 (4Hz to 8Hz), low alpha (8Hz to 10Hz), and beta bands (16Hz to 26Hz).

rmANOVA in the theta band (4-8 Hz, 300-500ms), 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 (8-10Hz, 200-400ms), 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 ($F < 1.2$; $p > 0.05$; $\eta_p^2 < 0.049$).

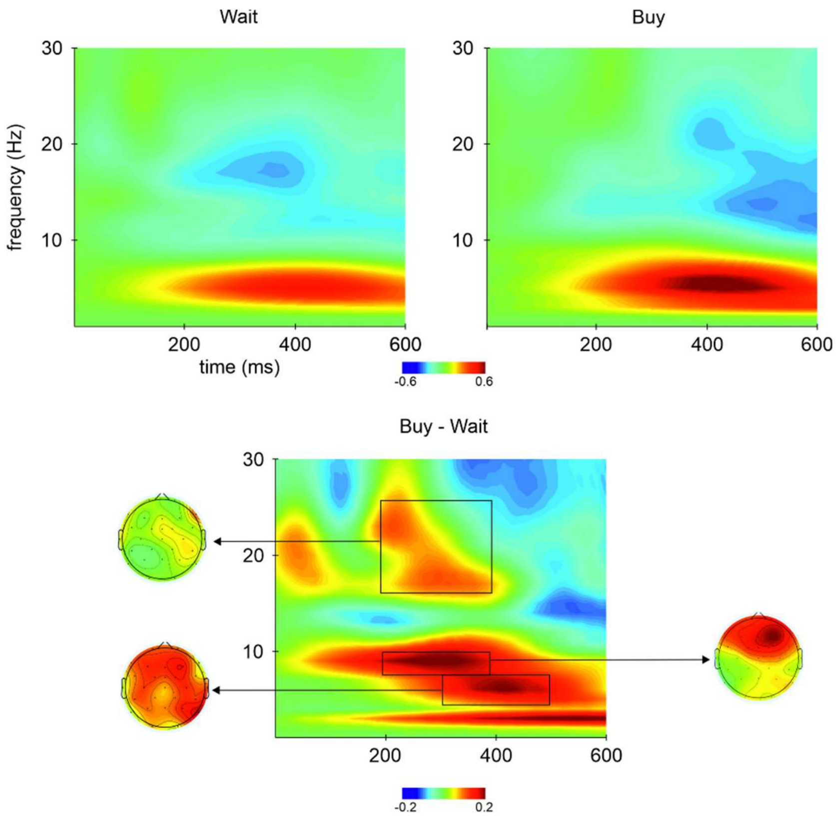

Figure 4: Time-frequency induced power analyses for both conditions. In the upper-left, graphical representation of induced power for wait condition (wait for another offer), upper-right figure for buy condition (buy the product at price showed). The bottom figures represent differences between buy and 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.

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 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 et al., 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 et al., 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 et al., 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 et al., 2009; Mas-Herrero et al., 2019; Mas-Herrero & Marco-Pallarés, 2014), 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 (Cavanagh, Zambrano-Vazquez, et al., 2012; Marco-Pallarés et al., 2010).

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 et al., 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 et al., 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, 2009; Kahneman & Tversky, 1984). 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; 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 et al., 2005). Future studies controlling these parameters are needed to determine how these different factors modulate the described neurophysiological responses associated with purchase decision-making.

Chapter 5
Study 3

Chapter 5: Study 3

Neurophysiological responses to price variations: monitoring changes in the decision context

The processing of the outputs of our decisions is one of the main elements required to optimize decision-making process. Despite this, we know little about how this process operates in decisions that do not provide immediate and explicit feedback, such as purchasing decisions. Our study sought to measure the neurophysiological responses associated to different types of variations between prices, while participants were deciding between buying the product and waiting for a new offer, using the PDMt experimental paradigm. EEG was recorded in 42 healthy subjects while they were performing the simulation of real economic decisions. Results reveals increases in the magnitudes of P2 and P3 ERP components and a significant increase in theta oscillatory activity when prices were higher than the previously presented ones. These results reflect the sensitivity of P3 and theta oscillatory activity to the valence and magnitude of variations of prices, acting as a monitoring mechanism for contextual variations and it information as an implicit feedback.

1. Introduction

Decision-making process involves a constant evaluation of previous outcomes to optimize subsequent choices, seeking, in turn, to reduce uncertainty and maximize the probabilities of choosing correctly (Wischnewski et al., 2018). In this process, the study of feedback processing has become an active area of study in cognitive neuroscience (Cohen et al., 2007).

Evidence suggest that feedback processing requires the existence of an internal model for predicting current feedback, which it is constantly tested via reward prediction errors (Wischnewski et al., 2018). Previous studies have identified that during evaluation of results of decisions process, various prefrontal, striatal, and dopaminergic structures are involved, allowing the integration of emotional, sensitive and memory information to facilitate the process of value-based choices (Berridge & Kringelbach, 2015; Denk et al., 2005; Hosking et al., 2015; Kurniawan et al., 2010, 2011; Salamone et al., 2007; Walton et al., 2006). Consequently, the reward prediction error corresponds to an incongruity between the expected outcome and the real one, with the main objective to regulate reward expectations, allowing to successfully adapt the behavior in contexts of uncertainty (Palidis & Gribble, 2020).

Thus, the existing evidence on the mechanisms that guide feedback processing is based on the use of experimental paradigms that include the presentation of explicit feedbacks to identify how correct or incorrect the action or decision was in each trial, such as gambling, or reinforcement learning tasks among others (Berridge & Robinson, 2003). However, in our daily lives we frequently must decide between different options without having a clear feedback on the results of our actions. An interesting example of this are purchase decisions. They are characterized by not having explicit feedback derived from each action. Other emotional, subjective, and indirect elements are used to evaluate the correctness of the action (Burnett & Lunsford, 1994). Every purchase decision has a result that depends on how the buyer evaluates the changing factors (such as context, personal satisfaction, and product quality) after the purchase. These factors can act as signals or feedback for the buyer to learn for future decisions. For instance, if we check the price of a product online every day before buying it, a new price can be both a cue for today's decision and feedback for yesterday's choice (not to buy and wait for a better price, Kahneman, 2009; Karimi et al., 2015).

Results of EEG studies with traditional decision-making paradigms, such as gambling tasks, have consistently reported the existence of a positive voltage deflection appearing between 300 and 600 ms after stimulus presentation and a centroparietal topographic distribution, the P3b ERP (Polich, 2007). Different studies have described a relation between this component and the complexity of experimental tasks (Polich, 2007), attentional requirements (Polich, 2007; Polich & Kok, 1995), the probability of appearance of stimulus (Bellebaum & Daum, 2008; Levi-Aharoni et al., 2020; Luo et al., 2011; Shahnazian et al., 2018) and the relevance of contextual information (Levi-Aharoni et al., 2020). Therefore, P3b is considered one of the main neurophysiological markers of information processing process (Bellebaum & Daum, 2008; Palidis & Gribble, 2020). In addition, studies have reported that the magnitude of the P3 component is sensitive to the valence and magnitude of the feedback presented (Balconi & Crivelli, 2010b; Ferdinand et al., 2012; Luo et al., 2011; Palidis

& Gribble, 2020; Pfabigan et al., 2014; San Martín, 2012; Wu & Zhou, 2009). Some studies support the idea that negative feedbacks leads to larger P3 amplitudes compared to positives ones (Chase et al., 2011; M. J. Frank et al., 2005; Novak & Foti, 2015; Philiastides et al., 2010) while others propose that beyond the type of feedback received, the magnitude of P3 is sensitive to the relevance of feedback received for the successful resolution of the task, (Kok, 2001; Mendes et al., 2022; Rac-Lubashevsky & Kessler, 2019).

Additionally, evidence supports the existence of two main oscillatory components related to the feedback processing, both theta (4-8 Hz) and beta bands (20-35 Hz; Andreou et al., 2017). Theta activity is modulated by stimulus novelty (Cavanagh, Figueroa, et al., 2012), changes in rules (switch cues; Cunillera et al., 2012), and the process of detection/resolution conflicts (Akam & Kullmann, 2012; Clayton et al., 2015; Cohen & Donner, 2013; Cunillera et al., 2012; Donner & Siegel, 2011). In addition, it has been proposed that frontocentral theta activity plays a key role in the computation of reward prediction errors or unexpected outcomes derived from decisions (HajiHosseini et al., 2012; Wang et al., 2016), and in cognitive control (Clayton et al., 2015; Cox & Witten, 2019). Thereby, increases in theta oscillatory activity have been consistently reported after negative feedback or unexpected results (Andreou et al., 2017; Cavanagh et al., 2010; Marco-Pallarés et al., 2008; Mas-Herrero et al., 2015; Van de Vijver et al., 2011), evidencing that it is highly sensitive to the valence and magnitude of the feedback and to the magnitude of the prediction error (Arrighi et al., 2016; Cavanagh et al., 2010; Cavanagh, Figueroa, et al., 2012).

In contrast, frontocentral beta power increase has consistently been reported after 200 to 400 ms after positive feedbacks or rewards (Andreou et al., 2017; Cohen et al., 2007; HajiHosseini et al., 2012; HajiHosseini & Holroyd, 2015; Marco-Pallarés et al., 2008, 2015; Mas-Herrero et al., 2015; Van de Vijver et al., 2011; Weismüller et al., 2019). Beta oscillatory activity has been found to be modulated by magnitude and probability of rewards (Marco-Pallarés et al., 2008; see Glazer et al., 2018, for review) and appears after improbable or unexpected wins (HajiHosseini et al., 2012), being proposed as a signal to maintaining the status quo of current cognitive state (Engel & Fries, 2010) and a possible maker of motivated learning and reward prediction error (Glazer et al., 2018; Luft, 2014; Marco-Pallarés et al., 2015; Van de Vijver et al., 2011).

Although the evidence seems to be consistent in identifying the neurophysiological correlates of the different types of feedback, there are no studies that investigate how replicable these results are when there is no explicit feedback, such as in purchase decisions. As stated before, deciding whether or not to buy a product at a specific time means assuming the uncertainty of future events (such as the next offers or prices) as well as not to have immediate feedback on how correct or incorrect the decision was. Consequently, it is possible to assume that in this experimental paradigm, given the uncertainty of the decision context and the limited information available, price variations between one offer and another would act as cues that would allow feedback on the decision made. Therefore, our study sought to analyze the electrophysiological activity associated with the different types of price variations while the participants carried out a purchase decision (Alí Diez & Marco-Pallarés, 2021).

We hypothesized that electrophysiological activity would vary in the different price-variations in terms of valence (increase/decrease) and magnitude (low/high), at early and late stage. In particular, we expected to find increases in early and late P3 ERP amplitudes attributable to high magnitude and negative valence (price increases). In addition, we expected to find increases in power-induced for theta band attributable to high magnitude and negative valence, while on the contrary increases in power-induced activity in beta band for high magnitude and positive valence (price decreases).

2. Method

Participants

Forty-two healthy young adults participated in the experiment (26 women and 16 men, mean age 25.60 ± 6.22 (SD)) for monetary compensation. 24 of these participants were analyzed a previous paper (Alí Diez & Marco-Pallarés, 2021), but current paper presents a new analysis with a different goal. Subjects received 25€ for their participation plus a bonus based on their performance on the task (1€ for every 50 coins saved; see below for more information on the experimental paradigm). The local ethics committee approved the experiment. Written informed consent was obtained from each participant prior to the experiment.

Design

We used the Purchase Decision-Making task (PDMt; Alí Diez & Marco-Pallarés, 2021), in which participants had to decide the optimal time to buy three products. Participants played the role of a maintenance manager of a boat company in Alaska and had to buy the three necessary products (spare parts, oil, and tools) to keep the company running. The use of products which were not familiar to the participants was decided to avoid the fact that the decisions were taken on the basis of previous experience with these products. In each series, participants had a maximum budget of 1,000 coins to buy the three required products, with the instruction: "try to save as much as possible in each sequence", to standardize the levels of motivation and final goal of the task. For each purchase, participants had a maximum of 10 offers (days in the cover of the experiment) to buy the product. Each sequence consisted on 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 to 20). Then, the information about the day (e.g., Day 1) and the price appeared on the screen for 1 second (fixed pre-decision time), and then the options (buy or wait) were presented until response. Participants could decide to buy at that price or not to buy and wait for the next price by pressing a corresponding button. If they decided to wait, the next day (e.g., Day 2) and another price appeared on the screen and the participant had to decide again. In the case of purchasing, 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 Figure 1A).*

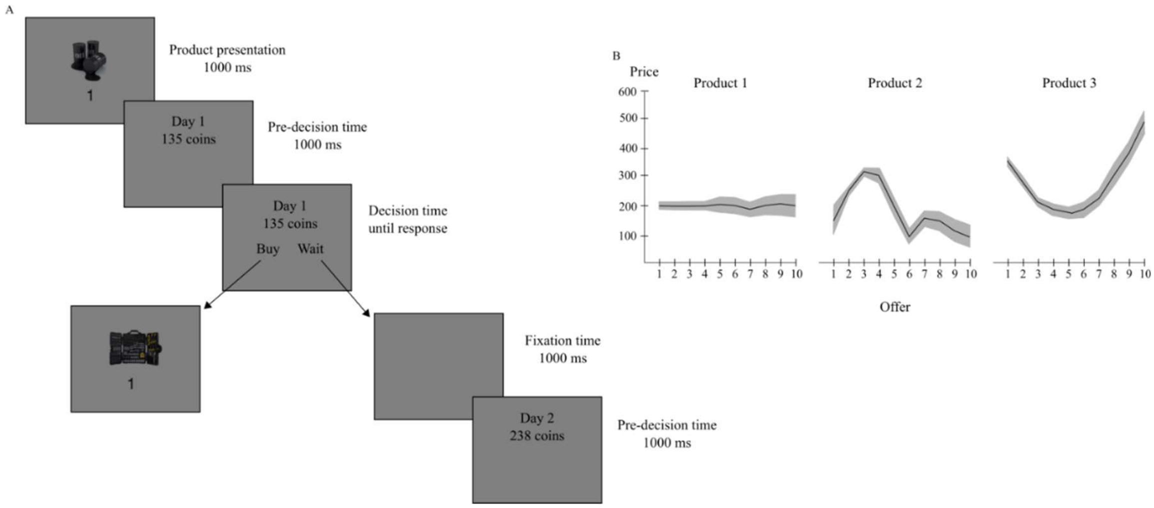

Figure 1: A. Task structure of the Purchase Decision-Making Task. Participants had to buy three different products in each trial. Each product could be bought on 10 "days". Each day a price was presented, and participants had to decide whether to buy the product at this price or to wait for the next 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.

Unknown to the participants, each product had a particular price distribution that was defined a priori (*see Figure 1B*). In the three distributions, the uncertainty increased with the time of acquisition. In this way, the different designed distributions allowed the generation of contexts with different levels of uncertainty. Given the difficulty of contextual uncertainty, products were presented in the same order during the entire task.

Electrophysiological recording

EEG was recorded from the scalp (0.01 Hz high-pass filter with a notch filter at 50Hz; 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 off-line re-reference. Additionally, vertical eye movements were monitored with an electrode at the infraorbital ridge of the right eye. All electrode impedances were kept below 5kΩ.

Data analyses

The difference between the prices presented in one decision and the previous one was used to determine the direction (increase or decrease of price) and the magnitude (high or low). Given that participants explored different number of options depending on whether they bought before or after, the division between high and low magnitude of the price variations was determined on the bases of all the explored prices along the task. Accordingly, we extracted the difference between the prices shown for each participant in each distribution and we estimated the variation of each price respect to the previous one. For that, we omitted all the initial offers in each sequence and distribution because these trials do not present a variation with respect to a previous price.

Following this, we calculate the medians of the absolute value of price variations seen by each participant and distribution, in order to classify each trial by type and magnitude of price variations. In consequence, trials were classified as decrease or increase respect the previous one, in addition to large (above the median) and small (equal to or less than the median) magnitude, for each participant.

Event-related brain potentials

EEG was low-pass filtered at 40 Hz offline using EEGLab 2020 under MATLAB (MathWorks, 2020). Epochs were extracted from -2000 ms before the stimuli to 2000 ms after it. Four conditions were studied: stimuli that show an increase in price above the median (large increase), an increase in price equal to or less than the median (small increase), a reduction in price above the median (large decrease), and the reduction equal to or less than the median (small decrease). To control for switching (Cooper et al., 2019) and novelty effects (Cavanagh, Zambrano-Vazquez, et al., 2012; Marco-Pallarés et al., 2010) on neurophysiological activity, we selected only those trials whose participant's subsequent response was to wait. Therefore, the final number of trials extracted for each participant and condition was 47.9 ± 12.06 trials.

Independent Component Analysis (ICA) was applied to the data and those components reflecting artifacts were removed (Bell & Sejnowski, 1995; Delorme et al., 2012; Lee et al., 1999). Then, 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. Repeated-measures ANOVA was computed in nine electrodes (Fz, F3/4, Cz, C3/4, Pz, P3/4) using four within factors: laterality (left, middle, right), anterior-posterior (frontal, central, and parietal), type of variation (increase and decrease) and magnitude (small and large).

Time-frequency analysis

To compute the induced time-frequency activity, we first subtracted the ERP for each condition from each single trial from -2000 ms to 2000 ms and then we convoluted them using a complex Morlet wavelet (Herrmann et al., 2004; Tallon-Baudry et al., 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) in two different time ranges, 200-300 and 300-600 milliseconds, to analyze early and late oscillatory activity. Repeated-measures ANOVA was computed as in the ERP analysis.

3. Results

Event-related brain potentials

Figure 2A shows the ERP for the four conditions in the Fz and Pz electrodes. Clear differences were observed among conditions, especially in the large negative condition. Therefore, we analyzed the two main time range where ERPs showed significant differences between conditions, 200-300 ms and 300-600 ms. Repeated measures ANOVA for early components (200-300ms), revealed significant effects of type of variation ($F(1,41) = 8.241$; $p = 0.006$; $\eta_p^2 = 0.167$) and magnitude ($F(1,41) = 5.541$; $p = 0.023$; $\eta_p^2 = 0.119$). In addition, rm-ANOVA also revealed significant interaction between type and magnitude of variations ($F(1,41) = 5.396$; $p = 0.025$; $\eta_p^2 = 0.116$), and interaction between laterality, type, and magnitude of variations factors ($F(2,82) = 5.614$; $p = 0.005$; $\eta_p^2 = 0.120$). Post-hoc test showed that early amplitude increased 0.421 ± 0.147 in increases of prices compared to the decreases ($t(40) = 2.871$; $p_{bonf} = 0.006$), in addition to an increase of 0.374 ± 0.159 in large compared to small magnitudes ($t(40) = 2.354$; $p_{bonf} = 0.023$), presenting the main differences in midline between conditions, where amplitude of evoked potential increase 0.857 ± 0.229 in large increases compared to small increases of prices ($t(20) = 3.746$; $p_{bonf} = 0.021$), and 0.916 ± 0.221 compared to large decreases condition ($t(20) = 4.146$; $p_{bonf} = 0.005$). Topographical representation of differences is presented in *Figure 2C*.

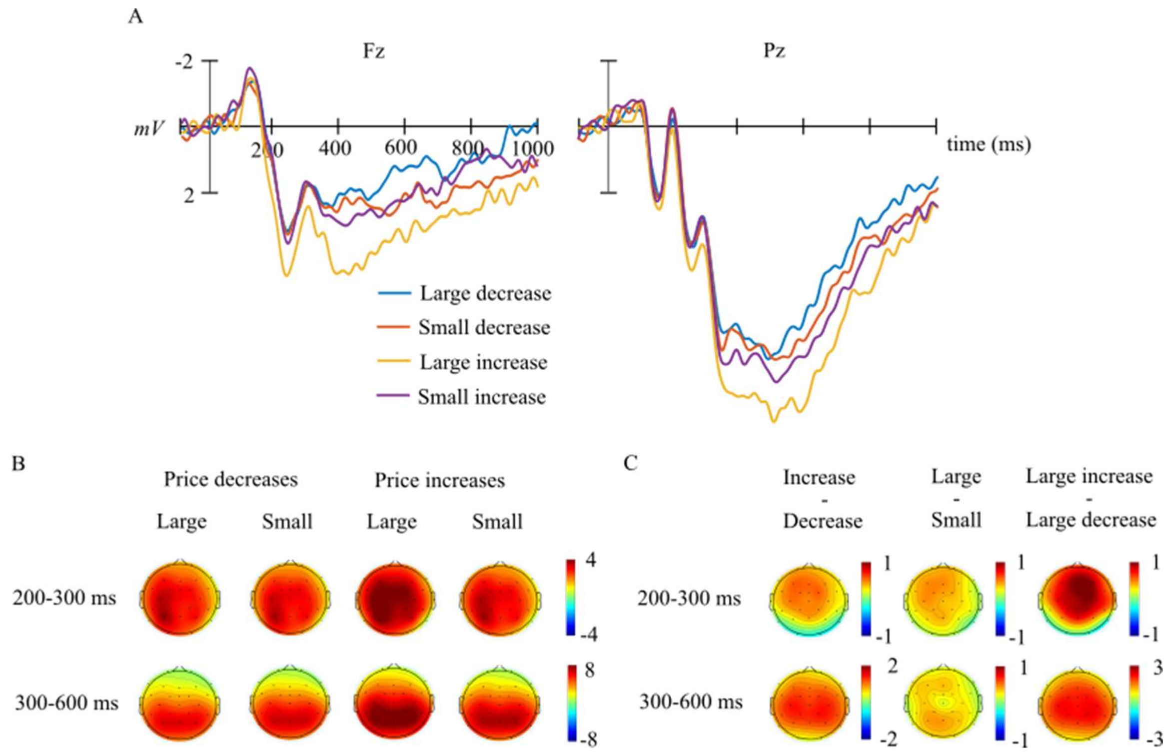

Figure 2: A. ERP for Fz and Pz electrodes for the 4 conditions: Large decreases (light blue), small decreases (red), large increases (yellow) and small increases (purple); B. Topographical representation by condition at early (200 to 300 ms) and late (300 to 600 ms) components; C. Topographical representation of differences found in rm-ANOVAS for early and late components.

On the other hand, topographical representation of ERP in late component (300-600 ms) revealed a main centro-parietal location of activity (see *Figure 2B*). Rm-ANOVA analysis revealed significant effects of type ($F(1,41) = 46.814$; $p < 0.001$; $\eta_p^2 = 0.533$), and magnitude of variations ($F(1,41) = 4.113$; $p < 0.049$; $\eta_p^2 = 0.091$) factors. In addition, significant interactions between type and magnitude of variations ($F(1,41) = 19.621$; $p < 0.001$; $\eta_p^2 = 0.324$) were found. Post-hoc analyses revealed that the amplitude of the ERP component increased 1.201 ± 0.175 in increases of prices compared to decreases ($t(40) = 6.842$; $p_{bonf} < 0.049$), and in large compared to small variations (0.335 ± 0.165; $t(40) = 2.028$; $p_{bonf} < 0.001$), particularly in large increases condition compared to large decreases (1.939 ± 0.242; $t(38) = 3.011$; $p_{bonf} < 0.001$), and in large increases compared to small increases (1.074 ± 0.235; $t(38) = 4.573$; $p_{bonf} < 0.001$, see *Figure 2C* for topographical representation of differences).

Time-frequency analysis

Figure 3A shows the induced power analyses for frequencies 1Hz to 30Hz for the four conditions studied. Differences between conditions were tested using rm-ANOVA for two early (200-300 ms) and late (300-600ms) oscillatory activity in the bands of activity showing the main variations, theta (4Hz to 8Hz), low beta (13Hz to 20Hz) and high beta (21Hz to 30Hz).

Rm-ANOVA in the early theta band activity (4-8 Hz, 200-300ms), revealed a significant effect only of type of variation ($F(1,41) = 14.783$; $p < 0.001$; $\eta_p^2 = 0.265$). Post-hoc tests showed that the early oscillatory activity in theta band was larger in increased compared to decreased of prices (0.090 ± 0.023, $t(40) = 3.845$; $p_{bonf} < 0.001$).

In late theta oscillatory activity (4-8Hz, 300-600ms), significant effect of type of variation ($F(1,41) = 18.435$; $p < 0.001$; $\eta_p^2 = 0.310$) was found. Also, significant interaction between anterior-posterior and type of variation ($F(2,82) = 4.420$; $p = 0.015$; $\eta_p^2 = 0.097$), laterality and magnitude ($F(2,82) = 3.138$; $p = 0.049$; $\eta_p^2 = 0.071$), and the four factor interaction (laterality, anterior-posterior, type, and magnitude; $F(4,164) = 4.329$; $p = 0.002$; $\eta_p^2 = 0.095$) were found. Post-hoc tests revealed that increases of prices increased 0.117 ± 0.027 the induced activity compared to decreases ($t(40) = 4.294$; $p_{bonf} < 0.001$), principally in frontal area compared to central (0.153 ± 0.033; t(36) = 4.637; $p_{bonf} < 0.001$) and parietal (0.119 ± 0.021; t(36) = 5.641; $p_{bonf} < 0.001$). Finally, post hoc of four-factor interaction reveals that increases in induced activity during large-increases of prices was significantly higher in frontal midline compared to parietal midline (0.126 ± 0.028; t(6) = 4.489; $p_{bonf} = 0.006$).

In contrast, beta band showed no significant effects for the factors tested at early nor late oscillatory activity neither in low (13-20 Hz) nor high (21-30 Hz) frequency ranges ($F < 2.5$; $p > 0.05$; $\eta_p^2 < 0.05$).

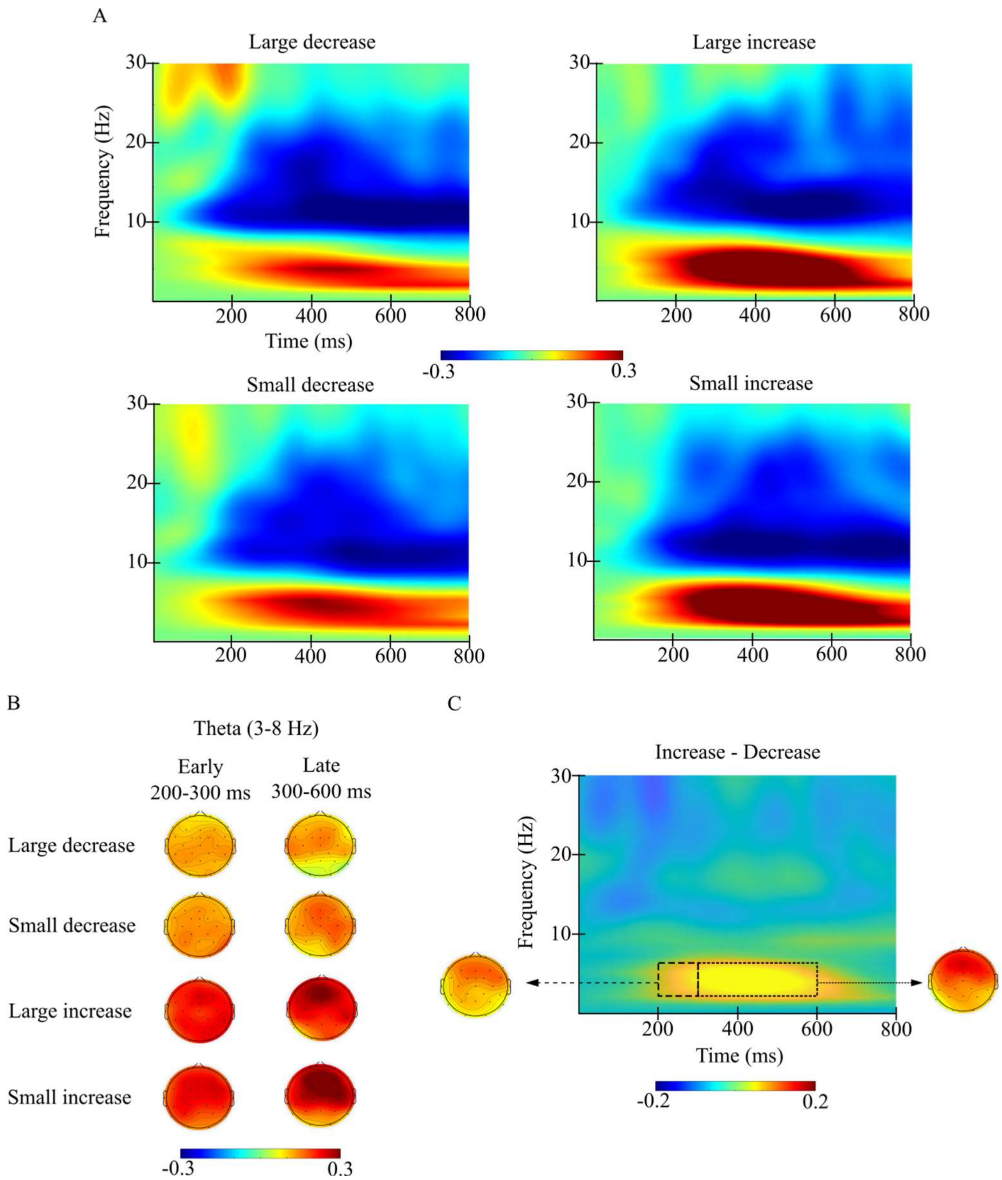

Figure 3: A. Time-frequency induced power analyses for all conditions. In the upper-left, graphical representation of induced power for a large decrease of prices, upper-right figure for large increases of prices, bottom-left figure for a small decrease of prices, and bottom-right figure for small increases of prices. B. Topographical representation of theta band (4-8Hz), for each condition in early (200-300ms) and late (300-600ms) time ranges. C. Differences between increase and decrease of prices. On the left side, topographical representation of differences in theta (4-8Hz) between 200-300ms, and on the right side between 300-600ms.

4. Discussion

The goal of the present study was to identify the neurophysiological signatures associated with the different types of price variations while the participants carried out the Purchase Decision Making task (PDMt; Alí Diez & Marco-Pallarés, 2021). To this end, we analyzed the differences in ERPs components and response-induced oscillatory activity between four type of price variations large/small decreases (small or large reduction of price respect a previous presented), and large /small increases (small or large increases of price respect a previous presented), using a pre-decision time in the PDMt.

Although there is no evidence linking the variations between prices to specific neurophysiological activity, we hypothesized that due to the nature of the experimental paradigm used (buy the products at the best possible price), increases, and decreases of prices between offers could act as feedback regarding to recent decisions. Therefore, we propose that an increase in a price in comparison to the previous one would be processed as negative feedback and, consequently, a decrease in price in comparison to the previous offer would be considered a positive feedback. In the two cases, the magnitude would be the amount of variation between previous and current prices.

As we expected, our results reveal increases in amplitudes of P2 (200-300 ms) and P3b (300-600 ms) ERP components for all studied conditions. Early P2 component showed significant interaction of both magnitude and valence, with more amplitude for the large increase of prices.

Evidence suggests that the early P2 component is highly sensitive to task difficulty (Kim et al., 2008) and stimulus relevance (Potts, 2004), being a neurophysiological marker of perceptual processing and mental speed (Ferrari et al., 2010). In particular, decision-making studies have described the P2 component as an expression of early stimulus processing and evaluation operations (Lee et al., 2011) which, in fact, could explain the existence of this early increase in the electric potential registered in our study. On the other hand, in our study price variations could generate prediction errors and discrepancies between expected and real variations, explaining increases in the electric field for increases and decreases of prices. Additionally, due to the characteristics of the experimental context designed, uncertainty led to increase the requirements of the stimulus evaluation, as well as the difficulty to fulfill the main objective in the task (buy at the best possible price), which would explain that the amplitudes of P2 were, for a same magnitude of variation, larger for price increases condition. In this sense, our findings are consistent with the evidence that indicates that the amplitude of the P2 component is sensitive to the magnitude of the feedback received, but above all, it allows us to assume that it is sensitive to the salience of the stimulus presented (Kok, 2001; Rac-Lubashevsky & Kessler, 2019).

In addition, we found that negative valence of price variations (price increases), and large magnitude of variations leads to higher amplitudes in P3b component in comparison to positive (price decreases) or smaller ones. These results allow us to identify that local variations, both positive and negative, present an electrophysiological correlate similar to that presented when explicit feedback is shown, being consistent with the studies that reported evidence of the sensitivity of the P3 component to the valence and magnitude of the feedback (Balconi & Crivelli, 2010b; Banis et al., 2014; Bellebaum et al., 2010; Chase et al., 2011; Ferdinand et al., 2012; Frank et al., 2005; Novak & Foti, 2015; Palidis & Gribble, 2020; Pfabigan et al., 2014; Philiastides et al., 2010; Riepl et al., 2016; San Martín, 2012; Wu & Zhou, 2009; Yeung & Sanfey, 2004). As we mentioned, the main objective of the task was to get the best possible price to make the purchase, so obtaining a higher price may imply the need to adapt the mental models to improve subsequent performance, which would be indexed by increase P3 amplitude (Nieuwenhuis et al., 2004; Wang et al., 2015). In agreement with the results obtained for the P2 component, the results of our study showed that the negative conditions substantially increased the amplitude of P3 component, demonstrating that due to the relevance of the information obtained, the negative conditions produce a greater impact because of the salience effect (Kok, 2001; Rac-Lubashevsky & Kessler, 2019).

In terms of oscillatory activity, we hypothesized that large and negative changes in prices (increase in current price in comparison to previous one) would lead to increases in power-induced oscillatory activity in the theta band, while large and positive changes (decrease in current price in comparison to previous one) would lead to increases in power-induced activity in beta band. Our results shows that, both early and late oscillatory activity in theta band was significantly higher in increases of prices compared to decreases, being consistent with previous studies that reported increases in theta oscillatory activity after negative feedback (Andreou et al., 2017; Cavanagh et al., 2010; Marco-Pallarés et al., 2008; Mas-Herrero et al., 2015; Van de Vijver et al., 2011). Interestingly, our results showed that the late frontal oscillatory activity in theta band (after 300 ms) was significantly higher when prices increase, especially with large magnitudes, reaffirming the idea that theta band is highly sensitive to the valence and magnitude of the feedback received (Arrighi et al., 2016; Cavanagh et al., 2010), even when, as in the present experiment, it is not explicit.

In our study, due to the structure of the experimental paradigm, each new offer implies a feedback respect the previous prices exhibited. Thus, of we only used trials where participants had a previous reference of price and where decision was wait for another offer. In this sense, trials that imply an increase in the price compared to the previous one, could suppose a conflictive trials and prediction errors, increasing the oscillatory activity in the theta band, been consistent with previous studies (Akam & Kullmann, 2012; Andreou et al., 2017; Cavanagh et al., 2010; Clayton et al., 2015; Cohen & Donner, 2013; Cunillera et al., 2012; Donner & Siegel, 2011; HajiHosseini et al., 2012; Marco-Pallarés et al., 2008; Wang et al., 2016).

Finally, we did not find significant effects in the beta band. Previous studies have identified the beta band as a neural marker of reward (Andreou et al., 2017;

Cohen et al., 2007; HajiHosseini et al., 2012; HajiHosseini & Holroyd, 2015; Marco-Pallarés et al., 2008, 2015; Mas-Herrero et al., 2015; Van de Vijver et al., 2011; Weismüller et al., 2019). A possible explanation for the absence of significant differences in oscillatory activity in beta band in our study may be related to the types of trials selected. As we mentioned previously, to control for the effect of different types of decisions on the neurophysiological response, we exclusively used trials where the subsequent response of participants was to wait. Consequently, given that the objective of the task was to buy at the best possible price and that, hypothetically, the best prices were those trials that were not analyzed. Therefore, beta could appear in those trials considered as real rewarding (that is, those in which participants decide to buy) and not in wait trials.

New studies should consider other elements to the analysis of this type of processing, due to the relevance of subjective values during decision making (Hayden, 2018; Kahneman, 2009) and, particularly, in economic decisions. In addition, future studies could explore and try to understand how these elements affect the final decisions made by the participants, trying to combine the study of this type of information with different final decisions, such as buying and waiting.

Chapter 6

Study 4

Chapter 6: Study 4

Predicting purchase decisions: a multilevel approach combining attitudinal, contextual, and neurophysiological measures.

Deciding what to buy, what price to pay or when is the optimal moment to do it is a complex process in which different emotional, contextual, attitudinal, and neurophysiological elements interact. Current evidence describes purchasing decisions as a process in which there is uncertainty at different levels, in which self-learning is the only input available to optimize future behaviors, being highly dependent on subjective variables and elements. Based on this, the present study sought to measure the predictive effect of different attitudinal, contextual, and neurophysiological variables in the decision to buy, using the Purchase Decision Making task (PDMt) experimental paradigm. EEG was recorded in 47 healthy subjects during the experiment. We found that changes in decisions were significantly predicted, using a mixed multilevel analysis, by levels of rationality and impulsivity, variations in neurophysiological markers in a pre-decision time (N2 and P3 amplitudes, theta, and alpha oscillatory activity) and changes in context of decision (variations between prices and their amplitudes), in addition to their interactions. These results reaffirm the importance of combining contextual, personal, and neurophysiological measures to explain changes in decisions in human behavior.

1. Introduction

The purchase decision making consists in choosing the most convenient or appropriate option among the different available alternatives, by assigning subjective values to each option (Huettel et al., 2006; Platt & Padoa-Schioppa, 2009; Schröder & Gilboa Freedman, 2020), leading to decisions such as, e.g., which product to buy and what price we are willing to pay for it. These decisions are modulated by different factors such as attitudes, personality traits, and previous experience of each person (Martinez-Selva et al., 2006; Sanbonmatsu et al., 2005; Schröder & Gilboa Freedman, 2020; Simon, 1959; Whiteside & Lynam, 2001). Evidence supports that, as consequence of the multiplicity of relevant factors or elements to consider for its study, research in purchase decision-making should consider different contextual and personal elements that interact to mobilize an action or behavior (Green & Myerson, 2004). Studies focusing on the effect of context have described that purchase decisions are made under uncertainty at different levels such as time (e.g., when is the optimal time to buy?), risk and, particularly, the absence of explicit feedback before deciding (Kahneman, 2009; Schröder & Gilboa Freedman, 2020; Simon, 1959). Therefore, buyers have to understand all these contingencies based on previous experience to take a correct decision (Cohen et al., 2011; Luu et al., 2003; San Martín, 2012; Sun & Wang, 2020; Van de Vijver et al., 2011; Walsh & Anderson, 2012; Wischnewski et al., 2018). Therefore, self-learning is a basic mechanism to adapt and optimize future behaviors or actions (Cohen et al., 2011; Kahneman, 2009; Karimi et al., 2015). In purchase decisions, self-learning plays an essential role in interpreting decisions as right or wrong, taking as reference the subjective expectations of consumers (Burnett & Lunsford, 1994). Another aspect that is relevant in purchase decision-making is the existence of individual differences in how people buy goods. Therefore, different studies have shown a close relationship between attitudes and this behavior (Ajzen & Fishbein, 1977; Alí Diez et al., 2021; Denegri et al., 2012). In particular, previous research has described the existence of three attitudinal styles (rational, impulsive, and compulsive) that mediate buying behavior (Castellanos et al., 2016; Denegri, 2010; Denegri et al., 2012; Gebaüer et al., 2003). They constitute behavioral, cognitive, and emotional predispositions to act in a particular way (Denegri, 2010; Denegri et al., 2012; Luna-Arocas & Tang, 2004) and, in turn, adapt to the characteristics of the different contexts, situations or products (Denegri, 2010). Given the importance of both context and individual differences, in recent years some studies have tried to combine personal and contextual elements, as personality (Schröder & Gilboa Freedman, 2020) and characteristics of particular products and brands (Kranzbühler et al., 2017), to describe segments of potential consumers more accurately (Laran, 2009; Laran & Wilcox, 2011; Mackenzie & Spreng, 1992; Sanfey et al., 2003).

Based on the characteristics described above, experimental studies have described neurophysiological correlates of purchase decisions. Results report that the N2 ERP component is significantly lower when they decide not buy or wait for a next offer (Alí Diez & Marco-Pallarés, 2021; Braeutigam et al., 2004). This component has also been considered as an indicative of the preference of one product over another (Telpaz et al., 2015). In addition, evidence supports that decision to buy is preceded by a significant increase in the P3 ERP component and in the theta oscillatory activity (Alí Diez & Marco-Pallarés, 2021), as well as to a significant increase in the frontocentral alpha activity (Alí Diez & Marco-Pallarés, 2021; Braeutigam et al., 2004). Increases in alpha activity have also been reported because of obtaining a price below normal (Arieli & Berns, 2010), even when this price of reference is subjective or non-explicit (Ravaja et al., 2013).

To date, there are no studies combining attitudinal, contextual, and neurophysiological information to describe purchase decision-making process. Thus, the present study aims to propose a predictive model of the decision to buy, controlling the effect of personal preferences, interests, motivation, and experiences of previous purchases of the same or similar products, through the use of the Purchase Decision-Making task (PDMt; Alí Diez & Marco-Pallarés, 2021). We hypothesize that different types of price variations and its magnitudes, modulation in the amplitude of different ERP components and oscillatory activity, and different attitudinal styles will significantly predict increases and decreases in the probability of purchase. In specific, we expect that increases in N2 and P3 amplitudes, in addition to increases in theta and alpha activity, will leads to increases in the probability of purchase. At contextual level, we expect that larger magnitudes of variations and decreases of prices will leads and increase in the probability of purchase, while, contrary, increases of prices will reduce this probability. Finally, at attitudinal level, we expect that higher levels of impulsivity and compulsivity will lead to a higher probability of purchase.

2. Method

Participants

Forty-nine young adults (17 men, mean age 25.47 ± 6.22 (SD)) voluntarily participated in the experiment for monetary compensation (fixed €25 plus a bonus of €1 for every 50 coins saved in the experimental task, see details above). Prior to experiment, each participant signed the written consent. The ethical committee of the University of Barcelona approved the study. Two participants were discarded from the final sample because their scores in the BIS-11 were < 52 points, which may reflect a bias of social desirability or false response (Stanford et al., 2009). As result of this, the final sample size was forty-seven young adults (17 men, mean age 25.28 ± 6.2 (SD)).

Experimental design

To assess the decision-making process in an experimental context, we used the "Purchase Decision-Making task" (PDMt; Alí Diez & Marco-Pallarés, 2021), 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 and 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.

In each series participants had to purchase three products, shown sequentially in the same order. First, participants saw the picture of the first product and the number of the trial (1–20) during 1000 ms. Then, the information about the day (e.g., Day 1) and the price appeared on the screen during 1000 ms (fixed pre-decision time). After it, two options appeared under the prices (buy and wait), and participants could decide to buy at price offered or not buy and wait for the next price, pressing a corresponding button (decision time). If they decided to wait, the next day (e.g., Day 2) and another price appeared on the screen repeating the pre-decision and decision time. In case of purchase, the image of the next product and the series number 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).*

As in the original experimental (Alí Diez & Marco-Pallarés, 2021), we used different price distributions for each product. 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)*. Using different distributions, we expected to create 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.

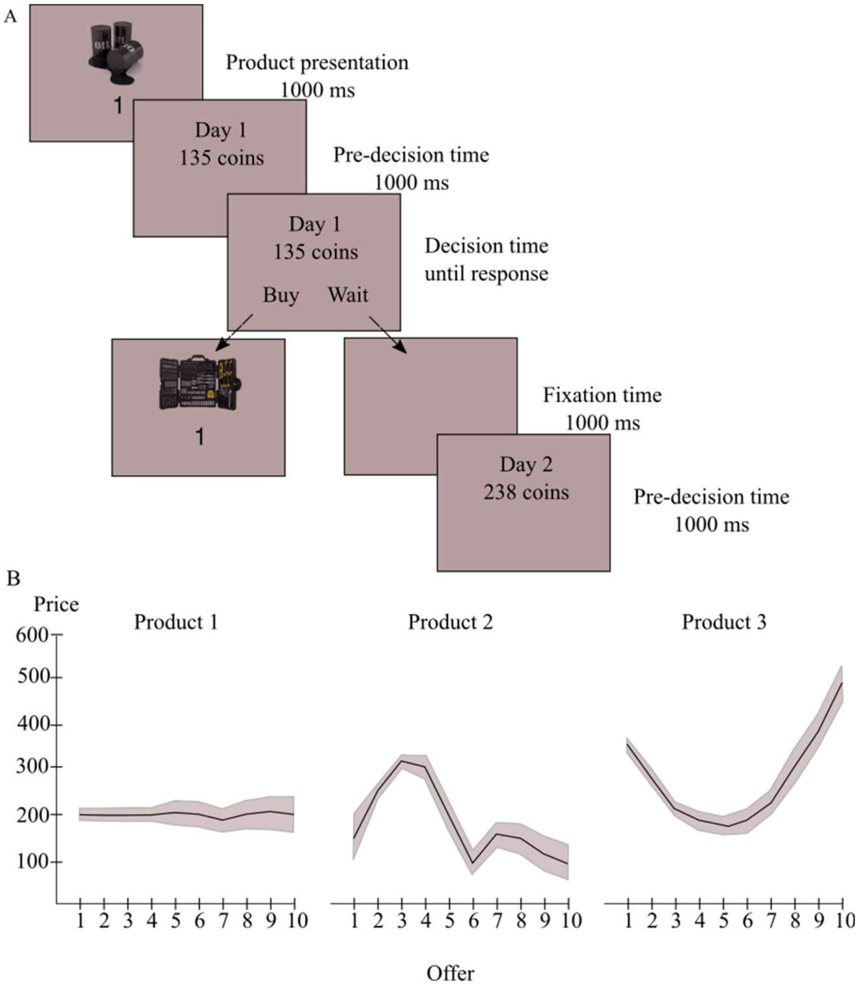

Figure 1: A. Task structure of the Purchase Decision-Making task adapted from Alí Diez & Marco-Pallarés (2021). Participants had to buy three different products in each series. Each product could be bought on 10 “days”. For each day, a price was presented, and participants had to decide whether to buy 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. Prices distributions for the three products across different “days” (offer). Note the increase in the SD of prices as the number of the offer increases.

Electrophysiological recording

EEG was recorded from the scalp (0.01 Hz high-pass filter with a notch filter at 50Hz; 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 off-line re-reference. Additionally, vertical eye movements were monitored with an electrode at the infraorbital ridge of the right eye. All electrode impedances were kept below 5kΩ.

Questionnaires

To determine their different attitudinal styles, participants completed the *Attitudes Toward Purchase* questionnaire (Gebaüer et al., 2003) which consists of the integration and adapted version of three different questionnaires to assess specific attitudinal dimensions using a check list of behaviors, emotions, and thinking’s related to purchase behaviors. First, Habits and Consumption Behaviors Questionnaire (Denegri et al., 1999) was adapted to generate the rationality dimension; Impulsivity in Purchase Scale (Quintanilla & Luna-Arocas, 1999) to the impulsivity dimension; and Compulsive Purchase Scale (Luna-Arocas & Fierres, 1998) to the compulsivity dimension.

To control for biased responses, the *Barratt Impulsiveness Scale Version 11 (BIS-11;* Patton et al., 1995), adapted for Spanish population (Oquendo et al., 2001), was used. The instrument is composed by 30 items Likert-type, measuring different dimensions of impulsivity, additionally to a general impulsivity factor. According to Stanford et al. (2009), scores in the general impulsivity factor lowers than 52 points, may reflect a bias of social desirability or false response.

Data analyses

Event-related brain potentials

EEG was low-pass filtered at 40 Hz offline using EEGLab 2020 (Delorme & Makeig, 2004) under MATLAB (MathWorks, 2020). Epochs were extracted from -2000 ms before the stimuli to 2000 ms after it. Two conditions were studied: the pre-decision time at which the participant bought the product (buy condition), and the pre-decision time in which participant did not buy (wait condition). Artefact rejection was made using the Independent Component Analysis (ICA; Bell & Sejnowski, 1995; Delorme et al., 2012; Lee et al., 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 for different electrodes on bases of the previous studies. Based on our previous results (Alí Diez & Marco-Pallarés, 2021), two ERP components were studied: an early frontocentral potential (Fz, F3/4, Cz, C3/4) 200 to 300 ms after price presentation; and a centroparietal P3 component (Cz, C3/4, Pz, P3/4), in the time range between 300 and 600 ms after stimulus presentation.

Time-frequency analysis

To obtain the induced time-frequency activity, we subtracted the ERP from each single trial for each condition from −2000 ms to 2000 ms and then we convoluted them using a complex Morlet wavelet (Herrmann et al., 2004; Tallon-Baudry et al., 1997) from 1 Hz to 30 Hz at 1 Hz steps. For each trial, we computed the mean change of power respect baseline. The oscillatory activity was obtained for different electrodes, on the basis of the previous results of Alí Diez & Marco-Pallarés (2021). Thus, theta oscillatory activity was computed by the mean of the change of power respect the baseline of the 4-8Hz bands during the 300 to 500 ms time range, for frontal, central and parietal electrodes (Fz, F3/4, Cz, C3/4, Pz, P3/4). Alpha oscillatory activity was extracted using the mean of the change of power respect the baseline of the 8-10Hz bands during the 200 to 400 ms time range for frontal electrodes (Fz, F3/4).

Multilevel analysis

Contextual variables were extracted for each decision and participant, following a structure of one decision for each offer, purchase, and product for each participant, allowing conforming the random structure of the Generalized Linear Mixed Effects Model (GLMM, see details below). Each decision was coded as binary response (wait = 0 or buy = 1). Independent contextual variables for each decision were the type (no variation = 0, increase = 1, and decrease = 2) and magnitude (absolute value of variation) of variations between current and previous prices. Additionally, for each participant we extract the scores for the three dimensions of the Attitudes toward Purchase questionnaire: rationality, impulsivity, and compulsivity.

The dataset was structured considering each trial as an observation, including the information of the type of distribution (three different distribution of prices used in the task), subject, purchase number, and offer. Therefore, the random-effect structure consisted of a four-level model with level 1 = offer, level 2 = number of purchase, level 3 = subject, and level 4 = price distributions (product 1; product 2, and product 3). The inclusion of the price distribution as the higher level of the random structure responded to the fact that the contextual information derived from the task depended directly on the pre-established price distribution. Therefore, the model random structure had to include the estimate of random intercept for each type of distribution.

To minimize differences in the measurement scales (Bates, Maechler, et al., 2015), attitudinal and neurophysiological measures were centered. The attitudinal measures did not have a natural zero point, so for the present study we considered the sample average as the zero point. Neurophysiological variables, on the other hand, were centered to the average activity of each participant, allowing obtaining the measures of increase and decrease in activity compared to their own activity. As additional criteria for neurophysiological variables, for each participant, trials that deviated more than three standard deviations from the participant mean were removed from the analysis.

Initial dataset included 13934 observations, 296 ± 63 (SD) by participant. After applying the aforementioned filters, final dataset included 13389 observations (285 ± 60 for each participant), which implied a rejection rate of 3.91% ± 0.68 of the total of trials by participant.

A Binary Logistic Generalized Linear Model with Mixed Effects (GLMM; Bates, Maechler, et al., 2015) was used to determine the predictive capacity of the attitudinal, contextual, and neurophysiological variables on the purchase decision. The model was built and tested using the lme4 package (Bates, Maechler, et al., 2015) in R (R Core Team, 2018), where the procedure started with a null model including only random effects, and systematically incorporating more predictors until we obtained the best model. As in mixed effect models p-values could present some nested effects that reduced the sensitivity to identify differences (Bates, Kliegl, et al., 2015; Harrison et al., 2018). Therefore, we included confidence interval analysis as an additional element to evaluate the significance of parameters included in final model. Multicollinearity of predictors was tested using the mer-utils R function (Frank, 2011), and variance explained by each model was estimated using the Pseudo-R-squared for generalized mixed-effect model statistics (Nakagawa et al., 2017). Due to the nature of the response variable (binomial variable), the theoretical method of variance was used, included in the MuMIn package in R (Bartoń, 2019).

Finally, to estimate the real fit of the model in predicting responses, we assessed the sensitivity (probability of the model to predict a true positive) and specificity (probability of predicting a true negative) of the model in the classification of responses (Dreiseitl & Ohno-Machado, 2002; Fluss et al., 2005; Ruopp et al., 2008). Therefore, a reliable model should have sensitivity and specificity levels greater than or equal to 62,5% (Fluss et al., 2005).

3. Results

Descriptive analyses

As a consequence of the differences in the number of trials for each condition, due to the structure of the experimental task in which participants could decide to wait more often than to buy, event-related potentials and oscillatory brain activity were not analyzed using tests of difference of means. Descriptive analysis of event-related potentials and brain oscillatory activity are presented below.

Event-related Potentials

Figure 2. A. shows ERPs for frontal and parietal midline electrodes (Fz and Pz) and the topographical representation of potentials evoked in the time range 200-300ms and 300-600ms. Differences between conditions (*Figure 2. B.*) showed reduced amplitude in the early time range corresponding to the N2 ERP in wait condition compared to buy conditions, especially in frontocentral areas. On the other hand, positive deflection in electric field between 300 and 600 ms after stimulus presentation peaking at centroparietal electrodes was observed for both conditions, corresponding to a P3b component (Luck, 2014; Polich, 2007). Topographical representation of difference between conditions revealed higher activity in pre-decision time for buy condition compared to wait at centroparietal electrodes.

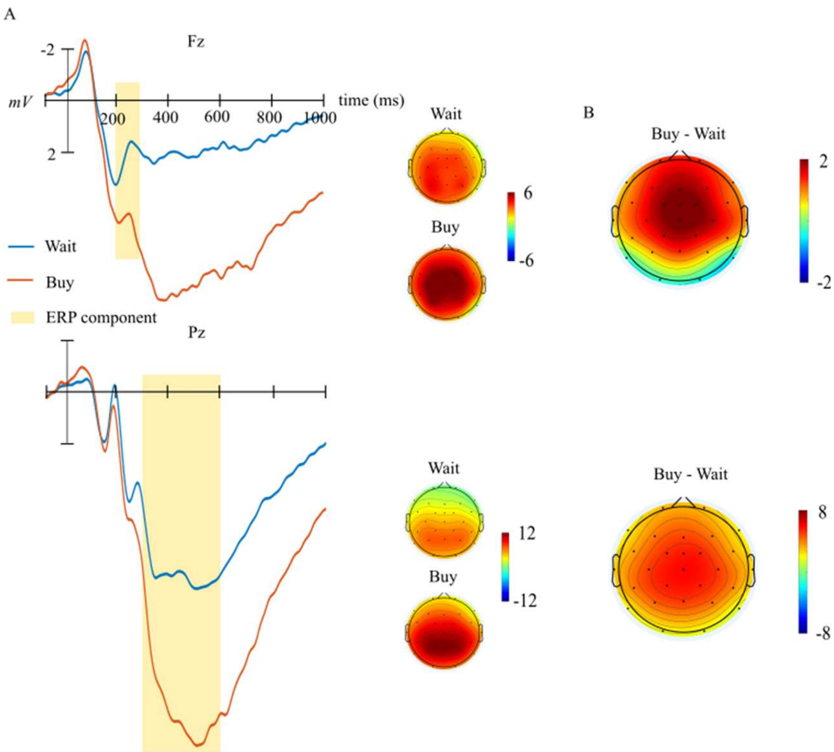

Figure 2. A. ERP for Fz and Pz electrodes for the two conditions: buy (buy the product at price showed; line in red) and wait (wait for another offer; line in blue), including topographical representations of each condition in the time range indicated by the yellow stripe. **B.** Topographical representation of differences between conditions in N2 (200 to 300 ms) and P3 (300 to 600 ms) components.

Oscillatory brain activity

Figure 3 shows the induced power analyses for frequencies 1Hz to 30Hz for the two conditions and their differences. Results showed that the wait condition presented an increase in the theta band around 200ms, while buy condition increased theta and alpha band oscillatory activity in the same time range. Differences between conditions revealed that main differences located at theta (4-8Hz) and alpha (8-10Hz) bands. Topographical representation of differences reveals that differences in theta were presented in all scalp distribution peaking in frontal positions, while differences in alpha were located in frontal electrodes (see *Figure 3.B.)*.

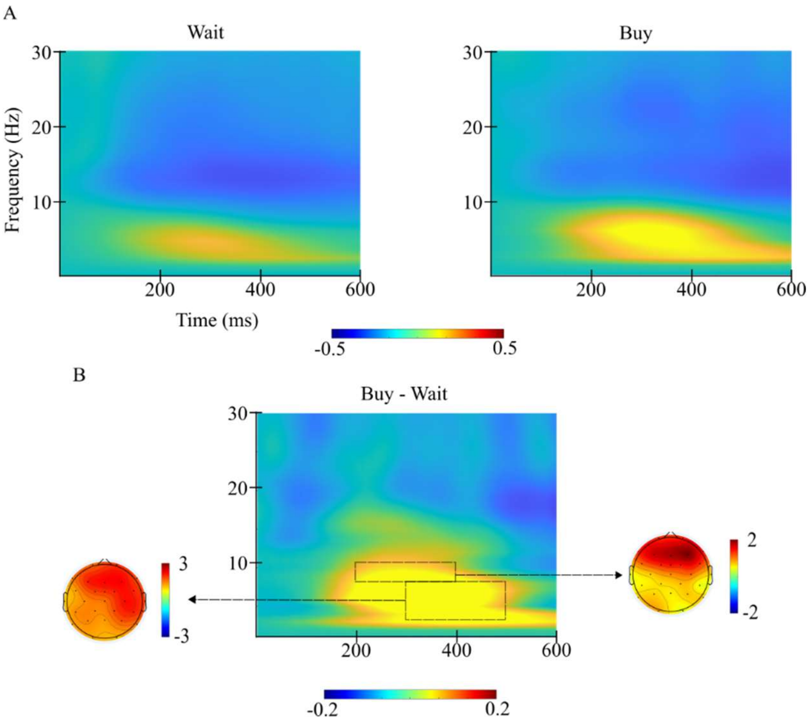

Figure 3. A. Time-frequency induced power analyses for both conditions. Upper-left figure for induced power for wait condition (wait for another offer), upper-right figure for buy condition (buy the product at price showed. B. Differences between buy and wait conditions in induced oscillatory activity (buy – wait conditions) and the topographical representation for the difference between conditions in the time frequency ranges indicated by the rectangular figures.

Generalized Linear Model with mixed effects

Null model analysis

A GLMM was computed to analyze the binary response variable at the different hierarchical levels of the data (e.g., distribution, participant, purchase number, offer). The null model revealed a significant effect of distribution on the intercept parameter, as well as variance attributable to the different random effects (see Table 1). Interestingly, the variations derived from this random structure and without the consideration of any predictor, explained 39% of the total variance observed in the sample. Also, as expected, variance of the random effects decreased substantially in the higher levels of the random structure, showing the consistency in the decisions of the participants and their dependence on local variations, presenting higher variance between offer in comparison to purchase number and participant. Therefore, the null model allowed us to identify that, even when there were no associated predictors, the structure of the experimental model and, therefore, of the random effects, fitted correctly to the dataset.

Consequently, the next step consisted in the progressive reduction of a full model including all predictors until the best fit of the model was obtained (backward elimination method), to then be compared with the initial null model.

Table 1. Estimates of purchase decision for the null model of the multilevel analysis

Parameters			
Random effects	Variance	Std. Dev.	
Distribution (Intercept)	1.282	1.132	
Participant	0.00001	0.003	
Purchase number	0.001	0.373	
Offer	0.140	0.373	
Fixed effects	Estimated	Std. Error	p-value
Intercept	-2.677	0.141	< 0.001
Akaike information criterion [AIC]	11964.7		
Marginal R^2	0%		
Conditional R^2	39%		

Final multilevel model of purchase prediction

As was detailed in method section, as a way to standardize different measurement scales among predictors tested, attitudinal and neurophysiological variables were centered. Scores in rationality, impulsivity and compulsivity were centered to the sample average for each dimension, reflecting the difference of participants score in comparison to the mean observed in the sample. On the other hand, N2, P3, theta and alpha variables were centered to each participant average, reflecting the increases or decreases of electrophysiological activity respect their own activity. Results of this procedure are presented in Table 2.

Table 2. Descriptive statistics for studied variables

Variable	Non-centered				Centered			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Rationality	15.77	4.90	5	23	0	4.37	-9.61	8.39
Impulsivity	25.70	7.58	10	42	0	6.82	-18.48	13.52
Compulsivity	12.04	5.11	7	26	0	4.48	-8.56	9.44
N2 ERP	3.06	8.53	-27.88	39.62	0.01	7.74	-30.52	32.78
P3 ERP	6.94	9.29	-31.80	42.04	-0.04	8.52	-35.74	34.29
Theta activity	0.13	0.64	-0.88	6.14	-0.01	0.61	-1.52	5.22
Alpha activity	-0.14	0.69	-0.99	5.00	-0.01	0.66	-1.53	5.03

Initial model included 9 direct effects and 33 interactions effects between different variables than were tested in multiple iterations of the modeling process. Because of the systematic modeling, impulsivity levels and their interactions with the other predictors (impulsivity by: variations magnitude, type of variation, N2 ERP, P3

ERP, theta activity, and alpha activity), were shown to be not significant predictors of the decision of buy ($Z < 1$; *p-value* > 0.05) and were removed from later models.

Table 3 shows the final predictive mixed effect model of purchase decision. As in the null model, highest levels of variance are concentrated in the smallest levels of the hierarchical structure, mainly in offer. In turn, model intercept turned out to be significantly different from zero (-1.111 ± 9.335 (SE); *p-value* < 0.001), being different for each price distribution. Additionally, model showed that type ($Z < -3$; *p-value* < 0.001) and magnitude of variations ($Z = 11.842$; *p-value* < 0.001), rationality levels ($Z = -5.053$; *p-value* < 0.001), N2 ($Z = -6.171$; *p-value* < 0.001) and P3 amplitudes ($Z = 2.673$; *p-value* $= 0.008$), and the frontocentral alpha activity ($Z =$ 5,300*;* *p-value* < 0.001), in addition to some interaction effects, were significant predictors of the buy decision.

Specifically, we found that for each increase in the amplitude of the N2 component, the probability of buying decreased 1,03 times (*Exp (β)* = 0.973; *p-value* < 0.001). In addition, price variations reduce the probability of buying when compared to the absence of variation, reducing the ODDS 83.80 times when increases (*Exp (β)* = 0.012; *p-value* < 0.001) and 1.46 times when decreases (*Exp (β)* = 0.685; *p-value* $<$ 0.001). On the contrary, we found that increases in the amplitude of the P3 component proportionally increase the ODDS of buying (*Exp (β)* = 1.021; *p-value* < 0.01), also presenting an interaction effect with the type of variation of prices where the type of variation moderates the effect of P3 component on the decision to buy. Specifically, we found that for each unit of increase in the amplitude of P3, the ODDS increase by 1.055 times when the price rises (*p-value* < 0.001) and 1.052 times when it falls (*p-value* < 0.001). On the other hand, results showed a mediation effect between the type of variation over the effect of theta oscillatory activity on the decision to buy, revealing that for each unit of increase in theta activity the ODDS of buying increases 1.781 times when the price rises (*p-value* < 0.001), and 1.251 times when the price falls (*p-value* = 0.042).

Table 3. Final multilevel model of predictors of purchase decision.

Parameters						
Random effects	Variance	Std. Dev.				
Distribution (Intercept)	3.931	1.983				
Participant	0.0001	0.004				
Purchase number	0.0007	0.026				
Offer	0.189	0.435				
				Confidence interval		
Fixed effects	Estimated	Std. Error	Exp(β)	Lower	Upper	p-value
Intercept	-1.111	9.335	0.329	-1.294	-0.928	***
Random intercept Distribution 1	-2.588		0.075			
Random intercept Distribution 2	0.946		2.575			
Random intercept Distribution 3	-3.711		0.024			
Variation type						

Price increase = 1	-4.428	1.774	0.012	-4.776	-4.080	***
Price decrease = 2	-0.378	1.054	0.685	-0.585	-0.172	***
Variation magnitude	0.011	0.0009	1.012	0.009	0.013	***
Rationality	-0.044	0.0087	0.957	-0.061	-0.027	***
Compulsivity	-0.010	0.006	0.990	-0.022	0.0007	
N2 ERP	-0.027	0.004	0.973	-0.036	-0.019	***
P3 ERP	0.021	0.008	1.021	0.006	0.036	**
Theta activity	0.065	0.100	1.067	-0.131	0.261	
Alpha activity	0.250	0.047	1.285	0.158	0.343	***
P3 ERP by Variation type (1)	0.053	0.015	1.054	0.024	0.082	***
P3 ERP by Variation type (2)	0.051	0.010	1.052	0.032	0.070	***
Theta activity by Variation type (1)	0.577	0.155	1.781	0.272	0.881	***
Theta activity by Variation type (2)	0.224	0.110	1.251	0.008	0.440	*
Variation magnitude by Rationality	0.0003	0.0001	1.001	0.00001	0.0006	*
P3 ERP by Variation magnitude	0.0002	0.0001	1.001	0.00005	0.0004	*
Alpha activity by Compulsivity	0.016	0.008	1.016	0.0005	0.031	*
Akaike information criterion [AIC]	9159.5					
Marginal R^2	49.4%					
Conditional R^2	60.8%					

Note: Variation type “no variation” set to zero for identification. P values not given for covariance parameters and goodness of fit. GLMM logistic parameter estimated

(Estimated), standard errors (Std. Error). Confidence intervals at 2.5% (lower) and 97.5% (Upper). “*” p-value < 0.05; “**” p-value < 0.01; “***” p-value < 0.001.

In addition, the resulting model shows that for each increase in the magnitude of the variations, the ODDS of buying increases 1.011 times (*Exp (β)* = 1.011; *p-value* < 0.001), while each increase in the levels of rationality leads to a 1,045 times reduction of the ODDS of buying. Importantly, we found that the rationality levels act as a moderator of the effect of the magnitude of the variations in the probability of purchase (*Exp (β)* = 1.0003; *p-value* = 0.045). On the other hand, we found that for each unit of increase in the amplitude of the P3 component there is a proportional increase in the probability of buying (*Exp (β)* = 1.021; *p-value* = 0.008), presenting a moderation effect between the amplitude of P3 and the magnitude of the variations in the decision to buy (*Exp (β)* = 1.0002; *p-value* = 0.014). Finally, we found that each increase in alpha frontocentral activity leads to an increase of 1,285 times in the ODDS of buying (*p-value* < 0.001), in addition to be moderate by the compulsivity levels (*Exp (β)* = 1.016; *p-value* = 0.043).

To identify possible multicollinearity problems, we analyzed the Variance Inflation Factor (VIF) of the model's predictors. Results revealed that there were no collinearity problems, being VIFs of predictors distributed between 1.01 and 5.66, and a general Kappa Index of 7.68. Results of the model fit parameters showed that relative to the null model, the final model exhibited significantly better parameters of model fit (AIC=9159.5; X2(16) = 2837.2*, p-value* < 0.001), suggesting that the final model adjusted better than the null model. Additionally, regarding to the explained variance, results showed that the proportion of explained variance by the marginal estimation was 49.4% (only including fixed effects; *R2m*= 0.494), while variance explained by the conditional estimation was 60.8% (including both fixed and random effects; *R2c*=0.608).

Finally, as a way to estimate the real fit of the model predicting responses, we analyzed the sensitivity and specificity of the model in the responses' classification. Results revealed an 87% of specificity and a 66% of sensitivity in the model, presenting low percentages of prediction errors and correctly classifying most of the responses (Ruopp et al., 2008;Fluss et al., 2005; Dreiseitl & Ohno-Machado, 2002).

4. Discussion

The current study employed a mixed effects multilevel approach, combining attitudinal self-report variables, measures of neurophysiological activity and task-based information extracted during the experimentation, to explore their potential effect on the prediction of purchase decisions while performing the Purchase Decision Making task (PDMt; Alí Diez & Marco-Pallarés, 2021).

The final model improved the classification of the responses and, therefore, reduced the percentage of prediction errors substantially when compared to the initial null model (Ruopp et al., 2008). In this sense, according to Fluss et al. (2005), our final model presents levels of specificity and sensitivity sufficient to be considered as a reliable predictive model. Overall, results of our study are consistent with our hypotheses that to explain a complex behavior such as purchase decision-making, variables of different nature are needed, and confirming the relevance of attitudinal, neurophysiological, and contextual variables in this decision. Specifically, we found that price variations reduce the probability of buying when compared to the absence of variation, while increases in the magnitudes of variations proportionally increase the probabilities of buying, highlighting the importance of local variations in uncertainty decision-making contexts (Sun & Wang, 2020). At the neurophysiological level, as we expected, we found that the amplitude of the centroparietal P3 component directly predicted the decision to buy, with larger amplitudes in buy condition, being consistent with the results reported in Alí Diez & Marco-Pallarés (2021). Interestingly, we also found that effect of P3 amplitudes was influenced by the magnitude and type of variations, revealing that variations in prices and, particularly, variations of higher magnitudes lead to larger amplitudes and, as consequence, higher probabilities of purchase. Previous studies have related the P3 amplitude with motivational significance and utility of the measured value (Nieuwenhuis et al., 2005), being consistent with our results and the evidence that propose that greater utility and variations of prices leads to greater emotional impact compared to constant prices (Kok, 2001; Rac-Lubashevsky & Kessler, 2019), particularly in higher magnitude variations and decision to buy.

In addition, we found that increases in frontal alpha oscillatory activity directly affect the probability of buying. In this sense, this result is consistent with previous studies that proposed that increases in alpha activity were related to the preference of products and prices (Braeutigam et al., 2004; Ravaja et al., 2013) and, even, the decision to buy (Alí Diez & Marco-Pallarés, 2021). Other studies have also related increases in alpha activity with complexity of the trial during economic decision-making experiments (Rappel et al., 2020), in addition to increases in the cognitive demand to processing the stimulus valence (Rossi et al., 2015). In our study, the decision to buy supposes an increase in the demand of the stimulus valence processing due to the analysis of the exposed price and its comparison with previous prices offered, in addition to the estimation of probabilities of obtaining a better price in the future, becoming more complex and less frequent trials during task execution.

Contrary to our hypotheses, we found that increases in the amplitude of the frontocentral N2 component reduce the probability of buying. Previous evidence proposed that amplitudes of N2 is indicative of the preference of one product over another (Telpaz et al., 2015), where larger negativity was found in non-buying conditions (Braeutigam et al., 2004) or when participants decide to wait for a new offer compared to the decision to buy (Alí Diez & Marco-Pallarés, 2021). Despite this, our result indicates that even when the decision to buy was preceded by a reduction in the N2 negativity, this reduction does not predict the posterior decision. Thus, this increase in amplitude of evoked potential may reflect the conflict resolution process in face of contradictory or complex stimuli (such as different prices between offers, prediction error, among others; Gajewski et al., 2016), without being directly related to the subsequent decision. Similarly, the oscillatory activity in the theta band alone was not shown be a significant predictor of the decision to buy, but rather its effect was mediated by price variations. In this sense, previous evidence has widely described the role of theta activity during cues and feedback processing in decision making (Cavanagh, Figueroa, et al., 2012; Cavanagh & Frank, 2014). Previous studies have shown that theta activity is modulated by the levels of uncertainty (Cavanagh et al., 2010; Cavanagh, Zambrano-Vazquez, et al., 2012; Mas-Herrero & Marco-Pallarés, 2014) and that it plays a key role in the prediction error computation (HajiHosseini et al., 2012; Wang et al., 2016). Thus, in our experiment, price variations could induce prediction errors because they imply a change in the decision scenario. Therefore, as observed in the present results, the effect of theta activity on the decision to buy is related to contextual variations, increasing 1.78 times the probability of buying when the price rises, and 1.25 times when the price falls, compared to the absence of variation.

Regarding the attitudinal measurements, contrary to our hypotheses, we found that neither impulsivity nor compulsivity predicted the decision to buy. In contrast, we found that the rationality levels significantly decreased the probability of buying, also presenting a small effect associated to the magnitude of variations. Previous evidence suggests that rational style presents a low emotional commitment associated with the act of buying (Quintanilla et al., 1998) and, above all, is characterized by the maximization of the cost-benefit analysis associated with each consumption decision and the avoidance of financial risk (Denegri, 2010). Considering this, it is coherent to propose that people with a higher level of rationality could be more sensitive to the magnitudes of variations due to the processing and cost-benefit analysis carried out during the decision-making process. Therefore, probability of buying increases in the face of losses (price increases) or gains (price reductions) of great magnitude, given the imminent risk existing in contexts of uncertainty.

One of the strengths of this study consists in the sensitivity of the statistical method used to measure the variations in the decisions of the participants at the longitudinal level and, in consequence, its sensitivity to identify the different levels of variability across the trials measured and between each participant of the study. Associated with this, the use of the experimental paradigm showed to be consistent in its implementation, allowing identifying the effects of the variables in decision-making. Thus, the main contribution of this study is the inclusion of variables of different nature in the prediction of the decision to buy, evidencing their interactions and opening new lines in the study of purchase decisions.

In contrast to the previously mentioned, the main limitation of this study is related to the replicability of the model, because this study was of an exploratory type and that, therefore, must be replicated for confirmation purposes. Based on this, new studies should consider a sufficient sample size to test, using structural equation models, the consistency of the proposed model, as well as the real causality effects derived from the interactions identified in the present study.

Chapter 7
General Discussion

Chapter 7: General Discussion

The four studies carried out in this thesis sought to propose an exploratory predictive model of the decision to buy, considering neurophysiological, attitudinal, and behavioral markers. For this, an experimental scenario was designed that sought to simulate the conditions of purchase products on digital platforms, controlling the effect of personal preferences, interest, motivation, and previous experience, using unconventional products. Thus, in Study 1, we designed the experimental paradigm and evaluated the differential role of attitudinal and contextual variables during decision-making in it. In Studies 2 and 3, we studied the neurophysiological markers of the decision to buy, as well as the neurophysiological variations based on the variations of the decision context. Finally, in Study 4, we proposed an exploratory predictive model of the decision to buy, studying the relevance of the variables identified in studies 1, 2 and 3 to predict this decision.

After presenting a brief summary of the specific results of each study, in this chapter I will discuss the main findings of the studies included in this doctoral thesis, integrating them from a comprehensive perspective. In the sections of each of the studies of this work, you can find a more detailed discussion of the results (chapters 3, 4, 5 and 6).

1. Summary of results

The main goal of **Study 1** was to design a new experimental paradigm, which allowed the identification of the contextual and individual differences' variables associated with purchase decision making in different scenarios. Previous studies have showed that during decision-making, behavior is adapted in concordance with the characteristics of the environment or context (Behrens et al., 2007; Mas-Herrero & Marco-Pallarés, 2014) and, in purchase decision making, attitudes have been frequently studied in the psychology of consumption to understand consumers' behavior (Alí Diez et al., 2021; Denegri et al., 2012; Luna-Arocas & Tang, 2004). Using the experiment designed, results revealed that the prediction of buying decision was explained by different variables, supporting the idea that decision making in economical settings is highly dynamic and dependent of the characteristics of the environment, the individual differences assessed, and their interactions (Whiteside & Lynam, 2001). Thus, the identified effects allow us to recognize the relevant variables during decision making, but, above all, it allows us to recognize the variability of the decisions of the same buyer in different scenarios (MacKillop et al., 2011). The main finding of study 1 was, in consequence, to demonstrate the importance of environmental and individual difference measures in the study of consumer behavior in uncertainty context, due to it dynamism and complexity. Additionally, its results confirm the sensitivity of the paradigm designed to capture variations in participant's decisions.

Study 2 sought to study the neurophysiological correlates of purchase decision-making in scenarios with temporal uncertainty using the Purchase Decision-Making task (PDMt) experimental paradigm, in a pre-decision time. Previous EEG studies suggest that the preference for a product over another is expressed by a reduction in N2 component amplitude and a weaker theta power in frontal areas (Telpaz et al., 2015), while obtaining a price below the normal one is expressed in a left frontal asymmetry, even when the normal price is an implicit and subjective reference (Ravaja et al., 2013), and increases in alpha activity (Arieli & Berns, 2010; Braeutigam et al., 2004). The main results of this study were the identification of a significant reduction of N2 amplitude and a significant increase of P3 amplitude for buy compared to wait condition, presenting both a clear frontocentral topography. Results of the oscillatory activity revealed a significant increase in the theta and alpha oscillatory activities in the buy condition compared to the wait one.

In **Study 3**, we aimed to analyze the electrophysiological activity associated with the different types of price variations while the participants carried out a purchase decision using the PDMt experimental paradigm. Previous studies have reported the relevance of feedback processing during output evaluation in the decision process (Berridge & Kringelbach, 2015; Hosking et al., 2015; Kurniawan et al., 2011), recognizing its important role in successfully adapting behavior in contexts of uncertainty (Palidis & Gribble, 2020). However, purchase decisions are characterized by not having explicit feedback derived from each action, but rather be driven by emotional, subjective and indirect elements that interacts to evaluate how correct or incorrect previous actions were (Burnett & Lunsford, 1994). Our results showed that the amplitudes of the P2 and P3 components were affected by negative conditions, as consequence of the relevance of the information obtained and the impact produced (Kok, 2001; Rac-Lubashevsky & Kessler, 2019). Theta oscillatory activity presented increases in negative conditions been consistent with traditional decision-making studies that reported increases in this band after negative feedback (Andreou et al., 2017; Cavanagh et al., 2010; Mas-Herrero et al., 2015; Van de Vijver et al., 2011), reaffirming the idea that theta band is highly sensitive to the valence and magnitude of the feedback received (Arrighi et al., 2016; Cavanagh et al., 2010), even when feedback was not explicit.

Finally, **Study 4** aimed to propose a predictive model of the decision to buy, controlling the effect of personal preferences, interests, motivation, and experiences on previous purchases of the same or similar products, through the use of the Purchase Decision-Making task (PDMt), and testing the attitudinal and neurophysiological markers identified in studies 1, 2 and 3. Our results confirmed the relevance of attitudinal, neurophysiological, and contextual variables in the purchase decision process, confirming that to explain complex behaviors attitudinal, neurophysiological and contextual variables are needed. In this sense, the main contribution is the demonstration that the inclusion of variables of different nature and their interactions is crucial in the prediction to buy, opening new lines in the study of purchase decisions.

2. Deciding when to buy... dynamism at the base of purchasing decisions

In this thesis work, we explored the different factors that influence the decision buying behavior. The results of the four studies are consistent with the background presented in the introduction to this thesis, mainly in relation to the diversity of determinant variables of economic behavior and their impact in the inhibition or stimulation of economic behavior (Cartwright, 2018; Denegri, 2010; Kahneman, 2009; Larsen, 2022). For example, we have shown in Study 1 and 4 that both contextual factors such as the variations in the price and price itself, and attitudinal factors such as rationality, were crucial to describe the decision to buy the product or wait for a better offer. These behaviors are highly complex and challenging to study, as they depend on many factors to capture a more realistic perspective on the phenomenon. In this sense, our results also show that interaction between these factors are explanatory of the behavior, supporting the complex interaction of factors of different nature in this process. Therefore, the results found in this thesis go along with the postulates of behavioral economics, since they show the relevance of subjectivity (Kahneman, 2009; Kahneman & Tversky, 1979), personal factors in the interpretation of contextual information available, in addition to the expression neurophysiology of its processing during the economic decision-making process (Frederick, 2005).

3. The certainty within the uncertainty: how we feedback our decisions?

As I have developed in the introductory chapter of this thesis, the characteristics of the influence context in decisions has been widely studied due to its relevance when analyzing the information available to optimize behavior (Huettel et al., 2006; Mas-Herrero & Marco-Pallarés, 2014). Thus, various studies have shown that when contexts are ambiguous or uncertain, local variations become highly relevant to adapt and optimize decisions, reducing the relevance of previously learned response models and highlighting the importance of new pieces of information over the experience (Berridge & Robinson, 2003; Graybiel, 2008; O'Doherty et al., 2017).

In the case of purchase decisions, to decide involves uncertainty at different levels as time, risk, and the absence of explicit feedback after decision (Bland & Rosokha, 2021; Kahneman, 2009; Schröder & Gilboa Freedman, 2020; Simon, 1959). This information is essential for comprehending, learning, making correct decisions and optimizing future choices (Cohen et al., 2011; Luu et al., 2003; San Martín, 2012; Sun & Wang, 2020; Van de Vijver et al., 2011; Walsh & Anderson, 2012; Wischnewski & Schutter, 2018).

This uncertainty and the limitation of the available information drives us to establish self-learning as the main source that allows us to adapt and optimize our future actions (Kahneman, 2009; Karimi et al., 2015; Lane, 2017). However, this mechanism might be highly influenced by emotional elements, personal beliefs and symbolic values that allow subjective expectations to be configured based on the interpretation of decisions as correct or wrong (Bland & Rosokha, 2021; Burnett & Lunsford, 1994; Hayden, 2018; Kahneman, 2009; Kahneman & Tversky, 1984; Slovic et al., 2004). Importantly, in this thesis we have been able to partially disentangle the neurophysiological mechanisms underlying this self-learning and the decision-making process. Consequently, the results of our studies 2 and 3 can contribute to the understanding of the relevance of contextual information in the construction of subjective expectations, due to its consistency with the previous scientific evidence based on the neurophysiological correlate of feedback processing during decisions. Thus, our findings showed that P3 component amplitude is modulated by the decision to buy a product or to wait for a better offer and, in waiting conditions, sensitive to the valence and magnitude of price variations, in accordance with previous studies that have associate it with feedback processing (Balconi & Crivelli, 2010a; Banis et al., 2014; Bellebaum et al., 2010; Chase et al., 2011; Ferdinand et al., 2012; Frank et al., 2005; Novak & Foti, 2015; Palidis & Gribble, 2020; Pfabigan et al., 2014; Philiastides et al., 2010; Riepl et al., 2016; San Martín, 2012; Wu & Zhou, 2009; Yeung & Sanfey, 2004). These results suggest that this component is related to the motivational meaning and the perceived usefulness of the value presented, being consistent with previously reported results that showed greater amplitudes in greater magnitudes of variation and negative results because of the emotional impact generated by the output obtained (Kok, 2001; Nieuwenhuis et al., 2005; Rac-Lubashevsky & Kessler, 2019).

Furthermore, our results showed that increases in theta oscillatory activity were related to increases of prices, especially in large magnitude increases. This is consistent with previous studies that reported increases in theta oscillatory activity after negative feedback (Andreou et al., 2017; Cavanagh et al., 2010; Marco-Pallarés et al., 2008; Mas-Herrero et al., 2015; Van de Vijver et al., 2011), reaffirming the idea that theta band is highly sensitive to the valence and magnitude of the feedback received (Arrighi et al., 2016; Cavanagh et al., 2010). Importantly, the feedback presented in our study was driven in part by subjective expectations. This allowed demonstrating the role of theta oscillatory activity as an adaptive control mechanism in situations of high uncertainty (Cavanagh, Figueroa, et al., 2012; Cavanagh & Frank, 2014).

4. Strengths and scientific contributions

One of the main antecedents that prompted the development of this doctoral thesis work was the existing scientific gap to describe the interaction of behavioral, neurophysiological, and contextual factors during purchase decision making.

Current scientific development had focused mainly on explaining the particular characteristics of certain segments and specific groups of consumers to predict the willingness to buy some products or brands (Ambler et al., 2000, 2004; Komalasari et al., 2021; Kranzbühler et al., 2017; Laran, 2009; Laran & Wilcox, 2011; Mackenzie & Spreng, 1992; Sanfey et al., 2003; Shastry & Anupama, 2021), leaving aside the study of the decision process for scientific development purposes. Thus, the present work sought to contribute from the construction of a new experimental paradigm that allows the study of this type of decisions in a dynamic way and incorporating variables of a different nature to offer rigorous descriptions of the study phenomenon.

Additionally, one of the main contributions of this work to scientific development is its proximity to real purchase scenarios, such as virtual stores. Every day we can see hoy online commerce grows and expands its market, becoming one of the most promising commerce in these times. Thus, studies such as these allow us to understand how we adapt our behavior, as well as the way in which our own personal characteristics motivate us to react in specific way to purchase situations in these contexts.

5. Limitations and future directions

Even though with the development of this doctoral thesis it was possible to provide answers to the questions posed for each study, there are some limitations and recommendations for future work that are relevant to consider.

- Future studies should consider complementing the measurements made with subjective estimation of some of the studied parameters (e.g., price variations), to have a more complete approximation of the subjective expectations in each decision.
- An important consideration is that the experimental paradigm designed presents some limitations in terms of motivation, needs, personal interests and preferences at the base of purchasing decisions. As presented in the studies, the designed paradigm sought to control motivation, shopping experiences, and personal interests in the products to be purchased to reduce the number of possible intervening variables in the results found. New studies could complement the experimental design to identify the possible differences in the purchase process when these subjective elements play an active role in the choice made, as proposed by complementary models, such as those of marginal utility or bounded rationality (Arrow, 1990; Cartwright, 2018; Jevons, 1871; Pammi & Miyapuram, 2011; Wheeler, 2020).
- The main objective of this work was to design an exploratory model that would allow predicting the decision to buy. New studies should consider using a larger sample size sufficient to allow the application of more complex statistical models to estimate intra- and inter-variable effects and to be able to verify the results obtained in this initial approximation.

- When we analyzed the neurophysiological correlate of price variations in study 3, to equate the number of trials to be compared, only those that had a subsequent response to wait were considered, leaving aside all those trials in which the participants decided buy. This decision could have had some impact on the results found and the inability to identify differences in the beta band. According to the existing literature, increases in beta oscillatory activity have been associated with obtaining rewards or profits (Andreou et al., 2017; Cohen et al., 2007, 2011; HajiHosseini et al., 2012; HajiHosseini & Holroyd, 2015; Marco-Pallarés et al., 2008, 2015; Mas-Herrero et al., 2015; Weismüller et al., 2019). In our study, by not considering the purchase trials, we omitted the profit effect produced by obtaining a convenient price or one that meets expectations. New studies should consider both conditions to investigate this point.

Chapter 8
Conclusions

Chapter 8: Conclusions

In this thesis we have provided new evidence on the attitudinal, neurophysiological, and contextual factors underlying purchase decision-making. General results confirm that neurophysiological mechanisms associated with purchase decision-making are similar to the ones found in general decision-making, revealing the relevance of contextual and attitudinal variables in the purchase decision. Through the studies carried out, we were able to answer the research questions presented in chapter 2 and, by integrating the results obtained, we can present different conclusions. First, wee designed a new experimental paradigm, the PDMt, which showed to be appropriate to capture variations in the decisions of the participants based on their personal characteristics and contextual information presented. Second, we measured the neurophysiological response associated with price variations, being able to show that, despite the fact that explicit feedback was not presented in the experiment, there is a response similar to that found in traditional decision-making experiments. Finally, in an exploratory level, the predictive model designed showed the importance of variables of different nature to predict purchase decisions, revealing the complexity at the basis of these behaviors.

Chapter 9
References

Chapter 9: References

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