Individual differences in decision-making through the Iowa Gambling Task: Perspectives from neuroimaging and neurostimulation

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Author: José Juan León Domene.

Thesis director: Pilar Flores Cubos.

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Abstract

Decision-making can be defined as the ability that allows organisms to choose one course of action from a set of alternatives. Decisions may take place under different circumstances and the way organisms decide may vary in accordance. For instance, the environment in which decisions are made could be uncertain and may involve risk, but also could be known and completely safe to the decision-makers. Thus, decision-making usually comprises a synthesis of different psychological processes that may play different roles depending on the characteristics of the context surrounding the decisions. At a behavioural level, several clinical populations such as Obsessive-Compulsive Disorder, Attention Deficit/Hyperactivity Disorder, and Substance Use Disorder, among others, have shown maladaptive decision-making that may underlie their clinical condition. In this sense, the Research Domain Criteria (RDoC) initiative has proposed various decision-making-related processes, such as reward responsiveness, reward valuation, cognitive control, or action planning, as transdiagnostic domains. At the physiological level, the study of the neurofunctional pathways of those processes has usually situated the prefrontal cortex as a critical brain region. Among other PFC subregions, the orbitofrontal, dorsolateral, and medial prefrontal cortices have received special attention. The investigation on this topic from a connectionist perspective may provide meaningful insights about the neurological basis of decision-making, through the study of functional connectivity, both at rest and during task performance, among dispersed brain areas.

In the present Doctoral Thesis, we studied decision-making through a traditionally well-established and widely used behavioural paradigm: the Iowa Gambling Task (IGT). The IGT is supposed to assess contingency-based decision-making processes under uncertain situations and has been proposed as a real-world decision-making model. Briefly, in this task, participants began with a certain amount of points or money and they are instructed to

maximize their long-term profits by making one hundred choices between four different decks. These decks differ in the magnitude of gains, in the frequency and magnitude of losses and in the long-term net outcome they offer. In addition, different neuroimaging techniques, such as functional Near-Infrared Spectroscopy (fNIRS) and Electroencephalography (EEG), and different Transcranial Electrical Stimulation, such as Transcranial Direct and Alternating Current Stimulation (tDCS and tACS) were used to study the neurological basis of decision-making under the IGT context.

The main aim of the present Doctoral Thesis was to study decision-making through IGT in order to understand the different strategies adopted by individuals to make decisions in situations of uncertainty, and to find out whether these strategies can be manipulated and predicted at a neurophysiological level. The research work is composed of four different studies, in which the performance on the IGT of a total of 409 participants, including healthy people and impulsive-compulsive spectrum disorder patients, was analysed and modulated from different approaches. Neurophysiological measures of electrical and haemodynamic activity of the functional networks are also provided.

The first study aimed to investigate the potential of tDCS to modulate the IGT performance as a function of sex. For that, we applied a single session of anodal- and sham-tDCS over the right orbitofrontal cortex in a pre-post experimental design in order to modulate IGT performance in healthy psychology undergraduates. Results revealed that only women under anodal-tDCS showed an increased net score after stimulation.

In the second study, we tried to go beyond the net score so we paid special attention to how and when individual deck preferences are developed aiming to clarify the behavioural mechanisms underlying the formation of different response strategies. Five differential decision-makers profiles based on how they developed their deck preferences during the task were revealed. These differences may be conceptualised under several dimensions proposed

by the RDoC. Bayesian data analysis was used from this study onwards for the statistical inference process, due to the many mean comparisons and statistical models that will be performed. Sex differences in the net score were not replicated in this study.

For the third study, we recruited healthy adults and impulsive-compulsive spectrum disorder patients and employed fNIRS to record resting-state functional connectivity (rsFC) between several important nodes of the frontoparietal network (FPN). We followed a similar methodology and theoretical framework to the previous investigation to identify three differential decision-making strategies that cut across diagnostic labels. Importantly, these behavioural profiles were replicated from the previous study. We found no credible evidence about the role of the rsFC between any FPN nodes as a biomarker of any decision-making strategy.

Lastly, the fourth study proposed a combined EEG-tACS approach to study the role of frontal-midline theta oscillatory activities in the performance of the IGT and the capability of tACS at theta frequency (6 Hz) to modulate the mentioned performance. Preliminary results, obtained by a Bayesian Logistic Regression Model, seem to point to a possible positive relationship between frontal-midline theta power and the final performance on the task of the sham group. No evidence of a frequency-specific effect of theta-tACS was found.

Taken together, we consider that the results of the present Doctoral Thesis highlight the importance of paying special attention to the individual differences that guide the decision-making processes that occur during the different stages of the IGT. We provided evidence about different, stable, and observable types of decision-makers among both healthy and clinical populations that may be useful for future research in understanding and inferring how and why people make decisions in contexts similar to the IGT. At the physiological level, our results seem to suggest an implication of the right orbitofrontal cortex and frontal-midline theta power in decision-making. However, further research is needed on this topic,

following homogenised conceptual and methodological approaches, in order to clarify the neurophysiological basis of decision-making.

Resumen

La toma de decisiones puede definirse como la capacidad que permite a los organismos elegir un curso de acción entre un conjunto de alternativas. Las decisiones pueden tomarse en distintas circunstancias y la forma en que los organismos deciden puede variar en función de las mismas. Por ejemplo, el ambiente en el que se toman las decisiones puede ser incierto y entrañar riesgos, pero también puede ser conocido y completamente seguro para los organismos. Así pues, la toma de decisiones comprende una síntesis de distintos procesos psicológicos que pueden desempeñar papeles diferentes en función de las características del contexto que rodea a las decisiones. A nivel conductual, varias poblaciones clínicas como el Trastorno Obsesivo-Compulsivo, el Trastorno por Déficit de Atención e Hiperactividad, y el Trastorno por Uso de Sustancias, entre otros, han mostrado una toma de decisiones desadaptativa que puede subyacer a su condición clínica. En este sentido, el *Research Domain Criteria* (RDoC) ha propuesto diversos procesos relacionados con la toma de decisiones, como la sensibilidad a las consecuencias, la valoración de la recompensa, el control cognitivo o la planificación de la acción, como dominios transdiagnósticos. A nivel fisiológico, el estudio de las vías neurofuncionales de dichos procesos habitualmente ha situado al córtex prefrontal como una región cerebral importante. Entre otras de sus subregiones, las cortezas orbitofrontal, dorsolateral y prefrontal medial han recibido especial atención. Por su parte, la investigación desde una perspectiva conexionista puede aportar conocimientos sobre las bases neurológicas de la toma de decisiones, a través del estudio de la conectividad funcional, tanto en reposo como durante tareas, entre áreas cerebrales dispersas.

En la presente Tesis Doctoral, se estudia la toma de decisiones a través de un paradigma conductual tradicionalmente bien establecido y ampliamente utilizado: la Tarea de Juego de Iowa (IGT, por sus siglas en inglés). Se supone que la IGT evalúa los procesos de

toma de decisiones en situaciones de incertidumbre, y se ha propuesto como modelo de toma de decisiones en el mundo real. En resumen, en esta tarea, los participantes comienzan con una cierta cantidad de puntos o dinero y se les instruye a maximizar sus beneficios a largo plazo realizando cien elecciones entre cuatro barajas de cartas diferentes. Estas barajas se diferencian en la magnitud de las ganancias, en la magnitud y en la frecuencia de las pérdidas y en la recompensa neta a largo plazo. Además, se emplean diferentes técnicas de neuroimagen, como la Espectroscopia funcional por infrarrojo cercano (fNIRS, por sus siglas en inglés) y la Electroencefalografía (EEG), y diferentes técnicas de Estimulación Eléctrica Transcraneal, como la Estimulación Transcraneal por Corriente Directa (tDCS, por sus siglas en inglés) y por Corriente Alterna (tACS, por sus siglas en inglés) para estudiar las bases neurológicas de la toma de decisiones en el contexto de la IGT.

El objetivo principal de la presente Tesis Doctoral fue estudiar los procesos de toma de decisiones a través de la IGT para entender en profundidad las diferentes estrategias de elección adoptadas por los individuos en situaciones de incertidumbre, e investigar si estas estrategias pueden ser manipuladas y predichas a nivel neurofisiológico. El trabajo de investigación está compuesto de cuatro estudios en los cuales el rendimiento en la IGT de un total de 409 participantes, entre los que se incluyen personas sanas y pacientes del espectro impulsivo-compulsivo, fue analizado desde diferentes perspectivas teóricas, aportando, además, medidas neurofisiológicas de actividad eléctrica y hemodinámica de las redes funcionales relacionadas con la toma de decisiones.

En el primer estudio, el objetivo fue investigar el potencial de la tDCS para modular la toma de decisiones, medida a través de la IGT, en función del sexo. Para ello, aplicamos una única sesión de tDCS anodal y placebo sobre el córtex orbitofrontal derecho en un diseño experimental pre-post para modular el rendimiento en la IGT de estudiantes de psicología

sanos. Los resultados revelaron que sólo las mujeres bajo la condición de tDCS anodal mostraron un aumento de la puntuación neta tras la estimulación.

En el segundo estudio, intentamos ir más allá de la puntuación neta en la IGT, por lo que prestamos especial atención a cómo y cuándo se desarrollan las preferencias por cada mazo, con el objetivo de aclarar los mecanismos conductuales que subyacen a la formación de diferentes estrategias de respuesta en la tarea. Identificamos cinco perfiles diferenciados en población sana en función del desarrollo de distintas preferencias por distintos mazos durante la tarea. Las diferencias entre estos perfiles pueden ser conceptualizadas bajo varias dimensiones propuestas por el RDoC. A partir de este estudio, el análisis de datos y el proceso de inferencia estadística siguió una aproximación Bayesiana debido a las numerosas comparaciones que van a ser analizadas, así como a la interpretación de los modelos estadísticos utilizados. Las diferencias de sexo en la puntuación neta no se replicaron en este estudio.

Para el tercer estudio, reclutamos adultos sanos y pacientes con trastornos del espectro impulsivo-compulsivo y empleamos fNIRS para registrar la conectividad funcional en estado de reposo (rsFC, por sus siglas en inglés) entre varios nodos importantes de la red frontoparietal (FPN, por sus siglas en inglés). Seguimos una metodología y un marco teórico similares a los de la investigación anterior para identificar tres diferentes estrategias de toma de decisiones que atraviesan las etiquetas diagnósticas. Estos perfiles conductuales fueron replicados del anterior estudio. No encontramos evidencia creíble sobre el papel de la rsFC entre ningún nodo de la FPN como biomarcador de ninguna estrategia de toma de decisiones.

Por último, el cuarto estudio propuso un enfoque combinado EEG-tACS para estudiar el papel de la actividad oscilatoria de frecuencia theta en el rendimiento en la IGT, así como la capacidad de la tACS a frecuencia theta para modular el dicho rendimiento. Los resultados preliminares parecen apuntar a una posible relación positiva entre la potencia theta y el

rendimiento final en la tarea del grupo placebo. No se hallaron evidencias de un efecto específico de la frecuencia de estimulación.

En conclusión, consideramos que los resultados de la presente Tesis Doctoral ponen de manifiesto la importancia de prestar especial atención a las diferencias individuales que guían los procesos de toma de decisiones que tienen lugar durante las diferentes etapas de la IGT. Se aportan evidencias sobre tipos de estrategia de respuesta diferentes, estables y observables tanto en población sana como en población clínica, que pueden ser útiles para futuras investigaciones en la comprensión e inferencia de cómo y por qué se toman decisiones en contextos similares al de la IGT. A nivel fisiológico, nuestros resultados parecen sugerir una implicación del córtex orbitofrontal derecho y de la potencia de la onda theta en la toma de decisiones. Sin embargo, es necesario seguir investigando sobre este tema, siguiendo enfoques conceptuales y metodológicos homogéneos, para aclarar la base neurofisiológica de la toma de decisiones.

Abbreviations

ACC. Anterior Cingulate Cortex.

ADHD. Attention-Deficit/Hyperactivity Disorder.

AM-tACS. Amplitude Modulated Transcranial Alternating Current Stimulation.

AUDIT. Alcohol Use Disorders Identification Test.

BA. Brodmann Area.

BOLD. Blood Oxygen Level Dependent.

CEN. Central Executive Network.

CSF. Cerebrospinal fluid.

DAST-10. Drug Abuse Screening Test.

DLPFC. Dorsolateral Prefrontal Cortex.

DMN. Default Mode Network.

EEFF. Executive Functions.

EEG. Electroencephalography.

EPF. Endogenous Peak Frequency.

ERPs. Event-Related Potentials.

EU. Expected Utility.

EUT. Expected Utility Theory.

EV. Expected Value.

FEM. Finite Element Method.

fMRI. Functional Magnetic Resonance Imaging.

FMT. Frontal-midline theta.

fNIRS. Functional Near-Infrared Spectroscopy.

FPN. Frontoparietal Network.

FRN. Feedback Related Negativity.

GLM. General Linear Model.

HbO_2. Oxy-haemoglobin.

HbR. Deoxy-haemoglobin.

HDI. Highest Density Interval.

IGT. Iowa Gambling Task.

JAGS. Just Another Gibbs Sampler.

MCMC. Markov Chain Monte Carlo.

MDD. Major Depressive Disorder.

MEPs. Motor-Evoked Potentials.

mPFC. Medial Prefrontal Cortex.

NIBS. Non-Invasive Brain Stimulation.

OCD. Obsessive-Compulsive Disorder.

OFC. Orbitofrontal Cortex.

ORL. Outcome-Representation Learning Model.

PFC. Prefrontal Cortex.

PG. Pathological Gambling.

pPC. Posterior Parietal Cortex.

PPC. Posterior Predictive Check.

PVL-Decay. Prospect-Valence Learning Model With Decay Reinforcement Learning Rule.

PVL-Delta. Prospect-Valence Learning Model With A Delta Learning Rule.

RDoC. Research Domain Criteria.

RL. Reinforcement Learning.

ROIs. Regions of Interest.

ROPE. Region Of Practical Equivalence.

rsFC. Resting State Functional Connectivity.

SCRs. Skin Conductance Responses.

SEM. Standard Error of the Mean.

SMH. Somatic Marker Hypothesis.

SNR. Signal-to-Noise Ratio.

SOGS. South Oaks Gambling Screen.

SSD. Stop Signal Delay.

SSRT. Stop Signal Reaction Time.

SST. Stop Signal Task.

STAI. State-Trait Anxiety Inventory.

SUD. Substance Use Disorder.

tACS. Transcranial Alternating Current Stimulation.

tDCS. Transcranial Direct Current Stimulation.

TENS. Transcutaneous Electrical Nerve Stimulation.

TES. Transcranial Electrical Stimulation.

TMS. Transcranial Magnetic Stimulation.

UPPS-P. Short Impulsive Behaviour Scale.

vmPFC. Ventromedial Prefrontal Cortex.

VPP. Value-Plus Perseverance Model.

WCST. Wisconsin Card Sorting Test.

WJ. Welch-James Test.

CHAPTER 1. INTRODUCTION

Decision-making is a critical capacity for the adaptability of organisms to the environment. It is a complex and multidimensional process that comprises several underlying factors. In other words, it is a synthesis of several psychological processes. Thus, to have an in-depth knowledge of how and why organisms make decisions is crucial to understand why organisms behave the way they do and, therefore, to develop specific rehabilitation strategies. This is why decision-making has been studied from different theoretical perspectives and paradigms. One of the most widely used behavioural paradigms for this purpose comes from the neuroscience field and is the Iowa Gambling Task. This task has been historically used by a vast amount of research and, despite it has been useful to provide insights about the decision-making processes in healthy and clinical populations, it also has left some gaps of knowledge about their underlying psychological factors. Likewise, the emergence of neuroimaging and neurostimulation techniques leads to a specific research field aiming to disentangle the neurological basis of different cognitive mechanisms, including decision-making.

The study of the dimensions or constructs related to decision-making can be framed within the Research Domain Criteria Project (RDoC; National Institute of Mental Health). RDoC is a framework for researchers and clinicians with the long-term goal of understanding the aetiopathogenesis and clinical manifestations of mental health problems, considering the study of the most relevant dimensions or mechanisms of biological and psychological systems (Cuthbert, 2020). From this perspective, decision-making may be studied from different levels of analysis and may constitute a relevant dimension to explain the variability between individuals due to its crucial role in daily and social functioning.

Taken together, decision-making research would be greatly benefited from integrating meaningful insights from different disciplines such as economics, psychology, and neuroscience, to be able to formulate not only descriptive but also explanatory models. Paying special attention to biological and behavioural individual differences, as well as to socio-economic factors, may provide useful information to formulate explanatory models of the different types of decision-making that may allow clinicians and researchers to focus on the specific processes driving adaptive or maladaptive decision-making. Therefore, the present Doctoral Thesis constitutes an attempt to better understand the neurophysiological and psychological mechanisms underlying human decision-making processes conceptualized under the Iowa Gambling Task context. The following sections of this chapter are intended to set the stage for the rationale and the approach to the study of decision-making processes employed during this work, providing some theoretical and historical perspectives from different research fields.

Decision-making from economics

> "[…] psychological theories of intuitive thinking cannot match the elegance and precision of formal normative models of belief and choice, but this is just another way of saying that rational models are psychologically unrealistic".
>
> Daniel Kahneman, 2003.

Human and non-human organisms share many features that had been naturally selected to guarantee survival. One of these shared features, perhaps the most important, is learning. Learning is the way through which the behaviour of organisms adjusts and adapts to increase their probability to survive in an unstable and changing environment. Although, as stated by Domjan (1982), "a universally accepted definition of learning does not exist", it seems to be evident that learning is at the basis of maintained behavioural strategies and cognitive skills presented by organisms.

Decision-making is one of these *learned* skills (Newell et al., 2015). Non-human and human animals have to make important decisions every day of their lives, from when to feed or when to sleep, to deciding on a safe place to raise offspring. Deciding implies choosing a course of action from a set of alternatives. Some of the most basic decisions for survival might be on whether it is appropriate to change one's behaviour or, on the contrary, to persist in the current action. For instance, when to go foraging. Foraging requires many decisions to be made (Stephens, 2008), so several factors must be assessed by the animal when going to search for food sources (McFarland, 1977) such as potential food gains, predation risk or increasing hunger (McFarland, 1977; Stephens, 2008), to decide whether to stay or to leave the nest. Then, the resulting behaviour (*staying* or *leaving*) will be often the one that maximizes the chances of survival and reproduction of the organism in its environment, or, in other words, the one

which increases its fitness, in a Darwinian sense of the term (Smith and Winterhalder, 2017).

Following classical decision theory, this would be very similar to what happens in humans; but in this case, a good decision has been traditionally understood as a *rational* decision. After all, human is labelled as the rational animal for a reason (Santos and Rosati, 2015). However, how is a rational choice defined? Many authors have situated the philosophical roots of the concept of rational choice in an exchange of letters between the mathematicians Blaise Pascal and Pierre Fermat (Hertwig et al., 2004). A rational choice would be defined as the choice associated with the highest expected value (EV) among other choices, being EV defined as *"the sum of the product of the probability of an outcome and the value of that outcome"* (Kahneman, 2011; Newell et al., 2015). For instance, consider a situation where one would win 50€ with a 30% probability and 25€ with a 70% probability. Then, the EV of that choice would be 32.5 (50 * .3 + 25 * .7). If a decision-maker had to choose between that situation and another like a 95% chance to win 25€ or 40% chance to win 60€ (EV = 25 * .95 + 60 * .4 = 47.75), then, following rational decision theory, they always would choose the situation presenting the highest EV.

Imagine a situation where a decision-maker had to choose between receiving certainly 2000€ and wagering an amount of money on the following game. A coin is to be flipped until it comes tails. If the coin comes tails in the first flip, the decision-maker would earn 2€. If it comes tail in the second flip, the gain would be 4€. If it occurs in the third, the total outcome would be 8€. Following this, the decision-maker would earn 2^n €, where n is the number of tosses needed to get tails on the coin. Two questions could be derived from this situation. First, should the decision-maker take the certain 2000€ or play the game? And second, how much money should the decision-maker bet if they

decide to play? Following rational decision theory, the decision-maker should not only play the game but bet everything at their disposal, as the game presented an infinite expected value. This is Nicholas Bernoulli's St. Petersburg paradox, which reflects that even in a gambling context with an infinite EV people will be willing to pay small amounts. His cousin, Daniel Bernoulli, warned that in this situation most humans would choose safe money because of risk aversion, so the classical formulation of the EV could be not representative of how humans evaluate those contexts to decide. Bernoulli introduced the concept of expected (or subjective) utility (EU) to resolve the St. Petersburg paradox. The EU supposes the replacement of the objective value of the outcome of a decision, with the subjective value that a certain outcome has for a decision-maker, so the utility of the outcome increases or decreases nonlinearly (as the EV does), but logarithmically with its the objective amount (Davis et al., 2013; Hertwig et al., 2004).

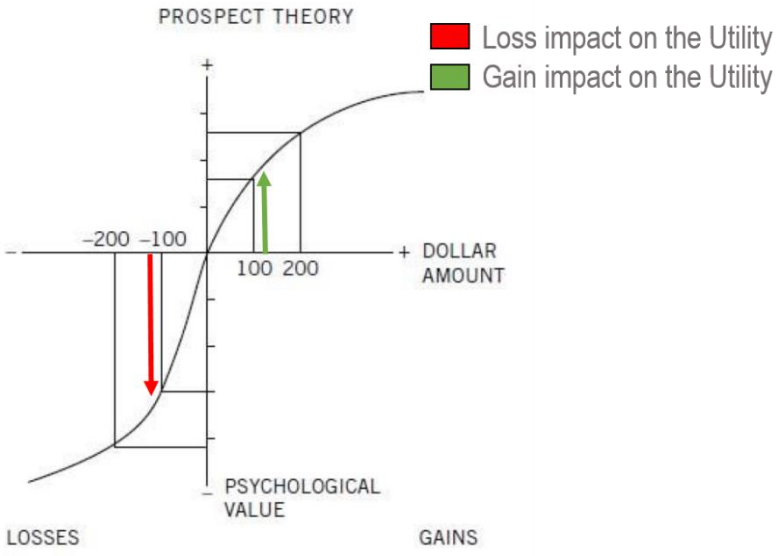
One of the most important attempts to build an axiomatic theory of rational decision-making comes from the mathematician John von Neumann and the economist Oskar Morgenstern when their book entitled *Theory of Games and Economic Behavior* (1947) was published. The Expected Utility Theory (EUT) is considered the "major paradigm in decision-making since the Second World War" (Schoemaker, 1982). The EUT proposes four mathematical axioms (transitivity, completeness, independence, and continuity) attempting to describe or define what underlies a rational decision-maker (von Neumann and Morgenstern, 1947).

The EUT has not been free of criticisms stemming from research testing each of its axioms. Perhaps, one of the most important critiques of the EUT comes from the Prospect Theory developed by Kahneman and Tversky (1979). Kahneman and Tversky developed a body of experimental work where participants were exposed to various

uncertain situations in which they had to choose between two alternatives. They provided clear evidence about the usual violations of the axioms of EUT when humans have to make such decisions. Following the Prospect Theory, the value of an outcome is multiplied by decision weights, which are not only probabilities (as in the EUT theory) but reflect the impact that a change of an outcome has on a reference point. Then, the gains and losses derived from a choice, and not the final amount, would drive the psychological value of an outcome. Furthermore, it is argued that losses will influence more negatively than gains positively on the psychological value of a possible outcome, which is named *loss aversion* (see Figure 1).

Figure 1

Graphical description of the utility function proposed by the Prospect Theory.



Note. Adapted from Kahneman, 2011. Thinking, Fast and Slow. Copyright: original publisher.

Despite the precision of the mathematical formulations of the EUT and their variants, observed decisions in humans (and non-human animals; Ferrari-Toniolo et al., 2022) usually deviate from the predictions of the EUT models. In other words, real choices do not always fit with the rational decisions that humans are supposed to make

(Arioli et al., 2018; Colman, 2003; Kahneman and Tversky, 1979; Sanfey, 2007; Santos and Rosati, 2015). The human described by the EUT is an *economic* human. Following Edwards (1954), the economic human is completely informed and rational, which means that they would be able to take all decision surrounding information, integrate it and make a choice that maximizes something. In contrast, Simon (1955) supported that the decision-maker is usually a *boundedly rational* agent, so a completely rational decision will be hardly made because of the limited capacity of the input information process. The real world is uncertain, and decision-makers are often unaware of all alternatives or consequences when decisions are made. At this point, a rapid or even automatic, evaluation, namely heuristics, of the whole decision context may lead the decision-maker to look for not an optimal (or rational) choice, but just a satisficing one (Fiori, 2011; Kahneman, 2003; Simon, 1955, 1990). Taken together, the existence (and inevitability) of heuristics makes classical normative models of decision-making not as desirable as expected to predict human behaviour (Tversky, 1975), especially in social interactions (Colman, 2003). Other *irrationalities*, such as preferences for a certain set of probabilities or the tendency to risk-taking behaviour, or even emotional states, may also challenge the basic assumptions of these economic decision theories (for an excellent review, see Edwards, 1954). In the end, human is not an *economic* organism, it is just human.

Decision-making from psychology and neuropsychology

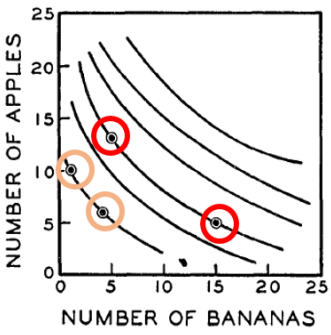
"It is therefore not without merit to suppose that in many decisions affect plays a more important role than we are willing to admit".

Robert B. Zajonc, 1980.

Making a decision requires a set of alternatives and a variety of courses of action to choose, and, usually, moves the decision-maker from one state into another one. Experimental psychologists have studied this process since the early 60s. Back a few years, the British economist Francis Edgeworth introduced a concept that was very useful for psychologists interested in decision-making: indifference curves (Edgeworth, 1881, from Edwards, 1954). The basic notion of the indifference curve is that, when choosing between two options and, assuming that utility is a continuum, there will be infinite points in which decision-makers will present an indifferent state, regardless of the expected utility of the choice. In Figure 2, each indifference curve links the combination of two equally desirable outcomes and the points represent states of indifference between each outcome. For instance, in the first indifference curve, there could be two (or more) states (points) in which the decision-maker would consider both options (10 apples and 0 bananas and 5 apples and 5 bananas) equally desirable.

Figure 2

A graphical example of a hypothetical indifference map.



Note. Adapted from Edwards, 1954, copyright: original publisher. Coloured circles represent indifference points.

In 1965, Frank A. Logan published an experimental work in which hungry rats were placed at one end of a double-alley maze while different amounts of food were being placed at different delays on two different food cups at the end of each of the alleys of the maze. Rats were exposed to free and forced choice trials to ensure all rats faced and learned all conditions. In free choice trials both alleys of the maze remained open, so rats could go through both. Rats were considered to be committed to an alley when they crossed a photobeam. In forced-choice trials, one of the guillotine doors was closed, so rats were forced to seek the open alley. Then, the number of choices of each reward in each delay condition was registered.

Obtained results suggested that different combinations of preferences depending on amounts of rewards and delays could be identified consistently among male hooded rats, shedding light on the amount-delay of reward interaction and the indifference points of decisions (Logan, 1965).

Rachlin and Green (1972) studied pigeons' choice behaviour using a concurrent-chains procedure, in which two schedules of reinforcement were involved. In one of these (Choice Y), pigeons had to choose between a larger-delayed (LD) reward and a smaller-sooner (SS) reward. In this case, pigeons always chose the SS reward. However, when another choice (Choice X) is offered after a delay, the preference of the pigeons depends on the amount of delay. Their main finding was that when pigeons had to wait for a long time to get to Choice Y, then they tended to choose the LD reward (Rachlin and Green, 1972). This procedure was designed to study choice commitment in pigeons, and their results set the basis of self-controlled behaviour research (Domjan, 1998).

One key behavioural concept regarding self-controlled behaviour is that the value (or utility) of a reinforcer decreases as a function of time. In other words, the more time the organism must wait to obtain a reward, the less value it has for it. James E. Mazur (1987) developed the so-called delay discounting function to account for the mentioned phenomena. An impressive body of research, in both human and non-human animals, has been devoted to the study of delay discounting phenomena (for reviews, see Odum, 2011) and it has been proposed that an excessive discounting rate could be a central trait in several psychopathologies such as Substance Use Disorder (SUD), Obsessive-Compulsive Disorder (OCD), Pathological Gambling (PG) and Attention Deficit-Hyperactivity Disorder (ADHD) (Carlisi et al., 2017; Dixon et al., 2003; Ong et al., 2019; Robles et al., 2011; Steinglass et al., 2017). However, the conceptualization of delay discounting as a transdiagnostic domain has not been exempted from methodological and theoretical criticism (Bailey et al., 2021).

In the previous section, we exposed the classical decision theories and some of their basic assumptions like the decision-maker as an *economic* human (Edwards, 1954). This theoretical framework has dominated the psychological research on decision-making for most of the past century, leading to a purely cognitive perspective of this process. Research had been focused on identifying the "cognitive errors" through which decision-makers misestimate the odds of consequences (for reviews see, Lerner et al., 2015; Loewenstein and Lerner, 2003). Thus, decision-making was understood as a purely cold function. The concept of bounded rationality introduced by Simon (1955) opened, in some way, a relatively new discussion about the cognitive constraints that challenge the pure rationality under which organisms were supposed to make decisions. In 1980, the social psychologist Robert B. Zajonc published a widely applauded paper entitled *Feeling and Thinking. Preferences Need No Inferences* (Zajonc, 1980). In this

review, Zajonc claims, based on empirical evidence, that affective reactions do not occur only after cognitive processing of the input stimuli as it was widely thought, but affective reactions are usually the first reaction of the organism when facing diverse challenging situations. Actually, the human decision-maker assumed by the Prospect Theory is mainly driven by the immediate emotional impact of gains and losses (Kahneman, 2011). Therefore, if affective reactions are primary, then they could shape posterior cognitive processing. In this line, by the 90s, the influence of emotional states on decision-making was empirically demonstrated by a vast amount of research (Schwarz, 2000).

Another cornerstone of the research on the interplay of emotion, cognition, and decision-making comes from the works of Antonio Damasio and his colleagues. In 1985, Eslinger and Damasio published an interesting case report (Eslinger and Damasio, 1985). Patient E.V.R suffered a brain tumour affecting mostly bilateral orbitofrontal (OFC) and ventromedial prefrontal (vmPFC) areas of the brain. Despite E.V.R. demonstrating an average (and, in some cases, above average) performance on neuropsychological evaluation, he was no longer able to take positive actions for their life in real-life equivalent hypothetical problems. The decision-making deficits found in E.V.R. and other vmPFC patients inspired Damasio to think that they could be due to an inability to integrate emotion-related body signals that are evoked when organisms have to evaluate different action options (Dunn et al., 2006). This is considered the starting point of the Somatic Marker Hypothesis (SMH), which was formally developed in Damasio's *Descartes's error* book (Damasio, 1994; Dunn, 2006). The SMH has been considered a biological explanation of the relationship between emotional states and real-life decision-making (Bechara, 2004). These "somatic markers" would be useful in the evaluation of available options and, therefore, they may influence the decision-

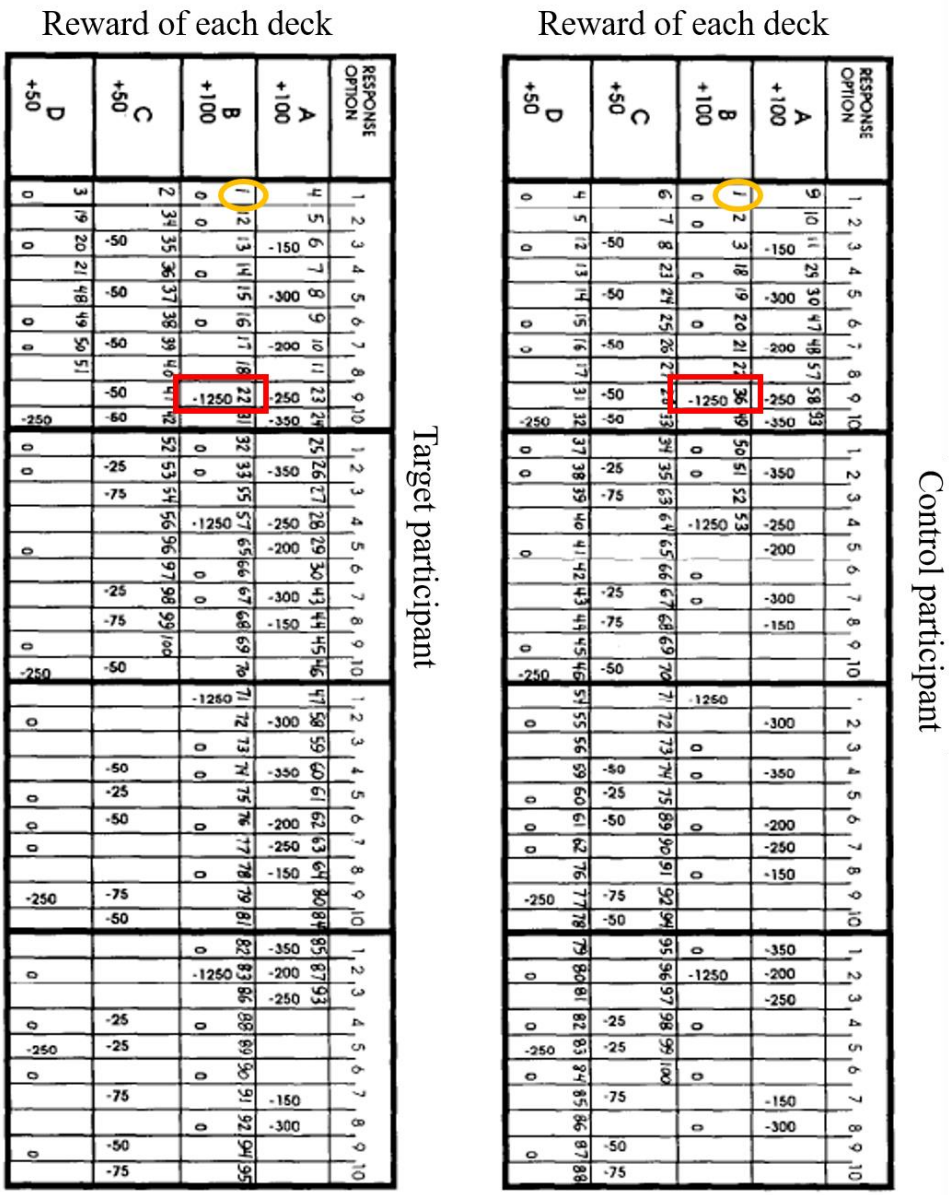
making process (Damasio, 1996), suggesting that decision is guided by emotion (Bechara et al., 1999; Bechara, 2004).

The first attempt to support the SMH with empirical evidence likely comes from Bechara, Damasio, Damasio, and Anderson (1994). In this work, Bechara and colleagues introduced to the field of the study of decision-making a new neuropsychological task to assess real-life decision-making problems: the Iowa Gambling Task (IGT; Bechara et al., 1994). The first time the IGT was applied, participants were given a starting loan of hypothetical $2000, and four different decks of cards were presented to them. Participants were instructed to maximize their profits by choosing cards, only one per trial, being free to switch from any deck to another, without knowledge about the total number of card selections they had to make. Each deck had a pre-programmed deterministic and sequential schedule of reward and punishment. An example of this can be seen in Figure 3. Each deck contained forty cards following a specific order. Picking any card from decks A or B yielded $100 while choosing decks C or D always resulted in $50. After choosing deck A 10 times, participants would have earned $1000, but they also would have encountered 5 punishments which sum would be $1250, resulting in a total net loss of $250. The same occurs with deck B, but the loss of $1250 happens all at once every ten cards. Decks C and D always offer $50 when chosen, and after 10 choices they result in a net gain of $250, but, similar to decks A and B, they differ in the frequency and magnitude of the punishment. Thus, decks A and B are called “disadvantageous decks” because they suppose a net loss in the long term, and decks C and D are “advantageous decks” because they result in a net gain in the long term (Bechara et al., 1994). The dependent variable was the net score, which is obtained by subtracting the number of disadvantageous decks picks from the number of advantageous deck picks (Bechara et

al., 1994). They found that E.V.R. and E.V.R.-type patients chose fewer cards from advantageous decks than healthy people and other brain-damaged patients. This finding was mainly interpreted as that kind of patients presented insensitivity to future consequences and were governed by immediate outcomes, what they called “myopia for the future” (Bechara, 2000; Bechara et al., 1994, 2000).

Figure 3

Examples of performance on the IGT of a healthy control and a typical target subject.



Note. Orange circles represent the trial in which each deck was chosen. Red rectangles represent the position of negative outcomes in each set of ten cards. Adapted from Bechara et al., 1994. Copyright: original publisher.

A few years later, the same research group conducted another interesting experimental procedure aiming to look for an explicit biological signal that was related to decision-making, or, in other words, a somatic marker. Bechara et al. (1999) compared the performance on the IGT of healthy people and bilateral amygdala (not vmPFC damage) and bilateral vmPFC patients. Additionally, they measured their skin conductance responses (SCRs) as an indicator of somatic (emotional) activation. They found amygdala and vmPFC-damaged patients underperformed healthy controls during the task. Both groups of patients presented less SCR, in general than the control group. However, when comparing the SCR generated by positive and negative feedback, only amygdala patients showed not to evoke SCRs. Findings were taken as evidence of the differential role of the amygdala (to generate somatic states associated with emotional attributes of stimuli) and vmPFC (to integrate somatic information) in decision-making processes (Bechara et al., 1999), and led, in some ways, to growing research aiming to the study of the neurological basis of decision-making.

Over the years, IGT has become one of the most widely used paradigms for evaluating decision-making. But also, critical reviews have increased together with their rise in popularity among the scientific community (for critical reviews, see Dunn et al., 2006; Steingroever et al., 2013; van den Bos et al., 2013). Potential influence variables for decision-making processes, such as personality factors (Suhr and Tsanadis, 2007), age (Beitz et al., 2014), sex (Reavis and Overman, 2001), educational level (Evans et al., 2004) and socio-economic status (Sheehy-Skeffington, 2020) have emerged. Conflictive and contradictory findings in both healthy and clinical populations have challenged the construct validity of the task and its clinical utility (Barnhart and Buelow, 2021; Buelow and Suhr, 2009). In addition, despite the effort that has been made by neuroscientists, the neurological basis of decision-making is still unclear.

Neuroimaging the decision-making processes

"So modern neuroimaging is like asking an astronaut in the space shuttle to look out the window and judge how America is doing".

David Eagleman, 2011.

Neuropsychologists have been historically devoted to disentangling the complex interactions between the central nervous system and behaviour (Savoy, 2001). This tradition began following a *localizationist* understanding of brain functions that was early influenced by Franz Joseph Gall's phrenology (Sutterer and Tranel, 2017). The first data supporting this localizationist view comes from acquired brain-damaged patients like Phineas Gage, "Tan" or H. M. (Savoy, 2001). Those patients shared the affection of specific functions (such as social skills, language, and memory) after their brain was injured, which will motivate future works on *brain mapping*.

Research in this field has stated that the prefrontal cortex is a critical region for decision-making (Aram et al., 2019; Friedman and Robbins, 2022). Among prefrontal cortex subregions, the orbitofrontal cortex (OFC) seems to play a very important role in this process. OFC corresponds to the ventral part of the frontal lobe and could be subdivided into five subregions (BAs 10, 11, 13, 14, and 47/12) (Wallis, 2007). It is mainly connected to somatosensory processing areas and limbic structures, due to which, it seems to be a crucial integration area, necessary to evaluate all aspects (hedonic and valence values, probabilities of success…) of a potential reward. OFC neurons have been shown to fire when presenting olfactory, visual, and gustatory information of a reinforcer, and even anticipating the outcomes (Schoenbaum et al., 1998; for a review, see Wallis, 2007). One of the main functions of the OFC, at least in primates (including humans), is the evaluation of the consequence of an action, or, in

other words, the evaluation of the stimulus-reinforcement association (Rolls, 2000; Rolls and Grabenhorst, 2008). The value (or utility, in decision theory terms) would be, therefore, represented by the OFC functionality (Hare et al., 2008; Kim et al., 2006; Rolls et al., 2008).

However, other studies have shown that those reward neurons can be found not only in the OFC but also in other areas such as the dorsolateral prefrontal cortex (DLPFC) (for a review, see Wallis, 2007). In this sense, Tanaka et al. (2004) established an interesting distinction in the role of different brain regions in the evaluation of the reward as a function of the delay of its presentation. While lateral OFC and striatum presented a significant activity when the learning process was based on immediate rewards, DLPFC, among other areas, was activated when participants learn to behave in a long-term goal-directed manner. DLPFC is another important subregion of the frontal lobe, functionally constituting BA46, 9, 9/46, and 8 (Carlen, 2017; Haber et al., 2022). DLPFC has been suggested to be a core area in executive functions (EEFF) (Koechlin and Summerfield, 2007; Miyake et al., 2000; Nejati et al., 2018). Working memory is a central executive function responsible not only for storing information but also for actively manipulating it in order to perform complex tasks (Baddeley, 1992). Following this definition, one feasible link between working memory and decision-making is that organisms would need to actively maintain the information related to a consequence of a certain choice and use this information to guide their behaviour in an adaptive way. So, DLPFC may be also implicated in decision-making, specifically in decision-making under explicit risk conditions (Brand et al., 2006; Schiebener and Brand, 2015) via working memory (Bechara and Damasio, 2005; Li et al., 2010). Actually, DLPFC has been proposed to take part in the neurological circuitry that underlies the IGT performance (Li et al., 2010). However, contradictory results from spatial neuroimaging

studies have been also reported in this sense (for a more detailed review, see Aram et al., 2019), which means that more research in this field is still needed.

Nowadays, the localizationist perspective is losing popularity in favour of other approaches based on the premise that cognitive functions are dependent not only on a brain area but on its connections with other regions (for an extensive review, see Sutterer and Tranel, 2017). Thus, another compendium of research has focused on the study of the neurological basis of decision-making from this *connectionist* perspective. Instead of exploring whether a certain brain region is activated or deactivated during a task, brain-connectivity-devoted researchers assume that the neurological basis of a cognitive process is not a region itself, but its connections with other regions. In other words, they focused on the synchrony between signals originating from different and dispersed regions of interest (ROIs). Three main and different approaches to brain connectivity have been proposed: neuroanatomical connectivity, functional connectivity, and effective connectivity (Fingelkurts et al., 2005). Neuroanatomical connectivity refers to the synaptic connection between close neurons or between spatial distant areas through the white matter (Lang et al., 2012). Functional connectivity refers to "the temporal correlation of a neurophysiological index measured in different brain areas" (Friston et al., 1993). It is worth noting that functional connectivity informs only about temporal correlations, not about directionality or causality between areas (Friston et al., 1993). Effective connectivity, on the contrary, is defined as the influence of one ROI over another one (Friston et al., 1993), which necessarily implies directionality and causality. Following Fingelkusts et al., (2005), functional connectivity represents the most challenging approach to brain connectivity and for theories aiming to explore brain-behaviour relationships.

The study of the brain as an efficient network has yielded a vast body of growing research aiming to discover functional networks, such as the default mode network (DMN) and the frontoparietal network (FPN) or central executive network (CEN) across the whole brain (van den Heuvel and Hulshoff Pol, 2010). The DMN is a large-scale functional network consequence of the synchronized functioning of the vmPFC, dorsomedial prefrontal cortex, the posterior cingulate cortex, and adjacent precuneus plus the lateral parietal cortex (Raichle, 2015). Recently, it has been proposed that the DMN would also comprise subcortical areas such as the basal forebrain, cholinergic nuclei, and anterior and mediodorsal thalamic nuclei (Alves et al., 2019). The DMN activity usually decreases when the organism is challenged by a task, so it could be a reflect of spontaneous brain activity during the resting state (Raichle, 2015; Smallwood et al., 2021). The discovery of the DMN has attracted the attention of many researchers interested in establishing relationships between spontaneous brain activity and psychiatric disorders (for reviews, see Bathelt and Geurts, 2021; Hu et al., 2017; Whitfield-Gabrieli and Ford, 2012; Zhang and Volkow, 2019). On the other hand, the FPN seem to be recruited in contexts where executive functioning is needed and comprises a broad range of areas such as DLPFC, OFC, frontopolar cortex, and anterior cingulate cortex (ACC), as well as subcortical regions such as the basal ganglia and cerebellum (Niendam et al., 2012).

However, fMRI-based research has not been free from criticism due to its methodological limitations, mostly the poor signal-to-noise ratio (SNR) when an event-based paradigm is applied (Greicius, 2008). Biswal et al. (1995, 1997) proposed an innovative experimental design in which they studied the functional connectivity of spontaneous low-frequency brain signals (blood level oxygen dependent, BOLD). In other words, they studied the resting-state functional connectivity (rsFC) of the

somatosensory cortex. This rsFC approach to brain connectivity is supposed to overcome some fMRI limitations and has led to an emerging new field of research in clinical neuroscience, revealing stable brain networks that could be the basis of neurological diseases (Greicius, 2008; Mulders et al., 2015; Sheffield and Barch, 2016). rsFC has been shown to be predictive of personality traits (Nostro et al., 2018), executive functions (Gordon et al., 2015), fluid intelligence (Cole et al., 2012; Finn et al., 2015) and the behavioural deficits following stroke (Siegel et al., 2016). Concerning the application in the clinical population, the disruption in rsFC networks is being considered a promising biomarker (Deco and Kringelbach, 2014; Yamada et al., 2017).

Recently, functional Near-Infrared Spectroscopy (fNIRS) has been emerging as a promising neuroimaging technique, since it can be used in unsuitable situations for fMRI, such as real-world and movement environments, and it is easy to combine with other techniques such as electroencephalography (EEG) or transcranial electrical stimulation techniques (TES). fNIRS is an optical and non-invasive neuroimaging technique that enables to monitor relative changes in the concentration of oxy- (HbO) and deoxy- (HbR) haemoglobin related to human cortical brain functions (haemodynamic activity) (Venclove et al., 2015). Within the last few years, fNIRS has been validated as a suitable method to provide valuable information about cortical functional connectivity, yielding comparable results to fMRI (Duan et al., 2012; Sasai et al., 2012). This technique offers a more versatile and easier data collection with a higher temporal resolution than fMRI (Pinti et al., 2018). However, as a limitation, only the haemodynamic activity of cortical areas can be registered.

Electroencephalography (EEG) is another promising non-invasive neuroimaging technique useful to understand the neural mechanisms that underlie cognitive processes, especially due to its excellent temporal resolution (Britton et al., 2016; Light et al.,

2010). EEG registers the electrical activity of the neurons as the summation of the synchronously generated postsynaptic potentials (Blinowska and Durka, 2006), consequently, it is a suitable technique to combine with neurostimulation tools. EEG signals could be divided into different bands based on different postsynaptic potentials frequencies. Low frequency bands would be delta (< 4 Hz) and theta (4-8 Hz), while high frequency bands would be alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-100 Hz). Each of these frequency bands have been associated to different, but also to overlapping psychological processes (Cavanagh and Shackman, 2015; Foxe and Snyder, 2011; Herrmann et al., 2004; Nicolas-Alonso and Gomez-Gil, 2012; Viviani and Vallesi, 2021).

A large body of EEG-based research has been aslso focused on event-related potentials (ERPs), which could be defined as small changes in the voltages of EEG activity generated by events or stimuli in a certain brain region. Thus, ERPs would manifest the time-locked activation of a neural population due to an external stimulus (Blackwood and Muir, 1990; Sur and Sinha, 2009). ERPs presented several components based on wave latency and amplitude and have been proposed as a suitable way to study the neurophysiology of several psychological processes (for a review, see Sur and Sinha, 2009).

Neuromodulating the decision-making processes

The notion of the use of electricity for medical purposes was born in the Roman Empire. The court physician of the emperor Claudius, Scribonious Largus, wrote about the use of the torpedo fish to treat headaches and gout, which could be considered the first proposal of transcutaneous electrical nerve stimulation (TENS) as a tool to alleviate pain (Wagner et al., 2007). For many years, neuroscientists had adopted an *observer perspective* when studying the neurological correlates of cognitive processes and behaviour in humans (Vosskuhl et al., 2018) until the irruption of non-invasive brain stimulation (NIBS) techniques in the scientific field. NIBS allowed neuroscientists to manipulate actively and safely the excitability of certain brain regions, and therefore, to propose new diagnostic and therapeutic approaches to better understand the brain-behaviour relationship (Boes et al., 2018; Vosskuhl et al., 2018).

The most established NIBS are transcranial magnetic stimulation (TMS) and transcranial electrical stimulation (TES) techniques (Vosskuhl et al., 2018). TMS was introduced by Baker, Jalinous, and Freeston in 1985 and, rapidly, it became one of the most used NIBS in clinical and research contexts (Hallett, 2000). For TMS, a wired coil is placed about the scalp and a magnetic field is generated through a high-current pulse into the coil. The magnetic field is produced by lines of flux that pass perpendicularly to the plane of the magnetic coil (Hallett, 2000, 2007). This magnetic field would flow through the scalp provoking neuronal depolarization and, therefore, action potentials (Barker and Shields, 2017) that may induce behavioural changes (Galletta et al., 2011). Thus, TMS is thought to be a reliable approach to better understanding the neural basis of cognitive processes and pathologies. TMS can be applied following three different methods. Single-pulse TMS consists of the administration of only one electrical pulse

every few seconds over the targeted area. In repetitive TMS protocols, on the contrary, a series of pulses are applied. TMS can also be applied through two different pulses, which is named paired-pulse TMS (Galletta et al., 2011). The physiological and behavioural effects of TMS may vary depending on the frequency of the stimulation, the geometry and positioning of the magnetic coil, the endogenous frequency, and the rate of stimulation, among other factors (Barker and Shields, 2017). TMS has been used in the clinical field to treat migraine (Barker and Shields, 2017; Lan et al., 2017), major depressive disorder (MDD; Croarkin and MacMaster, 2019), OCD (Carmi et al., 2019; Liang et al., 2021; Perera et al., 2021) and schizophrenia (Shi et al., 2014). However, its effect on cognition remains unclear (Beynel et al., 2019).

The starting point of TES could be situated along with Volta's invention of the electric pile (Paulus, 2011). As early as 1802, Hellwag and Jacobi already wrote about the potential therapeutic effects of the application of direct current in stroke patients (Paulus, 2011; Sarmiento et al., 2016). Early uses of weak (< 2 milliamperes) transcranial direct current stimulation (tDCS) can be observed around 1880 among German psychiatrists, but around 1930 tDCS disappeared from the clinical and research fields, due to unclear and varied methodological procedures (Sarmiento, 2016). As pointed out by Brunoni et al. (2012), the re-born of tDCS as a potentially useful tool to modulate brain activity could be situated in the work of Priori and colleagues (Priori et al., 1998). Two years later, Nitsche and Paulus (2000) applied a weak direct current to the motor cortex through a pair of electrodes (anode and cathode) and recorded the motor-evoked potentials (MEPs) by stimulation. They stated that anodal and cathodal weak direct stimulation is able to increase or decrease (respectively) the excitability of neurons of the target area. This modulation is not induced by a "direct" effect on the membrane potential, but by modulating the resting membrane potential. Therefore,

tDCS would facilitate or impede the fire of an action potential, but it does not cause an action potential *per se* (Brunoni et al., 2012). At a molecular level, excitatory tDCS effects seem to be related to GABAergic and glutamatergic (via N-methyl-D-aspartate receptors facilitation or its inhibition) systems (Liebetanz et al., 2002; Stagg et al., 2009), and to modulation of ionic concentration (Ardolino et al., 2005). As shown by Nitsche and Paulus (2001), continuous tDCS that last from nine to 13 minutes yielded an increasing MEP amplitude that lasted from 30 to 90 minutes, respectively.

So far, tDCS has shown great safety outcomes in its use for humans (Bikson et al., 2016). This fact together with its neuromodulatory capabilities has evoked an increasing interest, especially in the neurorehabilitation field (Dubljević et al., 2014). Administered over the PFC, the results comprehend improvements in executive functions (Boggio et al., 2006; Dockery et al., 2009; León et al., 2020; Zaehle et al., 2011). In clinical populations, prefrontal tDCS has shown promising clinical outcomes (Kekic et al., 2016; Kuo et al., 2014), decreasing psychiatric symptomatology in attention deficit hyperactivity disorder (Ditye et al., 2012; Soff et al., 2017), OCD (Brunelin et al., 2018) or schizophrenia (Brunelin et al., 2012). However, several meta-analyses (Dedoncker et al., 2016; Horvath et al., 2015; Tremblay et al., 2014) have reported that the benefits over cognitive performance are not completely consistent. Mixed, occasionally opposite, effects in various cognitive domains are common, especially in single-session protocols (Horvath et al., 2015; Senkowski et al., 2022). Thus, the scientific community devoted to tDCS claims a more deep understanding of the effects and underlying mechanisms of this technique over the stimulated region.

Another TES technique that has become core in the neuromodulation field is transcranial alternating current stimulation (tACS). In contrast to tDCS, tACS targets relevant brain oscillations in a frequency-specific manner (Ali et al., 2013; Herrmann et

al., 2013). As one may think, one of the key points of tACS is the stimulation frequency. Brain electrical activity can be divided into 5 different frequency bands depending on their frequency (delta, theta, alpha, beta, and gamma, from slow to fast) (Hanslmayr et al., 2019). Two main mechanisms of action of tACS have been proposed: oscillation entrainment and resonance (Ali et al., 2013; Herrmann et al., 2013; Nasr et al., 2022). On the one hand, entrainment is referred to the modulation of the natural rhythms of neural oscillations, by which neurons would start firing at the stimulation rhythms (Hanslmayr et al., 2019). On the other, resonance is the increase in the amplitude of the oscillations as a consequence of frequency-specific stimulation (Ali et al., 2013; Herrmann et al., 2013; Nasr et al., 2022). tACS at different frequencies have been used in basic research to study the neurophysiological basis of cognitive processes such as working memory (for an extensive review, see Senkowski et al., 2022), decision-making (Wischnewski and Compen, 2022; Yaple et al., 2017) and attention (Baldauf et al., 2016; Hopfinger et al., 2017).

NIBS techniques constitute a promising tool to better understand the neurological basis of different behavioural processes and a potential therapeutical strategy in the clinical field. Combined neuroimaging-NIBS and behavioural paradigms approaches may allow researchers to disentangle the brain-behaviour relationship underlying several psychological processes. First, NIBS allows an active manipulation of the basal functioning of a certain cortical area or a specific neuronal frequency band. Second, neuroimaging would serve to directly observe the magnitude of the induced manipulation. And third, researchers can observe whether the stimulation has produced a behavioural change. Despite the potentiality of such approach to the understanding of the brain-behaviour relationship, the mixed and, occasionally, contradictory findings and methodologies employed across research, call for further investigation on this topic.

CHAPTER 2. GENERAL RATIONALE AND APPROACH

As exposed in the first Chapter, human decision-making has been studied from different scientific fields such as economics, psychology, and neuroscience using different behavioural paradigms and neuroimaging and neurostimulation techniques, given that it is a process that is as complex as it is cardinal in daily life well-functioning. The present Doctoral Thesis aimed to fill some remaining gaps of knowledge about the decision-making process conceptualized under the IGT context, as well as its neurological basis, through four different studies that cover different levels of analysis within the RDoC framework. Specifically, at the behavioural level, all people who participated in the Studies were exposed to the IGT, which is one of the most widely used paradigms to assess contingency-based decision-making processes under uncertain situations. We paid special attention to individual differences in healthy people (Studies I and II) and impulsive-compulsive spectrum patients when performing the task (Study III). We also applied computational models of reinforcement learning to investigate the psychological aspects driving decision-making under the IGT context (Studies II and III). Eventually, we proposed novel theoretical and statistical approaches to the understanding of the IGT and its underlying psychophysiological processes (Studies II, III and IV). At the physiological level, we used fNIRS and EEG in combination with NIBS techniques such as tDCS and tACS for different purposes, which are discussed below

Study I was designed with the aim of investigating the sex differences that previous research had shown to emerge when the healthy population faces the IGT. Additionally, we were interested in the potential capability of tDCS to enhance decision-making, and in its differential effect as a function of sex when applied over an

IGT-related brain region such as the right orbitofrontal cortex. In this study, the total Net Score was used to make inferences about the performance of our participants.

This traditional conceptualization of the IGT performance adopted in Study I led to a period of rethinking the amount of useful information concerning the decision-making process that the total net score may be hiding. In Study II, therefore, we focused on how healthy undergraduates develop (or not) a preference for a certain deck as they are learning from their experience with them, and on how they respond in a changing environment. In other words, we aimed to identify idiosyncratic decision-making profiles or strategies and to explore whether these strategies are maintained when the environment changes.

Study III followed the same rationale, and aimed to identify those profiles not only in the healthy population but also in impulsive-compulsive spectrum patients. Also, measures of rsFC between nodes belonging to the frontoparietal network were recorded through fNIRS in order to investigate its role as a potential biomarker of maladaptive and/or adaptive decision-making strategies.

Lastly, Study IV tried to modulate, again, the decision-making process. In this case, instead of using tDCS, which effect might be unspecific, tACS was used to target a specific EEG frequency band. In particular, the aim was to investigate the role of frontal-midline theta oscillatory activities in the IGT performance, as well as the capability of tACS to modulate it. In this study, the identification of particular decision-making strategies was not possible due to the reduced number of subjects, so the IGT performance was conceptualized following a fully probabilistic approach, which may lead to clear definitions of different processes that occur during the task, and, therefore to a better understanding of them.

A detailed and specific rationale for each Study can be found within their respective Chapters. In addition, a summarized schedule of research objectives can be consulted in Table 1.

From Study I onwards we switched from frequentist statistics to Bayesian statistics in our approaches, we believe that, at this point, it is worthwhile to point out, briefly, a few basic concepts about Bayesian data analysis. When we try to study a natural phenomenon, we usually have a *prior* certain degree of information about the functioning of that phenomenon. Then, we make observations and update our prior knowledge towards the most plausible explanation of the phenomenon through the Bayes' rule, which is considered a reliable mathematical approach to this process (Kruschke and Liddell, 2018a, 2018b). The result of this process is a *posterior* degree of knowledge about each plausible explanation of the phenomenon. This is essentially Bayesian analysis: the "reallocation of credibility across possibilities" (Kruschke and Liddell, 2018a, 2018b).

Consider the following case. The neighbour's baby has started crying at ungodly hours. You have heard in the neighbourhood that the baby has been colicky for a few days, so likely your first intuition would be that the baby is crying because of pain. However, there may be many other explanations for the baby's crying. For example, they might be hungry, have had a bad dream, or be getting their parents' attention. All these possible explanations are called *parameters*, and, bearing in mind what we heard about the colic, we will allocate a *prior distribution* of plausible values to each one. To put an end to the uncertainty surrounding the baby's crying, you decide to go and ask your neighbour (or to collect data or observations). The neighbour's response (for example, my baby is hungry) will lead to an update of our *prior distribution* of

possibilities (or to a reallocation of the credibility of each parameter), which will result in an updated *posterior distribution* of each parameter.

This *posterior distribution* will reflect the degree of uncertainty about the credibility of the value of the parameters and can be directly examined to make inferences. Posterior distribution contains an updated (for prior distribution) range of the most credible values of each parameter of interest, given new observations (Kruschke and Liddell, 2018a, 2018b). The 95% of the most credible values of each parameter constitute the 95% of the high-density interval (HDI) or, in other words, the 95% of the HDI includes the 95% most credible values of each parameter of interest (Kruschke and Liddell, 2018a, 2018b). Therefore, statistical decisions can be made directly observing and comparing the HDIs of the posterior distribution of each parameter of interest.

Table 1

Summarized research schedule and objectives.

Study I.
Explore individual differences (sex-related differences) on the IGT.
Explore the role of the rOFC in decision-making under the IGT context.
Explore the capacity of anodal tDCS to modulate decision-making.
Explore the interaction between sex and anodal-tDCS in decision-making.
Study II.
Explore the idiosyncratic choice behaviour of undergraduate students on the IGT.
Explore the capability of undergraduate students to adapt their behaviuor to unexpected and changing contingencies.
Identify particular behavioural profiles that could emerge when performing the IGT.
Study III.
Explore the deck preferences of healthy and impulsive-compulsive spectrum patients during the IGT.
Identify particular decision-making profiles in impulsive-compulsive spectrum patients and healthy controls based on their deck choice behaviour during the IGT.
Investigate the role of rsFC between different regions of the FPN as a possible biomarker of this idiosyncratic choice behaviour.
Study IV.
Explore the role of frontal-midline theta power in IGT performance.
Explore the capability of theta-tACS to modulate the decision-making process.
Explore the potential of understanding the IGT performance from a fully probabilistic perspective.

CHAPTER 3. STUDY I: Transcranial direct current stimulation improves risky decision making in women but not in men: A sham-controlled study

This study constitutes the first contact with the IGT and neurostimulation techniques of the present Doctoral Thesis. We aimed, firstly, to explore sex-related differences in IGT and, secondly, to explore whether anodal-tDCS over the right OFC could boost the decision-making ability of our participants. We conducted a single-session pre-post experimental procedure. First, participants completed the IGT. Then, they were asked about their willing to continue with the stimulation phase. Anodal-tDCS and sham-tDCS over the rOFC were applied for 20 minutes, after which, participants performed the IGT again. Our main finding was a sex-dependent tDCS effect by which only women who were under anodal stimulation improved their performance between sessions.

This experiment was published in León, J.J., Sánchez-Kuhn, A., Fernández-Martín, P., Páez-Pérez, M.A., Thomas C., Datta A., Sánchez-Santed F., & Flores P. (2020). Transcranial direct current stimulation improves risky decision making in women but not in men: A sham-controlled study. *Behavioural Brain Research*. DOI: 10.1016/j.bbr.2020.112485.

Rationale

tDCS over the prefrontal cortex has shown clinical improvements in decision-making measured by IGT in Parkinson's disease (Benussi et al., 2017) and gambling disorder (Soyata et al., 2019), as well as an enhancement of decision-making in healthy adults (Fecteau, Knoch, et al., 2007; Fecteau, Pascual-Leone, et al., 2007; Ouellet et al., 2015). These studies have contributed to a new rehabilitation approach to risky decision-making, suggesting that this process could be modulated. However, with exception of Ouellet et al., (2015), these studies have targeted the DLPFC as the stimulated region. Some studies have been focusing on the role of the dorsolateral prefrontal cortex in IGT (Brand et al., 2006; Manes et al., 2002), although this task seems to be mainly related to right OFC activity (Lawrence et al., 2009; Verdejo-Garcia et al., 2007).

Previous literature has proposed sex as a modulating variable in IGT performance (Evans and Hampson, 2015; Reavis and Overman, 2001; van den Bos et al., 2013), being these differences attributed to a different sensitivity to punishment when long-term advantageous decks are chosen (Eriksson and Simpson, 2010; van den Bos et al., 2013). Following the abovementioned studies, both men and women choose deliberately advantageous decks when they realize they suppose a net gain, but women seem to need a greater number of trials to learn this strategy. Women's decision-making strategy is supposed to be driven more by punishment and gain-loss frequency, changing, and scattering their response strategy after each loss and preferring decks with rare losses (for an extensive review see van den Bos et al., 2013).

At a neuroanatomical level, sex-related different activation patterns have been also found during the IGT (Bolla et al., 2004; Reber and Tranel, 2017; Sutterer et al., 2015). In this sense, Bolla et al. (2004) have shown that men had right-hemisphere

lateralization and a significantly increased activation in the right lateral orbitofrontal cortex compared to women during the task performance, while women showed greater activation in the left medial frontal gyrus, left temporal lobe, and left medial orbitofrontal cortex.

Moreover, the tDCS technique presents high rates of inter-and intra-individual variability (Li et al., 2015), a decisive issue that needs to be clarified to move toward more effective and individualized-based treatments. This variability within the strength of the outcomes has been attributed due to different explanations, including the role of sex. tDCS studies have consistently reported results of an interaction effect between cortical modulation and sex, where women usually show higher behavioural benefits from the stimulation (for review see Dedoncker et al., 2016) and also heightened cortical excitability compared to age-matched male subjects (Chaieb et al., 2008). Therefore, previous literature points out that neuromodulation studies may find more meaningful results if they are analysed by sex (Russell et al., 2014). In this sense, while sex-dependent differences have not been explored in decision-making after tDCS, a different response to anodal tDCS has been reported in women and men in other cognitive functions. In this way, anodal tDCS has been shown to increase search behaviour (Yang et al., 2017), theory of mind ability (Adenzato et al., 2017), and emotion recognition (Boggio et al., 2008) in women but not in men. In addition, enhancement of verbal working memory depends on right DLPFC stimulation in women while left DLPFC in men (Meiron and Lavidor, 2013); and social norm compliance decreases in women and increases in men after anodal stimulation over right DLPFC (Chen et al., 2019).

The present work aims at exploring the interaction of sex and tDCS in decision-making processes by studying the specific stimulation of the rOFC over a healthy

sample of male and female participants. Following previous literature, we hypothesized that (1) men will show a better performance in IGT than women, (2) anodal tDCS over the rOFC would improve decision-making and (3) tDCS effects would be sex-dependent.

Method

Experimental procedure

Two different experimental phases were conducted. The first phase aimed to explore sex-related differences in IGT, in which ninety-one participants were recruited to perform this task. Sixty-one participants agreed to continue with the stimulation phase. These participants received a single session of anodal or sham tDCS for 20 min. Right before and immediately after the stimulation, participants completed parallel versions of the IGT. Additionally, a Stop Signal Task (SST) was used as a control task to ensure the focality of the montage. SST is a response inhibition measure that has been found to be unrelated to the activation of the rOFC (Aron, 2006; Jacobson et al., 2012). The experimental procedures were approved by the Bioethics Committee of Human Research of the University of Almeria, Spain. The volunteers gave their informed consent to participate in the study, which was performed following the ethical standards of the World Medical Association Declaration of Helsinki (1991; p.1194). All personal information was treated according to the Spanish Protection of Personal Data Law 15/1999 of 13 December.

Participants

In the first phase, ninety-one non-clinical volunteers were recruited from the University of Almeria (M_{age} = 20.76; SD = 3.08; 54.9% women) (see Table 2). A demographic and screening questionnaire was also administered to confirm the following inclusion criteria: (1) naïve to the behavioural tasks and tDCS, (2) absence of

consumption of drugs or psychotropic substances, (3) no diagnosed psychopathology, (4) no history of epilepsy, (5) under thirty-five years old, and (6) no metallic implants in the head area. A reward of five Euro was offered.

Table 2

Number (n) and age (Mean ± Standard Deviation) of the participants in the first experimental phase.

Group	Women	Men
N	50	41
Age (Mean ± Standard Deviation)	22.28±6.44	21.02±5.29

Sixty-one participants continued to the second phase (M_{age} = 20.75; SD = 2.82; 55.7% women). They were pseudo-randomly assigned to the anode or sham groups while controlling for sex distribution (see Table 3).

Table 3

Number (n) and age (Mean ± Standard Deviation) of the participants in each group in the second experimental phase.

Group	Anode		Sham	
	Women	**Men**	**Women**	**Men**
N	16	15	18	12
Age (Mean ± Standard Deviation)	21.06±3.53	20.53±1.24	20.61±2.27	20.83±4.01

Materials

Iowa Gambling task

In this task, which was adapted from Bechara et al. (1994), four decks of cards appeared on a computer screen. Each participant had to choose a card from any deck by clicking on it. The task consisted of 100 trials. For each choice, deck A and deck B produced profits of 100 points, while decks C and D produced 50-point profits. However, for every 10 trials, a choice of deck A or B resulted in a net loss of 250

points, while a choice of deck C or D resulted in a net gain of the same amount. Therefore, any choice of Deck A presented losses of 150/200/250/300/350 points in a 1:2 ratio. Deck B could make participants to lose 1250 points in a 1:10 ratio. Deck C choices were penalized with losses of 25/50/75 points in a 1:2 ratio. Lastly, with Deck D, participants could lose 250 points in a 1:10 ratio. Decks A and B are called disadvantageous decks, and the selection of these cards is considered risky, while decks C and D are called advantageous. All participants started with 2,000 points, and they were instructed to maximize their benefits. The literal instructions of the task were as follows for all Studies:

> *"In front of you, there are four decks of cards A, B, C, and D. I want you to select one card at a time from any deck you choose by pressing 1, 2, 3, or 4 number keys, respectively. I will give you some points each time you select a card. Every so often, however, you will have to pay me some points too. I will not tell you now when these payoffs will occur or how much they will cost you. You will find out as we go along. You are absolutely free to switch from one deck to the other at any time, and as often as you wish. The goal of the game is to win as many points as possible or avoid losing points as much as possible.*
>
> *All I can say is that some decks are worse than others. You may find all of them bad, but some are worse than others. No matter how much you find yourself losing, you can still win if you stay away from the worst decks. I will give you now a loan of 2000 points. In the end, I will collect back the loan and see how much you won or lost.*
>
> *If you have understood everything, press X to continue."*

The dependent variable was the Net Score, which is the difference between the number of advantageous and disadvantageous choices in 100 trials. In the post-test, we

applied a parallel test of IGT to avoid the learning effect. We changed the names of the decks (deck 1, deck 2, deck 3, and deck 4) and the order of presentation of the advantageous and disadvantageous alternatives.

Stop Signal task

The participants performed an adapted version of the SST (Verbruggen et al., 2008). After looking at a fixation cross on the computer screen, arrows pointing right or left appeared. The task required pressing as fast as possible the left response key if the arrow pointed to the left, or pressing the right response key if the arrow pointed to the right unless a signal beep was played after the presentation of the arrow (in this case, the response was to be stopped before execution). The delay between the presentation of the arrow and the signal beep (starting at 250 milliseconds) was adjusted up or down (by 50 milliseconds) depending on performance. The stop signal delay (SSD) was increased if the previous signal stop was successful (up to 1,150 milliseconds) or decreased if the previous signal stop was not successful (down to 50 milliseconds). The inter-trial interval was fixed at 2,000 milliseconds. Participants responded up until the next trial started. The variable measured was the Stop Signal Reaction Time (SSRT), which was defined as the estimated time required to stop an initiated response. SSRT was calculated following the tracking procedure by subtracting mean SSD from mean reaction time (Verbruggen et al., 2008; Verbruggen and Logan, 2009).

Transcranial direct current stimulation

tDCS was administered using a neuroConn Magstim DC-STIMULATOR PLUS (neuroCare Group GmbH, Ilmenau, Germany) on the right OFC (rOFC) (fp2) according to the International 10-20 system for EEG electrode placement. The selected area and both electrodes were soaked in physiological saline (~50 mL per participant). To determine the behavioural specificity of tDCS targeting the rOFC, the stimulation was

delivered to one side of the head with the reference electrode located over the contralateral trapezius. The target electrode (3 cm × 3 cm) was kept in place on the selected area (fp2) by an adjustable elastic headband, and the reference electrode (5 cm × 7 cm) was kept in place on the contralateral trapezius with hypoallergenic adhesive tape. The size of the target electrode was smaller than the reference electrode to improve focality (Nitsche et al., 2008) and reduce discomfort (Turi et al., 2014). Anodal stimulation was delivered at 1.5 mA for 20 min (plus fade-in and fade-out periods of 30 s), which is considered within safe parameters (Bikson et al., 2016). In the sham condition, the stimulation lasted only for the first minute. Total charge is an important parameter for tDCS safety criteria. Tissue damage has been detected at a minimum total charge of 216 C/cm^2 (Yuen et al., 1981). Our protocol involves a total charge of 0.033 C/cm^2, which is far below this threshold. In the sham condition, the real stimulation lasted only for the first min (plus fade-in and fade-out periods of 30 s) (0.001 C/cm^2) in a whole 20 min period. During stimulation, participants were told to be seated and relaxed. After completing the entire experiment, all participants were asked if they thought they had been stimulated. They could answer, “Yes”, “No” or “I am not sure” (no standardized questionnaire was used).

Numerical simulation of current flow distribution

We considered whole-body models from the Virtual Family dataset (Christ et al., 2010) which represents a collection of highly detailed high-resolution anatomical models derived from MRI data of volunteers. Our objectives to determine brain current flow were two fold: a) to support the choice of the experimental montage used and b) to explore potential differences due to known sex-based anatomical differences (Gennatas et al., 2017; Gur et al., 1999; Herron et al., 2015). We, therefore, considered a male representative model: Duke (34-year-old), and a female representative model: Ella (26-

year-old). We note that while a systematic evaluation of the influence of sex-related anatomical differences in current flow would need to involve a larger dataset (Thomas et al., 2019), the consideration of two representative models allows us to provide initial insight into potential dissimilarities, specifically using the montage employed. We adapted both models by identifying 14 different tissue compartments, ensured continuous cerebrospinal fluid (CSF), and integrated the exact stimulation electrode montage (mimicking the experimental montage) within the anatomical data (Synopsys Simpleware, USA). The whole-body models were truncated at the level of the torso, volumetric meshes were generated and finally exported to a solver for finite element method (FEM) computation (COMSOL Multiphysics, USA). The electrical properties of all compartments (tissue and electrode) were assigned representative isotropic average values in (S/m): skin: 0.465; bone: 0.01; CSF: 1.65; gray matter: 0.276; white matter: 0.126; muscle: 0.35; urinary bladder wall: 0.408; intestines: 0.164; heart: 0.381; cartilage: 1.01; liver: 0.221; kidney: 0.403; tongue: 0.255; air:1e-15; sponge: 1.4; and pad electrode: 5.9 e7.

The relevant boundary conditions for the tDCS dose used were imposed: Anode: 1.5 mA and Cathode: ground. All other exterior surfaces were treated as electrically insulated. The standard Laplacian equation for volume conduction was used and the induced cortical electric-field (e-field) magnitude was determined (Datta et al., 2012).

Statistical analysis

The statistical analysis was performed using SPSS Statistics 21 software (IBM Corporation, Armonk, NY, USA) and R software (R Core Team, 2018). First, we analysed the distribution of each dependent measure through the Shapiro-Wilk test and kurtosis and skew data to support the interpretation of the W statistic. We also analysed the homoscedasticity of the variance for each dependent variable through Levene's Test.

Z-scores of each participant were calculated and those who had ±2.5 z-score were removed from the corresponding analysis. Chi-squared test was applied to analyse the integrity of the blinding procedure.

Depending on the distribution of the data and following previous research, we performed different analysis. Since normality and homoscedasticity assumptions were not violated in the most of IGT measures, we performed a two-factor mixed ANOVA to analyse the IGT scores in the first experimental phase with one between-subject factor [sex (two levels: men and women)] and one within-subject factor [block (five levels: blocks of 20 trials)]. To analyse data from the second experimental phase, we performed a three-factor mixed-way ANOVA to analyse the IGT Net Score with two between-subject factors [sex (two levels: men and women) and group (two levels: anode and sham)] and one within-subject factor [session (two levels: pre- and post-intervention)]. We applied Mauchly's sphericity test to check the sphericity of variances and applied Greenhouse-Geisser correction when the sphericity assumption was violated. We calculated partial eta squared (η_p^2) as an estimation of the effect size as recommended by Lakens (2013).

Since normality and homogeneity of variance are not assumed in a sufficient number of measures to ensure the robustness of a parametric statistical model, we performed a Welch-James (WJ) test to analyse the SSRT using the "welchADF" R package (Villacorta, 2017). This test is able to deal with non-normal and heterogeneous distributions. WJ test was carried out with two between-subject factors [sex (two levels: men and women) and group (two levels: anode and sham)] and one within-subject factor [session (two levels: pre- and post-intervention)]. *p* values less or equal to 0.05 were considered statistically significant.

Results

Integrity of blinding

No significant differences were found between the groups when participants were asked about whether they thought they had received active tDCS (anodal tDCS = 48.4%; sham tDCS group = 36.7%; $\chi^2 = 2.466$, $df = 2$, $p = .291$). Therefore, we suggest that our blinding procedure was successful.

tDCS acceptability

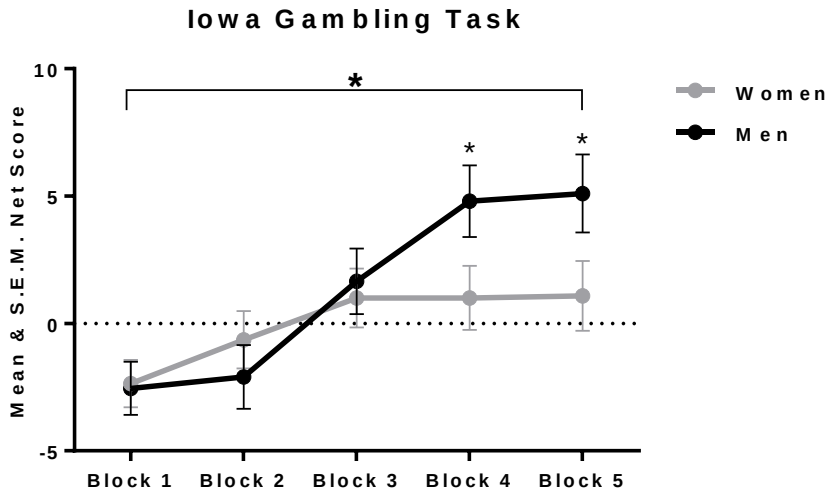
None of the participants reported any significant adverse effect during of after the tDCS procedure.

Phase 1: Sex-related differences in IGT

Two-factor mixed-way ANOVA showed a main effect of block ($F_{2.93,\ 257.85} = 14.013$; $p = .00$ $\eta_p^2 = .137$). However, we found no main effect of sex ($F_{1,88} = 1.11$; $p = .259$; $\eta_p^2 = .012$) nor group. The analysis revealed a significant sex × block interaction effect ($F_{2.93,\ 257.85} = 3.323$; $p = .021$; $\eta_p^2 = .036$). Post-hoc analysis comparing sex showed that men outperformed women in block 4 ($p = .04$) and block 5 ($p = .05$) (see Figure 4). When comparing blocks, post-hoc analysis showed statistically significant differences between block 1 and blocks 3 ($p = .027$), 4 ($p = .000$), and 5 ($p = .000$) in men. In women, there were no differences between block 1 and blocks 3 ($p = .071$), 4 ($p = .213$), and 5 ($p = .255$).

Figure 4

Mean and SEM of the Net Scores obtained in pre-intervention in each block of 20 trials of the Iowa Gambling task.



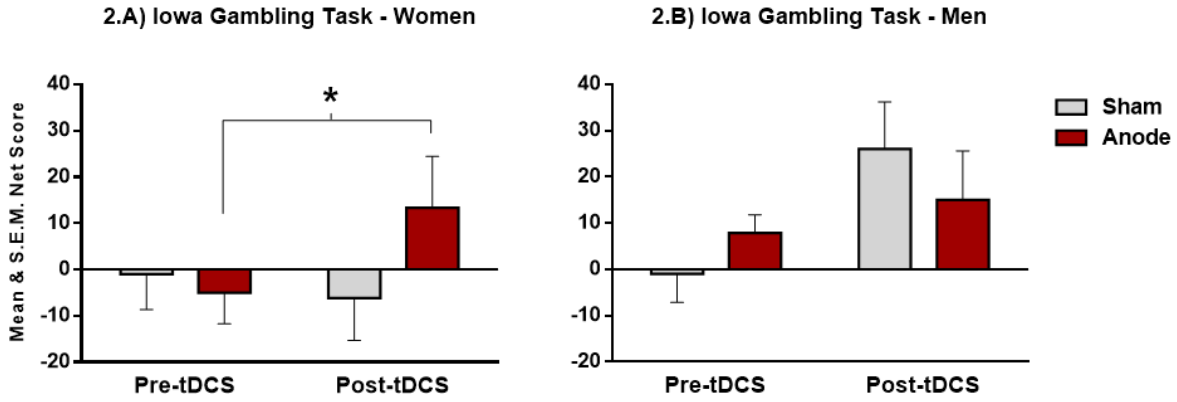
Phase 2: Neuromodulation of risky decision-making

Three-factor mixed-way ANOVA showed a main effect of session ($F_{1,56}$ = 7.127; p = .01 η_p^2 = .113). However, we found no main effect of sex ($F_{1,56}$ = 2.379; p = .129; η_p^2 = .041) nor group ($F_{1,56}$ = .195; p = .66; η_p^2 = .003). The analysis revealed a significant group × sex × session interaction effect ($F_{1,56}$ = 5.958; p = .018; η_p^2 = .096). We explored this effect by splitting all factors. When splitting by sex, we found a significant group × session interaction effect in women ($F_{1,32}$ = 5.063; p = .031; η_p^2 = .137). Post-hoc analysis revealed significant differences between sessions in anodal-stimulated women (p = .021) but not in sham-stimulated women (p = .481) (see Figure 5). When comparing groups, there were no differences in the pre-intervention session (p = .69) nor in the post-intervention session (p = .182). We also found no main effect of session ($F_{1,32}$ = 1.615; p = .231; η_p^2 = .048). In men, there was no significant group × session interaction effect ($F_{1,24}$ = 1.737; p = .200; η_p^2 = .068) but a main effect of session was found ($F_{1,24}$ = 5.137; p = .033; η_p^2 = .176) (see Figure 2.B). When splitting by

group, we found a significant main effect of session in the anode group ($F_{1,28}$ = 4.489; p = .043; η_p^2 = .138) but no main effect of sex ($F_{1,28}$ = .451; p = .507; η_p^2 = .016), nor sex × session interaction effect ($F_{1,28}$ = .87; p = .359; η_p^2 = .03). In the sham group, a sex × session interaction effect was found ($F_{1,28}$ = 6.043; p = .02; η_p^2 = .178). Post-hoc analysis revealed that, when comparing sex, there were significant differences in the post-intervention session between sham-stimulated men and women (p = .03). When comparing sessions, we found significant differences between pre- and post-intervention sessions in men (p = .013), but not in women (p = .541).

Figure 5

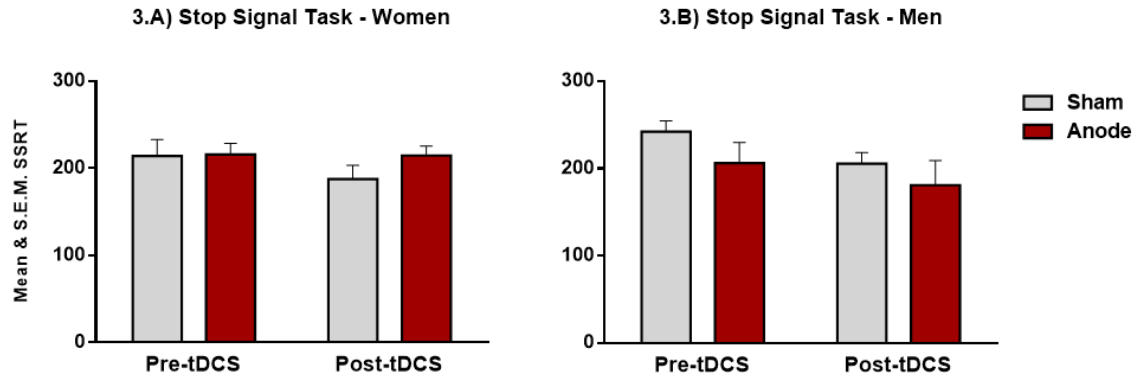
Mean and SEM of the total Net Scores obtained in the Iowa Gambling task by men and women before and after stimulation.



In the SST, results showed no main effects of group (T_{WJ}(1, 24.13) = .55; p = .50) or sex (T_{WJ}(1, 24.13) = .34; p = .56). There was no significant group × sex × session effect (T_{WJ}(1, 31.26) = .02; p = .60), sex × group (T_{WJ}(1, 24.13) = .04; p = .96), sex × session (T_{WJ}(2, 42) = .25; p = .88) or group × session (T_{WJ}(1, 31.26) = .39; p = .52). However, a main effect of session was found (T_{WJ}(1, 31.26) = 7.42; p = .006; δ_R = 1.658) (see Figure 6).

Figure 6

Mean and SEM of SSRT obtained in the SST by men and women before and after stimulation.



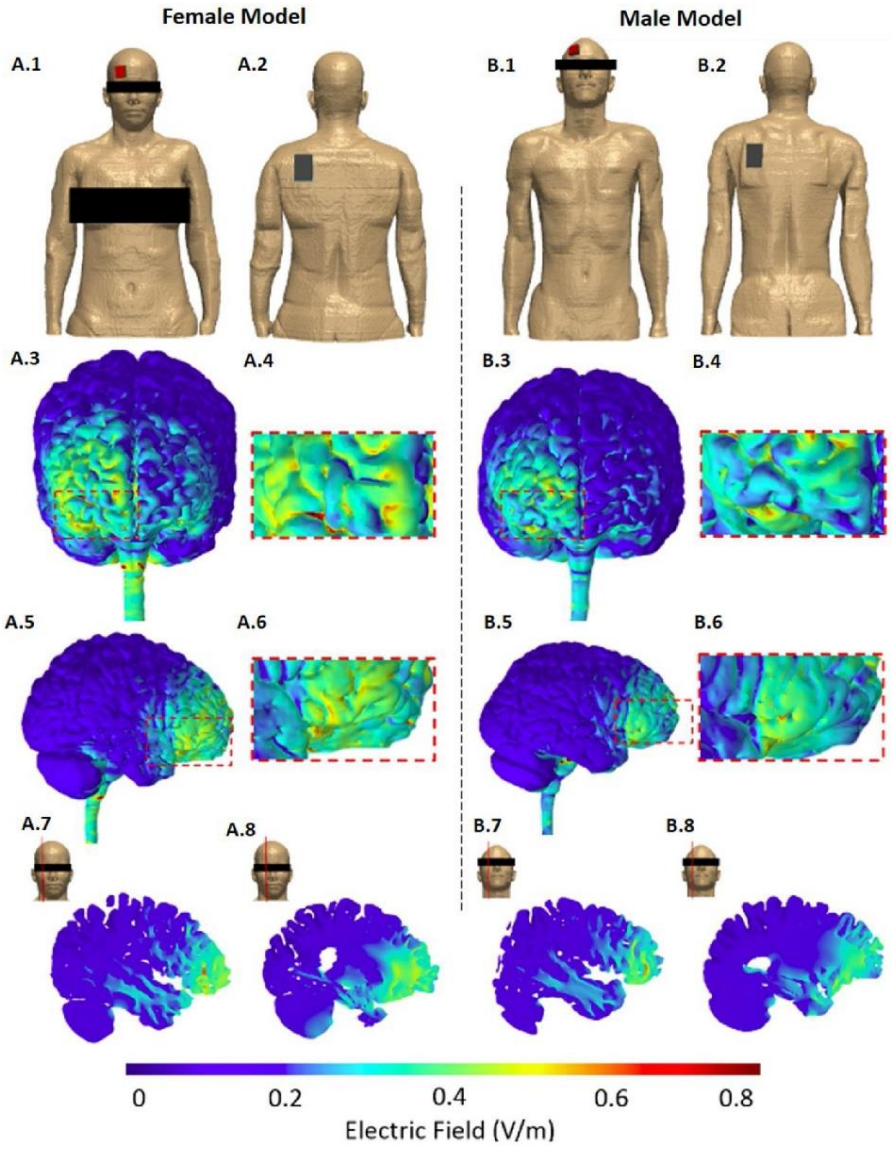
Numerical simulation of current flow distribution

With respect to our first objective, numerical simulations support the choice of the electrode montage employed. We note substantial e-field in the right orbitofrontal cortex (~.8 V/m) with other brain regions largely spared. With the cathode electrode on the contralateral trapezius, the simulations confirm the overall expected current flow – i.e. starting with the current flow in rOFC, current flows downward towards the brainstem and end at the contralateral side. The current flow pattern is similar for both head models. With respect to potential sex dis-similarity, we observe a higher average induced e-field in the female head model in comparison to the male head model (see Figure 7A. and Figure 7A.6 versus Figure 7B.4 and Figure 7B.6). We also note deeper current flow in the female head model as highlighted by the two representative 2D sagittal slices (see Figure 7A.7 and Figure 7A.8 versus Figure 7B.7 and Figure 7B.8). The left section of the Figure 4 displays results using the representative female model whereas the right section displays results using the representative male model. The first row shows the respective FEM models with the experimental montage employed (red: anode electrode and dark grey: cathode electrode). The second and third

rows show the corresponding 3-D front view and 3-D side view of surface e-field magnitude respectively. The dashed region is expanded in corresponding insets to show the zoomed surface e-field magnitude plots. The fourth and bottom-most rows show two 2-D sagittal views for both the female and the male model. The approximate level at which the slice is obtained in the rOFC region is indicated by the red line on the 3D head model in the top left.

Figure 7

Computational results of cortical current flow due to the experimental montage.



Discussion

This study proposed a combination of a neurostimulation technique and neurobehavioural tasks in order to explore the interaction of sex differences and tDCS in decision-making processes assessed by IGT. First, sex-related differences in IGT performance were confirmed. In addition, a differential effect of tDCS was found depending on sex in IGT. We found that anodal tDCS increased the net score in women, while in men tDCS did not produce any effect. We found no effect of tDCS nor sex in SST, supporting the specificity of the neuromodulation over rOFC.

To the best of our knowledge, this is the first study to show the relationship between sex-related differences in the IGT and tDCS. We found results in consonance with previous literature showing men outperforming women on the IGT, especially in the final trials (Evans and Hampson, 2015; Reavis and Overman, 2001; van den Bos et al., 2013). These studies suggest that women learn the reinforcement contingencies differently than men do (Byrne and Worthy, 2016; Cornwall et al., 2018) and that these differences are related to the different neuroanatomic activation and lateralization patterns observed during the task (Bolla et al., 2004; Reber and Tranel, 2017; Sutterer et al., 2015).

Results also supported the hypothesis that anodal tDCS would improve IGT performance, but this effect was restricted to female participants. A possible explanation for the present result is the fact that low performers have shown to be more responsive to tDCS (Hsu et al., 2014; Sánchez-Kuhn et al., 2018), which might have led to the greater benefit from tDCS obtained by women. Moreover, a constant finding across several studies (Berryhill and Jones, 2012; Fehring et al., 2019; Wu et al., 2014; Wu et al., 2016) is that the effect of tDCS commonly emerges in difficult tasks settings that are challenging for the participant. However, this explanation might be not fully

explicative, as in our study the behavioural differences between men and women were only observed in the first experimental phase. In the second experimental phase, we did not find any sex differences since the sample was smaller compared to the first phase. This may be explained by the fact of sex differences in IGT is a consistent but small effect that needs large samples to be observed (Li et al., 2010; Reavis and Overman, 2001; van den Bos et al., 2013; Weller et al., 2010).

As men and women did not differ in IGT performance in the second phase, we cannot assume that the differential effect of anodal tDCS is due to high or low performance. Therefore, we suggest that this could be explained by a different task-induced rOFC activity. Considering the previously mentioned neuroimaging data, we can assume that we have modulated a critical area to IGT performance (Lawrence, Jollant, and Daly, 2009; Tranel et al., 2002), which entailed women to choose more advantageous decks after the stimulation. In other words, stimulation led to a long-term advantageous contingency learning facilitation. Nevertheless, in men, there was no effect of anodal tDCS. One possible explanation is that rOFC is specially recruited during IGT performance in men but not in women (Bolla et al., 2004). In this sense, anodal tDCS over the rOFC in our female participants has been able to generate more neural activity in the area, facilitating its recruitment during the performing of the task and, therefore, the learning process. The OFC region belongs to the reward neural system and plays a key role in the evaluation of large rewards and also in the learning of stimulus–reward contingencies (Rolls, 2000; Rudebeck and Rich, 2018; Tsuchida et al., 2010). This region is critical for the adjustment of the behaviour to changing contingencies by a double mechanism carried out by different OFC-subregions. While medial OFC (Brodmann areas 11 and 13) is implicated in the evaluation of specific qualities of outcomes, lateral regions (Brodmann area 12) are involved in learning from

probabilistic feedback (Rolls, 2000). In this sense, the integrity of the OFC ensures the ability to behave flexibly, adapting the behaviour to the unexpected demands occurring in the environment. Decision-making processes assessed by IGT imply this kind of probabilistic reward/punishment learning since the task requires recognizing four different reward/punishment probabilistic contingencies and to choose deliberately the most advantageous one. Consequently, anodal tDCS-treated women might have improved their performance because of greater behavioural flexibility promoted by an increase in OFC activity. In contrast, task-induced rOFC recruitment might seem to be enough for men to perform the task properly. In fact, all of our male participants improved their performance between sessions despite anodal or sham tDCS.

Another possible explanation would refer to cortical excitability. In this way, some studies have shown sex-related differences regarding tDCS-induced changes in cortical excitability (for a review see Dedoncker et al., 2016). For instance, Chaieb et al., (2008) found a facilitating effect of anodal tDCS over the visual cortex in women, but not in men. This could be explained by a sex-related different cortical excitability, which could be influenced by gonadal sex hormones or the menstrual cycle (Inghilleri et al., 2004; Smith et al., 1999). In this sense, the consideration of the FEM model of tDCS-generated current flow highlights two important points: confirmation of the choice of the electrode montage and the likely presence of sex-related differences mediated by sex-specific morphological differences. The differential current flow pattern thereby provides another potential explanation of the differences in decision-making found between women and men in this study. This is rational given the fact that the e-field magnitude is a correlate for modulation. We have previously shown that a higher e-field (∼10 %) is induced in female head models than in male head models for the classic M1-SO montage across multiple metrics (mean and median) (Thomas et al.,

2019). The dataset consisted of 5 female and 5 male subjects with an age range spanning 27–47 years. We note that while we considered only one representative male and one representative female subject in this study, we observe a similar higher e-field magnitude induced in the female subject. This is not unexpected given the known anatomical differences with females having higher grey matter percentages and lower white matter and CSF percentages than males (Gur et al., 1999). Therefore, further research is needed to disentangle sex-related cortical excitability differences in high-order cognitive functions.

In response inhibition control measure, we found no effect of tDCS but only a main effect of the session, which supports the focality of our montage. All participants performed better in the post-intervention session regardless of sex and stimulation but due to learning effects. The absence of any stimulation effects over the rOFC suggests that this region might not be involved in response inhibition. This is in agreement with previous findings, which reported that this type of response inhibition is mainly related to other regions, such as the dorsolateral PFC, pre-supplementary motor area (Chikazoe, 2010; Swann et al., 2012), sub-thalamic nuclei (Mancini et al., 2019; Mirabella et al., 2012, 2013), the striatum (Li et al., 2008; Zandbelt and Vink, 2010), the premotor cortex (Mattia et al., 2013; Mirabella et al., 2011), the motor cortex (Coxon et al., 2006; Mattia et al., 2012) and inferior frontal gyrus (Aron et al., 2014; Chikazoe et al., 2009).

CHAPTER 4. STUDY II: Revealing idiosyncratic decision-making strategies in healthy undergraduates. A Bayesian approach

This study aimed to further investigate the behavioural mechanisms that drive the decision-making process during the IGT under stable and changing choice contingencies. 160 undergraduate students performed a modified IGT with three additional reversal-learning phases. We employed a cluster-based strategy and revealed five different *decision-maker* profiles that differed in their deck preferences during the task. We employed computational models of reinforcement learning to identify the core features of each differential profile. At this point, we moved from frequentist to Bayesian statistical methods in which statistical decisions are based on posterior probabilities of parameters of interest. Bayesian mean comparisons showed no credible differences between men and women regarding their overall performance.

This work corresponds to León, J. J., González-Rodríguez, A., Sayans-Jiménez, P., Sánchez-Santed, F., Cañadas, F., Estévez, A. F. and Flores, P. (2023). Revealing idiosyncratic decision-making strategies in healthy undergraduates. A Bayesian approach. *Under revision*.

Rationale

Traditionally, IGT decks have been divided into two disadvantageous decks, which provide a larger immediate gain but also a long-term loss, and two advantageous decks, which provide a smaller immediate gain but also a long-term benefit (Bechara et al., 1994), and good performance has been widely understood as a positive net score (or as a higher net score compared to other condition). This procedure has been shown to be useful to detect deficits in decision-making in different populations diagnosed with neuropsychological disorders such as ADHD (Malloy-Diniz et al., 2007), OCD (Cavedini et al., 2006), pathological gambling (Cavedini et al., 2002) or schizophrenia (Brown et al., 2015; Fond et al., 2013; Struglia et al., 2011). These clinical populations have presented worse net scores compared with healthy populations, suggesting an impairment to optimize their decision-making processes in the long term. Nevertheless, the literature also reveals some inconsistent results for some of these populations. As an example, studies carried out by Agay et al., (2010) and Ernst et al.,(2003) found no differences in the net score obtained by ADHD patients and healthy control group (for a review, see Groen et al., 2013). Conflictive results have also been found in OCD patients (Lawrence et al., 2006). Finally, some studies have also revealed a similar performance of people with schizophrenia and a healthy control group in the IGT (Rodríguez-Sánchez et al., 2005).

While the aforementioned studies focus mainly on the net score, the behaviour of the participants may differ depending on other factors that may be relevant for researchers. For instance, many studies have shown that healthy participants may present an idiosyncratic choice behaviour, preferring decks with infrequent losses (usually decks B and D) over those with frequent losses (usually decks A and C), rather than led by the estimation of the long-term outcomes of these decks (for a review, see

Steingroever et al., 2013). Concerning healthy people, there are some relevant variables to consider within this population, such as age (Beitz et al., 2014), sex (Reavis and Overman, 2001), educational level (Evans et al., 2004), and socio-economic status (Sheehy-Skeffington, 2020), as well as some personality traits, such as anxiety (Miu et al., 2008) and fun-seeking (Suhr and Tsanadis, 2007).

Decision-making tasks suppose a synthesis of several psychological processes, such as reinforcement learning and sensitivity to reward and punishment (Ahn et al., 2017). To overlook these variables when analysing the performance in the IGT may lead to conflictive and non-totally founded conclusions about the decision-making process that is being assessed during the task. As individual choices seem to be an important factor, novel computational modelling approaches have allowed researchers to calculate different parameters that may be useful to acquire a deeper understanding of the processes involved in decision-making (Haines et al., 2018; Steingroever, Wetzels, and Wagenmakers, 2013; Worthy et al., 2013). This information could be extremely useful to make a better conceptualization of the decision-making process in both healthy and clinical populations, as well as for developing treatments and intervention programs that could specifically focus on certain problems depending on the target population (Adida et al., 2011; Clark et al., 2011), since this may help clinicians to correctly interpret the performance on the IGT and act accordingly, as recent research has suggested (Barnhart and Buelow, 2021).

Another cognitive process that has been argued to be involved in decision-making is cognitive flexibility (Dunn et al., 2006; Fellows and Farah, 2005). Cognitive flexibility could be defined as the ability to modify behaviour to overcome changing circumstances. This ability has been widely studied by researchers using probabilistic reversal learning paradigms (Izquierdo et al., 2017). Reversal learning has been

proposed as a key feature of the IGT since participants need to gradually adjust their choices attending to the reward/punishment rules of each deck to perform properly (Dunn et al., 2006). Thus, despite Bechara et al., (2005) argued against the reversal learning explanation of the task, there is still some controversy about this issue. Concerning this, for example, Brand et al., (2007) found negative correlations between perseverative errors in a Wisconsin Card Sorting Test (WCST) and the net score obtained from the second block of the IGT onwards. In order to elucidate the impact of cognitive flexibility on the IGT, some authors have also modified the task including this component, switching the reward/punishment rules associated with each deck throughout the task (Dymond et al., 2010). In a study, patients with negative symptoms of schizophrenia have been found to present impairments only when these contingencies change and not during the original task (Turnbull et al., 2006).

Therefore, this study aims to explore the idiosyncratic choice behaviour of undergraduate students on the IGT, as well as their capability to adapt to unexpected and changing contingencies. We hypothesized that: (i) most participants will make choices based on the frequency of losses of each deck rather than based on the long-term profit associated with each deck; (ii) participants who identify the long-term advantageous choices during the IGT will perform better when the contingencies shift than those who do not identify them; (iii) men will outperform women on the latter stages of the IGT and, therefore, will also have a better performance when the contingencies shift; and (iv) identified decision-makers profiles will depend on the frequency of punishment instead of on the long-term profit associated with each deck and (v) parameters estimated using computational models that are positively or negatively related with the performance on the IGT, such as loss aversion and response

consistency (Worthy et al., 2013), will be related in the same way with the performance on the blocks in which contingencies shifts.

Method

Participants

A total of 160 (58.8% women) undergraduate students (M_{age} = 2.7; SD = 4.4) volunteered for the present study. Inclusion criteria were: (1) no previous experience in IGT and (2) no history of psychiatric illness. They all had a normal or corrected-to-normal vision and two academic credits were offered as a reward for participating. The study was approved by the Ethics Committee of the University of Almeria and was conducted following the Declaration of Helsinki.

Materials

Iowa Gambling Task with Reversal learning blocks.

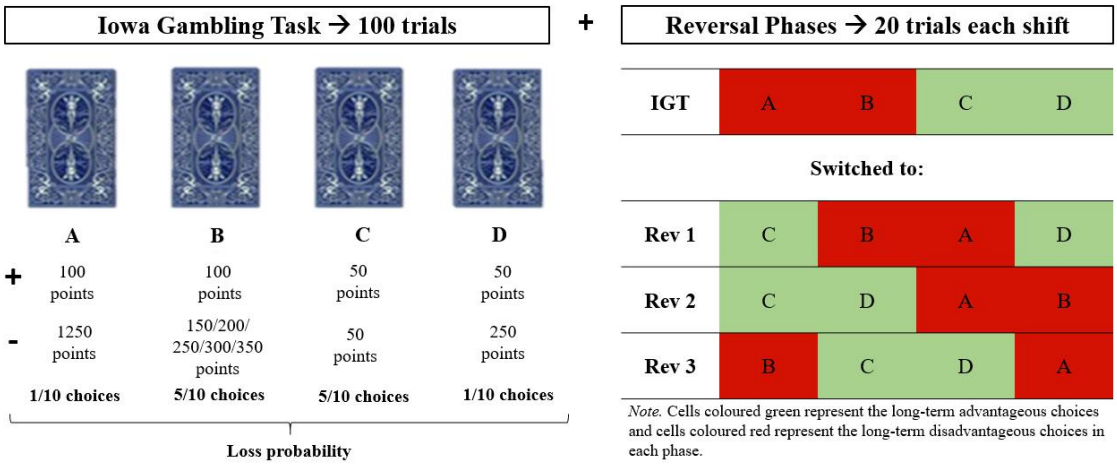
In this task, adapted from Bechara et al. (2000), four decks of cards appeared on the computer screen. Each participant had to wait for 5 seconds before responding. After that, a green dot (response signal) appeared centred on the top of the screen, indicating the participants could make a choice. They were instructed to choose a card from any deck by pressing the keys 1, 2, 3, or 4, each corresponding to decks A, B, C, and D, respectively. After each choice, a feedback display that showed the current amount of points and the received outcome was shown for 6 seconds. All participants started with a total amount of 2000 points, and they were instructed to maximize their benefits. The total duration of the task was about 30 minutes.

The task consisted of 160 trials. In the first 100 trials, decks A and B supposed a long-term loss, so they would be disadvantageous decks, and decks C and D supposed a long-term benefit, so they would be advantageous decks. Each choice of deck A offered 100 points but could make participants lose 1250 points in a 1:10 ratio. Deck B also

offered 100 points and could make participants lose an amount ranging from 150 to 350 points in intervals of 50 in a 1:2 ratio. When Deck C was chosen, the reward consisted of 50 points but a penalty of 50 points could be presented in a 1:2 ratio. Finally, Deck D was also associated with a reward of 50 points and a penalty of 250 points could be presented in a 1:10 ratio. These contingencies were adapted from Worthy et al. (2013) but the losses were presented probabilistically instead of sequentially in order to avoid a deterministic behaviour. The remaining 60 trials were divided into 3 blocks of 20 trials (3 reversal shifts), in which the outcomes associated with each deck were switched (see Figure 8).

Figure 8

Summary of the employed task.



Note. Cells coloured green represent the long-term advantageous choices and cells coloured red represent the long-term disadvantageous choices in each phase.

Computational learning models

The IGT can be characterized as a four-armed bandit problem (Berry and Fristedt, 1985) in which the participant needs to learn from an environment by picking different choices and experiencing the possible outcomes to estimate the optimal response. Several factors influence this process, such as poor reinforcement learning, hypersensitivity or hyposensitivity to rewards and losses, or response inconsistency. Computational modelling has been proposed as an effective tool that allows us to

estimate these factors. In the present research, we compared some models that, following the literature, have shown an adequate fit. The compared models were the Prospect-Valence Learning model with a delta learning rule (PVL-Delta), the Prospect-Valence Learning model with decay reinforcement learning rule (PVL-Decay), the Outcome-Representation Learning model (ORL), and the Value-Plus Perseverance model (VPP), from the "hBayesDM" R package (Ahn et al., 2017). As can be consulted in Appendix III, all reinforcement-learning models failed to simulate our participant's behaviour, so related information will be no longer mentioned during the present study.

Procedure

The study was carried out in a single session. Participants were seated in a quiet and well-acclimated room and received instructions about the entire procedure. After that, they were asked to sign an informed consent document. Participants were tested individually using an Asus ROG GL552VW laptop with a 15.6" screen. For other research purposes, equipment employed to register physiological data were attached to our participants. Concretely, this equipment consisted of two Ag-AgCl electrodes, attached to the distal phalanges of the second and fourth digits of their right hand, and a prefrontal headband with 15 optodes to obtain fNIRS haemodynamic activity data. After verifying that both systems were recording correctly and that participants had understood the instructions, the task began.

Data analysis

Clustering procedure

We aimed to explore the idiosyncratic deck choice behaviour of our sample to identify the key factors that determine their choices in the IGT. In order to better characterize our sample, we performed hierarchical combined with non-hierarchical cluster analysis methods. To perform those analyses, we divided the task into two

differentiated phases, an Early Stage, and a Late Stage. The Early Stage included the first 40 trials, while the Late Stage was composed of the last 60 trials (Li et al., 2019). This approach was motivated by previous research, which shows that from about trial 40 onwards, participants begin to identify advantageous decks so early uncertainty would decrease, leading to more explicit-risk based decision-making (FeldmanHall et al., 2016; Li et al., 2019). As we were interested on characterize participants based on their initial strategy (i.e. how they behave with less experience with decks) and on their final strategy (i.e. how they behave with enough experience with decks), we considered the total number of choices of each deck in each stage to generate the clusters.

All the analyses were performed using the free "R" software (R Core Team, 2019). First, we explored the possible number of clusters through a hierarchical clustering method (Hair et al., 2019) using the *hclust* function. In order to reduce the within-cluster variance, Ward's method was chosen (Szekely and Rizzo, 2005; Ward, 1963). The optimal cluster solution was determined using the Gap statistic method, which may help to avoid a biased and arbitrary decision about the best cluster solution based only on the elbow method (Tibshirani et al., 2001), and by observing the dendrogram. Finally, we performed a non-hierarchical K-means analysis to determine the cluster membership of our participants through the *hkmeans* function, which generates a *k* number of clusters using the centroids obtained in the previous step (Hair et al., 2019). Besides, we also explored whether sex was equally distributed in the different clusters using a Chi-Squared test.

Bayesian mean comparisons

As several analyses were going to be performed to test our hypotheses, we decided to employ Bayesian data analysis for mean comparisons. In Bayesian data analysis, decisions are based on posterior probabilities of the parameters of interest. In

contrast with frequentist statistics, there is no need to make corrections or adjustments to make decisions when exploring mean comparisons since there is only one posterior distribution that can be examined from multiple perspectives without affecting the inference process, substantially reducing the false alarm rate (Kruschke, 2015).

Posterior distributions may be used to make decisions along with their 95% Highest Density Interval (HDI), so values falling inside the HDI are more credible than those falling outside it. Also, a Region Of Practical Equivalence (ROPE) may be established. A ROPE is comprehended around values of interest, such as zero when we are doing mean comparisons or estimating the slopes of a regression line. If the ROPE completely excludes the HDI, we accept this value for practical purposes. If the HDI falls completely inside the ROPE, the effect is said to be not credible. If the HDI partially overlaps with the ROPE, we withhold making a decision (Kruschke, 2011).

Clusters, net score, and individual deck choices

Differences in the net score and individual deck choices depending on cluster membership were explored through Just Another Gibbs Sampler (JAGS) for Markov Chain Monte Carlo (MCMC) sampling and posterior inference. Our dependent variable was the net score and we considered cluster membership as a between-subject factor, and block (1, 2, 3, 4, and 5 in the first 100 trials; reversal 1, reversal 2, and reversal 3 in the reversal phase) as a within-subject factor using the program "Jags-Ymet-XnomSplitPlot-MnormalHom.R" from Kruschke (2015), available at https://sites.google.com/site/doingbayesiandataanalysis/. Similarly, to explore the differences between clusters in individual deck choices on the IGT and the reversal blocks, we employed the same method, using the number of choices as our dependent variable and understanding deck (A, B, C, D) as a new within-subject factor. For an exhaustive exploration of these data, the analysis was repeated isolating each level of

block and deck. For both purposes, an arbitrary ROPE of (-1, 1) for the difference of the means was used so no spurious differences of less than 1 choice will be considered if the HDI does not completely exclude these values. A total of 50000 samples were saved after 1000 adaptative and 2000 burn-in sampling with 4 chains for each analysis. The Gelman-Rubin test revealed a correct convergence of all the chains with values below 1.10 for all parameters (Gelman and Rubin, 1992) in all analyses.

Sex, net score, and individual deck choices

Analysed followed the same methods explained above for exploring cluster differences. The only difference was that we considered sex as the between-subject factor instead of cluster membership.

Results

To ease the reading of the results only credible differences and those comparisons that are essentially relevant to the hypotheses will be commented on. All the statistics can be found in Appendix I.

Clusters

Clustering procedure

After watching the dendrogram and following the Gap statistic method (Tibshirani et al., 2001) we observed an optimal solution of five clusters (see Figure 6). The K-means analysis resulted in 44 (A-Choosers; 30 women), 14 (C-Learners; 7 women), 22 (D-Learners; 10 women), 48 (Scattering; 25 women), and 32 (A-Exploiters; 22 women) participants composing each of the clusters. Please note the characteristics of decks A and B in this experiment are interchanged. The contingencies associated with Deck A in this study are those normally associated with Deck B, and vice versa (see Figure 9).

The sex distribution within each cluster was explored using a Chi-Squared test and no different sex distribution was found in any cluster (see Table 4). The individual preferences of each cluster are further explained below.

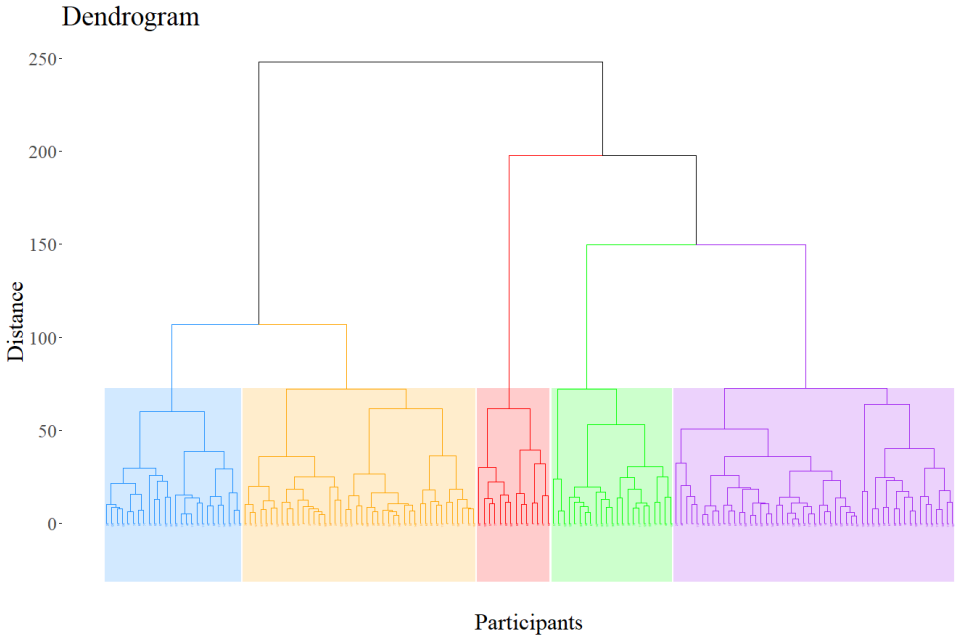
Table 4

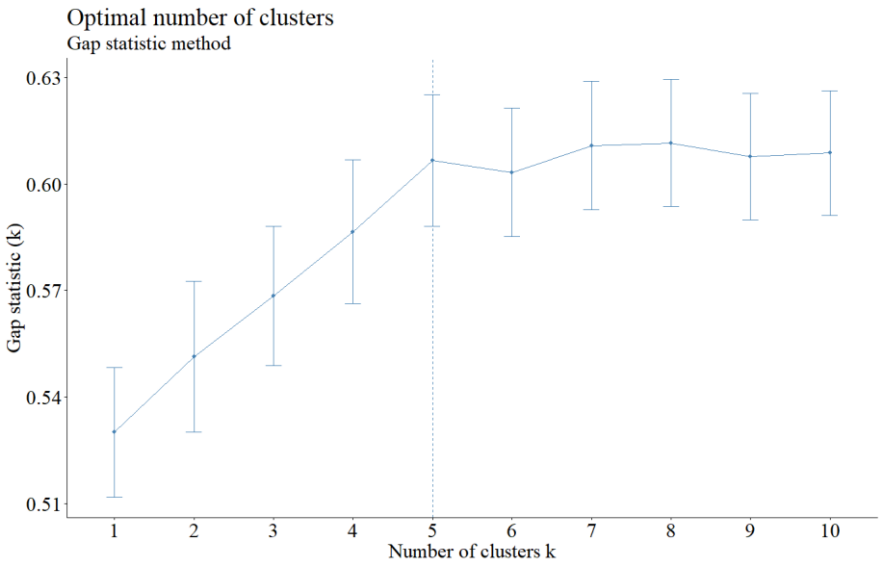
Number of men and women in each cluster and Chi-squared statistics as a function of sex.

Cluster	*n* (Men)	*n* (Women)	χ^2	*P*
Cluster 1 (A-Choosers)	14	30	1.61	.203
Cluster 2 (C-Learners)	7	7	.442	.506
Cluster 3 (D-Learners)	12	10	1.60	.205
Cluster 4 (Scattering)	23	25	.880	.348
Cluster 5 (A-Exploiters)	10	22	1.32	.250

Figure 9

Graphical representation of the best clustering solution.





Clusters and net score

IGT

The net score of the different clusters during the whole task is graphically depicted in Figure 10. As early as in the first block, A-Exploiters showed the worst performance in terms of a lower net score than A-Choosers, C-Learners, D-Learners, and Scatterers. This same pattern of differences was maintained during the first five blocks, except in block 5, in which the net score of A-Exploiters does not show credible differences with A-Choosers and Scattering.

From the second block onwards, C-Learners and D-Learners started showing a higher net score than A-Choosers and Scattering. C-Learners and D-Learners presented credible differences in their net scores only in the last block of the IGT.

In the fourth block, Scatterers started showing a higher net score than A-Choosers, which was maintained in block 5.

First reversal phase

C-Learners showed the highest net score compared to all other Clusters. D-Learners showed a higher net score than A-Choosers and A-Exploiters. Scatterers also showed a higher net score than A-Exploiters.

Second reversal phase

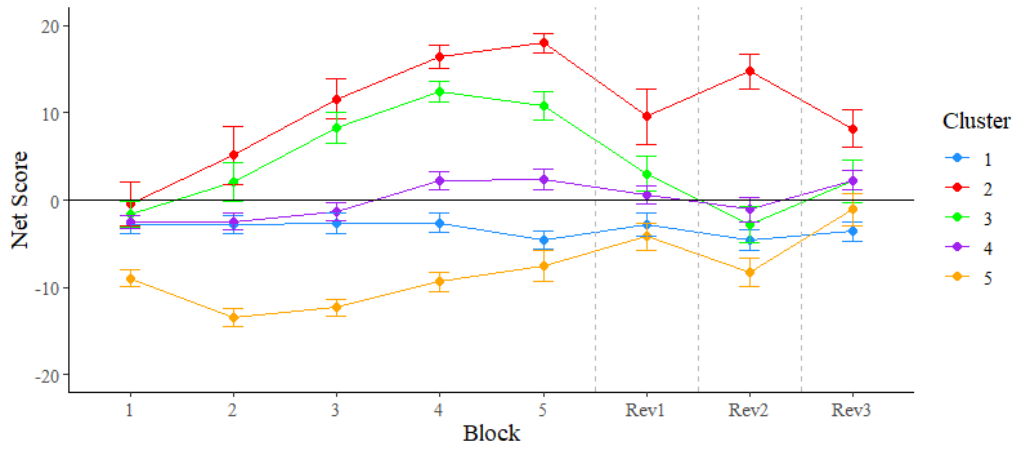
The same pattern of credible differences was maintained between the clusters, except for the difference between D-Learners and A-Choosers.

Third reversal phase

C-Learners showed again the highest net score. A-Choosers presented a lower net score than D-Learners and Scatterers.

Figure 10

Mean of the net score during the five blocks of the IGT and the reversal phases depending on cluster membership.



Note. The vertical bars represent the standard error of the mean.

Clusters and individual deck choices

IGT

The individual deck choices of the different clusters during the whole task are graphically depicted in Figure 11. Since Block 1, A-Choosers and A-Exploiters showed a higher preference for Deck A than for other decks. These preferences were maintained during the first five blocks of the task.

In contrast to A-Choosers, A-Exploiters presented a higher number of choices of Deck A than other Clusters since this first Block. A-Choosers started showing a higher

number of choices of Deck A than C-Learners, D-Learners, and Scatterers from Block 3 onwards and showed no credible differences with A-Exploiters in the number of Deck A choices in Block 5.

C-Learners started showing a higher number of choices of Deck C than of Deck B and Deck D in Block 2. Since Block 3, C-Learners also presented more choices of Deck C than Deck A. In addition, C-Learners presented the highest number of choices of Deck C compared to all other Clusters since Block 2 onwards.

D-Learners showed a higher preference for those decks in which losses are presented infrequently (Deck A and Deck D) since Block 2. Since Block 3, D-Learners also began to show a higher preference for Deck D than for Deck A, showing that they preferred the advantageous deck with infrequent losses. Furthermore, from Block 3 onwards, D-Learners is the group with the highest number of choices of Deck D compared to other Clusters.

Scatterers did not show any preference for any deck during the IGT (for a detailed description, see Appendix I).

First reversal phase

In the first reversal phase, A-Choosers and C-Learners looked for the same deck they chose in the last stages of the IGT. Surprisingly, D-Learners began to scatter among decks when the first shift was presented.

Second reversal phase

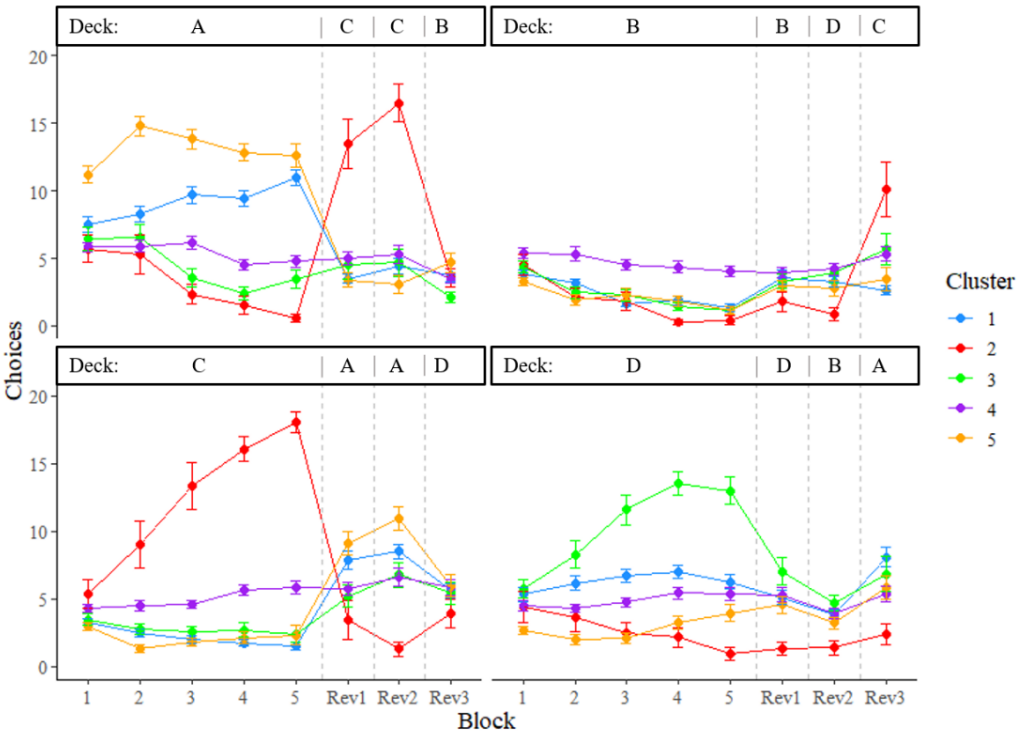
In the second shift, A-Choosers and A-Exploiters kept looking for their preferred deck, as well as C-Learners. D-Learners continued scattering among all decks. Scatterers began to prefer Deck C (previously Deck A) over Deck B (previously Deck D) and Deck D (previously Deck B).

Third reversal phase

In the last reversal phase, A-Choosers still looked for their previously preferred deck, presenting more choices of Deck D (previously Deck A) compared to Deck A (previously Deck B) and Deck B (previously Deck C). In addition, they presented more choices of Deck C (previously Deck D) than Deck B. C-Learners also searched their preferred deck. Regarding D-Learners, credible differences were found between the picks of Deck D and Deck A. No credible differences were found in the preferences of Scatterers and A-Exploiters.

Figure 11

Mean of the individual deck choices during the five blocks of the IGT and the reversal phases depending on cluster membership.



Note. The vertical bars represent the standard error of the mean.

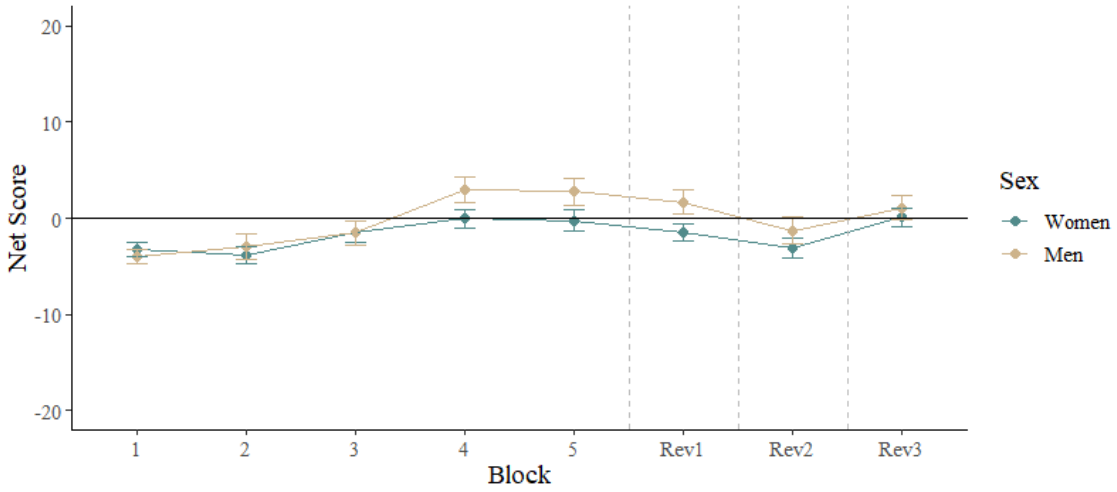
Sex

Sex, net score, and individual deck choices

The results of men and women during the whole task are depicted graphically in Figure 12. When exploring the performance of men and women, no credible differences between them were found during any of the blocks. The decision regarding differences between men and women in Block 4 and Block 5, as well as in the reversal phases, is to be withheld because part of the HDI is inside the ROPE threshold (-1, 1). Analyses also revealed that both, men and women, increased their net score from both Block 1 and Block 2 to both Block 4 and Block 5.

Figure 12

Mean of the net score of men and women during the IGT and the reversal phases.



Note. The vertical bars represent the standard error of the mean.

Regarding individual deck choices, parts of the ROPE are also always within the HDI in between-subject comparisons, so no credible differences between men and women were present during the IGT or the reversal phases. All these choices are graphically represented in Figure 13. However, there were some within-group differences in the pattern of responses during the IGT depending on sex. The most notable difference in these patterns was found in the third block of the IGT, where men

still preferred Deck A over Deck B and Deck C in this block. In contrast to men, women preferred Deck A over Deck B, Deck C, and also Deck D.

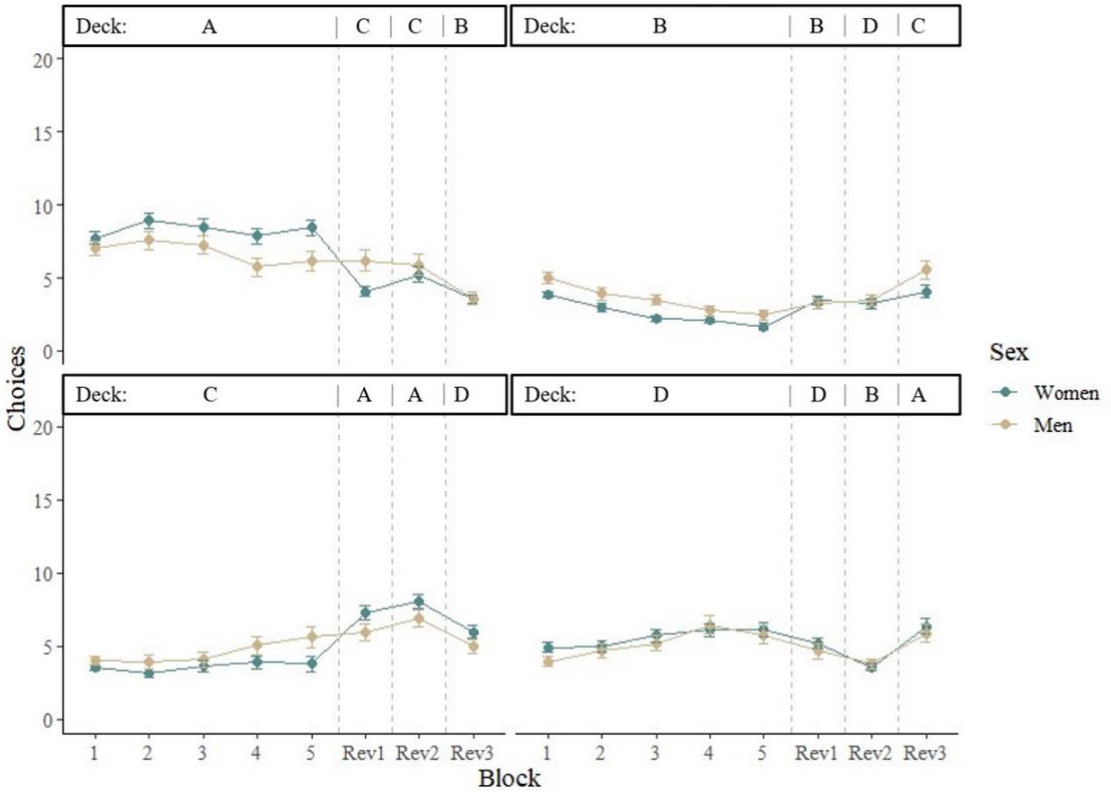
Besides, in the first reversal, men showed a higher preference for Deck A (previously Deck C) and Deck C (previously Deck A) over Deck B (previously Deck B). In contrast, women showed a higher preference for Deck C than for Deck A and Deck B. Nevertheless, no differences in deck choices between groups were present.

In the second reversal phase, men preferred Deck A (previously Deck C) over Deck B (previously Deck D) and Deck C (previously Deck A) over Deck B and Deck D (previously Deck B). However, women showed a higher preference for Deck C over Deck A, Deck B, and Deck D. As on the previous shift, no differences in deck choices between groups were present.

In the third reversal phase, women were the only ones showing a higher preference for Deck D (previously Deck A) over Deck A (previously Deck B). Men did not show any clear preference for any deck and there were not any differences between groups.

Figure 13

Individual deck choices of men and women during the IGT and the reversal phases.



Note. The vertical bars represent the standard error of the mean.

Discussion

The main purpose of this research was to identify those factors that may influence the performance of participants from a non-clinical population in both changing and unchanging environments using the IGT paradigm. We paid special attention to sex, which effect is inconsistent in the literature.

Regarding our first hypothesis, which was related to the deck choice preferences of our participants, cluster analysis revealed some interesting data. Our analysis revealed five different profiles of decision-makers based on participants' idiosyncratic deck choice behaviour. Only two clusters (C-Learners and D-Learners), which surprisingly summed only for 22.5% of our total sample, showed an optimal long-term performance during the IGT. In other words, 77.5% of our total sample showed a

negative or around zero net score at the end of the task, which is in consonance with recent research (Barnhart and Buelow, 2021).

C-Learners stuck to the advantageous deck associated with high-frequency and low-magnitude losses (Deck C during the IGT) from the early stages and kept exploiting that option even when contingencies changed. This Cluster rapidly identified this deck as a long-term advantageous one and spent the whole task exploiting it. We suggest the members of this Cluster are not so sensitive to the loss frequency, so their decision-making is not biased by an over-weight of the probabilities to receive a loss. It is worth noting that this cluster was composed of only the .0875% of our sample, even more, when in our adapted IGT this deck did not ever offer a net loss. This is consistent with previous research challenging the conception of this deck as an advantageous one (Chiu and Lin, 2007).

A-Choosers, D-Learners, and A-Exploiters preferred decks with a 1:10 win/losses ratio and summed for a total of 61.3% of the sample. Apparently, this choice preference (for decks with low-frequency and high-magnitude losses) was common among participants, as we predicted. Therefore, our participants were more leaded by the ratio of wins and losses than by the long-term outcomes, since, in contrast, less than a quarter part of our sample had a high preference for advantageous decks during the IGT. Following the Prospect Theory (Kahneman and Tversky, 1979), these participants would likely be over-weighting the more probable losses. However, they also differ in several key points. Both A-Choosers and A-Exploiters showed a high preference for the disadvantageous deck associated with low-frequency and high-magnitude losses (Deck A during the IGT). Nevertheless, while for A-Choosers this preference started to be observable since the third block of the task, A-Exploiters presented this preference from the beginning. These preferences were maintained when the contingencies changed

since they kept actively looking for this deck. Both groups present a pattern of behaviour that is extremely negligent to make long-term advantageous decisions in the task. This is in accordance with previous literature, in which it is argued that many healthy participants have some difficulties figuring out that the disadvantageous deck associated with low-frequency and high-magnitude losses is a bad deck in the long-term (Steingroever et al., 2013). These participants seem to be guided by an overestimation of the larger immediate reward and a negligent valuation of the magnitude and frequency of the loss, which results in a choice pattern consistent with what Bechara et al. (1994) called "myopia for the future". It is impressive that A-Exploiters rigidly maintained this disadvantageous strategy since so early, but it is also surprising that A-Choosers, after having experienced several outcomes from different decks, stuck to the same response.

As we previously mentioned, D-Learners also opted for a deck with low-frequency and high-magnitude losses. The difference between participants in this cluster and participants A-Choosers and A-Exploiters is that the choices preferred by D-Learners were advantageous in the long term (Deck D). We suggest that participants belonging to this Cluster could share some characteristics with A-Choosers and A-Exploiters because of their similar preference for low-frequency losses. However, we suppose that the impact of the outcomes on their decisions is lower for D-Learners, so they avoid the larger immediate rewards in favour of a long-term gain. Finally, Scatterers did not show a clear preference for any deck during the IGT nor during two of the three reversal phases.

Concerning our second hypothesis and contrary to our expectations, the only cluster that maintained a good performance when the contingencies changed was C-Learners. Although C-Learners and D-Learners were characterized by a high preference

for advantageous decks during the IGT, C-Learners preferred the deck associated with high-frequency, low-magnitude losses while D-Learners preferred the deck associated with low-frequency, high-magnitude losses. This difference leading to a different performance when contingencies change may be explained in several manners. One possible explanation is that the deck with high-frequency and low-magnitude losses, which has a similar ratio of trials with (1:2) and without (1:2) losses, is easier to detect since participants of C-Learners quickly find this deck in all the reversal phases, which could make it a more reliable choice than its counterpart with low-frequency and high-magnitude losses. Another possibility is that participants of D-Learners, who might have a higher aversion to frequent losses, may simply present a higher probability of taking risky choices when the uncertainty is higher, which is the condition in the changing environment. Previous studies have found that modifying the environment may have effects on the loss aversion of individuals, suggesting that even though participants may differ in their individual preferences and strategy, this latter may be sufficiently unstable and could change depending on the environmental influence (Rakow et al., 2020). The fact that D-Learners suddenly present a severe reduction in their performance could be in line with this finding.

Our behavioural results revealed that the decision about sex-related differences in the IGT performance is to be withheld. In fact, results from Bayesian mean comparisons suggest that, if any difference is even present between both groups, it could have an effect size so small that it does not credibly reach a difference of one choice per block. It is also interesting to note that the percentage of men and women in each of the clusters was not suggested to be different. Nevertheless, some within-group choice patterns differed when looking into both groups. In relation to deck preferences, we observed that in the third block women seemed to prefer Deck A over all the other

decks while men did not credibly choose Deck A over Deck D. In our experiment, both Deck A and Deck D are the choices associated with low-frequency, high-magnitude losses, so both men and women showed a higher preference for this type of decks. However, Deck A involves a disadvantageous long-term outcome while Deck D involves an advantageous long-term outcome. Thus, following this result, men could start to modify their preference towards advantageous decks before women (for an extensive review, see van den Bos et al., 2013). In addition, although the performance of men and women in the reversal phases seems to be similar when comparing the net score, women, apparently, prefer disadvantageous decks with high-magnitude and low-frequency losses, especially in the second reversal phase. Importantly, our sample included more women than men, which supposes a narrower HDI due to a lower standard error of the mean in our analyses for this first group, so these results may not be taken as conclusive.

Some of our results should be cautiously considered due to some limitations. Firstly, as we have previously commented, age has been proposed as a relevant variable to take into account when performing IGT (Caroselli et al., 2006; Cauffman et al., 2010). Secondly, socioeconomic status may also be an influential factor in decision-making processes (Sheehy-Skeffington, 2020) and, therefore, affect IGT performance through higher risk-taking behaviour (Ursache and Raver, 2015). In addition, some personality traits, such as impulsivity, should be taken into account when splitting participants into clusters to ensure that certain cluster is not overrepresented by certain personality trait. In this sense, future studies exploring these processes in a larger and more representative sample extracted from the general population instead of university students could cover broader age and socioeconomic status ranges and personality traits and could provide important insights. Thirdly, it is widely accepted that emotional states

may influence decision-making processes, especially those which take place under ambiguous conditions (Aïte et al., 2013; Brand et al., 2006; Heilman et al., 2010). Further research could also investigate emotion-related physiological variables, such as skin conductance response or heart rate variability (Bechara and Damasio, 2005; Boucsein et al., 2012), and check their relationship with the different parameters and the behavioural profiles. Lastly, clustering analyses considering individual choices should be repeated in future studies to test whether these profiles are also typical in the general population and do not underlie the specific composition of our sample.

CHAPTER 5. STUDY III: Decision-making and frontoparietal resting-state functional connectivity among impulsive-compulsive diagnoses. Insights from a Bayesian approach

This study is directly derived from the results obtained in the previous one. We followed the same rationale and applied the same clustering procedure and reinforcement learning modes in order to explore idiosyncratic decision-making profiles. In the present study, we investigate how healthy adults and impulsive-compulsive spectrum patients developed particular decision-making strategies during the IGT. Additionally, we recorded the frontoparietal resting-state functional connectivity of our participant and investigated the role of rsFC between different regions of the FPN as a possible biomarker of each idiosyncratic choice behaviour. We found three different *decision-makers* profiles, each of them composed of the same proportion of healthy and diagnosed participants. After applying a Bayesian General Linear Model, we found no evidence of frontoparietal rsFC as a biomarker or defective or adequate decision-making patterns, nor differences in the frontoparietal network of healthy and diagnosed participants.

This work corresponds to León, J.J., Fernández-Martin, P., González-Rodríguez, A., Rodríguez-Herrera, R., García-Pinteño, J., Pérez-Fernández, C., Sánchez-Kuhn, A., Amaya-Pascasio, L., Soto-Ontoso, M., Martínez-Sánchez, P., Sánchez-Santed, F., & Flores, P. (2023). Decision-making and frontoparietal resting-state functional connectivity among impulsive-compulsive diagnoses. Insights from a Bayesian approach. *Addictive Behaviors*. *Accepted with minor revision*.

Rationale

In line with RDoC initiatives, understanding brain resting-state functional connectivity (rsFC) as a transdiagnostic target may be helpful to identify specific neurobiological patterns associated (or not) with specific cognitive profiles (Siugzdaite et al., 2020). The frontoparietal network (FPN) seems to be implicated in coordinating and adapting behavior in a goal-driven manner (Marek & Dosenbach, 2018), and seems to comprise a wide-spread network including frontal and parietal main cores: the dorsolateral prefrontal cortex (DLPFC), orbital gyrus, medial prefrontal cortex, frontopolar areas and posterior parietal regions (Markett et al., 2014; Stern et al., 2012).

Frontoparietal network has shown to present an aberrant rsFC in some impulsive-compulsive spectrum disorder patients compared to healthy controls. Vaghi et al. (2017) showed reduced connectivity between the striatum and frontoparietal regions in OCD patients. In this line, recent meta-analysis and reviews have revealed a hypoconnectivity between caudate and FPN regions such as DLPFC and dorsomedial (dmPFC) prefrontal cortex and a general hypoconnectivity within the FPN (Gürsel et al., 2018; Liu et al., 2022). Regarding SUD patients, increased connectivity within orbitofrontal cortex has been reported in heroin users (Ieong and Yuan, 2017). Additionally, a recent meta-analysis has reported a reduced rsFC within the FPN in different SUDs (Taebi et al., 2022). Concerning ADHD, aberrant connectivity in the FPN has been also shown, although the directionality of the relationship between the strength of the rsFC and ADHD symptomatology remains unclear (Bush, 2011; Lin et al., 2015; Mostert et al., 2016; Silk et al., 2008).

In these terms, from a psychological perspective, rsFC could be a predictor of behavioural patterns, which could make rsFC a promising biomarker for decision-making. The predictive role of different rsFC networks, including FPN, has been

studied in decision-making paradigms such as the Delay Discounting Task (Hobkirk et al., 2019; Li et al., 2013) and the Balloon Analogue Risk Task (Wei et al., 2016). While these experimental works showed a negative relationship between the strength of the rsFC within and between different networks and impulsivity during decision-making tasks, other research has revealed a positive relationship and different interactions between the strength of the rsFC in the executive control network (or FPN) and other networks and ADHD symptomatology (Gao et al., 2019; Mostert et al., 2016). Also, a general dysconnectivity between different hubs of different networks, including FPN, has been proposed as a characteristic of OCD pathophysiology (Liu et al., 2022).

Although the rsFC of the FPN is supposed to be critical in controlling and adapting behaviour in a goal-directed manner during both, resting- and task-induced sates (Marek and Dosenbach, 2018), its relationship with IGT performance remains, to the best of our knowledge, unclear.

Taking into account all the above exposed, in this study, we aimed (i) to identify potential particular decision-making profiles in impulsive-compulsive spectrum patients and healthy controls based on their deck choice behaviour during the IGT through the application of an exploratory clustering approach and (ii) to investigate the role of rsFC between different regions of the FPN as a possible biomarker of each potential idiosyncratic choice behaviour. We hypothesized that (i) decision-making profiles will mainly depend on the frequency of punishment instead of on the long-term profit associated with each deck, (ii) decision-making profiles in healthy adults and impulse-compulsive spectrum patients will cut across diagnostic labels, and (iii) identified decision-making profiles will show different and specific predictive rsFC patterns. Specific directions of these effects are difficult to predict due to the abovementioned

inconsistences in the literature, so our approach regarding these issues will be mainly exploratory.

Method

Participants

A total of 114 adults participated in this study. All participants gave verbal and written informed consent. The study was approved by the local Ethics Committee and was conducted following the Declaration of Helsinki. Demographic and clinical features are detailed in Table 5.

41 inpatients with SUD were recruited from a recovery and relapse-prevention centre. A clinical psychologist introduced them to the study and checked the eligibility criteria. They must have been abstinent for at least 15 days. If so, they underwent a clinical interview and completed rating scales, including the Spanish version of the Beck Depression Inventory-II (Sanz et al., 2003) and the State-Trait Anxiety Inventory (Buela-Casal et al., 2015). 33 SUD patients had a diagnosis of polysubstance abuse while 8 SUD patients had been addicted to one substance (*n*=4 alcohol; *n*=3 cocaine; *n*=1 cannabis). All SUD participants were men because of the internal rules of the centre. 30 SUD patients were on pharmacological treatment.

OCD (*n*=25) and ADHD (*n*=14) participants were recruited from the mental health unit of the Torrecárdenas University Hospital (Almería, Spain). An experienced psychiatrist introduced them the project and assessed eligibility criteria by phone. They must have a clinical diagnosis of OCD/ADHD according to DSM-5 criteria (‘DSM V’, 2013). Healthy controls (HC; *n*=34) were recruited by word of mouth from the community. They must have no history of neurological or psychiatric diseases. After eligibility assessment, OCD, ADHD, and HC participants were administered a clinical interview and several questionnaires to confirm the diagnosis. They completed the

Spanish versions of the ADHD Rating Scale-5 (Richarte et al., 2017), the Obsessive Compulsive Inventory-Revised (Fullana et al., 2005), and the Adult Self-Report Scale (Achenbach and Rescorla, 2003). ADHD patients met criteria for Combined (*n*=5), Inattentive (*n*=6), Hyperactive (*n*=1) and non-specified (*n*=2) presentations. 18 OCD and 13 ADHD patients were undertaking medication. 6 OCD and 9 ADHD patients had a wash-out period of at least 24h.

Table 5

Demographics and clinical features of the sample.

	HC (*n*=34)	**OCD (*n*=25)**	**SUD[b] (*n*=41)**	**ADHD[b] (*n*=14)**	**Comparisons[e]**
Demographics					
% Women	58.82	40	0	21.42	$p < .05$
Age[a, d]	35.21±11.36	38.28±11.91	44.12±8.67	34.36±13.26	$p > .05$
Annual income[a]	22,117.65±11,996.3	13,464±12,373.32	6,091.625±5309.576	19,276.92±19,543.89	HC>OCD=SUD=ADHD
Years of formal education[a,c]	16.794±3.675	15.44±4.673	8.735±4.406	14.929±3.245	SUD<HC=OCD=ADHD
% comorbidities					
Depressive disorder	--	16	19.51	7.14	
Anxiety disorder	--	20	7.32	7.14	
Bipolar disorder	--	.00	2.44	.00	
Personality disorder	--	16	2.44	14.29	
Tics disorder	--	4	.00	7.14	
Learning disorder	--	.00	.00	28.57	
Eating disorder	--	12	.00	.00	
ADHD	--	4	.00	.00	
OCD	--	.00	.00	7.14	
SUD	--	4	.00	7.14	
ICD	--	.00	.00	7.14	
PTSD	--	4	.00	.00	
% Prescribed medication	--	72	73.17	92.86	
Stimulants	--	.00	.00	42.86	
Antihypertensive	--	.00	2.44	.00	
Antipsychotic	--	50	14.63	.00	
Antidepressant	--	77	31.71	14.28	
Anxiolytic	--	50	51.22	14.28	
Antiepileptic	--	.00	2.44	7.14	
Opioid	--	.00	21.95	.00	
Clinical measures[a]					
ADHD-RS-V	11.24±6.44	18.58±1.24	--	**31.07±7.74**	ADHD>OCD>HC
OCI-R	17.25±11.76	**39.91±13.49**	--	**23.93±13.22**	OCD>ADHD=HC
ASR DSM OCD	55.12±6.81	**72.52±8.70**	--	64.86±8.88	OCD>ADHD>HC
ASR DSM ADHD	56.68±7.18	64±11.09	--	**70±1.86**	ADHD=OCD>HC
BDI-II	--	--	**18.60±9.25**	--	
STAI-State	--	--	22.69±11.65	--	
STAI-Trait	--	--	25.77±1.89	--	

Note. SUD participants did not complete ADHD-RS-5, OCI-R and ASR questionnaires, while ADHD, OCD and HC participants did not complete BDI-II and STAI questionnaires because clinical groups belonged to two different funded research projects. Scores in the clinical range are boldfaced.
ICD =Impulse Control Disorder; PTSD = Post-traumatic stress disorder; ADHD-RS-V = ADHD Rating Scale-5; OCI-R = Obsessive-Compulsive Inventory-Revised; ASR DSM OCD = Adult Self-Report OCD DSM-Oriented Scale; ASR DSM ADHD = Adult Self-Report ADHD DSM-Oriented Scale; BDI-II = Beck Depression Inventory-II; STAI = State-Trait Anxiety Inventory.
[a]Mean ± SD is represented. [b]Information on prescribed medication and comorbid disorders from 4 SUD participants is missing. We could not collect annual income from nine of the SUD participants and from one of the ADHD participants. [c]Years of formal education from seven of the SUD participants is missing. [d]Age from six of the SUD participants is missing. [e]Statistical comparisons were performed using a Welch-James ANOVA. Fisher Exact Test was used to compare sex proportions between groups.

Materials

Iowa Gambling Task

We used a computerized version of the IGT. The task comprised 100 trials. In each trial, four decks of cards (A, B, C, and D) appeared on the screen. Participants had to press the keys 1, 2, 3, or 4, respectively, to pick one. After each choice, a feedback display showing the outcomes received was presented for 2000ms. During the whole task, Decks A and B entailed a long-term loss (disadvantageous decks) while decks C and D supposed a long-term benefit (advantageous decks). Decks could also be classified according to the frequency and magnitude of losses. Therefore, any choice of Deck A (high frequency-low magnitude losses) would result in a gain of 100 points, but participants could also receive a loss of 150/200/250/300/350 points in a 1:2 ratio. Deck B (low frequency-high magnitude losses) also offered 100 points but they could lose 1250 points in a 1:10 ratio. Deck C (high frequency-low magnitude losses) was rewarded with 50 points but penalized with losses of 25/50/75 points in a 1:2 ratio.

Lastly, Deck D (low frequency-high magnitude losses) also offered 50 points when chosen, but participants could lose 250 points in a 1:10 ratio.

All participants began with an amount of 2000 points and were instructed to maximize their benefits by picking cards from the different decks. They were not informed about the number of trials.

Computational learning models

We applied the same computational learning models as in the previous Study, which also showed poor simulations (Appendix III).

rsFC data acquisition

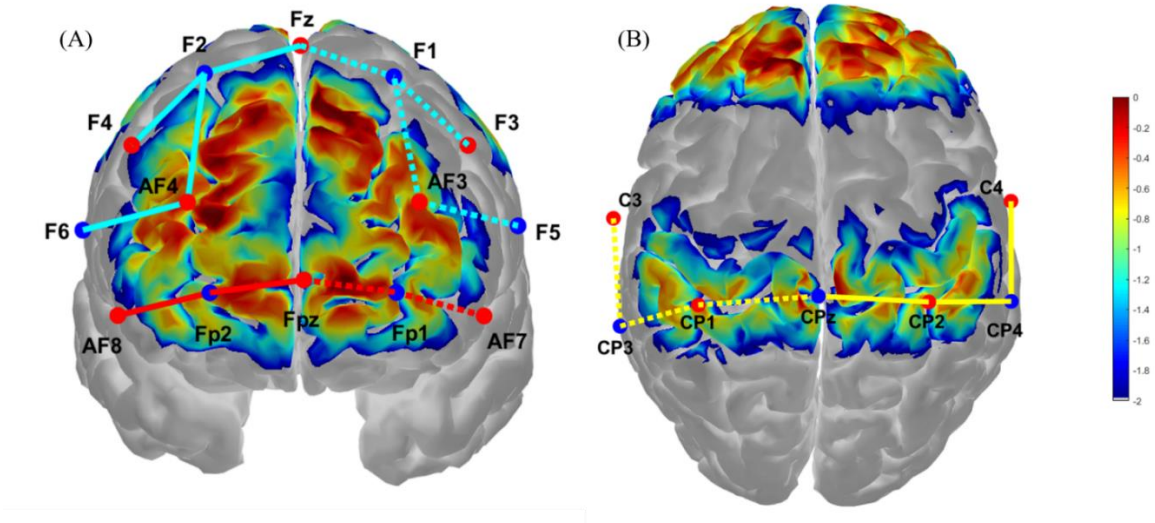
We recorded the relative changes in the concentration of oxy- (HbO_2) and deoxy- (HbR) hemoglobin in cortical areas of the FPN network during 10 minutes of resting state. We used two portable continuous-wave functional near-infrared spectroscopy (fNIRS) systems in tandem mode (NIRSport device, NIRx Medical Technologies LLC, Berlin, Germany). fNIRS data were acquired using the NIRStar Software version 15.0 (NIRx Medical Technologies LLC, Berlin, Germany) at a sampling rate of 3.41 Hz.

We employed a custom probe array of 32 optodes (16 light sources and 16 detectors at two wavelengths, 760 nm, and 850 nm) according to the International 10-10 system of electrode layout with an inter-optode distance of approximately 30 mm. This source-detector configuration resulted in 54 fNIRS measurement channels. In this study, we selected 18 channels that cover up six regions of interest (ROIs) from the FPN: dorsolateral prefrontal cortex (DLPFC), orbitofrontal cortex (OFC), and posterior parietal cortex (pPC), each of them in the right and left hemisphere. The remaining channels were used for a larger research project.

AtlasViewer software was employed to evaluate the probe sensitivity. Figure 14 depicts the spatial sensitivity profile obtained for each used measurement channel on the cortical surface after performing a Monte Carlo photon migration simulation with 10^7 photons.

Figure 14

Graphical visualization of the spatial sensitivity profile in log10(mm-1).



Note. Red and blue dots represent the position of sources and detectors. Solid and dotted lines represent right and left hemisphere. Red, light blue and yellow lines cover up, respectively, the defined ROIs: orbitofrontal, dorsolateral and posterior parietal cortex. (A) Coronal plane. (B) Horizontal plane.

rsFC data pre-processing

fNIRS signals were pre-processed and analysed using a customized MATLAB-based script from the open-source package NIRS Brain AnalyzIR toolbox (Santosa et al., 2018). We down-sampled the raw intensity signal to 1 Hz and then converted it into changes in optical density. We applied the modified Beer-Lambert Law to obtain the relative changes in the concentration of HbO_2 and HbR. We select HbO_2 signals to compute the analyses since it is the most correlated measure with the blood oxygen level-dependent (Duan et al., 2012). Pre-whitening and pre-weighting methods were

applied to ensure the correction of confounding signals such as systemic physiological noise and motion artifacts. The combination of both filtering methods has been suggested to be a reliable approach to better control type-I errors (Barker et al., 2013; Huppert, 2016; Santosa et al., 2017).

rsFC was computed at the time domain through a whole-brain correlation approach. Functional connectivity was then understood as the strength of the temporal correlation of the hemodynamic activity of each pairwise comparison. We conducted Pearson correlation analyses between the time series of every pair of ROIs to obtain the functional connectivity between the measured areas.

Procedure

First, we collected rsFC data for 10 minutes. Participants were instructed to be seated, relaxed, and as quiet as possible, keeping their eyes open and looking at a blank wall. The experimental room was well-acclimated and soundproofed. At least one researcher was always monitoring the recording. fNIRS data from 8 participants were discarded due to technical issues during the recording.

Afterward, we removed the fNIRS cap and participants completed the IGT, which lasted approximately 10 minutes. After they read the instructions, participants were asked to explain the task before starting to make sure they understood it correctly. Once they finished, we explicitly asked them (6.42% of the participants were asked) whether they thought there was an optimal strategy to maximize their profits and, if so, which decks they had to pick.

Statistical analysis

Clustering procedure

We used hybrid hierarchical K-means clustering analyses to identify specific behavioural profiles associated with the IGT. This method combines hierarchical

(Ward's linkage method on Euclidean distance) and non-hierarchical (K-means) methods to deal with the randomness of initial centroids selection (Hair et al., 2019). This algorithm was performed over the whole sample on the standardized number of choices of each deck in each 20-trial block of the IGT. We selected the optimal number of clusters based on dendrogram visualization and the gap statistic method (Tibshirani et al., 2001). Proportion tests were then performed to check if the number of cases in each cluster concerning to the total sample for each diagnostic group was different from the expected. All analyses were run in R software (R Core Team, 2021).

Bayesian data analysis

We were interested in the number of choices of each deck in each block, as well as in the effect that rsFC, traditional diagnostic labels, and cluster membership, may exert on these choices. As several comparisons were going to be made, we decided to employ Bayesian data analysis, which allows us to explore a single posterior distribution from multiple perspectives granting a higher control over Type I errors (Kruschke, 2015). For making these estimations, we designed a General Linear Model (GLM) that considers, for each deck, block, and group, an estimated number of choices that may also be affected by the standardized rsFC between each of the ROIs of each individual. Additionally, Bayesian mean comparisons were used to explore whether there were differences in rsFC between diagnostic groups or cluster membership between the ROIs. For each of these purposes, two different models were run, with the only difference between them being the variable used as "Group", which could be diagnostic group or cluster membership. The full details of these models are specified as follows.

In all the equations, the symbol "~" means "distributed as", and N(x, y) indicates a normal distribution with mean = x and SD = y, while Exp(x) indicates an exponential distribution with λ = x. The number of cases is represented by [i].

$$\text{Choices}[i] \sim N(\mu\_\text{choices}_{[i]}, \sigma\_\text{choices}_{[\text{Group}[i],\ \text{DB}[i]]}) \quad (1)$$

$$\mu\_\text{choices}_{[i]} = \alpha_{[\text{Group}[i],\ \text{DB}[i]]} + \beta_{rsFC1\ [\text{Group}[i],\ \text{DB}[i]]} * \text{rsFC1}_{[i]} +$$

…

$$\beta_{rsFC15\ [\text{Group}[i],\ \text{DB}[i]]} * \text{rsFC15}_{[i]} \quad (2)$$

$$0 < \sigma\_\text{choices}_{[\text{Group}[i],\ \text{DB}[i]]} \sim Exp(1/2) \quad (3)$$

$$\alpha_{[\text{Group}[i],\ \text{DB}[i]]} \sim N(5, \sigma\_\alpha_{[Group[i],\ DB[i]]}) \quad (4)$$

$$0 < \sigma\_\alpha_{[\text{Group}[i],\ \text{DB}[i]]} \sim Exp(1/5) \quad (5)$$

$$\beta_{rsFC1\ [\text{Group}[i],\ \text{DB}[i]]} \sim N(\mu\_\beta_{rsFC1[\text{DB}[i]]}, \sigma\_\beta_{rsFC1[\text{DB}[i]]}) \quad (6)$$

…

$$\beta_{rsFC15\ [\text{Group}[i],\ \text{DB}[i]]} \sim N(\mu\_\beta_{rsFC15[\text{DB}[i]]}, \sigma\_\beta_{rsFC15[\text{DB}[i]]}) \quad (20)$$

$$0 < \sigma\_\beta_{rsFC1[\text{DB}[i]]} \sim Exp(1) \quad (21)$$

…

$$0 < \sigma\_\beta_{rsFC15[\text{DB}[i]]} \sim Exp(1) \quad (35)$$

$$\mu\_\beta_{rsFC1[\text{DB}[i]]} \sim N(0, 1) \quad (36)$$

…

$$\mu\_\beta_{rsFC15[\text{DB}[i]]} \sim N(0, 1) \quad (50)$$

The number of cases [i] was equal to the number of different decks (4; A, B, C, or D) times the number of blocks (5) times the number of participants (n = 114) so the total number of cases was 2280. The variable Group[i] may present a number of different values equal to the levels of the grouping variable employed in each run of the model, which was either the traditional diagnostic labels (Control, OCD, SUD, or ADHD) or the cluster membership (D-Learners, B-Exploiters, or Scattering). On the

other hand, the variable DB[i] always could acquire 20 different values, which result from the combination of each type of deck (A, B, C, or D) in each of the blocks of the IGT (block 1, 2, 3, 4, or 5). To choose the priors of our model we considered values that may be plausible in the linear space of our variables, as recommended in McElreath (2018).

Equation (1) represents the likelihood of the model, which targets the number of choices in each case [i]. In equation (2), μ_choices aims to provide the mean estimate of this number of choices. Parameter α accounts for the intercept of the model, which may present different values depending on the group of the participant, indicated by Group[i], and each deck and block, indicated by DB[i]. Additionally, regression coefficients β_{rsFC1} to β_{rsFC15} evaluate the possible effect that the standardized rsFC between our ROIs detailed in the "rsFC data acquisition section" may exert on the number of these choices, allowing these coefficients to vary for each group, type of deck, and block. In participants who had not had their rsFC registered due to technical issues (n = 8), their behaviour was predicted using only the α parameter. Equation (3) represents the prior of σ_choices, which provides an estimate of the SD for each number of choices that may also vary depending on each group, type of deck, and block, for which we chose an exponential distribution with a rate of 2.

In equation (4) we have the prior for the intercept parameter α, a normal distribution centered at 5 since this would indicate an equal number of choices of each deck in each block, but with a standard deviation σ_α that may vary for each group, type of deck, and block, and for which we choose an exponential distribution σ_α with a rate of 5 aiming to be able to capture a wide but plausible variability between conditions, as exposed in equation (5).

Equations (6) to equation (20) represent the priors for the regression coefficients β_{rsFC1} to β_{rsFC15} for each group, type of deck, and block. A normal distribution depending on higher-level populational parameters was decided for the means (parameters μ_β_{rsFC1} to μ_β_{rsFC1}) and the SDs (parameters σ_β_{rsFC1} to σ_β_{rsFC15}) of these distributions. For the priors of the populational means of these parameters, we assumed a normal distribution centred at 0 and with an SD of 1, as exposed in equations (21) to (35), while for the priors of the populational SDs were assumed an exponential distribution with a rate of 1, as can be seen in equations (36) to (50). The reason for establishing this hierarchical structure was to be able to check whether a credible effect of the rsFC is detected when all individuals are taken into account, which may indicate that rsFC could be associated with the number of choices of each deck in each block for everybody. Additionally, we would also be able to detect if this effect is specific to a particular diagnostic group or cluster, which would mean that rsFC between our ROIs may present different roles depending on these individual features.

To estimate the differences between means regarding the number of choices in the different conditions, we generated new posterior distributions from the subtractions of α parameters on each sample of the posterior corresponding to each group and condition we aimed to compare.

Additionally, we also wanted to explore whether there were differences in connectivity between diagnostic groups or cluster membership among, those participants who had their rsFC registered (n = 106). Bayesian mean comparisons were performed assuming the following priors:

$$\mu_{[Group[i],\, rsFC[i]]} \sim N(\, 0,\, \sigma\_\text{rsFC}_{[Group[i],\, rsFC[i]]}\,) \quad (51)$$

$$0 < \sigma\_\text{rsFC}_{[Group[i],\, rsFC[i]]} \sim Exp(1) \quad (52)$$

Equation (51) represents the prior of the mean μ, one for each group and connectivity between our ROIs. The distribution for these priors will be centered at 0 and may present a different standard deviation σ_rsFC depending on these same variables, following an exponential distribution with a rate of 1 as exposed in equation (52). These priors will adapt to the specific distribution of each measure, which may allow for an accurate estimation of each mean of interest. After all, these means were estimated, to estimate the differences between means, we generated new posterior distributions from the subtractions between means estimated on each sample of the posterior of the groups we aimed to compare.

After the models were run, statistical decisions were made employing the 95% Highest Density Intervals (HDIs) as well as Regions Of Practical Equivalence (ROPEs), which determine a range around specific values of interest, such as zero when we estimate the difference between means or the value of regression coefficients. When the HDI completely excludes the ROPE, we will conclude that the values inside the ROPE are not credible (Kruschke, 2011). Regarding the number of choices, we will only consider as relevant those effects that suggest at least a change of one in the number of decks chosen per block, so we will establish a ROPE of (-1,1) for mean comparisons and a ROPE of (-.5, .5) on the standardized regression coefficients of the rsFC between our ROIs, which would suppose a difference of at least one choice when this measure varies by two standard deviations (SDs). On the other hand, when we explore differences in rsFC between our ROIs in the different groups, we will consider as relevant all the differences in which the 95% HDIs exclude the value. As this measure is given as the correlation between two areas and since our approach here is exploratory, we have no a priori knowledge of which amount of change would suppose a relevant difference.

All analyses were performed using the RStan package (Stan Development Team, 2022). For each analysis, we extracted 12000 samples using Markov Chain Monte Carlo (MCMC) sampling, each of the 4 chains having 2000 warmup samples and saving 3000 samples. Traceplots for all chains and parameters, as well as the Gelman-Rubin test (Gelman and Rubin, 1992), showed an appropriate convergence with all $\hat{R}$ values below 1.05.

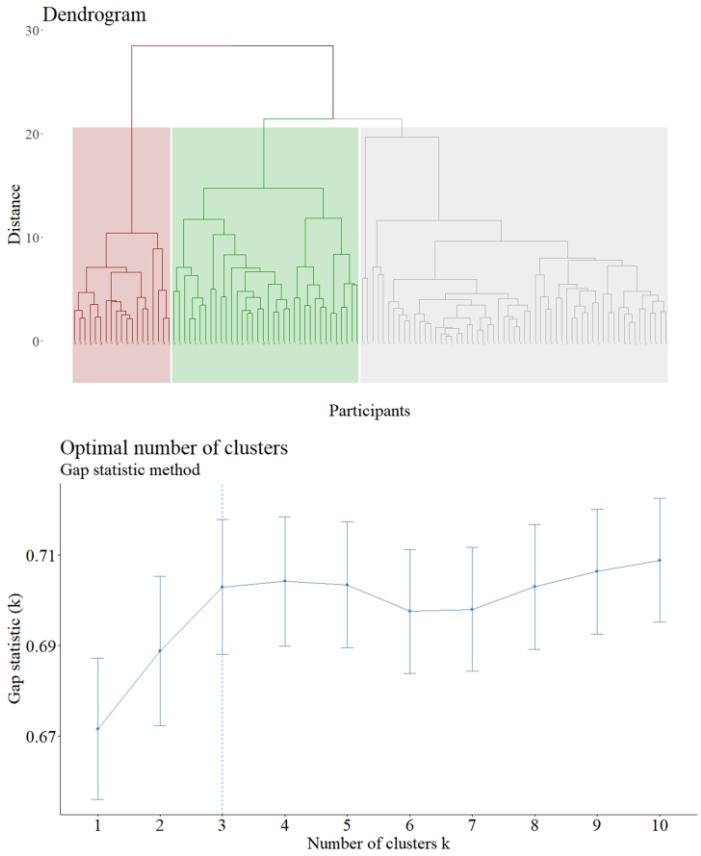
Results

Clustering analyses

A three-cluster structure was the optimal solution to characterize all participants' deck choice behaviour according to the Gap statistic method. Graphical exploration of the dendrogram also supported this clustering solution (see Figure 15).

Figure 15

Graphical representation of the best clustering solution.



The first cluster (n =27; M_{age} = 37.72, SD_{age} = 9.71) exhibited a preference for Deck D. The second cluster (n=25; M_{age} = 43.37, SD_{age} = 1.41) exhibited a preference for deck B. The third cluster (n=62; M_{age} = 37.81, SD_{age} = 12.14) did not develop a preference for any deck. Thus, we labelled these profiles as "D-Learners", "B-Exploiters" and "Scattering", respectively. Proportion tests suggested there were no differences in the number of individuals belonging to each cluster depending on their diagnostic group when compared to the expected proportion of cases within each cluster (see Table 6 and Figure 16).

Table 6

Participants' proportional distribution in each cluster according to each diagnostic label.

Cluster	**HC (*n* = 34)**	**OCD (*n* = 25)**	**SUD (*n* = 41)**	**ADHD (*n* = 14)**
D-Learners (*n* = 27)	*n* = 9 χ^2=.03 *p*=.09	*n* = 10 χ^2=2.84 *p*=.09	*n* = 6 χ^2=1.39 *p*=.24	*n* = 2 χ^2=.26 *p*=.61
B-Exploiters (*n* = 25)	*n* = 5 χ^2=.66 *p*=.42	*n* = 6 χ^2=.000 *p*=.99	*n* = 9 χ^2=.000 *p*=.99	*n* = 5 χ^2=.85 *p*=.36
Scattering (*n* = 62)	*n* = 20 χ^2=.12 *p*=.73	*n* = 9 χ^2=2.71 *p*=.10	*n* = 26 χ^2=1.02 *p*=.32	*n* = 7 χ^2=.004 *p*=.95

Figure 16

Graphical representation of the percentage of participants in each cluster based on their diagnostic *label.*

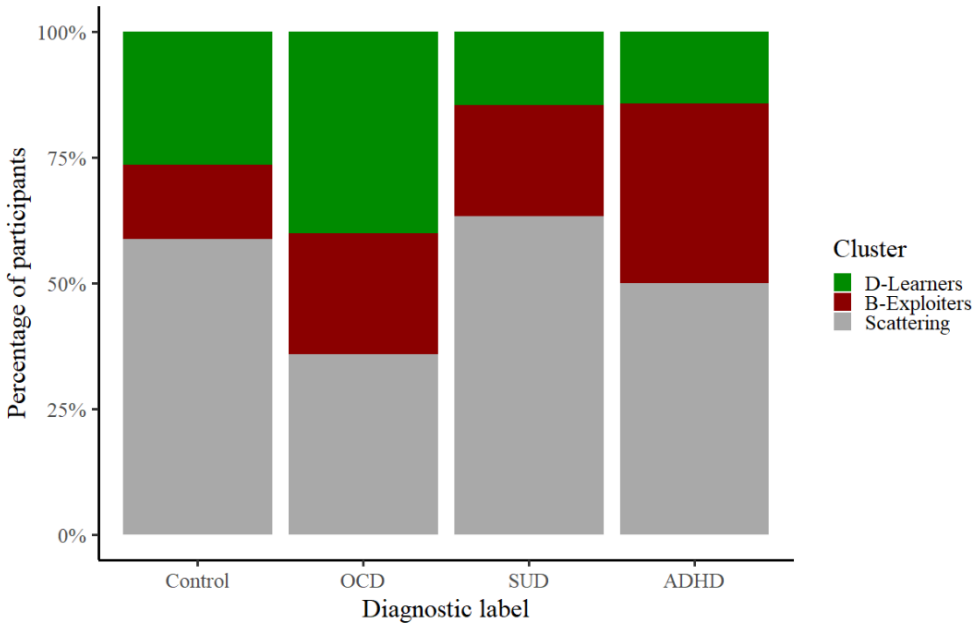


Table 7

Demographic information of each cluster.

Cluster	Number of women	Annual income[a]	Years of formal education[b]
D-Learners (*n* = 27)	8 χ^2=.00 *p* = .999	14,30.46 ± 11,15.65	15.58 ± 5.62
B-Exploiters (*n* = 25)	8 χ^2=.012 *p* = .911	11,352.38 ± 9,83.70	11.65 ± 5.20
Scattering (*n* = 62)	17 χ^2=.024 *p* = .876	16,209.12 ± 15,249.68	13.62 ± 5.02

Note. [a]We could not collect annual income from nine of the SUD participants and from one of the ADHD participants. [b]Years of formal education from seven of the SUD participants is missing.

Deck preference

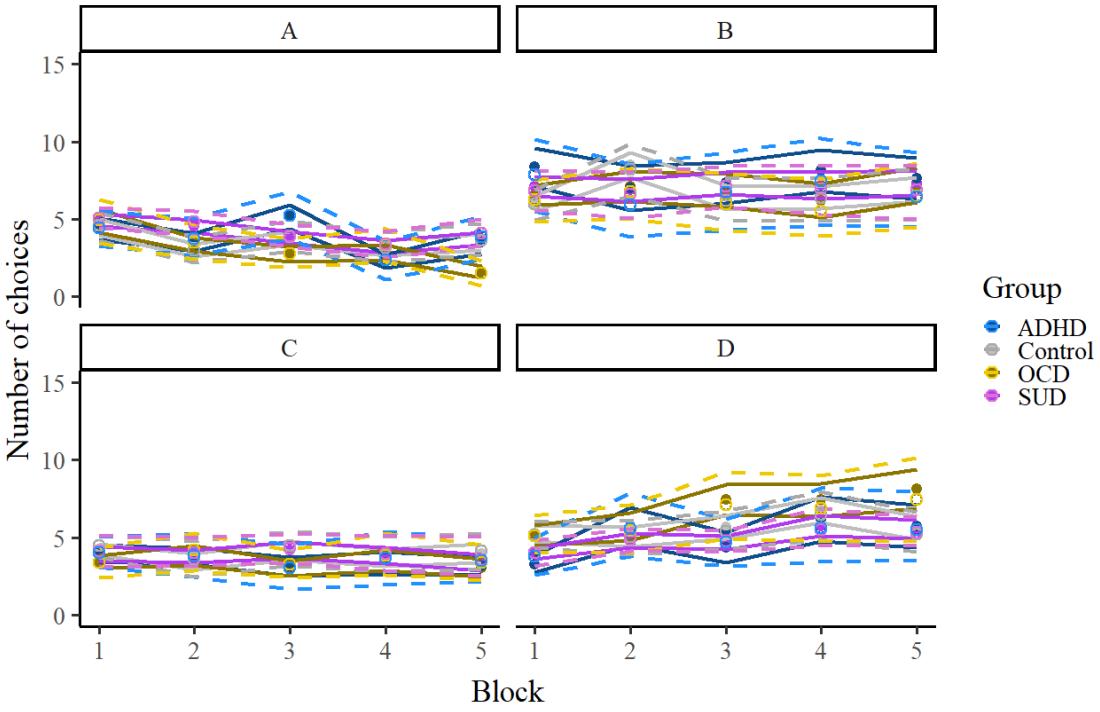
To ease the comprehension of the results, only credible differences will be commented on. Statistics regarding the differences in means are exposed in Appendix II.

Diagnostic group

Participants did not show any credible differences regarding deck choice0 behaviour in the IGT as a function of their diagnostic group (see Figure 17).

Figure 17

Real (solid points) and predicted (blank points) number of choices of each deck as a function of diagnostic group and block, respectively representing the true means and the mean of the posteriors.



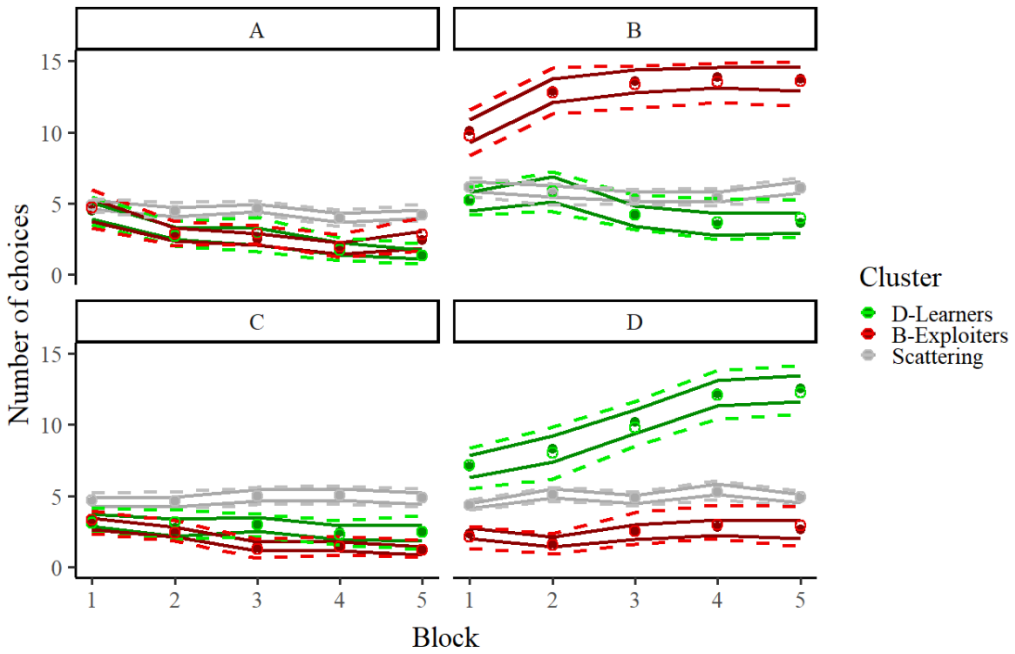
Note. The solid and dashed lines represent the standard error of the mean (SEM) and the 95% HDIs.

Cluster membership

"D-Learners" (Cluster 1) showed a preference for Deck D from the beginning of the task when compared with the other clusters, which was maintained until the last block of the task. Starting on Block 3, this cluster showed a higher preference for Deck D than for the other decks. "B-exploiters" (Cluster 2) revealed a preference for Deck B starting in the first block and also maintained until the last block of the task. These participants showed a higher preference for this deck from the first block of the task onward. Lastly, "Scattering" (Cluster 3) was distinguished by showing no credible differences between any of the chosen decks in any of the blocks, suggesting they had no preferred strategy and responded randomly. This information is graphically depicted in Figure 18.

Figure 18

Real (solid points) and predicted (blank points) number of choices of each deck as a function of clusters and blocks, respectively representing the true means and the mean of the posteriors.



Note. The solid and dashed lines represent the standard error of the mean (SEM) and the 95% HDIs.

Resting-state functional connectivity differences

Bayesian mean comparisons revealed no credible differences in the rsFC between any of the ROIs neither comparing Clusters nor diagnostic groups. Data regarding these values are exposed in Figure 19 and Figure 20.

Figure 19

Real (solid bars) and predicted (stripped bars) rsFC values between each ROI as a function of clusters, representing the true means and the mean of the posteriors.

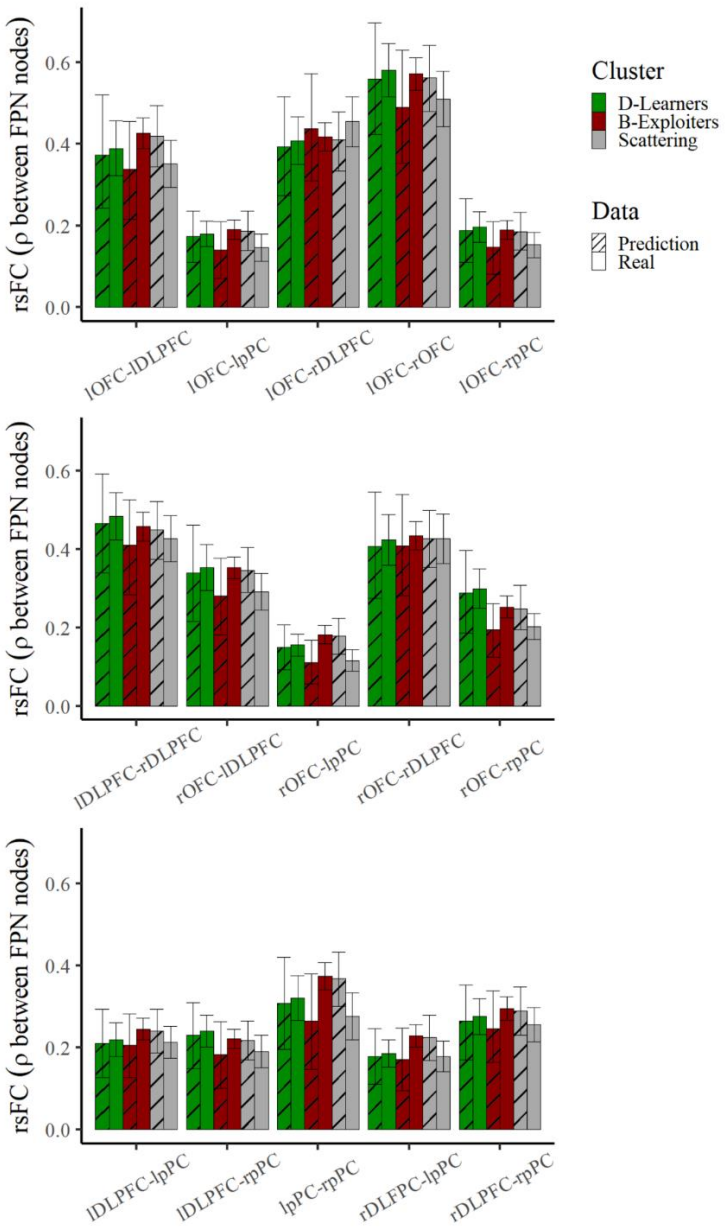
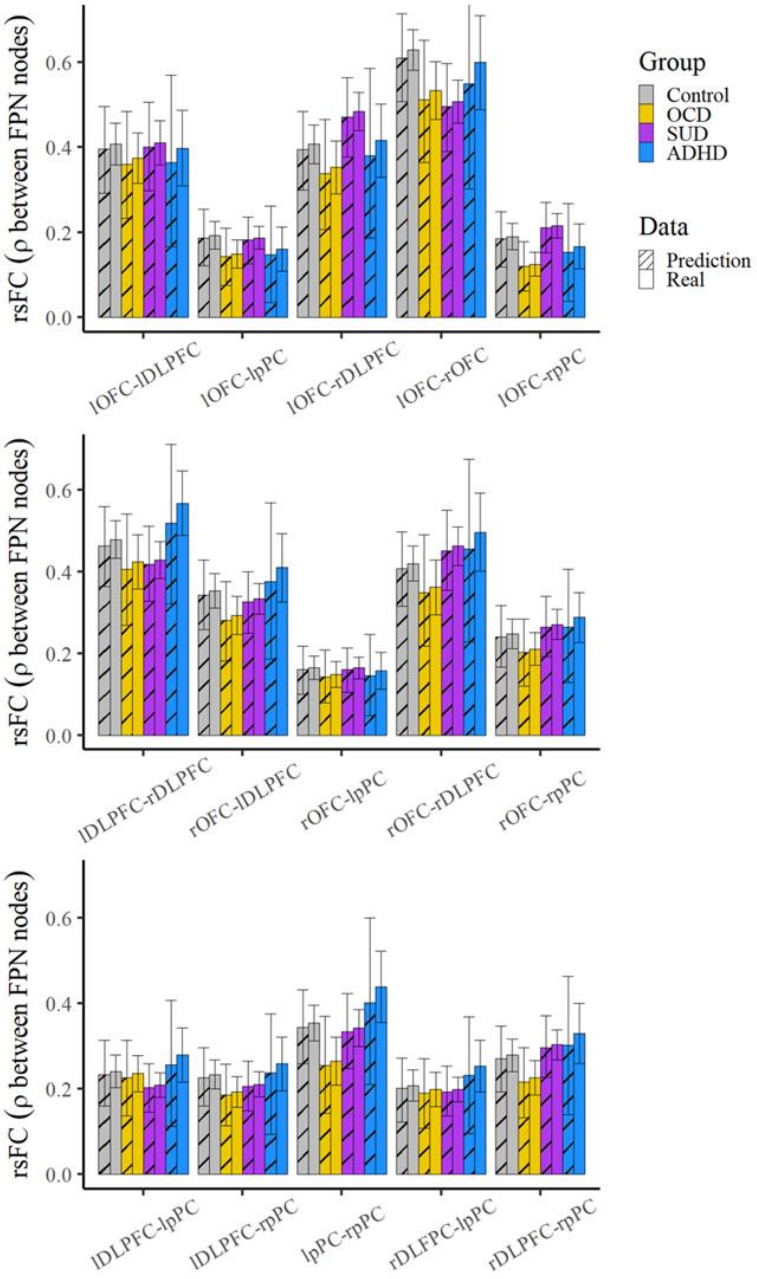


Figure 20

Real (solid bars) and predicted (stripped bars) rsFC values between each ROI as a function of diagnostic group, representing the true means and the mean of the posteriors.



Note. The vertical bars represent the standard error of the mean (SEM) or the 95% HDIs. Abbreviations correspond to left orbitofrontal cortex (lOFC), right orbitofrontal cortex (rOFC), left dorsolateral prefrontal cortex (lDLPFC), right dorsolateral prefrontal cortex (rDLPFC), left parietal prefrontal cortex (lpPC) and right parietal prefrontal cortex (rpPC).

Resting-state functional connectivity as a predictor of deck choice behaviour

Analyses showed no credible relationship between the rsFC between any of the ROIs and deck choice behaviour in any stage of the task, neither at the whole sample level nor in any diagnostic group or cluster.

Discussion

In this study, we employed hybrid clustering analyses to identify specific decision-making profiles among a sample of healthy adults and OCD, ADHD, and SUD patients during the IGT. We also applied a bayesian GLM to explore the role of rsFC between cortical areas of the FPN as a biomarker of deck choice behaviour in the IGT.

Our first hypothesis is partially supported since two of the clusters show a notable preference for decks associated with infrequent losses. Concretely, cluster analyses revealed three different subpopulations. Importantly, all clusters presented no differences regarding sex distribution, annual income, or years of formal education, which have been proposed as critical variables for IGT performance (Evans et al., 2004; Ursache and Raver, 2015; van den Bos et al., 2013). The first cluster, “D-Learners”, developed a long-term advantageous decision-making strategy, characterized by a preference for advantageous choices that carried low-frequency but high-magnitude losses. The second cluster, “B-Exploiters”, was characterized by the exploitation, since the early stages of the task, of the disadvantageous deck that also offers low-frequency but high-magnitude losses. This could be understood as a long-term maladaptive strategy. Lastly, a fully scattering-based strategy profile was shown by the third cluster. These latter participants did not develop a preference for any deck at any stage of the task.

Theoretically, developing a long-term advantageous strategy during the IGT requires, in the first place, exploring the different choices to learn the contingency rules

of each deck. After this, behaviour may be adapted in a goal-directed manner, exploiting the most profitable choice. “D-Learners” seem to show this exploration-exploitation strategy since at the beginning of the task they had a similar number of choices of each deck, and from the third block onwards, they show a high preference for Deck D.

On the other hand, presenting a non-profitable behaviour in the IGT may be due to different reasons. Scarce early exploration could generate a lack of information about the possible decisions and their outcomes, which inevitably leads to a biased representation of the alternatives presented in the task. In our case, in pursuit of early exploitation, “B-Exploiters” revealed a notable preference for Deck B since the beginning of the task. Another explanation of this behaviour could be a negligent evaluation, driven by a high outcome sensitivity and a low loss aversion, of the expected utility of this deck considering the frequency and magnitude of gains and losses, which may be in accordance with models that aim to explain the way people evaluate decisions under risk (Kahneman and Tversky, 1979). This profile is also consistent with the so-called prominent Deck B phenomenon (Lin et al., 2007; Toplak et al., 2005) by which non-defective decision-makers would also tend to choose this deck over the rest. It has been used to claim a reformulation of the basic assumptions of the IGT (Lin et al., 2007).

Contrarily, showing excessive exploration may also be undesirable in this paradigm, since the maximization of profits requires the exploitation of specific choices over the rest. The “Scattering” cluster does not present a preference for any deck in any stage of the task, which may suggest they do have not a clear representation of the different outcomes carried out by each deck, which may make them evaluate all choices similarly. Another possibility is that participants could have learned a fictitious do-not-exploit-a-deck rule, which is consistent with a sequential exploration pattern (Ligneul,

2019), and would reflect an incorrect evaluation of the ratios and magnitudes of the gains and losses of each deck. In this sense, when asked, many participants (43.07% of asked participants) declared that the optimal strategy was to switch when a loss appears, or even when no penalties were given.

The existence of such differential response styles also highlights the importance of studying decision-making processes at the individual level, especially when the IGT is employed, because it is a complex task that encompasses a wide variety of possible strategies to be followed (Verdejo-Garcia et al., 2022). Importantly, even our healthy individuals reflect this same variability of preferences, so we think more caution should be taken when drawing inferences from findings when assuming that either (i) healthy people will adapt a long-term advantageous behaviour or (ii) that maladaptive patterns detected in clinical populations are due to the key features of the clinical diagnoses.

Regarding our second hypothesis, we predicted that these profiles would cut across diagnostic labels, which has also been supported by data. We observed that maladaptive decision-making in the IGT is not a core feature of patients with a diagnosis of ADHD, OCD, and SUD. Instead, participants from each diagnostic group, as well as healthy participants, showed not a different probability of being included in each of the abovementioned clusters. When we explored the number of choices of each deck in each of the blocks we did not find any credible differences between diagnostic groups and healthy participants either. So, according to our data, variability in deck choice behaviour during the IGT seems to be similarly distributed among individuals with and without diagnoses. These findings are in line with studies reporting no differences in IGT performance between ADHD and OCD and healthy people (Groen et al., 2013; Norman et al., 2018). However, it has been widely reported that SUD patients underperform healthy controls in the IGT (Bartzokis et al., 2000; Bechara and Martin,

2004; Kovács et al., 2017; Verdejo-Garcia et al., 2007), which is inconsistent with our results.

These studies usually report the net score as a measure of decision-making, which may lead to the loss of valuable information. We suggest that deck preferences develop as individuals experience the contingencies associated with each deck and that this process will be mediated by individual differences in factors such as loss aversion, risk aversion, reward sensitivity, or error processing, which are not possible to address paying attention only to the net score. Global outcomes such as the net score hide the genuine behavioural pattern of the participants and may contribute to contradictory results in the literature. Instead, focusing on how each individual develops a certain deck preference during the task may provide insightful information about the underlying mechanisms of decision-making that may drive the formation of an optimal or suboptimal choice strategy. In this sense, following Steingroever et al. (2013), healthy participants would prefer decks offering infrequent losses instead of those which offer a long-term profit, which is also supported by Kumar et al. (2019) and would present an idiosyncratic choice behaviour. We consider that our results are in line with this research, and to some extent, extend it to impulsive-compulsive spectrum diagnosed patients' behaviour.

Regarding clinical implications, our results may shed light on disentangling symptoms heterogeneity and guiding novel conceptualizations of psychiatric dimensions. Here we show that not all individuals belonging to clinical groups commonly attributed with a defective decision-making process manifest this deficit, and if they do, they do not manifest it in the same way. Understanding these individual differences may be important to identify relevant psychological traits across the spectrum of psychopathology, and, therefore, to design effective and personalized

interventions. Future research could try to further investigate this issue since the replication of the obtained decision-making profiles may suggest a need for a paradigm shift in the way performance in the IGT is conceptualized.

Concerning our third and last hypothesis, rsFC between ROIs has not shown any relationship with the behaviour of the participants at any level. In contrast to other research (Hobkirk et al., 2019; Li et al., 2013; Wei et al., 2016), we found no evidence to support rsFC as a biomarker of decision-making processes in the IGT, as has been suggested by the absence of credible differences in connectivity patterns between different clusters, as well as by the lack of influence of the rsFC between ROIs on the number of choices of any deck in any block. A possible explanation for this result would be in line with the hypothesis of the FPN as a flexible cognitive control node. Following this, the FPN would be functionally connected to other specialized networks, such as salience or default mode networks, which have been not assessed in the present study, and it would be especially implicated in rapidly adapting the connectivity across widespread brain regions according to task demands (Cole et al., 2013; Zanto and Gazzaley, 2013). Following this hypothesis, further research could investigate the between-networks functional connectivity (instead of only within-network functional connectivity) and its potential role in uncertain decision-making. Another explanation could be derived from the imbalance between the DMN and the FPN in resting- and task-induced states. While the DMN connectivity usually decreases under challenging tasks, so it could be a reflect of spontaneous brain activity during resting-state (Raichle, 2015; Smallwood et al., 2021), FPN seems to be recruited in contexts where executive functioning is needed (Niendam et al., 2012). In relation to this, functional changes in FPN connectivity from rest to IGT context have been reported. However, no relationship between those changes and IGT performance was found (Bolt et al., 2016).

Some limitations of this study should be noted. First, most patients were on medication without a wash-out period, so we could not control its influence on IGT performance and rsFC recording. Second, the absence of a real monetary reward in a gambling paradigm as the IGT might have a negative impact on participants' motivation (Bowman and Turnbull, 2003). Third, IGT performance seems to recruit subcortical brain areas (Li et al., 2010), but, as a limitation of the fNIRS technique, they could not be measured in this study. Fourth, other variables such as risk aversion or reward sensitivity, which may be at the basis of individual differences driving the development of different decision-making strategies (Capa and Bouquet, 2018; Penolazzi et al., 2012; Tom et al., 2007), have not been directly assessed in the present study. In this sense, further research could focus directly on these variables, applying an event-related design, to investigate the individual differences in neural reward/punishment processing driving deck choice preferences during the IGT. Finally, some authors have suggested that larger sample sizes could be required to extract more reliable conclusions from brain and behaviour studies (Marek et al., 2022; Turner et al., 2018), so it could also be desirable to increase the sample size to diminish the standard error of the employed measurements.

CHAPTER 6. STUDY IV: Frontal-Midline Theta and Iowa Gambling Task: A Transcranial Alternating Current Stimulation Preliminary Study

This Study was carried out during an international research stay in the Charité – Universitätsmedizin Berlin (Berlin, Germany). Bearing in mind everything learned during the development of the present Doctoral Thesis, this experimental procedure is designed to combine tACS and EEG to investigate the role of the frontal-midline theta oscillation activities in the performance and learning on the IGT, which will be understood from a probabilistic approach. We administered frontolateral in-phase tACS at theta frequency (6-Hz) for eight minutes before the task. We applied a Bayesian logistic regression model to explore the relationship between theta power and frequency mismatch and behavioural parameters. We found a positive relationship between theta power and final performance in the sham group. No evidence of effect of theta-tACS was found. Please note that the presented results of this Study are preliminary.

This experiment is part of a larger research project that corresponds to Leon, J.J., Fernández-Martin, P., Haslacher D., Soekadar, S., and Flores P. (2023). Frontal-Midline Theta and Iowa Gambling Task: A Transcranial Alternating Current Stimulation Preliminary Study. *In preparation*.

Rationale

Frontal-midline theta (FMT; 4-8 Hz) has been proposed as a neural communication signal by which top-down control mechanisms would be recruited in highly cognitively demanding environments (Cavanagh and Frank, 2014). In other words, it is understood as an electrophysiological brain signal of "need-for-control" that drives behavioural adaptations in uncertain contexts (Cavanagh and Frank, 2014). FMT is supposed to be generated by prefrontal regions such as the anterior cingulate cortex (ACC) and medial prefrontal cortex (mPFC) (Cavanagh and Frank, 2014) and to synchronize as task cognitive demands increase (Klimesch, 1999). In this sense, theta power (the number of neurons firing synchronously at theta frequency) has been proposed as a mediating variable for working-memory, attention, conflictive choice behaviour, outcome processing and reward-based learning (Cavanagh et al., 2010, 2012; Cavanagh and Frank, 2014; Cohen, 2014; Marco-Pallares et al., 2008; Mas-Herrero and Marco-Pallarés, 2014; Rajan et al., 2019; Sauseng et al., 2005, 2008; van de Vijver et al., 2011). In addition, previous studies have linked an increased theta power to worse IGT performance, proposing a relationship between theta power and reward sensitivity (Massar et al., 2014; Schutter and van Honk, 2005), and to risk-taking behaviour during a Balloon Analogue Risk Task (Sela et al., 2012).

The application of tACS at theta frequency has been widely used to modulate executive functions (for a review, see Klink et al., 2020) as visuospatial and working memory (Jaušovec et al., 2014; Jaušovec and Jaušovec, 2014; Kleinert et al., 2017; Meng et al., 2021; Pahor and Jaušovec, 2018), and fluid intelligence and reasoning (Jaušovec et al., 2014; Pahor and Jaušovec, 2014). However, conflictive, and opposite findings have been also found by other researchers when applying theta-tACS to

modulate theta band oscillatory activities (Dantas et al., 2021; Feurra et al., 2012; Soutschek et al., 2021; Wischnewski et al., 2021; Wischnewski and Compen, 2022).

One possible explanation for the inconsistencies of the effect of tACS is the mismatch between the stimulation frequency and the endogenous peak frequency of each individual (Lorenz et al., 2019; Stecher et al., 2021; Kasten et al., 2019). In this sense, the effect of tACS has been proposed to be highly dependent on pre-stimulation brain states (Herrmann et al., 2013). Therefore, individual differences should be taken into account to deeply understand the potential tACS effects on neurophysiology and behaviour (Stecher and Herrmann, 2018). Two different approaches have been proposed to overcome this potential limitation of the combination of tACS and EEG recordings. One the one hand, closed-loops stimulation protocols use to be designed to tune the stimulation parameters based on the current brain state, instead of pre-tuning them, showing promising results (Jones et al., 2018; Ketz et al., 2018; Lorenz et al., 2019; Stecher et al., 2021). On the other hand, frequency mismatch could be understood as the absolute distance between endogenous and stimulation frequency and some research has shown effects of tACS at different frequencies only when the frequency of the stimulation closely targets the individual endogenous frequency (i.e., when the mismatch is close to zero) (Javadi et al., 2017; Krause, 2022).

Despite FMT oscillatory activities are crucial for reinforcement learning and cognitive control in uncertain situations, its implications in reward-based decision-making under ambiguous conditions, such as those recreated during the IGT, remain unclear. Additionally, the capability of theta-tACS to modulate decision-making processes during the IGT through the entrainment of theta activity remains unexplored. Thus, this study aimed to clarify the role of theta power on IGT performance and the capability of theta-tACS to modulate the decision-making process. We hypothesized

that (i) theta power will predict the performance on the IGT and, (ii) frequency mismatch between theta-tACS and endogenous theta peak frequency will modulate the relationship between theta power and the performance on the IGT in a frequency-specific manner.

Method

Participants

Forty-four volunteers were recruited through mailing lists, advertisements, and word of mouth. Participants must be at least 18 years old and met the following inclusion criteria: (a) naïve to the Iowa Gambling Task, (b) no neurological or genetic disease, (c) no history of psychiatric disorders, and (d) no contraindications to transcranial electrical stimulation described by safety and regulatory application guidelines (Screening questionnaire for Transcranial Electrical Stimulation, University of Göttingen). Demographic information about the sample can be consulted in Table 8. Participants were informed about the objectives and procedure of the study and provided verbal and written informed consent before starting the session. Participants were paid 10€ per hour and, as they were informed, got an extra payment depending on task performance (proportionally to IGT net score). The entire experimental procedure lasted for approximately two hours.

Table 8

Demographics of the sample.

Group	Active (*n*=22)	Sham (*n*=20)
Demographics		
Age	27.91 ± 5.31	27.70 ± 6.53
% Women	40.91	40
Years of formal education	17.95 ± 3.64	17.15 ± 3.45
Clinical measures		
UPPS-P	41.32 ± 7.69	43.15 ± 7.77
DAST-10	.95 ± 1.76	1.30 ± 2.00
STAI-Trait	40.00 ± 8.31	39.10 ± 8.24
STAI-State	44.77 ± 8.61	43.20 ± 6.35
AUDIT	5.32 ± 6.03	5.25 ± 5.89
SOGS	.18 ± .59	.95 ± 2.11

Note. Mean ± SD is represented. UPPS-P: UPPS-P Impulsive Behaviour Scale; DAST-10: Drug Abuse Screening Test; STAI: State-Trait Anxiety Inventory; AUDIT: Alcohol Use Disorders Identification Test; SOGS: South Oaks Gambling Screening.

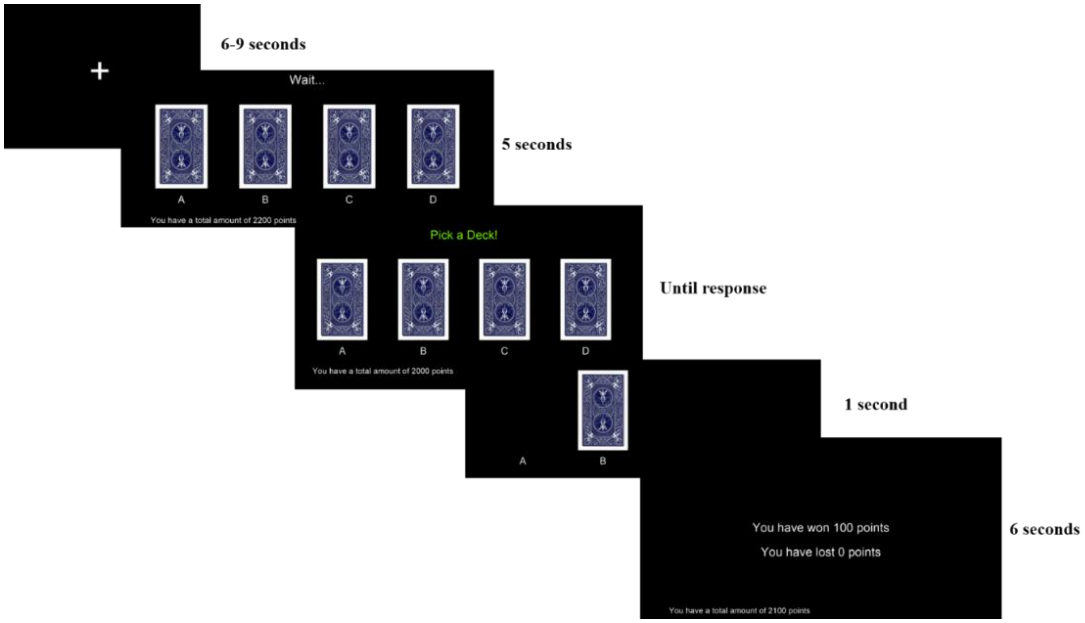
Materials

Iowa Gambling Task.

The IGT was applied following the same contingency rules as in the previous Study. We modified the inter-trial interval (ITI) and the duration of the feedback display to make the task suitable as an event-related design for neuroimaging (haemodynamic fNIRS data) measures, which will be used for other research purposes. Each trial began with the appearance of a fixation cross for a variable ITI ranging from six to nine seconds. After that, the four decks appeared on the screen. Participants were able to respond after 5 seconds of the decks presentation. After each choice, a screen showing the selected deck was displayed for one second. Finally, a six seconds duration feedback screen was shown. A graphical depiction of the task can be observed in Figure 21.

Figure 21

Graphical summary of the experimental task used.



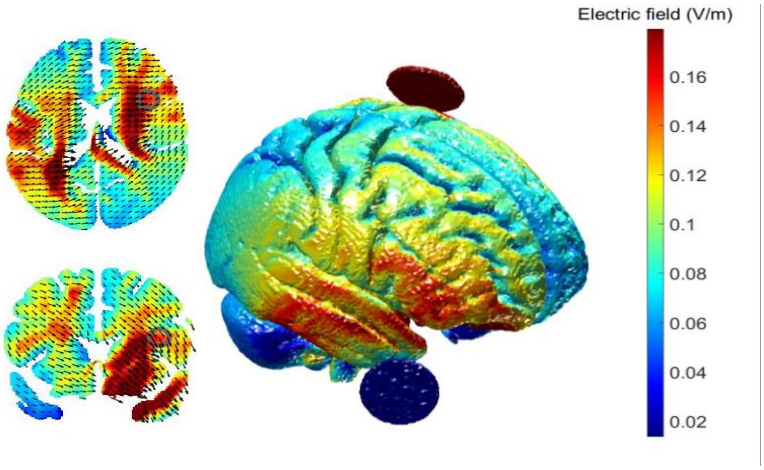
Transcranial Alternating Current Stimulation

Amplitude-Modulated Transcranial Alternating Current Stimulation (AM-tACS) was administered by a neuroConn Magstim DC-STIMULATOR PLUS (neuroCare Group GmbH, Ilmenau, Germany). Two circular rubber electrodes (34 mm diameter, 2mm thickness) were placed over C1 and FTT10h, following the 10-5 International EEG System. Electrodes were attached to the scalp using conductive ten20 paste (Weaver and Co, Aurora, CO, USA). Stimulation was applied using a carrier frequency of 40 Hz, an envelope frequency of 6 Hz, and a current amplitude of 1mA peak-to-peak. In the sham condition, alternating current was administered only for the first minute and was preceded by 30 seconds of ramp-up and followed by 30 seconds of ramp-out. The impedance of the electrodes was kept below 10 kΩ. A simulation of the generated electrical field is represented in Figure 22.

At the end of the session, the Questionnaire of sensations related to transcranial electrical stimulation from the University of Göttingen (http://www.neurologie.uni-goettingen.de/downloads.html) was administered to all participants.

Figure 22

Simulated electrical field.



EEG data acquisition

32-channel electroencephalography (EEG) was recorded using actiCAP slim active electrodes attached to a LiveAmp wireless amplifier (Brain Products GmbH, Germany). Impedances were kept below 20 kOhm. EEG was recorded at a sampling rate of 500 Hz.

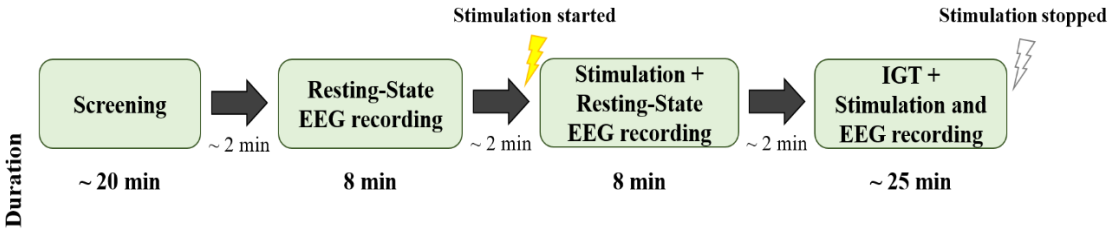
Procedure

This study followed a single-session, single-blind, sham-controlled, and mixed design with frontolateral theta-tACS as the experimental manipulation (see Figure 23). After a detailed explanation of the entire procedure and after the participants had signed the informed consent form, first, we screened our participants in clinical outcomes through the Alcohol Use Disorders Identification Test (AUDIT) (Saunders et al., 1993), Drug Abuse Screening Test (DAST-10) (Skinner, 1982), Short Impulsive Behaviour Scale (UPPS-P) (Cyders et al., 2014), South Oaks Gambling Screen (SOGS) (Lesieur and Blume, 1987) and the State-Trait Anxiety Inventory (STAI) (Spielberger et al., 1983). Then, we recorded 8 minutes of resting-state functional connectivity from each participant through EEG approach. After that, we began with the stimulation period (without stopping the recording), which lasted until the end of the task. Participants

were stimulated during 8 minutes before the start of the task. Participants were sequentially assigned to the active or sham condition trying to ensure the same number of participants belonging each group. Additionally, we controlled for sex and age distribution in the assignment process. Finally, participants performed the IGT. Brain activity was recorded during the whole session, which lasted approximately two hours. This procedure was approved by the local Ethical Committee.

Figure 23

Graphical summary of the experimental procedure.



Statistical analysis

EEG analysis

EEG was analysed using MNE-Python (Gramfort et al., 2013). First, data in absence of AM-tACS and during AM-tACS were bandpass-filtered between 4 – 8 Hz using a zero-phase finite impulse response filter. To obtain the individual peak theta frequency, a Welch power spectral estimate was performed on the data in absence of AM-tACS. Subsequently, the FOOOF method (Donoghue et al., 2020) was used to parametrize the resulting power spectra averaged across frontocentral EEG channels (Fz, FCz, FC1, and FC2 of the international 10-10 system), and the frequency of the largest peak in between 4 and 8 Hz was extracted. To suppress stimulation artifacts during AM-tACS, covariance matrices of the bandpass-filtered data in absence of and in the presence of AM-tACS were computed, and stimulation artifact source separation (Haslacher et al., 2021) was applied to the data in the presence of AM-tACS. To

compute theta power, a Welch power spectral estimate was used, and the resulting power values were averaged between 4 and 8 Hz.

Bayesian Logistic Regression Model

We were interested in the frequency-specific effect of tACS, as well as in the role of theta power on performance on the IGT. We followed a fully probabilistic approach to the understanding of the performance on the task for several reasons. First, we think that this approach could be useful to avoid misunderstandings when interpreting the participant's performance during the task. Second, this approach allows us to observe the performance of the participants on a trial-by-trial basis, which, in our view, may provide meaningful insights about how participants make choices along the whole task. Third, this approach allows us to establish precise definitions of the processes in which we are interested. We considered choices of Deck C and Deck D (long-term advantageous decks) as correct responses, while choices of Deck A and Deck B (long-term disadvantageous decks) were considered as incorrect responses, so choices will follow a binomial distribution between 0 (incorrect responses) and 1 (correct responses). Three main behavioural parameters were then defined. First, we defined "final accuracy" (α) as the probability to make an advantageous choice in the last trial of the task. "Learning" (β_{Trial}) was defined as a credible change between the probability to make an advantageous choice in the first trial and the last trial, that is, the difference between the first and the last trial. "Learning speed" (γ) was understood as the velocity at which a certain participant progresses from its initial to its optimal state.

We decided to design a Bayesian Logistic Regression Model for several reasons. First, we aimed to estimate the probability to make an advantageous choice at the end of each block of the task depending on the type of stimulation (active- vs. sham-tACS). Second, we also were interested in the role that theta power and tACS after may exert

over the performance on the task. Third, we wanted to explore the relationship between theta power and other parameters related to learning, such as learning speed. Standardized theta power and frequency mismatch were used as predictors of the probability of choosing an advantageous deck in the last trial of the task and as moderators of the learning speed parameter. Frequency mismatch was calculated as

$$| 6 - EPF |$$

Where EPF would be the endogenous theta peak frequency of each participant and 6 accounts for the stimulation frequency. We then transformed this value as follows:

$$1 - (\frac{Frequency\ mismatch}{2})$$

After applying the transformation, we got values ranges from 0 to 1, where 0 would mean maximum distance within theta frequency range (4 Hz or 8 Hz) and 1 would mean no mismatch (i.e., the stimulation frequency is equal to endogenous peak frequency). Estimation for participants who presented missing data in the predictors was performed considering only the behavioural parameters. FMT data from active group were discarded due to the presence of artifacts derived from stimulation in most of the participants. The model was defined as follows. As explained in the Method section of the previous chapter, in all the equations, the symbol "~" means "distributed as", and *N*(x, y) indicates a normal distribution with mean = x and SD = y. Binomial(x, y) indicates a binominal distribution with probability of success (x) = y.

$$\text{Choice}[i] \sim \textit{Binomial}(1\ ,\ p[i]\ ) \quad (1)$$

$$p_{[i]} = \alpha_{[\text{Group}[i]]} + \beta_{Mismatch\ [\text{Group}[i]]} * \text{Mismatch}_{[i]} -$$

$$\beta_{theta\_power\ [\text{Group}[i]]} * \text{Theta\_power}_{[i]} +$$

$$(\beta_{Trial[\text{Group}[i]]} * (((100\text{-}n_{trial}[i])/99.0) \wedge (\gamma_{[\text{Group}[i]]} * (1 + (\text{mod}_{\gamma}))))) \quad (2)$$

$$\text{mod}_{\gamma} = \beta_{mismatch\_\gamma[\text{Group}[i]]} * \text{Mismatch}_{[i]} + \beta_{theta\_power\_\gamma[\text{Group}[i]]} * \quad (3)$$

Theta_power[i]

$\alpha_{[Group[i]]} \sim N(0, 2)$ (4)

$\beta_{mismatch[Group[i]]} \sim N(0, .1)$ (5)

$\beta_{theta\_power\ [Group[i]]} \sim N(0, .2)$ (6)

$\beta_{Trial[Group[i]]} \sim N(0, 1)$ (7)

$0 > \gamma_{[Group[i]]} \sim N(2, .5)$ (8)

$\beta_{mismatch\_\gamma[Group[i]]} \sim N(0, .1)$ (9)

$\beta_{theta\_power\_\gamma[Group[i]]} \sim N(0, .2)$ (10)

The number of cases [i] was equal to the number of trials (100) times the number of number of participants (n = 38) so the total number of cases was 3800. The variable Group[i] may present a number of different values equal to the levels of the grouping variable (Active tACS or Sham tACS). Variable n_{trial} represents the number of trials of the task, so it is ranging between 1 and 10.

Equation (1) represents the likelihood of the model, which targets the probability to make an advantageous choice in each case [i]. In equation (2), p[i] aims to provide the estimated probability (in *logit*) to make an advantageous choice in each case [i]. Parameter α represents the intercept of the model, which may present different values depending on the group of the participant, indicated by Group[i]. Following the equation, α would account for the probability to make an advantageous choice in the last trial for each Group. Regression coefficients $\beta_{Mismatch}$ and β_{theta_power} represent the effect that the frequency mismatch and theta power, respectively, may exert on that mentioned probability for each Group. β_{Trial} accounts for the difference in the probability to make a correct response between the first and the last trial of the task for each Group. β_{Trial} is moderated by a value resulting from the exponential of γ over a number that represents the number of the trial [i]. The task is composed by 100 trials, so we substract the n_{trial}[i]

from 100 and then it is divided by 99. This number will range from 1 (first trial) to 0 (last trial) based on the number of trial (n_{trial}) of each case [i]. This allow us to test the impact of each trial in the subsequent decision. The exponential γ would take values depending on the Group [i] and will be moderated by mod_{γ}. As exposed in equation (3), mod_{γ} is a generated variable that accounts for the moderation of the frequency mismatch and theta power over the exponential γ. Then, this exponential would account for the speed of each Group [i] to change from their initial state to their optimal state.

Equations (4) to (10) represent the priors of each parameter. The prior for the intercept of the model (Equation 4) is set to follow a normal distribution with mean equals to zero and standard deviation equals to two, because we consider plausible high and low probabilities of making advantageous choices in each block and in each group. Prior for frequency mismatch related regression coefficients were to follow a normal distribution centred in 0 with .1 SD, while priors related to theta power were centred in 0 with .2, considering plausible only small size effects. We would expect the impact of the trial on *p*[i] to be greater than the frequency mismatch and theta power so its respective prior is centred at 0 considering as plausible SDs equals to 1. We restricted the possible values of γ to be positive to avoid mathematically irresolvable exponentials. We centred it at 2 assuming a quadratic learning progression. In this case, we would consider plausible variations of .5 standard deviations from the centre.

As in the previous Study, the model was applied using the RStan package (Stan Development Team, 2022). Statistical inferences were made based on the 95% HDIs and ROPEs. In this case, we established a ROPE (-.05, .05) so we only considered as credible the effects that imply a variation of more than 5% chance of probability of a correct response. We extracted 12000 samples using Markov Chain Monte Carlo (MCMC) sampling, each of the 4 chains having 1000 warmup samples and saving 3000

samples. Traceplots for all chains and parameters, as well as the Gelman-Rubin test (Gelman and Rubin, 1992) showed an appropriate convergence with all $\hat{R}$ values below 1.05.

Results

EEG-tACS montage acceptability

From the Active group, 18.8% of the participants reported no influence of tACS on their general state. 54.55%, 22.73%, and 4.55% of the participants informed about a slight, considerable, and much influence of tACS on their general state, respectively. Regarding the sham group, no influence was reported by 35% of the participants, while slight, considerable, and much influence was reported by 50%, 10%, and 5% of the participants, respectively. Fisher's exact test showed no significant differences in the proportion of participants reporting different tACS sensations between groups.

Integrity of blinding

From the active group, 31.82% of participants were not sure about the experimental condition they were under, 59.09% manifested that it was active condition and 9.09% thought they were under sham stimulation. From the sham group, 40%, 45% and 15% of participants reported that they were not sure about the experimental condition, that they were in the active condition and that they were in the sham condition, respectively. Then, we suggest that our blinding procedure was successful (χ^2 = .90, df = 2, p = .637).

Bayesian Logistic Regression Model

Mean of the posterior distribution for each parameter can be seen in Table 9. Active and sham group showed no different probability to make an advantageous choice in the last trial of the task (α: mean of the differences = .140, 95% HDI from -.473 to .206). The difference between the first and the last trial seems to be credibly higher in

the active than in the sham group (β_{Trial}: mean of the differences = .605, 95% HDI from .151 to 1.061). A positive relationship between theta power and the probability to make an advantageous (see Figure 24) choice in the last trial was found in the sham group (standardized β_{theta_power}, mean of posterior = .295, 95% HDI from .186 to .407). No credible differences between groups in the learning progression parameter were found (γ: mean of the differences = -.654, 95% HDI from -1.741 to .415). No credible relationship between frequency mismatch and performance in the las trial was found ($\beta_{mismatch}$: Mean of posterior = -.078, 95% HDI from -.236 to .084). Also, no moderation effects of theta power nor frequency mismatch over the learning speed parameter were found ($\beta_{mismatch\_\gamma}$: Mean of posterior = -.057, 95% HDI from -.239 to .123; standardized $\beta_{thtea\_power\_\gamma}$: Mean of posterior = .191, 95% HDI from -.118 to .510). Real and simulated probability of making an advantageous choice in each trial as a function of group and in the whole sample is depicted in Figure 25 and Figure 26, respectively.

Table 9

Mean of the posterior distribution (and 95% HDIs) in active and sham groups, and mean of the differences (and 95% HDIs) of the estimated parameters.

Parameter	Active Group	Sham Group	Mean of the differences
α	.632 (.394, .886)	.772 (.558, 1.006)	-.144 (-.473, .206)
β_{Trial}	1.660 (1.346, 1.965)	1.055 (.715, 1.395)	.605 (.151, 1.061)
Γ	1.277 (.832, 1.746)	1.931 (.937, 2.909)	-.654 (-1.741, .416)
$\beta_{thtea\_power\_\gamma}$	—	.191 (-.118, .510)	—
β_{theta_power}	—	.295 (.186, .407)	—
$\beta_{mismatch\_\gamma}$	1.931 (.937, 2.909)	—	—
$\beta_{mismatch}$	-.078 (-.236, .084)	—	—
Total Net Score	-6.646 (-5.839, -7.512)	2.474 (19.570, 21.358)	-27.120 (-28.287, -25.867)

Note. (—): Missing data due to the reduced number of observations to estimate parameters.

Figure 24

Scatterplot representing the relationship between standardized theta power and the probability to make an advantageous choice in the last trial of the task (α) for the Sham group.

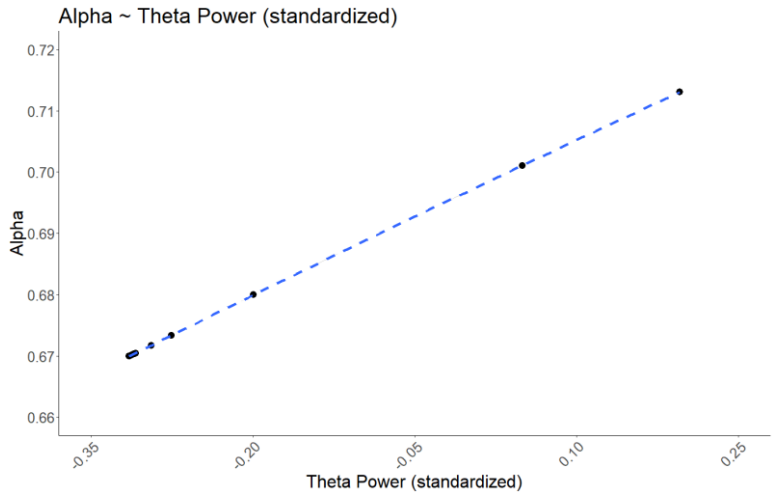
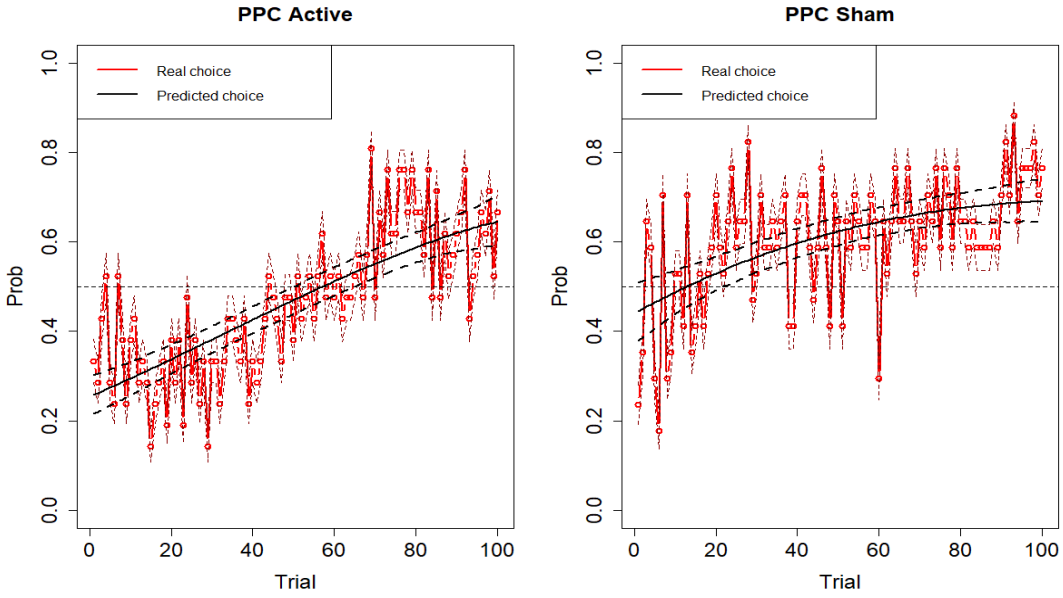


Figure 25

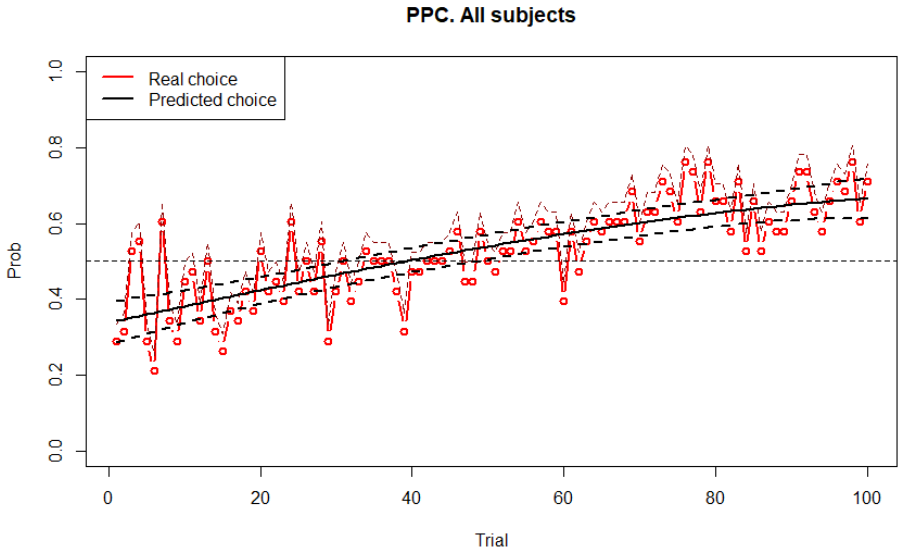
Posterior predictive checks for the active and the sham group. Mean of the real (red lines and points) and predicted (black line) probability of making an advantageous choice in each trial as a function of group, respectively.



Note. The dashed lines represent the standard error of the mean (SEM) and the 95% HDIs.

Figure 26

Posterior predictive checks for the whole sample. Mean of the real (red lines and points) and predicted (black line) probability of making an advantageous choice in each trial as a function of group, respectively.



Note. The dashed lines represent the standard error of the mean (SEM) and the 95% HDIs.

Discussion

This study proposed a combined tACS-EEG approach to explore the role of theta power on the IGT performance and the potential of tACS to modulate decision-making processes. We hypothesized, firstly, a predictive role of theta power in the performance on the IGT mediated by theta-tACS application, and, secondly, a frequency-specific effect of tACS on theta power and, therefore, in behaviour.

Our first hypothesis was only partially supported by the obtained results. We found a positive relationship between theta power and the probability to make an advantageous choice in the last trial in the sham group. This result seems to be not in

consonance with previous research showing a negative relationship between resting-state theta power and learning scores (Massar et al., 2014) and, also, a positive relationship between the same variable and the percentage of disadvantageous choices during the IGT (Schutter and van Honk, 2005). However, we tested the predictive role of theta power recorded during the task. IGT is an uncertain context that requires learning from experience with the decks to adapt the behaviour in a long-term goal-directed manner. In this sense, frontal-midline theta oscillations have been proposed as a signal for implementing cognitive control in an adaptive way when conflict appears in uncertain contexts (Cavanagh et al., 2012; Cavanagh and Frank, 2014) and has been related to feedback processing (Cohen et al., 2014), which may be more in line with our results.

Other research has also found a positive relationship between theta power and unsigned prediction error and learning rate in a probabilistic reversal learning task (Mas-Herrero and Marco-Pallarés, 2014). In this latter investigation, researchers also studied the relationship between theta power and feedback related negativity (FRN). FRN is a relevant component of the event-related potentials (ERPs) for decision-making processes. FMT and FRN share several features such as the brain location where they are evoked, the time window in which they usually peak and both signals are supposed to by modulated by prediction error (Cavanagh and Frank, 2014; Marco-Pallares et al., 2008; Mas-Herrero and Marco-Pallarés, 2014). Actually, FRN is supposed to reflect phase-locked FMT activity (Cavanagh et al., 2012), so they could be understood as "two sides of the same coin" (Wischnewski et al., 2021). Following the reinforcement learning theory of the FRN (Holroyd and Coles, 2002), this signal would be elicited by the activity of mesencephalic dopaminergic neurons of the ACC, which occurs when the consequence of an action is worse than expected. Although several studies have stated

that the FRN is related to negative feedback only (Miltner et al., 1997), other research support that FRN would represent the prediction error independently of the valence of the outcome (Alexander and Brown, 2011), so would be a surprise signal representation (Hauser et al., 2014).

Therefore, our results may suggest that increased theta power could serve as a physiological encoding of conflict detection and subsequent behavioural adaptation in a long-term advantageous manner via outcome unsigned prediction error. This would be in line with the notion of FMT as a "need-for-control" signal (Cavanagh and Frank, 2014). Previous research has shown that theta oscillatory activity would be sensitive to both negative and positive prediction errors, suggesting that it is a neurophysiological representation of surprise (Hauser et al., 2014; Talmi et al., 2013) and of need for adaptive control, so, consistent with our results, larger FMT signals would predict behavioural adaptation in uncertain conditions (Cavanagh and Shackman, 2015).

However, this result should be interpreted cautiously for several reasons. Firstly, individual differences in theta power have been proposed as the main driver of its relationship with behavioural and physiological aspects (Massar et al., 2012; Pinner and Cavanagh, 2017), so the use of such a small sample size as in the present study may likely bias our results. Actually, we consider that visual inspection of Figure 24 should make us extremely cautious in this respect. As can be observed in mentioned Figure, our participants showed a big range of standardized theta power values, and relevant changes in the probability of making an advantageous choice in the last trial (at least one percent of change) are shown only by three subjects. The rest of participants showed an insignificant increase in α caused by an increase in standardized theta power.

Secondly, theta power was computed regardless of the feedback valence, which may be conflicting with the argued dissociable impact of negative and positive feedback

in FMT signals (Andreou et al., 2017; Marco-Pallares et al., 2008). Therefore, we suggest that this result would be enriched by such approach since it would contribute to a better understanding of the neurophysiological basis of feedback processing and decision-making. Thirdly, the causal role of FMT remains unclear since FMT data from the active group could not be properly pre-processed due to artifacts derived from the stimulation.

Regarding our second hypothesis, which was related to a frequency-specific effect of tACS on behavioural performance during the IGT, we found no credible relationship between the frequency mismatch and any behavioural parameter, so it is not supported by results. Despite active group seem to present a greater difference in the probability to make an advantageous choice between the first and the last trial than the sham group, which would reflect a stronger learning effect, this cannot be attributed to a frequency-specific effect of tACS. We consider worth to note that active group performed worse than sham group in the first trials of the task, and then reached the same endpoint. This could be due to differences in resting-state (pre-task) theta power induced by tACS. In other words, the application of theta tACS before the task might have decreased resting-state theta oscillatory activities generated by the ACC (Onoda et al., 2017), making it more difficult for participants in this group to identify advantageous decks at the beginning of the task. However, behavioural effects of tACS have been as widely reported as contradictory, following recent research. Thus, no effect of theta-tACS has been found in exploratory and risk-taking behaviour (Wischnewski and Compen, 2022), working memory (Jones et al., 2019; Pavlov et al., 2021), response inhibition (Brauer et al., 2018), decision-making (Mansouri et al., 2019) and probabilistic learning (Zavecz et al., 2020). Taken together, this hypothesis is just speculative and further research should investigate this issue specifically.

Additionally, behavioural differences between groups must be considered with caution. Despite posterior predictive checks showed a relatively good fit of the model to the real observations for the whole sample, the reduced number of subjects per group could lead to over or underestimate probabilities in some trials, biasing the inference process. Further research could try to replicate this result using a larger sample size that allows to better infer performance from the model, as well as to include other variables as moderators and predictors of behaviour. We suggest that this may help to clarify the potential FMT-decision-making relationship.

CHAPTER 7. INTEGRATION OF RESEARCH FINDINGS

The present Doctoral Thesis aimed to investigate the psychological and neurophysiological aspects driving different and particular decision-making strategies in uncertain conditions and to neuromodulate them through non-invasive transcranial electrical stimulation techniques.

As exposed during this work, we consider the exploration of individual differences to be key to deeply understanding the underlying mechanisms of human decision-making. In Study I, we found a specific sex-dependent tDCS effect by which only anodal stimulated women showed a greater preference for advantageous decks, which is traduced as a higher total net score, after the stimulation was applied. This result was interpreted as a tDCS-induced boost of decision-making in that sample by a recruitment facilitation of the rOFC, which would enhance the evaluation of the stimuli-reward association and, therefore, the identification of advantageous decks after the switch that we applied trying to mitigate the practice effect. Women decision-making strategy is supposed to be driven more by punishment impact and gain-loss frequency, changing, and scattering their response strategy after each loss and preferring decks with rare losses (for an extensive review see van den Bos et al., 2013). However, following other research (Kahneman and Tversky, 1979; for review see Steingroever et al., 2013), this characteristic would be present in the general population, not only in women. In fact, as revealed in Study II, only some within-subject deck preferences were found. Additionally, we found a similar proportion of women belonging to each particular decision-making profile, so sex differences may not be consistent among different samples.

Contrarily to Study II, we did not explore the specific deck choice behaviour nor reinforcement learning models in Study I, so we cannot ensure what of many aspects

involving decision-making we modulated. It seems to be established that tDCS effect varies depending on individual differences, so assuming that revealed profiles are consistent among healthy population, the modulation effect could also be profile-dependent. In other words, stimulation could have affected a specific profile of women characterized by a specific contingency valuation process. Additionally, the dependent variable we used to infer changes in performance after stimulation was the total net score, which may be not as accurate as desirable. One could reach the same total net score following completely different strategies or choice patterns. For instance, a total net score of zero would mean that participant has chosen the same number of advantageous and disadvantageous decks, which would be interpreted as a suboptimal performance. However, this interpretation will be totally dependent on when and why participant decided to pick a certain deck. In other words, a fully scattering strategy could result in a net score of zero as much as a participant that identifies the advantageous decks at the latter stages of the task.

Studies II and III attempted to characterise healthy people and impulsive-compulsive spectrum patients based on individual differences, which are conceptualised as the development of different deck choice preferences. We suggest that deck preferences develop as individuals experience the contingencies associated with each deck. That is, as individuals win or lose after choosing each of the decks, their expectations and, therefore, their preferences will change. It is in this process where individual differences play a fundamental role. Based on this, we identified five different profiles among healthy undergraduate students in the Study II and three of them (D-Learners, B-Exploiters and Scattering) were replicated in the Study III. Importantly, in Study III, we grounded in a transdiagnostic and dimensional approach, assuming that the factors that drive decision-making would rest on a continuum that

may cut across different individuals, including diagnosed patients. In this sense, we found the same proportion of healthy and clinical groups belonging to each revealed profile. As a note, the two remaining profiles (C-Learners and A-Choosers) were also revealed in the sample of the Study III after forcing a 5-cluster solution. However, a too small number of participants composed these resulting clusters, so the inference process would not be feasible.

We also applied several computational RL models to try to identify the underlying psychological factors driving each idiosyncratic profile of Study II and Study III. Unfortunately, all RL models failed in simulating the specific behaviour of each profile and each diagnostic group in both Studies, showing poor predictive capacity. We found two main reasons for this. First, there are no parameters in any model accounting for the reference point of the participants when they make their choices, which would be the total amount they have when they make their following choice. The reference point changes with each choice and may affect the following decision in different ways by the interaction with several variables, such as risk aversion, loss aversion, or emotional states. Then, not considering a decision-makers' reference point may lead to a misprediction of their subsequent decision, just as following the error of Bernoulli's utility theory (Kahneman, 2011). Second, continually experiencing gains or losses with a deck could evoke different emotional *strike-induced* states that can influence decisions. For instance, repeatedly winning after choosing a long-term disadvantageous deck may situate the decision-maker in an emotional *winning-strike-induced* state that may attenuate the impact of a potential loss, and therefore, the changes in the utility of a certain deck by an underestimation of the loss's odds. Contrarily, participants could also find themselves in a situation where they identify all decks as undesirables due to the exposure to continuous negative outcomes

after choices. This emotional *losing-strike-induced* state could lead to different response strategies motivated by indifference or frustration.

This could be avoided by setting the consequence matrix of each deck in a fixed and deterministic way, as in the original task (Bechara et al., 1994). However, this procedure could negatively affect the construct validity and the ecological validity of the task, as it drastically reduces the uncertainty surrounding the decision-making situation that is intended to be simulated by this paradigm. Further investigation should explore the feasibility of an RL model that includes the parametrization of these factors, which might occur due to the uncertainty conditions proposed by the IGT, so they could provide important insights for targeting those specific behaviours that may be relevant from a clinical point of view (Adida et al., 2011; Clark et al., 2011).

In the Study IV, since we could not perform a similar cluster analysis due to the reduced number of participants we were able to recruit, we tried to apply a novel approach to the understanding of the performance on the IGT. This approach is mainly based on a fully probabilistic consideration of the behaviour during the task. For that, we designed a customized Bayesian Logistic Regression Model, which included three main parameters accounting for behaviour. Importantly, this model allowed us to study the performance of the task focusing on the trial-by-trial probability to make a long-term advantageous choices.

Those parameters were “final performance”, “learning” and “learning speed”. Final accuracy (α) was an indicator of the probability to make an advantageous choice at the last trial of the task. The learning parameter (β_{Trial}) reflected the difference in the accuracy between the first and the last trial of the task. In other words, learning was understood as a change in the probability to make an advantageous choice at the end of the task compared to the beginning. In addition, “learning speed” (γ) referred to the

speed with which participants change from their initial state to their final state. Despite sham group presented a higher net score compared to active group, we found that they had the same probability to make an advantageous choice at the end of the task and both groups did not differ in the learning speed parameters. Actually, the active group showed a higher difference between the early and late stages of the task, reflecting increased learning. So, we interpret this as a piece of evidence of the misunderstanding and the conflictive inferences that might be derived from the total net score as a measure of how good or how bad people make decisions and learn from their experience with different contingencies. And, also, about the effect of TES on these processes, which could occur at different levels during the task. In this sense, we found no evidence of the effect of tACS on the performance of the IGT. The increased learning showed by the active group in the Study IV cannot be causally linked with the stimulation protocol in a frequency-specific manner, since the frequency mismatch was not related to any behavioural parameters. We suggest that further research at the individual level is needed in this topic to clarify the specific effect of TES on specific neurophysiological factors of decision-making and their relationship with important behavioural processes.

During the development of the present Doctoral Thesis, we tried to identify a biomarker of particular patterns of choices or optimal/suboptimal decision-making strategies. On the one hand, resting-state functional connectivity between important hubs of the FPN, such as OFC, DLPFC and pPC was recorded using fNIRS. On the other hand, FMT during the IGT was computed from EEG recordings.

The World Health Organization (WHO) (2001), along with other organizations, defined biomarker as *"any substance, structure, or process that can be measured in the body or its products and influence or predict the incidence of outcome or disease"*.

Then, by definition, considering the rsFC as a biomarker implies looking for evidence about its predictive capacity. Although a possible involvement of the rOFC in the IGT seems to emerge from Study I, in the Study III we found no evidence supporting the role of the connectivity of this region and other important areas for the IGT performance such as DLPFC (or any established ROIs) as a biomarker of a certain type of behaviour. In this line, and contrary to our results, Li et al. (2013) proposed rsFC of the FPN as a biomarker of impulsivity and choice behaviour. However, the behavioural paradigm used in that study was a Delay Discounting Task and rsFC was obtained by fMRI. To the best of our knowledge, our experiment was the first attempt to establish a similar prediction between the rsFC of the FPN, obtained by fNIRS, and deck choice behaviour during the IGT.

No credible differences in the strength of the connectivity between regions were found between diagnostic groups or clusters. This finding was not in line with previous research that supports the presence of abnormalities in resting-state FPN in ADHD (Mostert et al., 2016), OCD (Stern et al., 2012), and SUD (Taebi et al., 2022) patients. In this sense, it is relatively well-established that rsFC presents high variability across individuals. rsFC is sensitive to many potential confounding variables such as pharmacological treatment, early-stress, personality and behavioural traits and even different genotypes (Gordon et al., 2015; Marek and Dosenbach, 2018; Vaidya and Gordon, 2013). Additionally, the variability across employed methodologies in different studies, as well as the interpretation of results may hinder the clarity of inferences about the brain-behaviour relationship. Taken together, the study of the type of existent relationship between brain resting-state activity and behaviour would be greatly benefited from research carried out on a large enough sample size and from

methodological and conceptual homogenisation (Marek et al., 2022; Marek and Dosenbach, 2018).

Regarding EEG measures, FMT power was the only possible candidate we directly observed to be related to IGT performance, although, as mentioned in the Discussion section of the Study IV, this result has to be considered cautiously. FMT has been proposed to be implicated in the synchronization of disperse brain regions when the organism realizes the need to implement adaptive control when habitual behaviour is not adequate to resolve a conflict. In other words, when the consequence of an action is unexpected, or surprising, FMT would react leading to the entrainment of other brain networks to implement cognitive control and behavioural outcome-based adjustment (Cavanagh and Frank, 2014), which are critical to the IGT performance. Due to the lack of spatial resolution of the EEG and the lack of temporal resolution of the fNIRS, we consider that a multimodal EEG-fNIRS approach may be useful to locate spatially and temporally the generation of the FMT implicated in decision-making and uncertain valuation in cortical areas, which may shed some light on the complex brain-behaviour interaction underlying decision-making processes in both clinical and healthy population.

In general, the development of the present Doctoral Thesis has faced to several limitations. Firstly, the sample of the first two Studies was composed of psychology undergraduate students, a particular population group that is likely to share many socio-demographic characteristics such as age, socio-economic status, and years of formal education received. This fact may difficult the generalization of our results to the general population. We suggest that further investigation could try to replicate those findings, especially those of Study II, in the general population. If any of these profiles, especially those characterised by negligent outcome valuation, could be consistently

identified in the general population, it may serve as a basis for developing individualized intervention strategies in the clinical field.

Secondly, the Studies would have been greatly enriched by the use of self-reported measurements about relevant personality variables for decision-making, such as impulsivity or mood states. The application of such measurements could have improved the external validity of our clustering solutions and could have provided more specific information about the TES-modulated processes. In addition, it would have been interesting to apply other related behavioural tasks such as DDT or Probabilistic Reversal Learning with the same objective of validating our clustering solutions. If the composition of each cluster is mainly driven by idiosyncratic characteristics, such as loss aversion, risk aversion, or reward sensitivity, then they should show similar behaviour, related with the same characteristics, in different contexts. In other words, those factors should be steadily driving the choice process of different decision-makers in diverse environments, and maybe they could be proposed as transdiagnostic targets.

Lastly, the medication status and comorbidities of clinical sample were nearly impossible to control during the Study III, especially of SUD participants, due to the internal rules of the relapse-prevention centre in which they were inpatients. As abovementioned, medication status may influence both rsFC and behavioural measurements, so further research may try to homogenise it among clinical samples.

CHAPTER 8. CONCLUSIONS

Following the results obtained from experimental work, the conclusions of the present Doctoral Thesis are:

→ In the first Study, sex related differences in IGT performance were revealed. Anodal tDCS at 1.5mA over the right orbitofrontal cortex resulted in a higher total net score only in women. Right orbitofrontal cortex seems to be implicated in the IGT performance. No effect of tDCS was found in the SST.

→ In the second Study, sex related differences in IGT performance were not replicated. Five differential idiosyncratic decision-making profiles were found. First, A-Choosers were characterized by early exploration and late exploitation of low-frequency and high-magnitude losses of a long-term disadvantageous deck (usually Deck B, Deck A in this study). Second, C-Learners were characterized by the exploitation, since early stages of the task, of high-frequency and low-magnitude losses of a long-term advantageous deck (Deck C). Third, D-Learners developed a preference for a low-frequency and high-magnitude losses of a long-term advantageous deck (Deck D). Fourth, Scattering cluster did not develop a remarked preference for any deck during the whole task, nor during reversal phases. Lastly, B-Exploiters showed a lack of early exploration in pursuit of an early exploitation of a low-frequency and high-magnitude losses of a long-term disadvantageous deck (usually Deck B, Deck A in this study).

→ Individual differences lead to the appearing of particular decision-making profiles that must be taken into account when describing how people make decisions during IGT.

→ Applied computational reinforcement learning models were not useful to predict optimal or suboptimal decision-making strategies during the IGT.

→ A definition of a new computational reinforcement-learning model is needed to identify the psychological mechanisms that underlie particular decision-making strategies under uncertain contexts.

→ Three of five profiles (D-Learners, B-Exploiters, Scattering) were replicated in the third Study. These profiles cut across impulsive-compulsive spectrum diagnoses, so impulsive-compulsive spectrum patients and healthy controls seem to share some underlying mechanisms driving their decision-making strategy during the task. This could suggest that deck choice behaviour during the IGT is not a core feature of our diagnostic labelled patients. But it also could mean that the IGT is not such an appropriate paradigm to detect the alleged decision-making deficits that are assumed in those populations.

→ We found no evidence to support the role of frontoparietal rsFC as a biomarker of defective or adaptive decision-making processes regarding any diagnostic group or any behavioural cluster. Further research is needed in this sense in order to clarify the core features of decision-making under uncertainty of healthy people and impulsive-compulsive spectrum disorder patients and its neurofunctional basis.

→ No evidence of the effect of amplitude modulated theta tACS in the IGT performance was found. The application of TES to modulate the performance on the IGT must be guided by individual differences.

→ FMT is a possible candidate as a biomarker of IGT performance. The reduced number of participants in Study IV and the individual variability in FMT power values makes further research needed to try to replicate this preliminary result.

→ The interpretation of the net score as an index of how good or how bad people make decisions under uncertainty may lead to a misunderstanding and conflictive inferences about the outcome-based decision-making processes.

DISSEMINATION OF SCIENTIFIC PRODUCTION

The experimental work developed during the present Doctoral Thesis has been disseminated as follows:

Journal articles from the Doctoral Thesis:

León J.J., Sánchez-Kuhn A., Fernández-Martín P., Páez-Pérez M.A., Thomas C., Datta A., Sánchez-Santed F., Flores P. (2020). Transcranial direct current stimulation improves risky decision making in women but not in men: A sham-controlled study. *Behavioural Brain Research*. doi: 1.1016/j.bbr.202.112485.

León, J.J., González-Rodríguez, A., Sayans-Jiménez, P., Sánchez-Santed, F., Cañadas, F., Estévez, A. F. & Flores, P. (2023). Is computational modelling an effective tool to detect negligent decision-making strategies? A Bayesian approach. *Under revision*.

León, J.J., Fernández-Martin, P., González-Rodríguez, A., Rodríguez-Herrera, R., García-Pinteño, J., Pérez-Fernández, C., Sánchez-Kuhn, A., Amaya-Pascasio, L., Soto-Ontoso, M., Martínez-Sánchez, P., Sánchez-Santed, F., & Flores, P. (2023). Decision-making and frontoparietal resting-state functional connectivity among impulsive-compulsive diagnoses. Insights from a Bayesian approach. *Addictive Behaviors*. *Accepted with minor revision*.

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Journal articles from other collaborations:

Sánchez-Kuhn, A., **León, J.J.**, Gôngora, K., Pérez-Fernández, C., Sánchez-Santed, F., Moreno, M., & Flores, P. (2017). Go/No-Go task performance predicts differences in compulsivity but not in impulsivity personality traits. *Psychiatry Research*. 257, 270-275. doi: 1.1016/j.psychres.2017.07.064

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APPENDIXES

i. Study II. Detailed results

Table 10

Bayesian mean comparisons between groups (and 95% HDI) in the number of Deck A choices in each of the blocks.

	Block 1	Block 2	Block 3	Block 4	Block 5	Reversal 1	Reversal 2	Reversal 3
Men vs. Women	-1.15 (-2.06, -.15)	-1.47 (-2.35, -.57)	-1.39 (-2.26, -.45)	-1.79 (-2.77, -.91)	-1.87 (-2.85, -.96)	1.87 (.72, 3.01)	.72 (-.36, 1.75)	.17 (-.94, 1.30)
C1 vs. C2	2.76 (.77, 4.68)	**3.64 (1.72, 5.56)**	**6.99 (5.16, 8.90)**	**7.45 (5.57, 9.36)**	**9.39 (7.44, 11.34)**	**-9.73 (-11.53, -7.85)**	**-11.63 (-13.49, -9.78)**	-.20 (-2.10, 1.66)
C1 vs. C3	1.68 (.01, 3.39)	2.26 (.55, 3.91)	**5.80 (4.17, 7.46)**	**6.59 (4.90, 8.25)**	**7.05 (5.37, 8.69)**	-.98 (-2.53, .57)	-.24 (-1.84, 1.28)	1.58 (.00, 3.10)
C1 vs. C4	1.93 (.57, 3.30)	**2.52 (1.16, 3.86)**	**3.52 (2.16, 4.84)**	**4.72 (3.38, 6.10)**	**5.85 (4.48, 7.22)**	-1.50 (-2.75, -.24)	-.83 (-2.08, .42)	.23 (-.98, 1.51)
C1 vs. C5	**-3.75 (-5.23, -2.24)**	**-6.14 (-7.64, -4.63)**	**-4.06 (-5.55, -2.59)**	**-3.44 (-4.92, -1.95)**	-1.91 (-3.42, -.43)	.11 (-1.28, 1.51)	1.33 (-.06, 2.71)	-.92 (-2.35, .44)
C2 vs. C3	-1.07 (-3.12, .99)	-1.38 (-3.45, .70)	-1.19 (-3.24, .90)	-.86 (-2.93, 1.19)	-2.34 (-4.51, -.33)	**8.75 (6.70, 1.76)**	**11.39 (9.31, 13.43)**	1.79 (-.29, 3.86)
C2 vs. C4	-.83 (-2.75, 1.00)	-1.12 (-3.03, .72)	**-3.47 (-3.47, -1.66)**	-2.74 (-4.60, -.89)	**-3.54 (-5.41, -1.66)**	**8.23 (6.37, 1.01)**	**1.80 (8.99, 12.66)**	.44 (-1.42, 2.30)
C2 vs. C5	**-6.51 (-8.54, -4.45)**	**-9.78 (-11.74, -7.81)**	**-11.05 (-13.06, -9.14)**	**-1.90 (-12.93, -9.00)**	**-11.30 (-13.32, -9.37)**	**9.84 (7.97, 11.79)**	**12.96 (1.98, 14.87)**	-.72 (-2.66, 1.27)
C3 vs. C4	.25 (-1.39, 1.90)	.26 (-1.41, 1.84)	-2.28 (-3.92, -.67)	-1.88 (-3.54, -.27)	-1.20 (-2.86, .37)	-.52 (-2.06, 1.01)	-.59 (-2.11, .98)	-1.35 (-2.86, .19)
C3 vs. C5	**-5.44 (-7.22, -3.61)**	**-8.40 (-1.14, -6.69)**	**-9.86 (-11.60, -8.11)**	**-1.04 (-11.76, -8.26)**	**-8.97 (-1.71, -7.26)**	1.09 (-.56, 2.73)	1.57 (-.12, 3.20)	-2.50 (-4.16, -.84)
C4 vs. C5	**-5.68 (-7.16, -4.21)**	**-8.66 (-1.10, -7.17)**	-.17 (-1.49, 1.15)	**-8.16 (-9.64, -6.72)**	**-7.76 (-9.20, -6.28)**	1.61 (.25, 2.98)	2.15 (.81, 3.54)	-1.16 (-2.53, .19)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 11

Bayesian mean comparisons between groups (and 95% HDI) in the number of Deck B choices in each of the blocks.

	Block 1	**Block 2**	**Block 3**	**Block 4**	**Block 5**	**Reversal 1**	**Reversal 2**	**Reversal 3**
Men vs. Women	1.01 (.54, 1.50)	.93 (.46, 1.39)	1.08 (.60, 1.60)	.80 (.27, 1.26)	.88 (.38, 1.34)	-.03 (-1.09, 1.00)	.28 (-.76, 1.27)	1.18 (.08, 2.28)
C1 vs. C2	.13 (.84, 1.03)	.78 (-.09, 1.68)	.11 (-.81, .98)	.91 (.02, 1.87)	.62 (-.25, 1.50)	1.45 (-.40, 3.32)	1.91 (.03, 3.78)	**-6.43 (-8.46, -4.36)**
C1 vs. C3	-.19 (-1.01, .58)	.38 (-.42, 1.19)	-.34 (-1.15, .47)	.25 (-.52, 1.06)	.10 (-.67, .89)	.21 (-1.37, 1.82)	-.60 (-2.17, 1.02)	**-2.85 (-4.47, -1.26)**
C1 vs. C4	**-1.85 (-2.57, -1.12)**	**-2.23 (-2.90, -1.56)**	**-2.65 (-3.36, -1.99)**	**-2.40 (-3.07, -1.73)**	**-2.54 (-3.23, -1.88)**	-.38 (-1.67, .94)	-.89 (-2.14, .46)	**-2.57 (-3.85, -1.23)**
C1 vs. C5	.43 (-.28, 1.18)	.80 (.02, 1.59)	-.28 (-1.09, .49)	.17 (-.57, .88)	.22 (-.52, .92)	.55 (-.88, 1.98)	.45 (-1.01, 1.86)	-.85 (-2.30, .57)
C2 vs. C3	-.31 (-1.24, .67)	-.39 (-1.33, .56)	-.46 (-1.39, .49)	-.66 (-1.63, .29)	-.52 (-1.47, .41)	-1.24 (-3.25, .83)	-2.51 (-4.57, -.40)	**3.59 (1.45, 5.73)**
C2 vs. C4	-1.98 (-3.03, -.90)	**-3.01 (-3.87, -2.13)**	**-2.76 (-3.61, -1.88)**	**-3.31 (-4.29, -2.42)**	**-3.16 (-4.06, -2.29)**	-1.83 (-3.67, .02)	-2.81 (-4.70, -.97)	**3.87 (1.82, 5.78)**
C2 vs. C5	.31 (-.70, 1.31)	.02 (-.87, .97)	-.39 (-1.30, .52)	-.74 (-1.72, .22)	-.40 (-1.32, .50)	-.91 (-2.82, 1.05)	-1.46 (-3.40, .50)	**5.58 (3.48, 7.68)**
C3 vs. C4	-1.66 (-2.54, -.77)	**-2.62 (-3.41, -1.85)**	**-2.30 (-3.07, -1.52)**	**-2.66 (-3.48, -1.89)**	**-2.64 (-3.46, -1.88)**	-.59 (-2.12, 1.04)	-.30 (-1.85, 1.27)	.28 (-1.32, 1.83)
C3 vs. C5	.62 (-.22, 1.49)	.42 (-.39, 1.27)	.06 (-.77,.88)	-.08 (-.93,.75)	.12 (-.70, .93)	.34 (-1.37, 1.98)	1.04 (-.65, 2.72)	2.00 (.33, 3.71)
C4 vs. C5	**2.28 (1.54, 2.99)**	**3.03 (2.27, 3.78)**	**2.36 (1.61, 3.07)**	**2.58 (1.87, 3.30)**	**2.76 (2.05, 3.49)**	.92 (-.51, 2.32)	1.34 (-.12, 2.73)	1.72 (.34, 3.14)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 12

Bayesian mean comparisons between groups (and 95% HDI) in the number of Deck C choices in each of the blocks.

	Block 1	**Block 2**	**Block 3**	**Block 4**	**Block 5**	**Reversal 1**	**Reversal 2**	**Reversal 3**
Men vs. Women	.75 (.01, 1.46)	.84 (.13, 1.55)	.67 (-.08, 1.39)	1.05 (.35, 1.77)	1.40 (.62, 2.24)	-1.23 (-2.25, -.28)	-1.14 (-2.13, -.16)	-1.03 (-2.02, -.03)
C1 vs. C2	**-2.53 (-3.97, -1.13)**	**-6.73 (-8.10, -5.35)**	**-11.25 (-12.63, -9.89)**	**-14.10 (-15.52, -12.76)**	**-16.19 (-17.54, -14.77)**	**4.28 (2.33, 6.18)**	**6.19 (4.10, 8.24)**	2.19 (.13, 4.25)
C1 vs. C3	-.17 (-1.36, .98)	-.32 (-1.53, .82)	-.56 (-1.75, .61)	-.98 (-2.15, .18)	-.95 (-2.16, .20)	2.37 (.64, 4.03)	1.67 (-.02, 3.30)	.37 (-1.33, 2.05)
C1 vs. C4	-1.05 (-1.99, -.09)	**-2.04 (-2.97, -1.08)**	**-2.58 (-3.54, -1.64)**	**-3.92 (-4.85, -2.96)**	**-4.32 (-5.26, -3.38)**	1.94 (.53, 3.29)	1.76 (.36, 3.12)	-.03 (-1.42, 1.36)
C1 vs. C5	.37 (-.69, 1.40)	1.11 (.05, 2.14)	.24 (-.83, 1.26)	-.38 (-1.44, .65)	-.82 (-1.88, .22)	-1.24 (-2.77, .27)	-2.19 (-3.74, -.66)	-.56 (-2.10, .97)
C2 vs. C3	2.35 (.79, 3.89)	**6.41 (4.87, 7.95)**	**1.70 (9.17, 12.24)**	**13.12 (11.61, 14.66)**	**15.24 (13.70, 16.77)**	-1.92 (-4.05, .23)	**-4.52 (-6.78, -2.33)**	-1.82 (-3.97, .32)
C2 vs. C4	1.48 (.09, 2.87)	**4.69 (3.32, 6.05)**	**8.70 (7.30, 1.04)**	**1.18 (8.79, 11.52)**	**11.87 (1.49, 13.23)**	-2.35 (-4.19, -.37)	**-4.44 (-6.50, -2.48)**	-2.22 (-4.15, -.22)
C2 vs. C5	**2.90 (1.40, 4.32)**	**7.84 (6.42, 9.28)**	**11.49 (1.07, 12.96)**	**13.71 (12.27, 15.14)**	**15.37 (13.92, 16.82)**	**-5.52 (-7.55, -3.49)**	**-8.38 (-1.70, -6.16)**	-2.75 (-5.00, -.54)
C3 vs. C4	-.88 (-2.03, .28)	-1.72 (-2.89, -.56)	-2.03 (-3.17, -.86)	**-2.94 (-4.11, -1.78)**	**-3.37 (-4.52, -2.19)**	-.43 (-2.06, 1.23)	.08 (-1.56, 1.74)	-.40 (-2.04, 1.26)
C3 vs. C5	.54 (-.67, 1.81)	1.43 (.19, 2.68)	.80 (-.44, 2.07)	.60 (-.65, 1.84)	.13 (-1.14, 1.35)	**-3.60 (-5.42, -1.85)**	**-3.87 (-5.66, -2.09)**	-.93 (-2.73, .95)
C4 vs. C5	1.42 (.39, 2.44)	**3.15 (2.11, 4.16)**	**2.82 (1.81, 3.86)**	**3.54 (2.51, 4.56)**	**3.50 (2.45, 4.53)**	**-3.17 (-4.69, -1.68)**	**-3.95 (-5.50, -2.42)**	-.53 (-2.08, 1.08)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 13

Bayesian mean comparisons between groups (and 95% HDI) in the number of Deck D choices in each of the blocks.

	Block 1	**Block 2**	**Block 3**	**Block 4**	**Block 5**	**Reversal 1**	**Reversal 2**	**Reversal 3**
Men vs. Women	-.60 (-1.46, .18)	-.31 (-1.07, .46)	-.41 (-1.18, .35)	-.05 (-.83, .83)	-.35 (-1.14, .40)	-.44 (-1.43, .50)	.05 (-.92, 1.06)	-.40 (-1.36, .56)
C1 vs. C2	1.39 (-.32, 3.10)	**2.77 (1.08, 4.47)**	**4.11 (2.45, 5.82)**	**4.57 (2.87, 6.25)**	**4.86 (3.16, 6.58)**	**3.52 (1.88, 5.20)**	**3.02 (1.19, 4.80)**	**4.66 (2.87, 6.52)**
C1 vs. C3	-.96 (-2.44, .58)	-2.41 (-3.88, -.92)	**-4.74 (-6.17, -3.24)**	**-6.15 (-7.62, -4.65)**	**-6.36 (-7.88, -4.90)**	-1.17 (-2.77, .36)	-.68 (-2.12, .82)	.53 (-1.08, 2.18)
C1 vs. C4	.92 (-.26, 2.13)	1.80 (.58, 2.98)	1.90 (.71, 3.11)	1.52 (.32, 2.70)	.93 (-.28, 2.11)	.18 (-1.11, 1.44)	.23 (-1.05, 1.49)	1.90 (.47, 3.39)
C1 vs. C5	**2.77 (1.48, 4.10)**	**4.08 (2.75, 5.40)**	**4.46 (3.11, 5.75)**	**3.70 (2.35, 5.00)**	**2.41 (1.04, 3.71)**	.76 (-.57, 2.13)	.78 (-.58, 2.13)	1.76 (.39, 3.17)
C2 vs. C3	-2.35 (-4.34, -.31)	**-5.18 (-7.04, -3.25)**	**-8.85 (-1.70, -6.96)**	**-1.71 (-12.64, -8.83)**	**-11.21 (-13.20, -9.31)**	**-4.69 (-6.63, -2.81)**	**-3.70 (-5.61, -1.77)**	**-4.13 (-5.97, -2.30)**
C2 vs. C4	-.47 (-2.17, 1.22)	-.97 (-2.65, .71)	-2.21 (-3.87, -.54)	**-3.04 (-4.74, -1.39)**	**-3.92 (-5.63, -2.22)**	**-3.34 (-5.03, -1.66)**	**-2.79 (-4.47, -1.11)**	**-2.76 (-4.41, -1.12)**
C2 vs. C5	1.38 (-.37, 3.19)	1.31 (-.45, 3.08)	.35 (-1.42, 2.09)	-.87 (-2.62, .90)	-2.45 (-4.26, -.67)	**-2.76 (-4.50, -1.02)**	-2.24 (-3.99, -.43)	**-2.90 (-4.69, -1.20)**
C3 vs. C4	1.88 (.41, 3.43)	**4.21 (2.77, 5.70)**	**6.64 (5.23, 8.13)**	**7.67 (6.22, 9.16)**	**7.29 (5.82, 8.76)**	1.35 (-.06, 2.85)	.91 (-.60, 2.35)	1.37 (-.08, 2.78)
C3 vs. C5	**3.73 (2.11, 5.34)**	**6.49 (4.92, 8.05)**	**9.20 (7.63, 1.76)**	**9.85 (8.25, 11.40)**	**8.77 (7.19, 1.34)**	1.93 (.37, 3.52)	1.46 (-.07, 2.99)	1.23 (-.29, 2.80)
C4 vs. C5	1.85 (.57, 3.17)	2.27 (.95, 3.55)	**2.56 (1.25, 3.86)**	2.17 (.84, 3.44)	1.47 (.17, 2.78)	.58 (-.73, 1.90)	.55 (-.78, 1.87)	-.14 (-1.50, 1.17)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 14

Bayesian mean comparisons of the net score (and 95% HDI) in each of the blocks.

	Men	**Women**	**C1**	**C2**	**C3**	**C4**	**C5**
Block 1 vs. Block 2	-.74 (-2.97, 1.46)	.37 (-1.59, 2.28)	-.01 (-2.73, 2.71)	-4.50 (-9.15, .04)	-3.27 (-7.01, .56)	-.089 (-2.71, 2.51)	3.93 (.75, 7.12)
Block 1 vs. Block 3	-2.28 (-4.49, -.12)	-1.84 (-3.77, .05)	-.37 (-3.09, 2.40)	**-1.01 (-14.80, -5.32)**	**-8.84 (-12.77, -5.11)**	-1.26 (-3.86, 1.37)	2.68 (-.51, 5.94)
Block 1 vs. Block 4	**-6.01 (-8.38, -3.54)**	**-3.54 (-5.60, -1.52)**	-.56 (-3.40, 2.15)	**-14.33 (-19.07, -9.52)**	**-12.76 (-16.60, -8.85)**	**-4.71 (-7.35, -2.07)**	-.24 (-3.48, 2.94)
Block 1 vs. Block 5	**-5.80 (-8.30, -3.43)**	**-3.35 (-5.40, -1.32)**	1.24 (-1.50, 4.07)	**-15.55 (-2.47,-1.73)**	**-11.37 (-15.2, -7.52)**	**-4.87 (-7.46, -2.21)**	-1.85 (-4.99, 1.39)
Block 2 vs. Block 3	-1.54 (-3.70, .72)	-2.21 (-4.13, -.32)	-.36 (-3.04, 2.39)	-5.52 (-1.05, -.92)	**-5.57 (-9.22, -1.71)**	-1.17 (-3.79, 1.48)	-1.25 (-4.30, 2.06)
Block 2 vs. Block 4	**-5.27 (-7.56, -3.01)**	**-3.91 (-5.88, -1.98)**	-.55 (-3.33, 2.16)	**-9.83 (-14.46, -5.25)**	**-9.49 (-13.36, -5.77)**	**-4.62 (-7.29, -2.01)**	-4.17 (-7.32, -.97)
Block 2 vs. Block 5	**-5.06 (-7.33, -2.77)**	**-3.72 (-5.67, -1.77)**	1.25 (-1.53, 4.01)	**-11.05 (-15.65 -6.32)**	**-8.11 (-11.86, -4.35)**	**-4.78 (-7.40, -2.14)**	**-5.79 (-8.98, -2.64)**
Block 3 vs. Block 4	**-3.74 (-6.12, -1.47)**	-1.70 (-3.67, .28)	-.19 (-2.90, 2.54)	-4.32 (-8.88, .25)	-3.92 (-7.64, -.15)	-3.45 (-6.06, -.81)	-2.92 (-6.19, .17)
Block 3 vs. Block 5	**-3.52 (-5.91, -1.25)**	-1.51 (-3.51, .44)	1.61 (-1.14, 4.37)	**-5.53 (-1.24, -1.05)**	-2.54 (-6.33, 1.23)	-3.61 (-6.25, -.97)	**-4.54 (-7.79, -1.41)**
Block 4 vs. Block 5	.22 (-1.93, 2.41)	.19 (-1.68, 2.10)	1.80 (-.95, 4.50)	-1.22 (-5.83, 3.24)	1.38 (-2.32, 5.20)	-.16 (-2.75, 2.48)	-1.61 (-4.65, 1.64)
Rev 1 vs. Rev 2	2.43 (.07, 4.88)	1.70 (-.34, 3.80)	1.71 (-1.20, 4.61)	-1.82 (-7.08, 3.17)	4.04 (.11, 8.14)	1.66 (-1.12, 4.42)	3.24 (-.03, 6.73)
Rev 1 vs. Rev 3	.10 (-2.27, 2.56)	-1.14 (-3.27, .94)	.43 (-2.48, 3.35)	.52 (-3.72, 5.13)	.31 (-3.36, 4.19)	-1.33 (-4.21, 1.41)	-2.20 (-5.58, 1.17)
Rev 2 vs. Rev 3	-2.33 (-4.69, .06)	-2.84 (-4.92, -.67)	-1.28 (-4.20, 1.70)	2.34 (-3.39, 7.90)	-3.73 (-7.69, .13)	-2.99 (-5.78, -.14)	**-5.43 (-9.15, -1.64)**

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 15

Bayesian mean comparisons within groups (and 95% HDI) in the number of Deck A choices between each of the blocks.

	Men	**Women**	**C1**	**C2**	**C3**	**C4**	**C5**
Block 1 vs. Block 2	-.57 (-1.58, .42)	-.89 (-1.82, .03)	-.71 (-2.07, .69)	.17 (-2.02, 2.38)	-.13 (-1.99, 1.68)	-.12 (-1.44, 1.19)	**-3.09 (-4.70, -1.49)**
Block 1 vs. Block 3	-.30 (-1.29, .68)	-.54 (-1.42, .36)	-1.89 (-3.24, -.49)	2.35 (.11, 4.61)	2.23 (.36, 4.14)	-.29 (-1.59, 1.03)	-2.19 (-3.80, -.61)
Block 1 vs. Block 4	.74 (-.29, 1.84)	.10 (-.82, 1.01)	-1.61 (-3.01, -.20)	3.09 (.81, 5.38)	**3.30 (1.38, 5.22)**	1.18 (-.13, 2.51)	-1.30 (-2.91, .28)
Block 1 vs. Block 5	.37 (-.67, 1.47)	-.35 (-1.29, .56)	**-2.97 (-4.40, -1.56)**	**3.67 (1.41, 6.07)**	2.41 (.53, 4.27)	.95 (-.36, 2.29)	-1.12 (-2.73, .45)
Block 2 vs. Block 3	.27 (-.71, 1.24)	.36 (-.54, 1.21)	-1.18 (-2.56, .22)	2.18 (.00, 4.45)	2.36 (.45, 4.20)	-.17 (-1.49, 1.15)	.90 (-.70, 2.43)
Block 2 vs. Block 4	1.31 (.22, 2.42)	.99 (.06, 1.91)	-.90 (-2.33, .48)	2.91 (.64, 5.15)	**3.43 (1.57, 5.38)**	1.30 (-.03, 2.60)	1.79 (.19, 3.36)
Block 2 vs. Block 5	.94 (-.07, 2.02)	.54 (-.35 1.45)	-2.26 (-3.71, -.87)	3.50 (1.14, .72)	2.54 (.66, 4.40)	1.08 (-.22, 2.42)	1.97 (.35, 3.52)
Block 3 vs. Block 4	1.04 (-.02, 2.10)	.63 (-.27, 1.54)	.27 (-1.09, 1.64)	.74 (-1.49, 2.92)	1.07 (-.79, 2.92)	1.47 (.11, 2.74)	.89 (-.70, 2.45)
Block 3 vs. Block 5	.67 (-.36 1.73)	.19 (-.70, 1.10)	-1.08 (-2.45, .30)	1.32 (-.84, 3.54)	.17 (-1.66, 2.03)	1.25 (-.04, 2.59)	1.07 (-.49, 2.66)
Block 4 vs. Block 5	-.37 (-1.36, .61)	-.45 (-1.33, .41)	-1.35 (-2.71, .03)	.58 (-1.62, 2.73)	-.89 (-2.73, .95)	-.22 (-1.54, 1.08)	.18 (-1.37, 1.78)
Rev 1 vs. Rev 2	.14 (-1.06, 1.31)	-1.02 (-2.01, .00)	-.92 (-2.21, .35)	-2.83 (-5.05, -.62)	-.19 (-1.94, 1.65)	-.26 (-1.46, .98)	.29 (-1.20, 1.80)
Rev 1 vs. Rev 3	**2.29 (1.08, 3.60)**	.59 (-.44, 1.63)	-.18 (-1.42, 1.14)	**9.34 (7.07, 11.64)**	2.38 (.61, 4.19)	1.55 (.31, 2.77)	-1.22 (-2.72, .28)
Rev 2 vs. Rev 3	2.15 (.97, 3.33)	1.60 (.64, 2.62)	.74 (-.54, 2.00)	**12.17 (9.77, 14.44)**	2.56 (.78, 4.37)	1.80 (.59, 3.03)	-1.51 (-3.00, .02)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 16

Bayesian mean comparisons within groups (and 95% HDI) in the number of Deck B choices between each of the blocks.

	Men	**Women**	**C1**	**C2**	**C3**	**C4**	**C5**
Block 1 vs. Block 2	1.00 (.46, 1.57)	.92 (.43, 1.43)	.86 (.18, 1.56)	1.51 (.50, 2.60)	1.43 (.56, 2.36)	.48 (-.28, 1.17)	1.22 (.47, 2.02)
Block 1 vs. Block 3	1.51 (.97, 2.07)	**1.58 (1.10, 2.08)**	**1.96 (1.23, 2.66)**	1.95 (.99, 3.01)	1.80 (.96, 2.70)	1.16 (.44, 1.85)	1.25 (.43, 2.01)
Block 1 vs. Block 4	**2.00 (1.45, 2.60)**	**1.80 (1.28, 2.30)**	**1.98 (1.27, 2.65)**	**2.76 (1.64, 3.98)**	**2.42 (1.54, 3.38)**	1.42 (.69, 2.15)	1.72 (.94, 2.49)
Block 1 vs. Block 5	**2.36 (1.80, 2.94)**	**2.22 (1.71, 2.72)**	**2.45 (1.77, 3.15)**	**2.95 (1.92, 4.10)**	**2.74 (1.86, 3.66)**	**1.76 (1.02, 2.50)**	**2.24 (1.46, 3.00)**
Block 2 vs. Block 3	.52 (-.05, 1.06)	.66 (.15, 1.14)	1.10 (.36, 1.85)	.44 (-.56, 1.38)	.37 (-.51, 1.21)	.67 (.03, 1.35)	.02 (-.84, .84)
Block 2 vs. Block 4	1.01 (.46, 1.58)	.88 (.38, 1.38)	1.12 (.44, 1.83)	1.25 (.28, 2.29)	.99 (.13, 1.84)	.95 (.29, 1.62)	.49 (-.32, 1.30)
Block 2 vs. Block 5	1.36 (.81, 1.93)	1.30 (.80, 1.80)	1.59 (.90, 2.30)	1.44 (.49, 2.44)	1.31 (.45, 2.17)	1.28 (.62, 1.94)	1.01 (.21, 1.79)
Block 3 vs. Block 4	.49 (-.08, 1.09)	.22 (-.30, .72)	.02 (-.69, .73)	.82 (-.15, 1.90)	.62 (-.24, 1.50)	.26 (-.41, .92)	.47 (-.30, 1.24)
Block 3 vs. Block 5	.84 (.30, 1.44)	.64 (.13, 1.14)	.49 (-.22, 1.17)	1.00 (.06, 2.03)	.94 (.09, 1.82)	.59 (-.09, 1.25)	.99 (.23, 1.78)
Block 4 vs. Block 5	.35 (-.21, .91)	.42 (-.09, .91)	.47 (-.20, 1.16)	.18 (-.84, 1.12)	.32 (-.53, 1.17)	.33 (-.35, .98)	.52 (-.25, 1.29)
Rev 1 vs. Rev 2	-.13 (-1.23, .96)	.19 (-.76, 1.11)	.30 (-1.01, 1.64)	.76 (-1.47, 2.99)	-.50 (-2.28, 1.33)	-.21 (-1.52, 1.01)	.21 (-1.29, 1.77)
Rev 1 vs. Rev 3	-1.94 (-3.18, -.75)	-.73 (-1.74, .26)	.80 (-.55, 2.16)	**-7.09 (-9.57, -4.65)**	-2.26 (-4.06, -.43)	-1.40 (-2.69, -.12)	-.60 (-2.17, .90)
Rev 2 vs. Rev 3	-1.82 (-3.01, -.68)	-.92 (-1.90, .03)	.49 (-.87, 1.84)	**-7.85 (-1.39, -5.33)**	-1.76 (-3.55, .09)	-1.18 (-2.44, .10)	-.81 (-2.32, .76)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 17

Bayesian mean comparisons within groups (and 95% HDI) in the number of Deck C choices between each of the blocks.

	Men	**Women**	**C1**	**C2**	**C3**	**C4**	**C5**
Block 1 vs. Block 2	.17 (-.60, .95)	.27 (-.43, .94)	.80 (-.14, 1.77)	**-3.40 (-5.12, -1.76)**	.65 (-.69, 1.99)	-.19 (-1.11, .73)	1.55 (.42, 2.66)
Block 1 vs. Block 3	-.03 (-.80, .73)	-.09 (-.79, .58)	1.23 (.27, 2.19)	**-7.48 (-9.22, -5.79)**	.85 (-.49, 2.22)	-.30 (-1.21, .64)	1.11 (-.01, 2.25)
Block 1 vs. Block 4	-.73 (-1.56, .05)	-.42 (-1.14, .28)	1.52 (.52, 2.46)	**-1.05 (-11.78, -8.32)**	.71 (-.63, 2.06)	-1.35 (-2.30, -.45)	.77 (-.37, 1.87)
Block 1 vs. Block 5	-1.08 (-1.98, -.20)	-.42 (-1.17, .30)	1.74 (.76, 2.67)	**-11.93 (-13.70, -1.19)**	.96 (-.38, 2.32)	-1.52 (-2.46, -.61)	.55 (-.57, 1.68)
Block 2 vs. Block 3	-.20 (-.99, .57)	-.36 (-1.06, .32)	.43 (-.51, 1.40)	**-4.09 (-5.74, -2.38)**	.20 (-1.17, 1.53)	-.11 (-1.01, .85)	-.44 (-1.56, .69)
Block 2 vs. Block 4	-.90 (-1.73, -.10)	-.69 (-1.40, .02)	.72 (-.23, 1.69)	**-6.65 (-8.38, -4.97)**	.06 (-1.28, 1.43)	-1.16 (-2.10, -.25)	-.78 (-1.89, .36)
Block 2 vs. Block 5	-1.25 (-2.16, -.38)	-.69 (-1.42, .06)	.94 (-.02, 1.91)	**-8.53 (-1.22, -6.82)**	.31 (-1.09, 1.63)	-1.34 (-2.28, -.43)	-.99 (-2.12, .13)
Block 3 vs. Block 4	-.69 (-1.53, .09)	-.33 (-1.02, .38)	.28 (-.69, 1.26)	-2.56 (-4.20, -.86)	-.14 (-1.46, 1.22)	-1.05 (-1.96, -.12)	-.34 (-1.47, .76)
Block 3 vs. Block 5	-1.04 (-1.99. -.18)	-.33 (-1.09, .41)	.50 (-.46, 1.46)	**-4.43 (-6.09, -2.72)**	.11 (-1.20, 1.52)	-1.23 (-2.15, -.31)	-.56 (-1.70, .55)
Block 4 vs. Block 5	-.35 (-1.17, .42)	-.01 (-.67, .73)	.22 (-.72, 1.20)	-1.88 (-3.54, -.19)	.60 (-.65, 1.84)	-.18 (-1.08, .76)	-.22 (-1.36, .89)
Rev 1 vs. Rev 2	-.86 (-1.93, .24)	-.76 (-1.69, .21)	-.64 (-2.03, .77)	1.27 (-1.05, 3.66)	-1.33 (-3.22, .55)	-.82 (-2.17, .49)	-1.60 (-3.26, -.03)
Rev 1 vs. Rev 3	.96 (-.10, 2.07)	1.17 (.23, 2.14)	2.00 (.58, 3.42)	-.09 (-2.31, 2.18)	.01 (-1.88, 1.90)	.03 (-1.35, 1.34)	2.68 (.99, 4.34)
Rev 2 vs. Rev 3	1.83 (.74, 2.94)	1.94 (.98, 2.91)	**2.64 (1.23, 4.04)**	-1.36 (-3.87, 1.24)	1.34 (-.53, 3.18)	.85 (-.47, 2.23)	**4.27 (2.51, 6.03)**

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

Table 18

Bayesian mean comparisons within groups (and 95% HDI) in the number of Deck D choices between each of the blocks.

	Men	**Women**	**C1**	**C2**	**C3**	**C4**	**C5**
Block 1 vs. Block 2	-.45 (-1.37, .45)	-.17 (-.95, .64)	-.74 (-1.96, .48)	.64 (-1.40, 2.63)	-2.19 (-3.91, -.56)	.14 (-1.02, 1.30)	.57 (-.83, 2.00)
Block 1 vs. Block 3	-1.00 (-1.91, -.10)	-.82 (-1.62, -.02)	-1.27 (-2.45, -.03)	1.45 (-.58, 3.49)	**-5.05 (-6.76, -3.28)**	-.29 (-1.45, .89)	.42 (-.97, 1.86)
Block 1 vs. Block 4	-1.91 (-2.96, -.95)	-1.37 (-2.25, -.53)	-1.58 (-2.80, -.35)	1.60 (-.46, 3.66)	**-6.76 (-8.58, -4.99)**	-.97 (-2.18, .19)	-.65 (-2.06, .79)
Block 1 vs. Block 5	-1.48 (-2.42, -.59)	-1.24 (-2.08, -.44)	-.88 (-2.10, .33)	2.59 (.53, 4.75)	**-6.27 (-8.12, -4.53)**	-.86 (-2.05, .29)	-1.24 (-2.63, .19)
Block 2 vs. Block 3	-.55 (-1.43, .35)	-.65 (-1.46, .13)	-.53 (-1.75, .67)	.81 (-1.19, 2.84)	**-2.86 (-4.57, -1.21)**	-.43 (-1.64, .71)	-.15 (-1.53, 1.30)
Block 2 vs. Block 4	-1.46 (-2.44, -.59)	-1.21 (-2.02, -.39)	-.83 (-2.05, .41)	.96 (-1.02, 3.07)	**-4.58 (-6.31, -2.85)**	-1.11 (-2.27, .04)	-1.21 (-2.66, .18)
Block 2 vs. Block 5	-1.03 (-1.92, -.15)	-1.07 (-1.87, -.27)	-.14 (-1.33, 1.11)	1.95 (-.09, 4.05)	**-4.09 (-5.80, -2.37)**	-1.00 (-2.20, .16)	-1.80 (-3.21, -.39)
Block 3 vs. Block 4	-.91 (-1.84, .00)	-.55 (-1.37, .26)	-.31 (-1.52, .91)	.15 (-1.87, 2.14)	-1.71 (-3.36, -.03)	-.68 (-1.83, .52)	-1.07 (-2.49, .34)
Block 3 vs. Block 5	-.48 (-1.38, .38)	-.42 (-1.21, .37)	.39 (-.83, 1.59)	1.14 (-.89, 3.19)	-1.22 (-2.85, .49)	-.57 (-1.77, .57)	-1.66 (-3.07, -.24)
Block 4 vs. Block 5	.43 (-.45, 1.34)	.13 (-.66, .94)	.70 (-.56, 1.93)	.99 (-1.03, 2.98)	.49 (-1.13, 2.17)	.11 (-1.03, 1.32)	-.59 (-1.97, .85)
Rev 1 vs. Rev 2	1.01 (-.09, 2.06)	1.50 (.57, 2.45)	1.25 (.02, 2.46)	.75 (-1.20, 2.47)	1.74 (.24, 3.41)	1.30 (.13, 2.48)	1.27 (-.14, 2.59)
Rev 1 vs. Rev 3	-1.16 (-2.23, -.11)	-1.13 (-2.05, -.22)	-2.19 (-3.65, -.78)	-1.05 (-2.79, .73)	-.49 (-2.05, 1.15)	-.47 (-1.71, .80)	-1.20 (-2.56, .15)
Rev 2 vs. Rev 3	**-2.17 (-3.27, -1.08)**	**-2.63 (-3.56, -1.66)**	**-3.45 (-4.87, -2.02)**	-1.80 (-3.56, .18)	-2.23 (-3.78, -.67)	-1.77 (-3.03, -.49)	**-2.46 (-3.84, -1.09)**

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1,1]) are boldfaced. C1: A-Choosers; C2: C-Learners; C3: D-Learners; C4: Scattering; C5: A-Exploiters.

ii. Study III. Detailed results

Table 19

Mean of the differences (and 95% HDIs) between clusters of the estimated number of choices of each deck in each block.

	Cluster	Block 1	Block 2	Block 3	Block 4	Block 5
Deck A	C1 vs. C2	-.126 (-1.830, 1.557)	.021 (-1.261, 1.257)	-.027 (-1.446, 1.416)	-.226 (-1.390, 1.012)	-1.309 (-2.770, .027)
	C1 vs. C3	-.373 (-1.503, .780)	-1.545 (-2.586, -.477)	-2.014 (-3.376, -.692)	**-2.163 (-3.198, -1.139)**	-2.882 (-3.825, -.633)
	C2 vs. C3	**-.247 (-1.788, -1.166)**	-1.566 (-2.654, -.482)	**-1.987 (-2.856, -1.115)**	-1.937 (-3.349, -.914)	-1.572 (-2.865, -.179)
Deck B	C1 vs. C2	**-4.826 (-6.831, -3.004)**	**-7.029 (-9.192, -4.730)**	**-8.851 (-1.878, -6.885)**	**-9.688 (-11.737, -7.647)**	**-9.550 (-11.698, -7.475)**
	C1 vs. C3	-1.034 (-2.269, .233)	.077 (-1.561, 1.757)	-1.087 (-2.507, .212)	-1.583 (-3.177, .036)	-2.207 (3.872, -.633)
	C2 vs. C3	**3.791 (2.106, 5.783)**	**7.105 (5.270, 8.944)**	**7.764 (6.145, 9.395)**	**8.105 (6.590, 9.684)**	**7.343 (5.586, 9.153)**
Deck C	C1 vs. C2	.143 (-1.127, 1.330)	.337 (-.933, 1.611)	1.625 (.555, 2.712)	.882 (-.287, 2.048)	1.192 (-.287, 2.443)
	C1 vs. C3	-1.377 (-2.478, -.324)	-1.789 (-3.000, -.547)	-2.040 (-3.104, -.986)	**-2.616 (-3.769, -1.492)**	-2.407 (-3.903, -.928)
	C2 vs. C3	-1.519 (-2.591, -.515)	**-2.125 (-3.083, -1.157)**	**-3.665 (-4.563, -2.741)**	**-3.498 (-4.495, -2.546)**	**-3.599 (-4.445, -2.660)**
Deck D	C1 vs. C2	**4.682 (3.083, 6.297)**	**6.383 (4.462, 8.386)**	**7.531 (5.619, 9.556)**	**8.976 (6.889, 11.048)**	**9.597 (7.487, 11.796)**
	C1 vs. C3	**2.620 (1.161, 4.067)**	**2.869 (1.013, 4.786)**	**5.391 (3.377, 7.186)**	**6.637 (4.811, 8.464)**	**7.562 (5.779, 9.277)**
	C2 vs. C3	**-2.063 (-2.932, -1.128)**	**-3.515 (-4.462, -2.608)**	-2.140 (-3.349, -.914)	-2.339 (-3.705, -.947)	-2.035 (-3.500, -.592)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 20

Mean of the differences (and 95% HDIs) within clusters of the estimated number of choices of each deck between each block.

	Block	D Learners	B Exploiters	Scattering
Deck A	Block 1 vs. Block 2	1.665 (.239, 2.927)	1.792 (.044, 3.339)	.472 (-.348, 1.213)
	Block 1 vs. Block 3	1.797 (.190, 3.394)	1.896 (.231, 3.355)	.156 (-.668, .881)
	Block 1 vs. Block 4	**2.758 (1.451, 4.047)**	2.658 (.933, 4.170)	.968 (.181, 1.731)
	Block 1 vs. Block 5	**3.084 (1.789, 4.299)**	1.901 (.059, 3.622)	.575 (-.218, 1.332)
Deck B	Block 1 vs. Block 2	-.612 (-2.488, 1.047)	-2.815 (-5.324, -.331)	.499 (-.588, 1.568)
	Block 1 vs. Block 3	.755 (-.729, 2.485)	-3.270 (-5.513, -.868)	.703 (-.191, 1.595)
	Block 1 vs. Block 4	1.279 (-.520, 3.094)	**-3.584 (-5.733, -1.487)**	.730 (-.244, 1.731)
	Block 1 vs. Block 5	1.244 (-.450, 3.016)	**-3.481 (-5.680, -1.111)**	.072 (-1.050, 1.060)
Deck C	Block 1 vs. Block 2	.385 (-1.031, 1.755)	.579 (-.553, 1.687)	-.341 (-1.228, .508)
	Block 1 vs. Block 3	.322 (-.953, 1.484)	1.805 (.690, 2.864)	-.341 (-1.228, .508)
	Block 1 vs. Block 4	.844 (-.496, 2.092)	1.583 (.527, 2.719)	-.395 (-1.292, .541)
	Block 1 vs. Block 5	.826 (-.589, 2.381)	1.875 (.822, 2.934)	-.204 (-1.101, .727)
Deck D	Block 1 vs. Block 2	-1.074 (-3.380, 1.218)	.627 (-.508, 1.696)	--.825 (-1.486, -.173)
	Block 1 vs. Block 3	**-3.224 (-5.285, -1.092)**	-.375 (-1.721, 1.009)	-.453 (-1.069, .218)
	Block 1 vs. Block 4	**-5.077 (-7.281, -2.823)**	-.784 (-2.161, .650)	-1.060 (-1.837, -.296)
	Block 1 vs. Block 5	**-5.410 (-7.604, -3.174)**	-.492 (-2.028, 1.131)	-.468 (-1.131, .227)

Note. Pairwise comparisons that showed credible differences (HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 21

Mean of the differences (and 95% HDIs) within clusters between the estimated number of choices of each deck in each block.

	Deck	Block 1	Block 2	Block 3	Block 4	Block 5
D Learners	A vs B	-.585 (-2.022, .834)	**-2.842 (-4.565, -1.151)**	-1.627 (-3.551, .367)	-2.064 (-3.672, -.325)	-2.425 (-3.999, -.861)
	A vs C	1.261 (-.074, 2.626)	.002 (-1.385, 1.330)	-.214 (-1.869, 1.232)	-.653 (-1.827, .618)	-.999 (-2.374, .634)
	A vs D	-2.415 (-4.170, -.705)	**-5.134 (-7.050, -3.014)**	**-7.436 (-9.677, -5.238)**	**-1.251 (-12.050, -8.253)**	**-1.910 (-12.784, -9.085)**
	B vs C	1.846 (.565, 3.228)	**2.844 (1.091, 4.730)**	1.413 (-.163, 2.874)	1.411 (-.331, 3.157)	1.428 (-.371, 3.235)
	B vs D	-1.830 (-3.484, -.061)	-2.292 (-4.565, .077)	**-5.809 (-7.794, -3.731)**	**-8.187 (-1.460, -5.990)**	**-8.485 (-1.691, -6.308)**
	C vs D	**-3.767 (-5.322, -2.040)**	**-5.136 (-7.193, -3.017)**	**-7.222 (-8.963, -5.339)**	**-9.598 (-11.617, -7.733)**	**-9.913 (-11.986, -7.899)**
B Exploiters	A vs B	**-5.285 (-7.406, -3.176)**	**-9.891 (-11.707, -7.971)**	**-1.451 (-12.213, -8.830)**	**-11.527 (-13.184, -9.920)**	**-1.666 (-12.676, --8.734)**
	A vs C	1.530 (-.122, 3.095)	.318 (-.804, 1.502)	1.439 (.457, 2.439)	.455 (-.641, 1.573)	1.505 (.130, 2.799)
	A vs D	2.393 (.778, 3.900)	1.229 (.146, 2.489)	.122 (-1.206, 1.411)	-1.049 (-2.538, .367)	-.003 (-1.792, 1.689)
	B vs C	**6.814 (5.003, 8.724)**	**1.209 (8.369, 11.980)**	**11.890 (1.194, 13.549)**	**11.982 (1.435, 13.518)**	**12.170 (1.517, 13.907)**
	B vs D	**7.678 (5.900, 9.564)**	**11.120 (9.292, 12.891)**	**1.572 (8.763, 12.527)**	**1.478 (8.588, 12.253)**	**1.663 (8.571, 12.762)**
	C vs D	.863 (-.258, 2.039)	.911 (-.154, 1.967)	-1.317 (-2.649, -.048)	-1.503 (-2.957, -.177)	-1.508 (-2.973, -.050)
Scattering	A vs B	-1.246 (-2.144, -.448)	-1.220 (-2.211, -.194)	-.700 (-1.471, .072)	-1.485 (-2.376, -.591)	-1.751 (-2.761, -.744)
	A vs C	.258 (-.530, 1.044)	-.241 (-1.113, .628)	-.239 (-1.053, .544)	-1.106 (-2.004, -.174)	-.522 (-1.396, .406)
	A vs D	.578 (-.088, 1.190)	-.720 (-1.567, .065)	-.031 (-.758, .692)	-1.450 (-2.403, -.524)	-.466 (-1.396, .406)
	B vs C	1.504 (.568, 2.481)	.978 (-.018, 2.008)	.460 (-.385, 1.314)	.379 (-.559, 1.348)	1.228 (.224, 2.293)
	B vs D	**1.824 (1.034, 2.633)**	.500 (-.479, 1.466)	.668 (-.094, 1.428)	.034 (-.898, 1.047)	1.284 (.312, 2.238)
	C vs D	.320 (-.419, 1.034)	-.479 (-1.280, .345)	.208 (-.604, 1.033)	-.344 (-1.306, .624)	.056 (-.781, .966)

Note. Pairwise comparisons that showed credible differences (95% HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 22

Mean of the differences (and 95% HDIs) between diagnostic groups of the estimated number of choices of each deck in each block.

	Group	Block 1	Block 2	Block 3	Block 4	Block 5
Deck A	HC vs. OCD	-.368 (-1.787, 1.230)	.416 (-1.791, .826)	1.105 (-.154, 2.424)	.045 (-1.350, 1.336)	2.026 (.848, 3.340)
	HC vs. SUD	-.466 (-1.590, .613)	-1.696 (-2.839, .535)	-.031 (-1.201, 1.147)	-.076 (-1.258, 1.092)	-.427 (-1.746, .806)
	HC vs. ADHD	.238 (-1.233, 1.742)	-.684 (-2.158, .727)	-1.195 (-2.830, .450)	.920 (-.486, 2.288)	-.207 (-1.935, 1.607)
	OCD vs. SUD	-.098 (-1.559, 1.318)	-1.280 (-2.508, -.067)	-1.136 (-2.233, .052)	-.120 (-1.367, 1.123)	-2.453 (-3.691, -1.367)
	OCD vs. ADHD	.606 (-1.113, 2.486)	-.268 (-1.797, 1.358)	-2.300 (-4.029, -.668)	.876 (-.572, 2.341)	-2.233 (-3.762, -.596)
	SUD vs. ADHD	.704 (-.527, 2.095)	1.012 (-.437, 2.405)	-1.164 (-2.958, .216)	.996 (-.334, 2.307)	.220 (-1.253, 2.057)
Deck B	HC vs. OCD	-.425 (-2.070, 1.069)	1.782 (-.636, 3.989)	.121 (-2.263, 2.375)	.503 (-1.766, 2.668)	.073 (-2.476, 2.639)
	HC vs. SUD	-1.041 (-2.561, .444)	1.745 (-.207, 3.800)	-.959 (-2.848, .972)	-.786 (-2.928, 1.219)	-.236 (-2.276, 1.973)
	HC vs. ADHD	-2.206 (-4.449, .244)	2.162 (-.620, 4.545)	-.725 (-3.332, 2.078)	-1.418 (-4.276, 1.393)	-.147 (-2.747, 2.770)
	OCD vs. SUD	-.616 (-2.483, .996)	-.037 (-2.210, 2.032)	1.080 (-3.196, 1.401)	-1.289 (-3.544, 1.111)	-.309 (-2.954, 2.480)
	OCD vs. ADHD	-1.781 (-4.206, .838)	.380 (-2.532, 3.040)	-.846 (-3.902, 2.038)	-1.921 (-4.960, 1.168)	-.220 (-3.340, 3.016)
	SUD vs. ADHD	-1.165 (-3.611, 1.262)	.417 (-2.148, 2.965)	.234 (-2.440, 2.969)	-.632 (-3.554, 2.380)	.089 (-2.782, 2.889)
Deck C	HC vs. OCD	.972 (-.208, 2.180)	-.671 (-2.529, .880)	1.103 (-.301, 2.441)	-.031 (-1.777, 1.692)	.790 (-.938, 2.321)
	HC vs. SUD	.325 (-.850, 1.627)	-.357 (-1.693, 1.001)	.114 (-1.423, 1.506)	-.070 (-1.553, 1.484)	.639 (-.901, 2.190)
	HC vs. ADHD	.342 (-.895, 1.552)	-.370 (-2.142, 1.114)	1.219 (-.591, 2.918)	.209 (-1.805, 2.047)	.707 (-1.094, 2.557)
	OCD vs. SUD	-.647 (-2.005, .698)	.315 (-1.197, 1.815)	-.989 (-2.235, .369)	-.039 (-1.703, 1.652)	-.151 (-1.687, 1.380)
	OCD vs. ADHD	-.630 (-2.033, .638)	.302 (-1.366, 1.933)	.117 (-1.433, 1.762)	.240 (-1.904, 2.313)	-.083 (-1.969, 1.599)

	Group	Block 1	Block 2	Block 3	Block 4	Block 5
	SUD vs. ADHD	.017 (-1.383, 1.405)	-.013 (-1.545, 1.488)	1.105 (-.638, 2.676)	.279 (-1.652, 2.148)	.068 (-1.708, 1.823)
Deck D	HC vs. OCD	.043 (-1.346, 1.478)	-.476 (-2.389, 1.139)	-1.836 (-4.044, .579)	-.336 (-2.854, 2.338)	-2.192 (-4.792, .427)
	HC vs. SUD	1.131 (.009, 2.405)	.210 (-.990, 1.404)	.628 (-.739, 2.091)	.969 (-1.017, 2.901)	.026 (-1.468, 1.619)
	HC vs. ADHD	1.566 (.121, 3.034)	-.431 (-2.541, 1.630)	.876 (-.879, 2.896)	.750 (-1.944, 3.231)	-.111 (-2.484, 2.106)
	OCD vs. SUD	1.089 (-.293, 2.567)	.686 (-.811, 2.414)	2.464 (.402, 4.520)	1.306 (-.997, 3.674)	2.218 (-.337, 4.606)
	OCD vs. ADHD	1.523 (-.173, 3.196)	.046 (-2.405, 2.378)	2.712 (.185, 5.472)	1.086 (-1.725, 3.985)	2.081 (-.880, 5.094)
	SUD vs. ADHD	.435 (-1.054, 1.943)	-.640 (-2.842, 1.307)	.248 (-1.234, 2.140)	-.220 (-2.556, 2.150)	-.137 (-2.538, 1.849)

Note. Pairwise comparisons that showed credible differences (95% HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 23

Mean of the differences (and 95% HDIs) within diagnostic groups of the estimated number of choices of each deck between each block.

	Block	HC	OCD	SUD	ADHD
Deck A	Block 1 vs. Block 2	1.518 (-.196, 2.693)	1.470 (-.006, 3.192)	.288 (-.617, 1.330)	.596 (-1.211, 2.120)
	Block 1 vs. Block 3	.673 (-.615, 1.921)	2.147 (.500, 3.599)	1.108 (.086, 2.053)	-.760 (-2.663, .896)
	Block 1 vs. Block 4	1.357 (-.012, 2.625)	1.770 (.132, 3.343)	1.748 (.681, 2.754)	2.039 (.221, 3.533)
	Block 1 vs. Block 5	.968 (-.336, 2.314)	**3.362 (1.799, 4.793)**	1.006 (-.022, 1.980)	.522 (-1.331, 2.464)
Deck B	Block 1 vs. Block 2	-2.434 (-4.112, -.544)	-.227 (-2.379, 1.900)	.352 (-1.561, 2.191)	1.933 (-1.338, 4.776)
	Block 1 vs. Block 3	-.314 (-1.959, 1.333)	.232 (-2.115, 2.319)	-.232 (-2.141, 1.526)	1.167 (-1.981, 4.417)
	Block 1 vs. Block 4	-.307 (-1.938, 1.293)	.621 (-1.647, 2.807)	-.052 (-2.200, 1.952)	.481 (-2.780, 3.674)
	Block 1 vs. Block 5	-.906 (-2.668, .710)	-.408 (-2.774, 2.026)	-.101 (-2.025, 1.769)	1.154 (-1.936, 4.319)
Deck C	Block 1 vs. Block 2	.902 (-.449, 2.111)	-.741 (-2.193, .755)	.220 (-1.075, 1.556)	.190 (-1.463, 1.678)
	Block 1 vs. Block 3	.076 (-1.238, 1.334)	.207 (-1.041, 1.442)	-.135 (-1.436, 1.326)	.954 (-.787, 2.536)
	Block 1 vs. Block 4	.579 (-.748, 1.801)	-.425 (-1.977, 1.206)	.184 (-1.399, 1.760)	.446 (-1.425, 2.241)
	Block 1 vs. Block 5	.347 (-1.074, 1.700)	.166 (-1.214, 1.701)	.662 (-.776, 2.105)	.713 (-1.033, 2.412)
Deck D	Block 1 vs. Block 2	.083 (-1.232, 1.312)	-.436 (-2.264, 1.387)	-.838 (-1.863, .262)	-1.913 (-4.316, .191)
	Block 1 vs. Block 3	-.250 (-1.777, 1.173)	-2.128 (-4.236, .248)	-.753 (-1.814, .361)	-.939 (-2.749, 1.218)
	Block 1 vs. Block 4	-1.332 (-3.004, .571)	-1.711 (-3.946, .600)	-1.494 (-2.929, -.128)	-2.148 (-4.727, .049)
	Block 1 vs. Block 5	1.081 (-.385, 2.471)	-2.454 (-5.115, .022)	-1.325 (-2.616, -.089)	-1.896 (-4.251, .377)

Note. Pairwise comparisons that showed credible differences (95% HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 24

Mean of the differences (and 95% HDIs) within diagnostic groups between the estimated number of choices of each deck in each block.

	Deck	Block 1	Block 2	Block 3	Block 4	Block 5
HC	A vs B	-1.291 (-2.575, -.116)	**-3.864 (-5.377, -2.402)**	-1.996 (-3.438, -.634)	**-2.579 (-3.960, -1.200)**	**-2.571 (-4.046, -1.150)**
	A vs C	.161 (-.960, 1.265)	-.488 (-1.700, .735)	-.370 (-1.695, .869)	-.539 (-1.808, .715)	-.428 (-1.792, .853)
	A vs D	-.626 (-1.863, .596)	-1.786 (-2.997, -.447)	-1.436 (-2.778, .068)	**-2.651 (-4.158, -1.191)**	-1.607 (-3.029, -.121)
	B vs C	1.452 (.324, 2.540)	**3.376 (1.680, 4.920)**	1.626 (.082, 3.125)	2.020 (.597, 3.470)	2.143 (.676, 3.743)
	B vs D	.665 (-.568, 1.874)	2.078 (.431, 3.685)	.560 (-1.121, 2.138)	-.072 (-1.626, 1.600)	.964 (-.599, 2.696)
	C vs D	-.787 (-1.908, .324)	-1.298 (-2.658, .086)	-1.066 (-2.567, .499)	-2.112 (-3.665, -.588)	-1.179 (-2.705, .337)
OCD	A vs B	-1.667 (-2.684, .439)	-2.437 (-4.004, -.930)	**-2.666 (-4.305, -1.088)**	-2.087 (-3.764, -.511)	**-4.012 (-5.704, -2.373)**
	A vs C	1.296 (-.118, 2.753)	-.546 (-1.905, .796)	-.327 (-1.461, .852)	-.593 (-2.008, .818)	-1.564 (-2.847, -.291)
	A vs D	-.173 (-1.850, 1.440)	-1.763 (-3.309, -.274)	**-3.207 (-4.825, -1.610)**	-2.687 (-4.322, -.982)	**-4.276 (-6.047, -2.539)**
	B vs C	**2.463 (1.126, 3.796)**	1.891 (.263, 3.516)	2.339 (.783, 3.912)	1.494 (-.283, 3.272)	2.448 (.732, 4.183)
	B vs D	.993 (-.555, 2.493)	.674 (-1.075, 2.446)	-.541 (-2.505, 1.347)	-.600 (-2.579, 1.347)	-.263 (-2.466, 1.775)
	C vs D	-1.469 (-2.851, -.097)	-1.217 (-2.843, .385)	**-2.880 (-4.499, -1.311)**	-2.093 (-3.933, .286)	-2.712 (-4.637, -.999)
SUD	A vs B	-1.516 (-2.796, -.295)	-1.555 (-2.863, -.227)	**-2.634 (-3.885, -1.349)**	**-2.912 (-4.334, -1.487)**	-2.388 (-3.778, -.974)
	A vs C	.887 (-.243, 1.977)	.724 (-.354, 1.838)	-.268 (-1.349, .822)	-.531 (-1.727, .611)	.399 (-.825, 1.522)
	A vs D	.975 (-.031, 1.999)	-.102 (-1.159, 1.031)	-.745 (-1.717, .278)	-2.033 (-3.304, -.731)	-1.308 (-2.471, -.052)
	B vs C	**2.402 (1.119, 3.729)**	2.279 (.938, 3.602)	2.365 (.936, 3.739)	2.381 (.839, 3.866)	**2.788 (1.246, 4.303)**

	Deck	Block 1	Block 2	Block 3	Block 4	Block 5
	B vs D	**2.491 (1.235, 3.720)**	1.452 (.116, 2.811)	1.889 (.545, 3.163)	.879 (-.742, 2.521)	1.081 (-.587, 2.593)
	C vs D	.089 (-1.011, 1.214)	-.827 (-1.900, .253)	-.476 (-1.598, .685)	-1.502 (-2.858, -.087)	-1.707 (-3.025, -.351)
ADHD	A vs B	-2.140 (-4.002, -.262)	-1.779 (-3.652, -.009)	-.861 (-2.835, 1.121)	**-3.410 (-5.314, -1.561)**	-2.015 (-3.832, -.029)
	A vs C	.263 (-1.102, 1.608)	-.110 (-1.497, 1.356)	1.559 (-.092, 3.298)	-1.153 (-2.659, .510)	.285 (-1.236, 1.958)
	A vs D	.598 (-.953, 2.022)	-1.466 (-3.244, .336)	1.559 (-.092, 3.298)	-2.618 (-4.472, -.767)	-1.291 (-3.145, .678)
	B vs C	2.403 (.608, 4.159)	1.669 (-.231, 3.451)	2.421 (.570, 4.351)	2.257 (.238, 4.248)	2.300 (.398, 4.219)
	B vs D	2.737 (.861, 4.534)	.312 (-1.755, 2.378)	1.349 (-.666, 3.349)	.792 (-1.409, 3.019)	.724 (-1.431, 2.987)
	C vs D	.334 (-1.025, 1.673)	-1.357 (-3.159, .399)	-1.072 (-.813, 2.236)	-1.465 (-3.387, .560)	-1.575 (-3.389, .375)

Note. Pairwise comparisons that showed credible differences (95% HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 25

Means of the posterior of rsFC between each ROI and mean of the differences in these values between each cluster. The values within parentheses represent the 95% HDIs.

	D Learners	Scattering	B exploiters	D Learners – Scattering	D Learners – B exploiters	Scattering – B exploiters
lOFC-rOFC	.559 (.424, .697)	.563 (.480, .642)	.490 (.353, .631)	-.003 (-.157, .157)	.069 (-.122, .273)	.072 (-.087, .236)
lOFC-lDLPFC	.374 (.243, .520)	.420 (.345, .495)	.338 (.215, .456)	-.046 (-.199, .116)	.036 (-.152, .218)	.082 (-.062, .219)
lOFC-rDLPFC	.393 (.273, .517)	.410 (.334, .479)	.439 (.310, .572)	-.018 (-.152, .125)	-.046 (-.232, .126)	-.028 (-.176, .121)
lOFC-lpPC	.173 (.110, .236)	.187 (.138, .235)	.141 (.071, .209)	-.014 (-.092, .069)	.033 (-.062, .126)	.046 (-.038, .128)
lOFC-rpPC	.188 (.110, .266)	.185 (.141, .233)	.147 (.080, .209)	.003 (-.085, .095)	.041 (-.059, .141)	.038 (-.040, .117)
rOFC-lDLPFC	.339 (.217, .462)	.346 (.289, .404)	.280 (.181, .377)	-.006 (-.135, .132	.059 (-.094, .214)	.065 (-.046, .179)
rOFC-rDLPFC	.407 (.274, .545)	.427 (.352, .498)	.409 (.281, .539)	-.019 (-.181, .129)	-.002 (-.185, .198)	.017 (-.132, .164)
rOFC-lpPC	.150 (.093, .207)	.179 (.132, .224)	.111 (.056, .168)	-.029 (-.101, .044)	.039 (-.039, .120)	.068 (-.007, .139)
rOFC-rpPC	.289 (.186, .396)	.248 (.194, .307)	.195 (.125, .262)	.040 (-.078, .160)	.094 (-.030, .219)	.054 (-.034, .141)
lDLPFC-rDLPFC	.465 (.400, .592)	.499 (.374, .522)	.410 (.284, .525)	.016 (-.131, .162)	.055 (-.123, .225)	.039 (-.098, .183)
lDLPFC-lpPC	.210 (.126, .293)	.241 (.187, .294)	.205 (.126, .281)	-.031 (-.130, .069)	.005 (-.107, .121)	.035 (-.059, .127)
lDLPFC-rpPC	.230 (.148, .309)	.217 (.169, .264)	.182 (.100, .263)	.013 (-.079, .106)	.048 (-.062, .159)	.035 (-.059, .131)
rDLFPC-lpPC	.179 (.110, .245)	.225 (.168, .279)	.171 (.095, .247)	-.046 (-.136, .038)	.007 (-.102, .105)	.053 (-.038, .149)
rDLPFC-rpPC	.265 (.169, .352)	.289 (.230, .347)	.246 (.163, .338)	-.024 (-.136, .085)	.019 (-.103, .148)	.043 (-.059, .152)
lpPC-rpPC	.307 (.195, .420)	.368 (.300, .432)	.265 (.147, .380)	-.060 (-.185, .076)	.043 (-.113, .208)	.103 (-.029, .236)

Note. Pairwise comparisons that showed credible differences (95% HDI does not include the ROPE [-1, 1]) are boldfaced.

Table 26

Means of the posterior of rsFC between each ROI and mean of the differences in these values between each diagnostic group. The values within parentheses represent the 95% HDIs.

	HC	OCD	SUD	ADHD	HC – OCD	HC – SUD	HC - ADHD
lOFC-rOFC	.610 (.507, .714)	.512 (.365, .652)	.496 (.390, .598)	.550 (.303, .814)	.098 (-.072, .278)	.114 (-.033, .254)	.060 (-.222, .326)
lOFC-lDLPFC	.396 (.292, .467)	.359 (.233, .485)	.400 (.299, .507)	.365 (.166, .570)	.036 (-.131, .195)	-.004 (-.154, .139)	.031 (-.199, .249)
lOFC-rDLPFC	.395 (.299, .485)	.337 (.207, .465)	.472 (.378, .564)	.381 (.187, .585)	.057 (-.110, .211)	-.076 (-.204, .055)	.015 (-.207, .231)
lOFC-lpPC	.187 (.121, .254)	.143 (.075, .209)	.183 (.126, .236)	.148 (.034, .262)	.044 (-.052, .139)	.004 (-.083, .091)	.039 (-.092, .171)
lOFC-rpPC	.185 (.119, .249)	.120 (.063, .177)	.210 (.151, .270)	.153 (.038, .267)	.065 (-.023, .148)	-.026 (-.113, .062)	.032 (-.099, .162)
rOFC-lDLPFC	.342 (.259, .429)	.281 (.182, .375)	.325 (.249, .400)	.376 (.187, .567)	.061 (-.073, .186)	.017 (-.098, .129)	-.033 (-.248, .196)
rOFC-rDLPFC	.408 (.316, .497)	.348 (.217, .490)	.451 (.354, .549)	.455 (.228, .675)	.059 (-.109, .220)	-.043 (-.180, .081)	-.047 (-.281, .196)
rOFC-lpPC	.160 (.100, .218)	.143 (.079, .209)	.160 (.105, .214)	.145 (.048, .246)	.017 (-.071, .102)	-.001 (-.083, .078)	.015 (-.102, .125)
rOFC-rpPC	.240 (.167, .316)	.203 (.119, .284)	.264 (.192, .340)	.264 (.128, .406)	.037 (-.075, .148)	-.024 (-.024, -.130)	-.024 (-.188, .128)
lDLPFC-rDLPFC	.463 (.363, .559)	.406 (.269, .541)	.417 (.327, .511)	.519 (.321, .711)	.057 (-.106, .227)	.045 (-.087, .179)	-.056 (-.281, .154)
lDLPFC-lpPC	.233 (.159, .314)	.225 (.136, .313)	.202 (.145, .259)	.256 (.112, .406)	.008 (-.111, .124)	.031 (-.067, .124)	-.023 (-.187, .142)
lDLPFC-rpPC	.226 (.160, .297)	.185 (.113, 258)	.205 (.149, .264)	.237 (.093, .374)	.041 (-.059, .140)	.021 (-.067, .124)	-.011 (-.165, .148)
rDLFPC-lpPC	.200 (.121, .271)	.190 (.108, .270)	.193 (.136, .252)	.232 (.095, .368)	.011 (-.097, .123)	.008 (-.087, .099)	-.031 (-.184, .124)
rDLPFC-rpPC	.270 (.192, .346)	.216 (.132, .297)	.296 (.226, .370)	.302 (.139, .463)	.054 (-.061, .165)	-.026 (-.131, .080)	-.033 (-.214, .141)
lpPC-rpPC	.343 (.259, .431)	.254 (.141, .370)	.334 (.248, .422)	.401 (.210, .600)	.089 (-.051, .234)	.009 (-.107, .135)	-.058 (-.267, .155)

Note. Pairwise comparisons that showed credible differences (95% HDI does not include the ROPE [-1, 1]) are boldfaced.

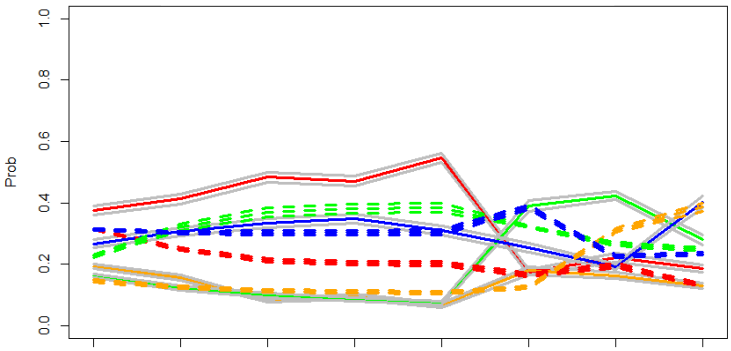
iii. Studies II and III. Simulations of behaviour from reinforcement-learning models

All simulations were performed in R Software. We generated 1000 simulations for each group (clusters or diagnostic groups) from the estimated values of each parameter obtained from each applied model. Using the same mathematical formulation of each model, we took 1000 random combinations of parameters that were given from each model for each subject and simulate 1000 probabilities of choice of each deck for each subject. In all graphics, solid lines represent the real probability of choices of each deck while dashed lines represent the simulated probabilities. Decks A, B, C and D are represented by red, orange, green and blue, respectively. None of the models showed an appropriate simulation of real data in any group. VPP and ORL models seem to overestimate the advantageous choices, while PVL-Delta and PVL-Decay models seem to overestimate the low loss-frequency decks.

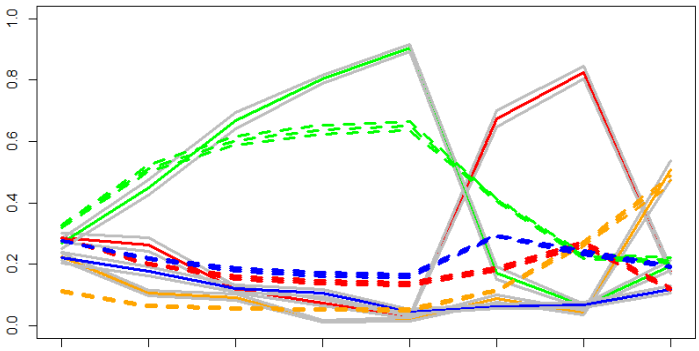
Study II

Value Plus Perseverance (VPP) Model

A-Choosers



C-Learners



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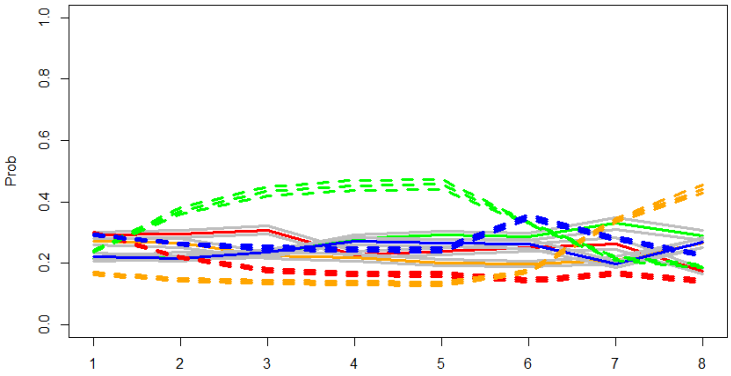

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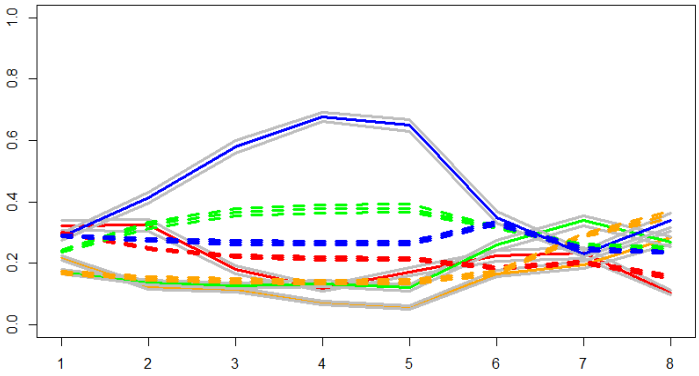

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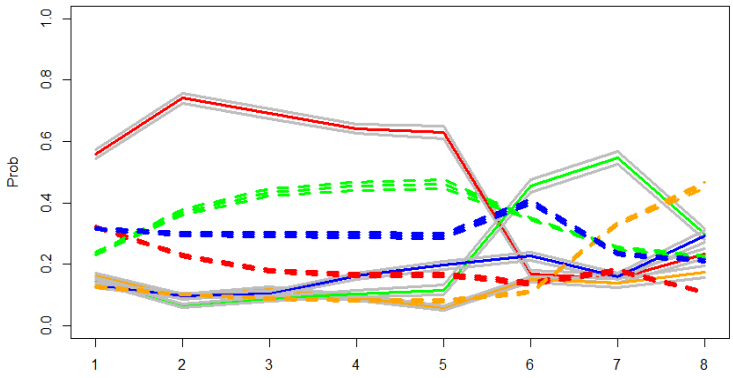
B-Exploiters



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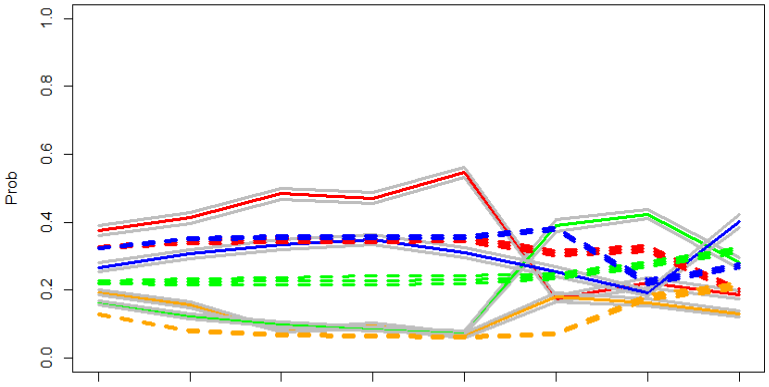
Prospect Valence Learning (PVL) Decay Model

A-Choosers



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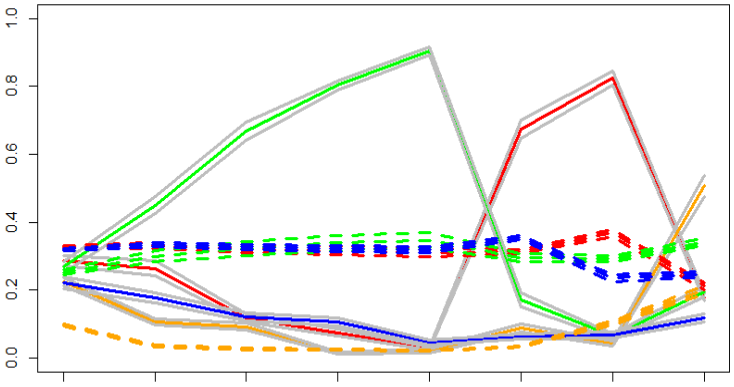

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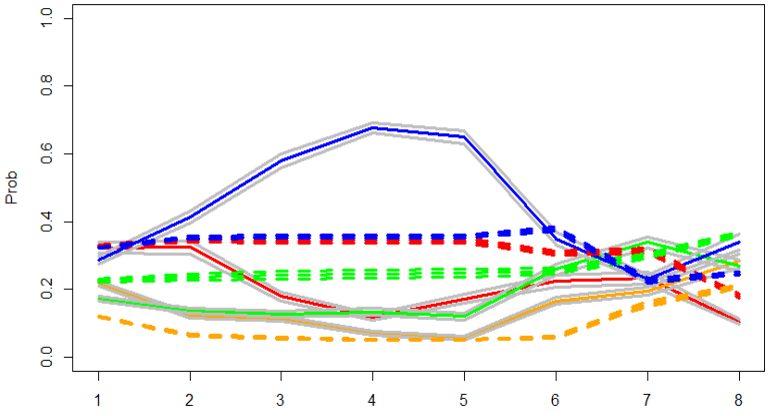

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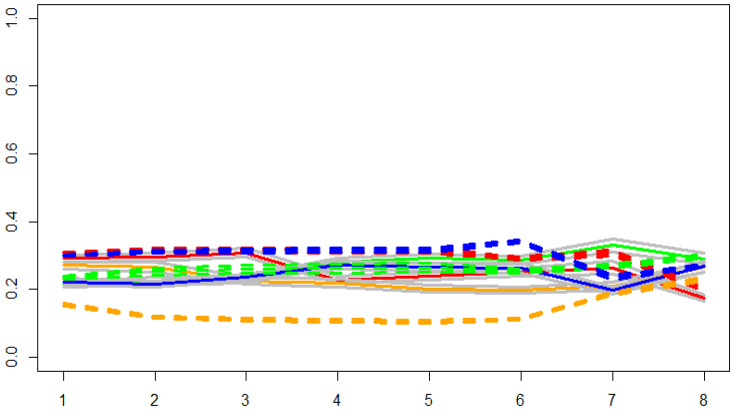

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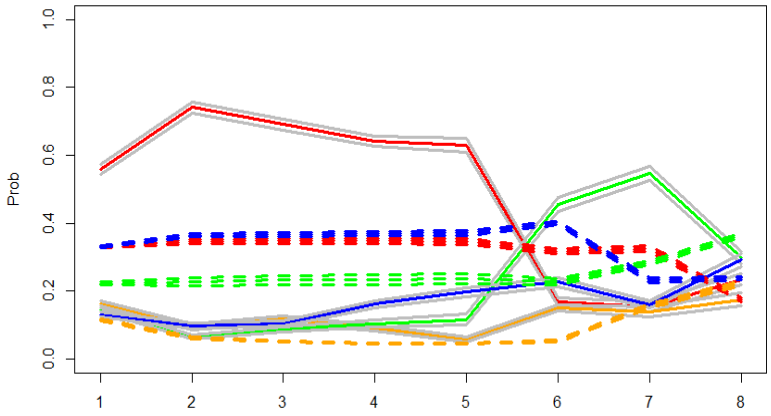

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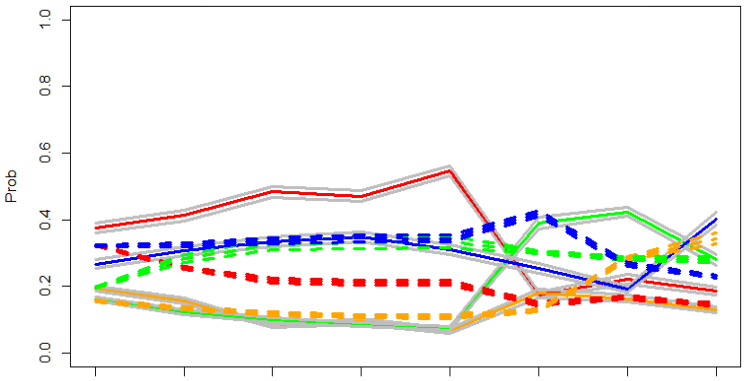
Prospect Valence Learning (PVL) Delta Model

A-Choosers



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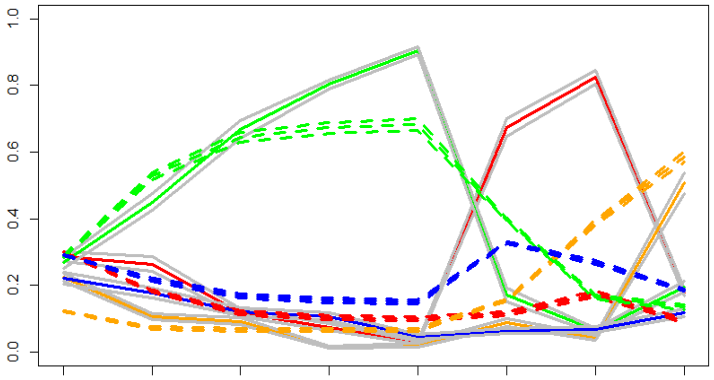

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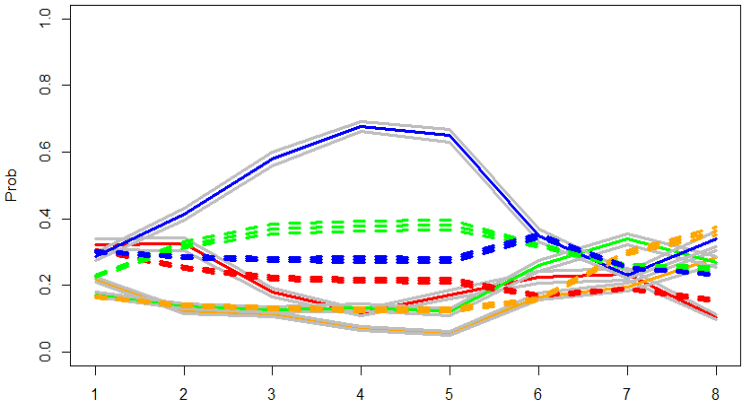

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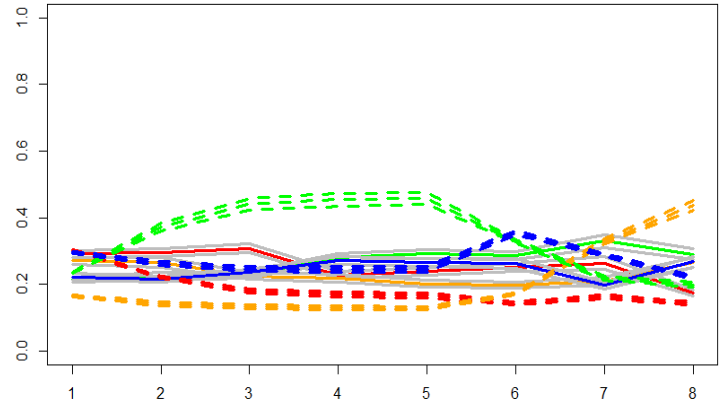

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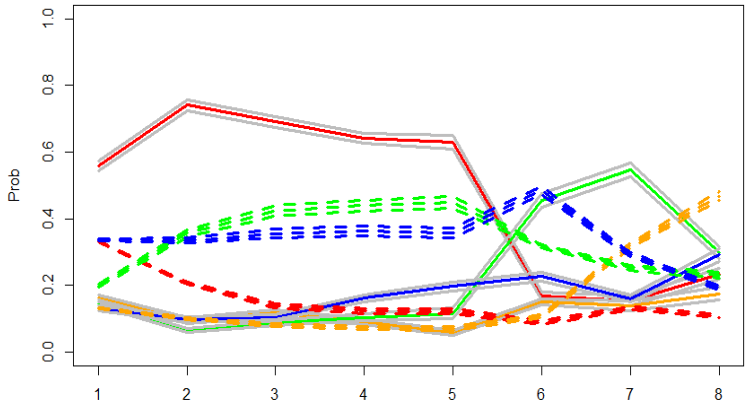

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Outcome Representation Learning (ORL) Model

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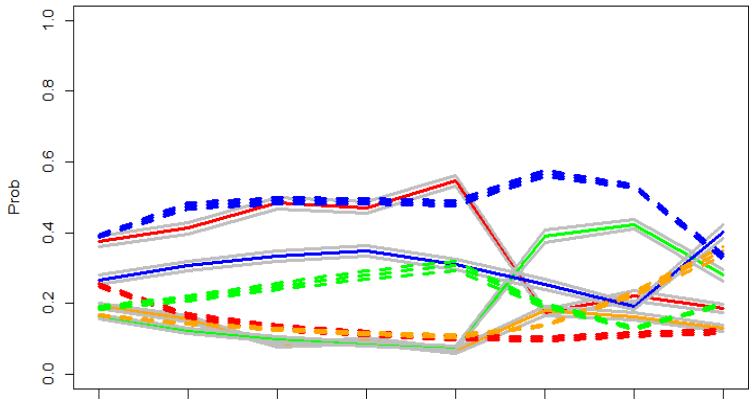

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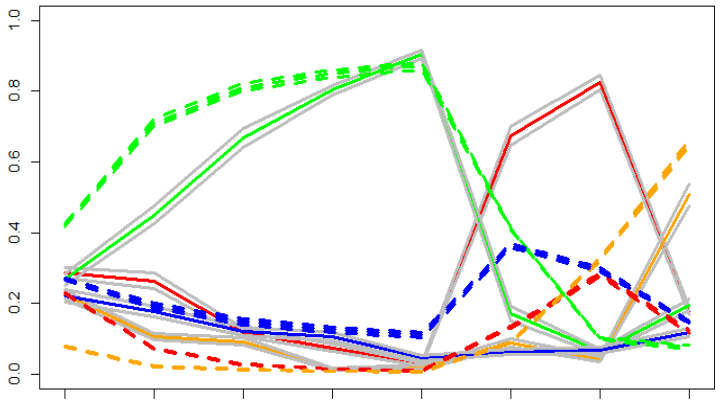

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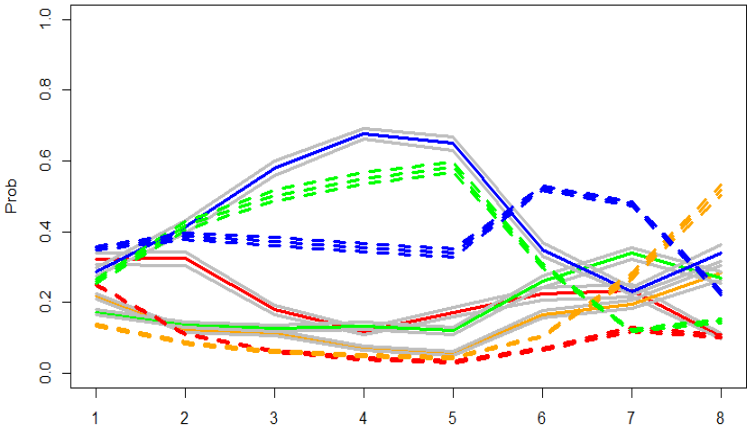

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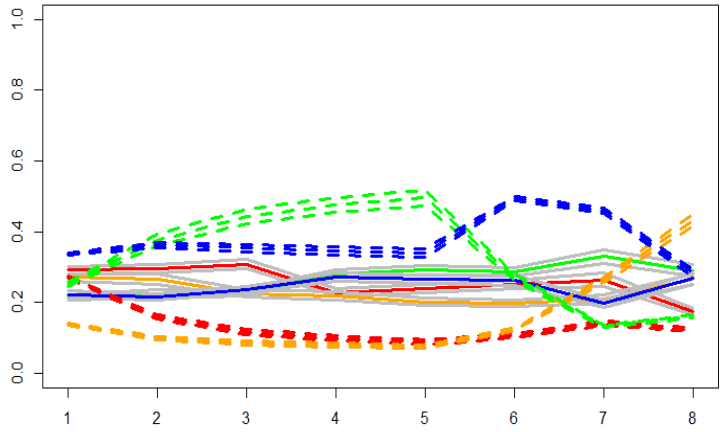

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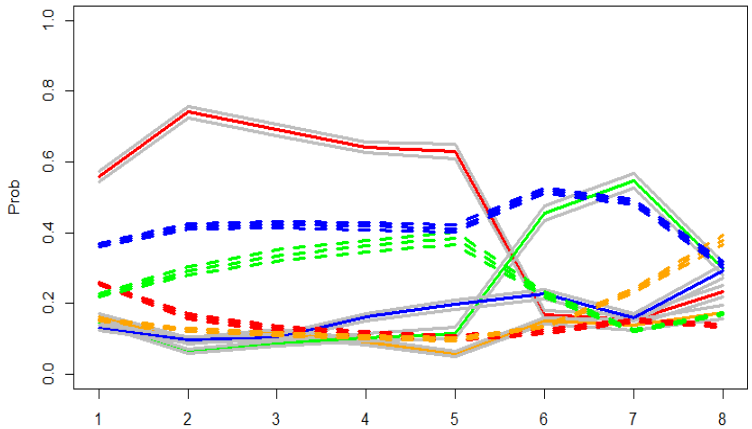

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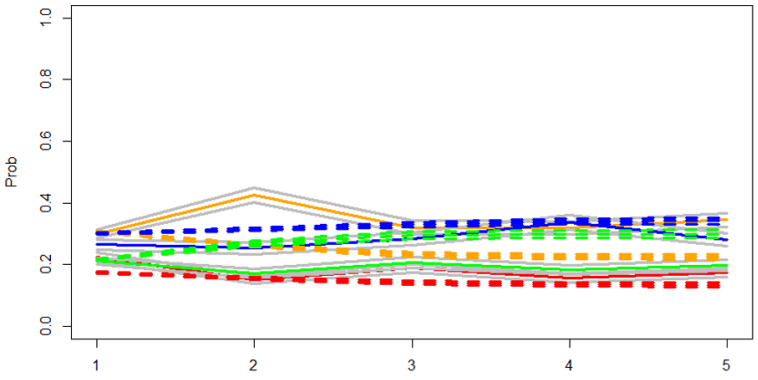
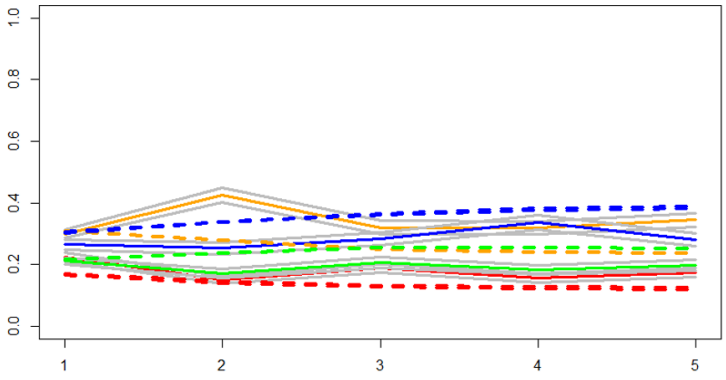
Study III

Control group

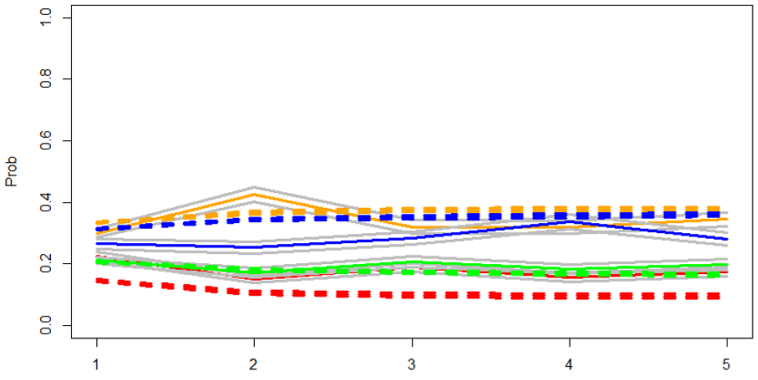
PVL Delta



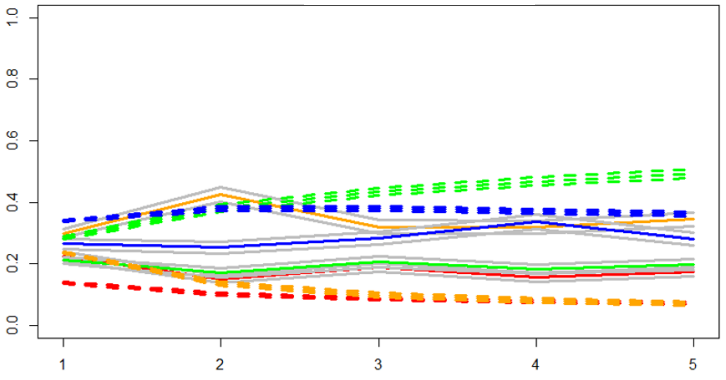
VPP



PVL Decay

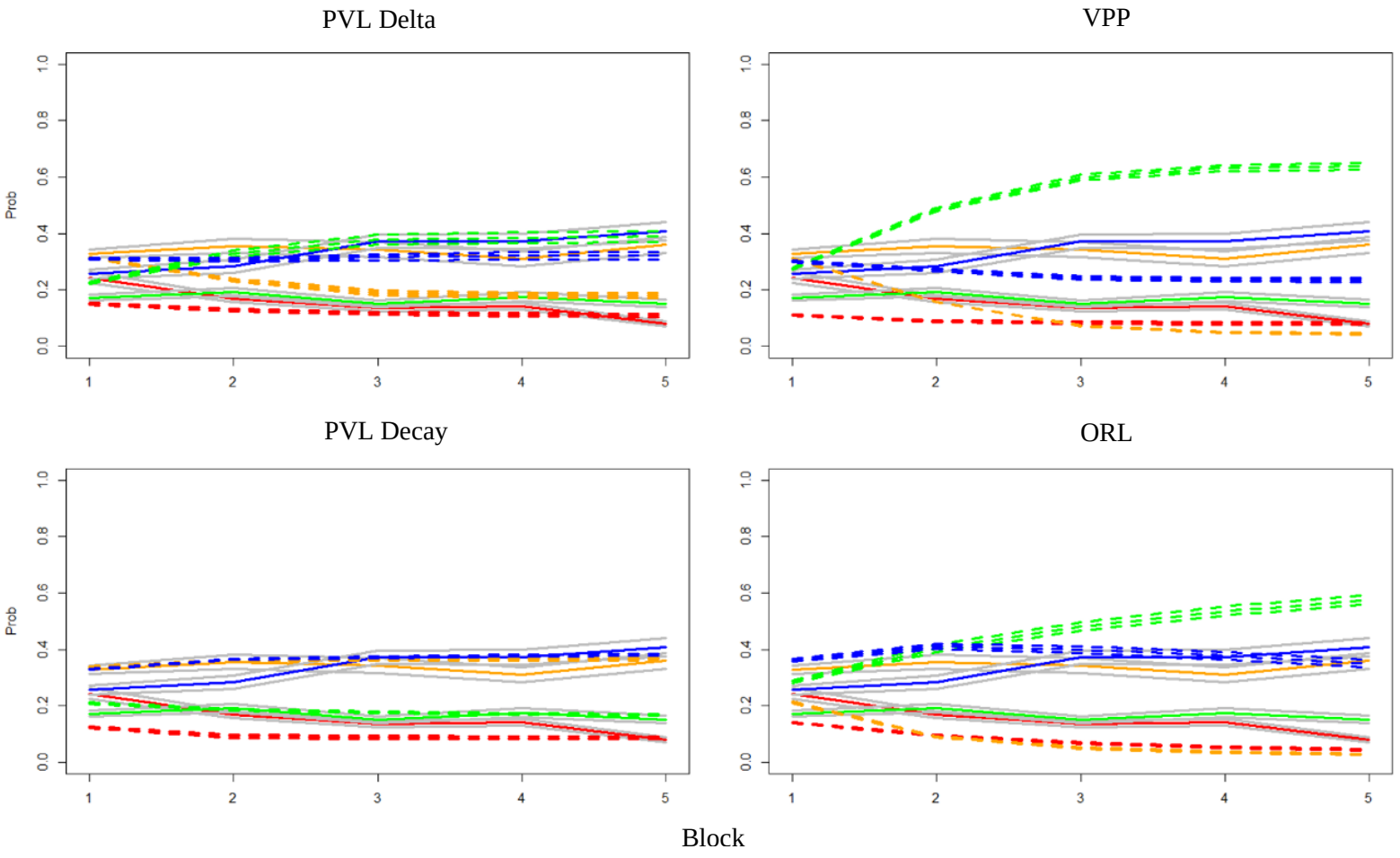


ORL



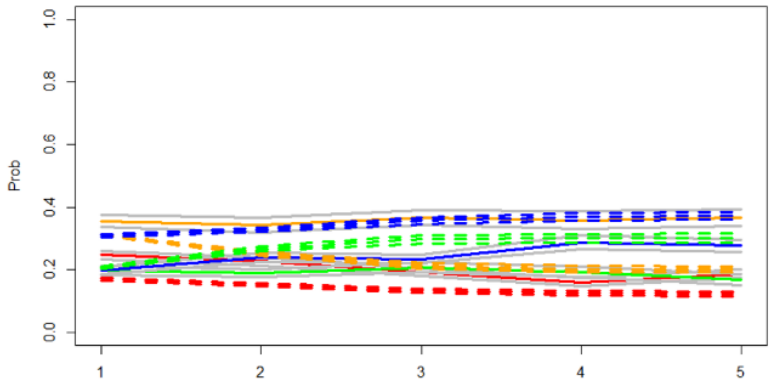
Block

Obsessive-Compulsive Disorder group



Substance Use Disorder group

PVL Delta



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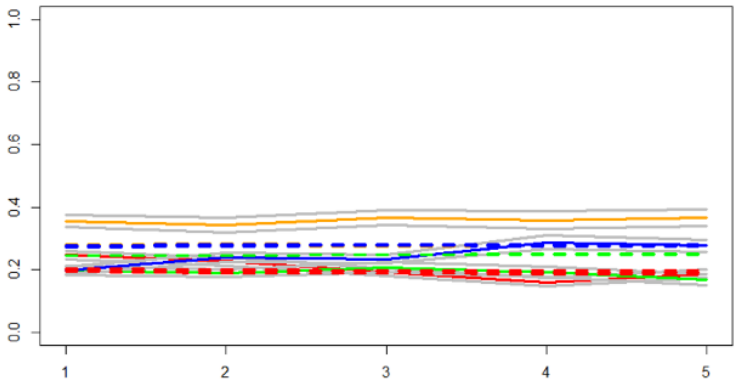

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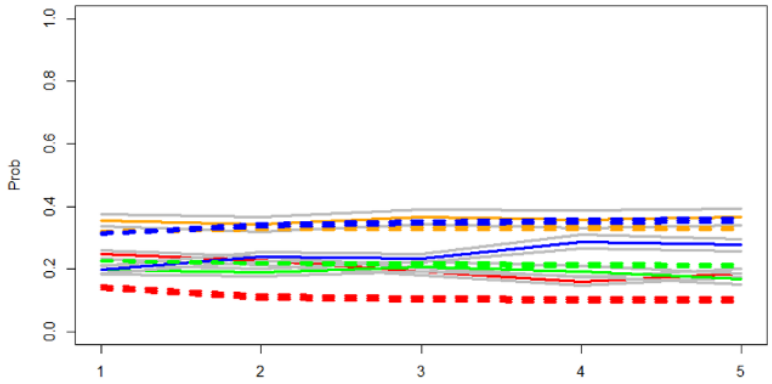

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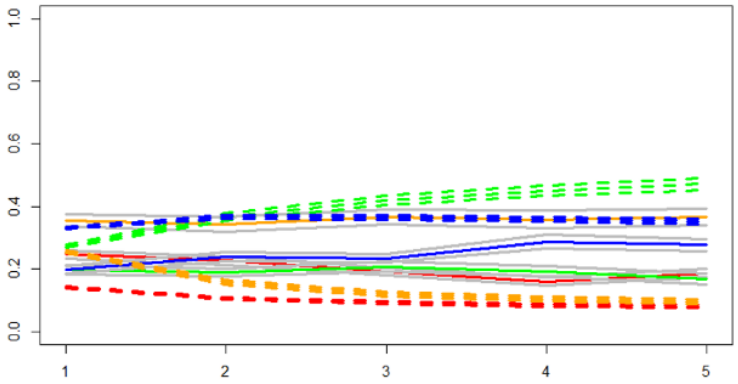
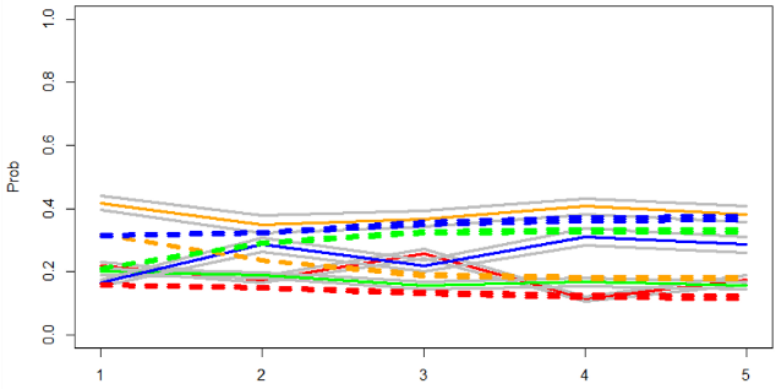


Block

Attention-Deficit/Hyperactivity Disorder group

PVL Delta



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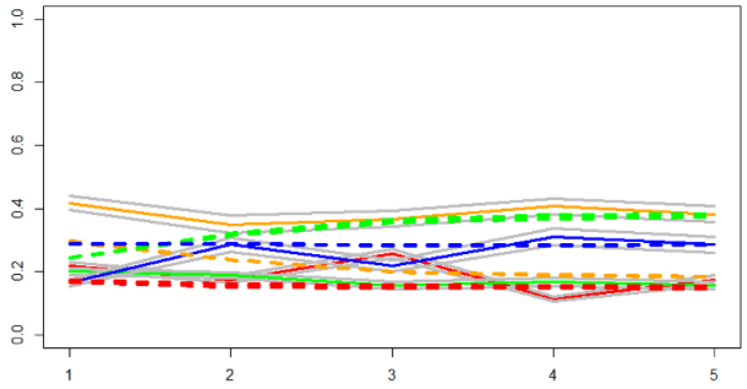

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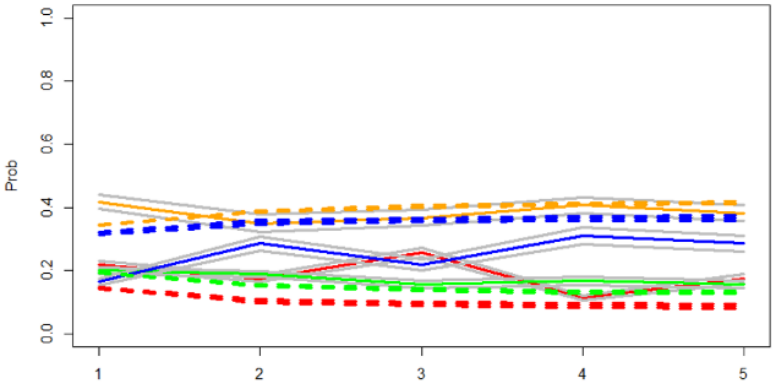

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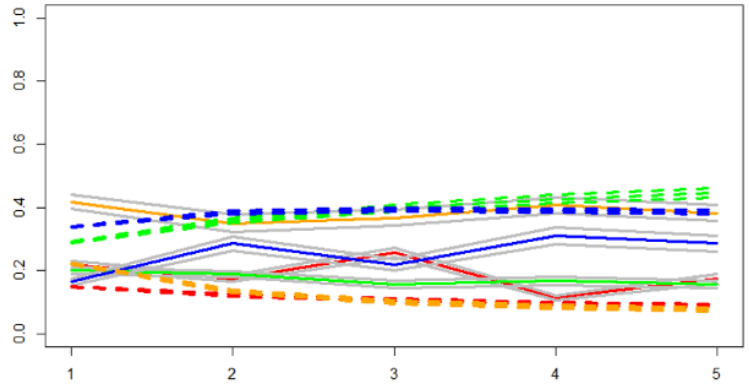
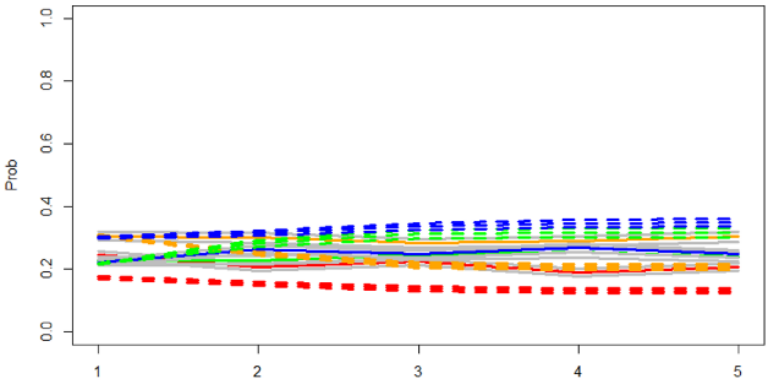


Block

Scattering

PVL Delta



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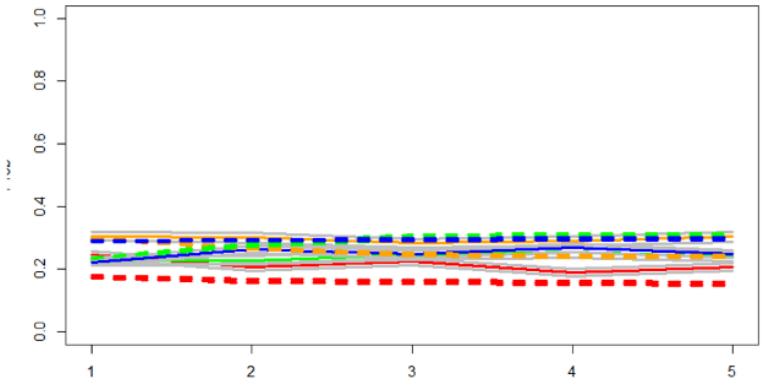

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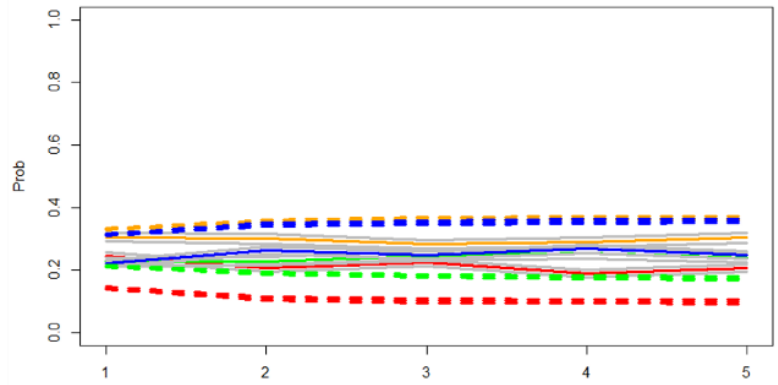

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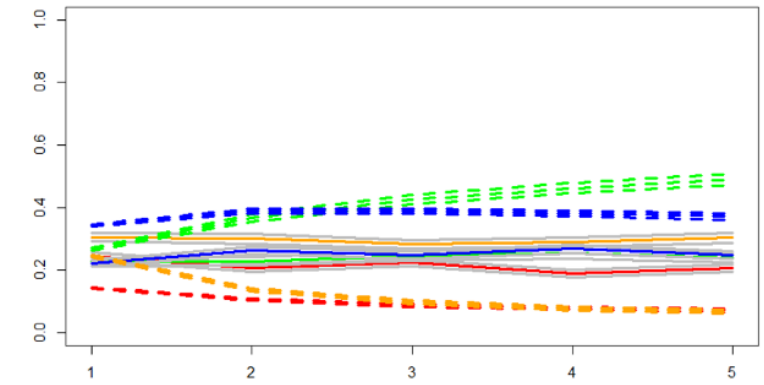
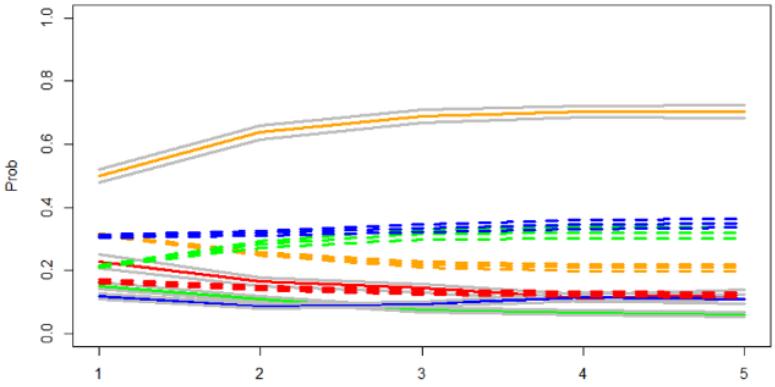


Block

B-Exploiters

PVL Delta



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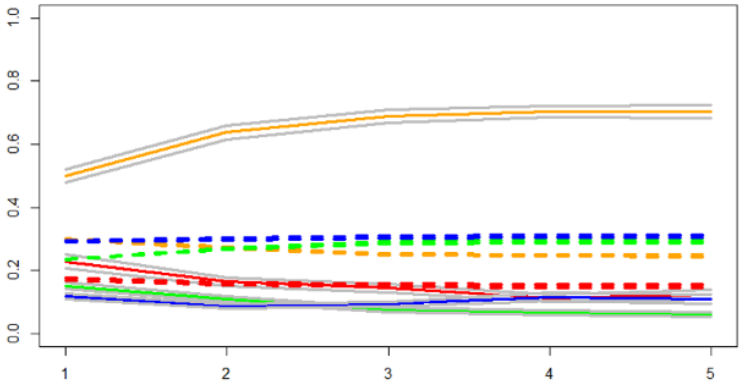

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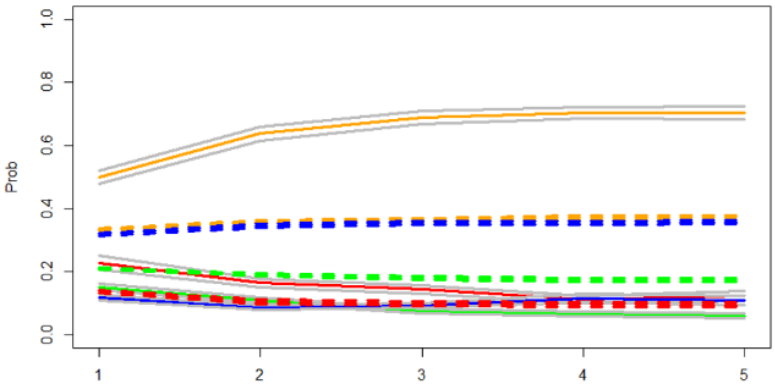

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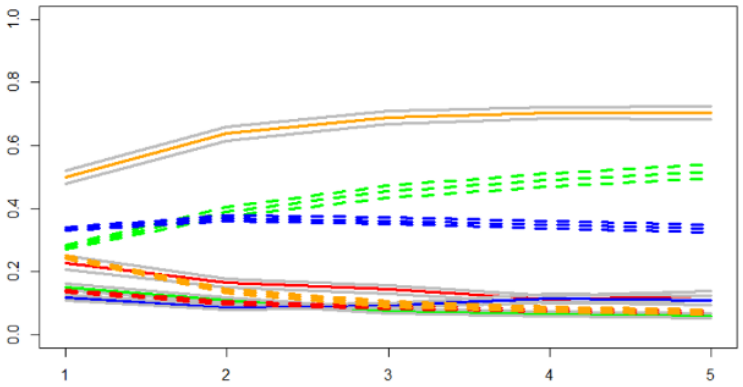
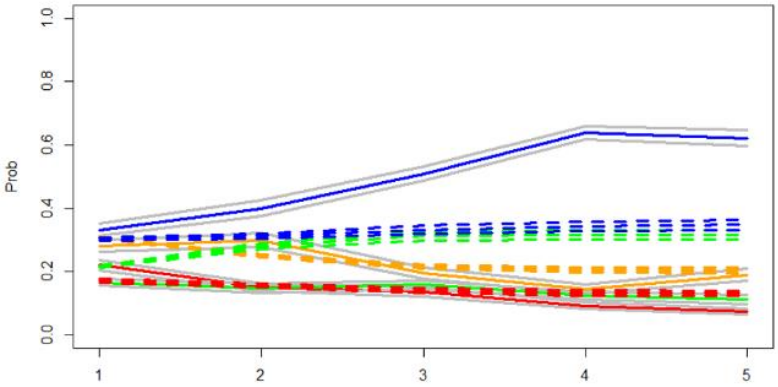


Block

D-Learners

PVL Delta



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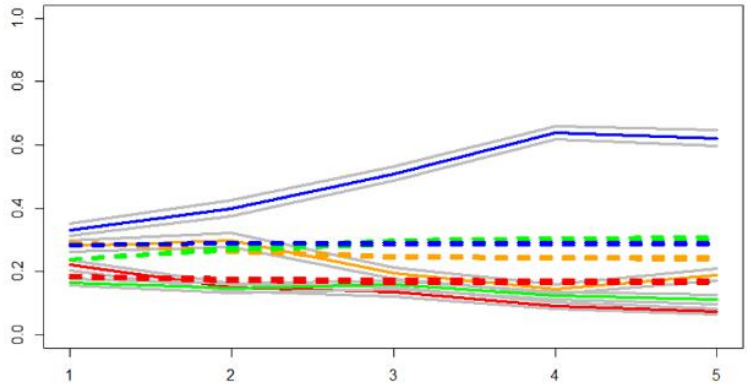

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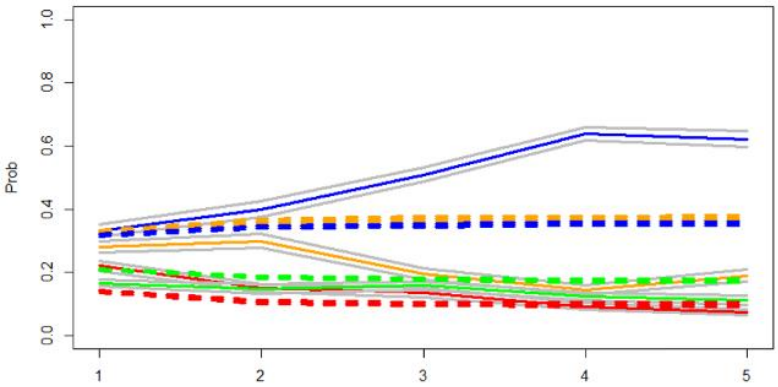

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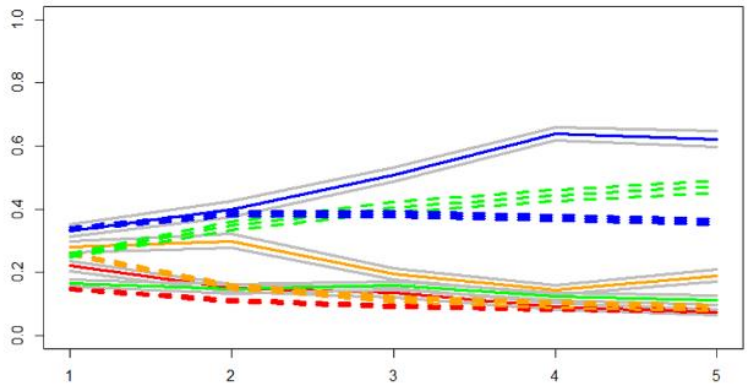

Block

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