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FULL-LENGTH REPORT

Spatio-temporal EEG dynamics during decision-making in online poker players with problem gambling

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ABSTRACT

Background and aims: Gambling activity evolves along a continuum from recreational to Gambling Disorder (GD) and a particular challenge is to identify whether there are some neurophysiological particularities already present in gamblers at an early stage. Our main goal was to determine whether, in the gamblers' population, neural responses generated during uncertain decisions were different depending on problematic gambling risk defined by the Canadian Problem Gambling Index (CPGI). We tested the following hypothesis, that the Problem Gambling group would show a different brain activity related to outcomes processing than people with low risk. *Methods:* For this purpose, we established a relatively homogeneous population of Online Poker Players divided into two groups according to the CPGI (Low Risk and Problem Gambling). By means of high-density EEG, we compared the spatio-temporal dynamics generated during the completion of the Iowa Gambling Task. *Results:* One specific topographic map was observed between 150–175 ms after a negative outcome for both groups, whereas it was displayed in the win condition only for the Problem Gambling group. We found that the Global Field Power of this map was negatively correlated with participants' adherence to a strategy. Source localization identified Anterior Cingulate Cortex and Temporal regions as generators of this map. *Discussion and conclusions:* Reward hypersensitivity EEG responses identified in the early outcome process could constitute a potential biomarker of problematic gambling.

KEYWORDS

problem gambling, decision-making, high-density EEG, Iowa Gambling Task

INTRODUCTION

Gambling Disorder (GD) was the first behavioral addiction to be recognized by international institutions, in the fifth edition of the *Diagnostic and Statistical Manual* (DSM-5) (American Psychiatric Association, 2013). The estimated prevalence in adults worldwide of moderate risk of gambling is 2.43% and 1.29% for problematic gambling (Gabellini, Lucchini, & Gattoni, 2023). Gambling activity evolves along a continuum from recreational to gambling disorder and the risk levels between these two extremes are defined as light, moderate and high by the Canadian Problem Gambling Index (CPGI) (Potenza et al., 2019). The term "problem

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gambling" assimilates within the same group of the moderate and high risk ranges of CPGI (Vita et al., 2021). Today, we know that delays in diagnosing GD have a major impact on the severity of psychosocial damage, leading to additional pressures that can aggravate the disorder (Månsson et al., 2023). So, one of the challenges we face is to identify people at risk of developing GD at an early stage (Månsson et al., 2023), and to better understand the processes involved in the transition from recreational activity to GD.

To identify a neuronal brain activity specific to this risk, we focused on a known cognitive disability in the GD population. Decision-making deficits in addictive disorders, and more specifically in GD, have long been recognized (Bechara, 2005; Kovács, Richman, Janka, Maraz, & Andó, 2017). Decision-making ability under conditions of uncertainty can be evaluated using the Iowa Gambling Task (IGT) (Bechara, Damasio, Damasio, & Anderson, 1994). In this task, participants are given a choice between four decks of cards and, via successive choices, learn to choose the advantageous decks (Bechara et al., 1994). The development of an appropriate strategy is reflected by the number of advantageous choices, and the adhesion to a quick and/or sustainable strategy can be reflected by the rigidity score (Cabeza et al., 2019).

Although altered performance in this task in individuals with GD is no longer up for debate (Goudriaan, Oosterlaan, de Beurs, & van den Brink, 2005; Linnet, Røjskjaer, Nygaard, & Maher, 2006), contrary data that could be explained by the type of gambling activity subjects engage in have been reported (Brevers, Noël, He, Melrose, & Bechara, 2016).

In terms of gambling, there are a wide variety of practices that we can divide into two categories, non-strategic and strategic, but also by their mode of delivery (online or land-based operations) (Potenza et al., 2019). One of the best-known strategic games of chance is poker, largely thanks to the advent of online gambling (MacKay, Bard, Bowling, & Hodgins, 2014). Online poker is associated with a higher risk of GD than offline gambling (Dufour et al., 2020). However, playing poker involves knowing the rules, skills, mathematics and psychology to influence the game outcome (MacKay et al., 2014). Consequently, assiduous practice can increase playing ability that contributes in part to the development of a professionalization of this activity, but an increase in time spent could also reflect a loss of control over behavior and entry into a GD (Griffiths, 2012; Slepian, Young, Rutchick, & Ambady, 2013). Playing poker requires choosing between the short- and long-term consequences of an action (Brevers et al., 2016), which involves a variety of executive (Griffiths, 2012) and emotional controls (Moreau, Sévigny, Giroux, & Chauchard, 2020), similar to those required for good IGT performance. Thus, we might expect poker players to show less impaired performance on the IGT than other gamblers, even if they suffer from GD. But, performing the IGT places individuals in decision-making conditions that generate brain activity that could be sufficient to discriminate between poker players at risk.

Over and above performance, the IGT places subjects in a decision-making context which induces brain activity, enabling certain population groups to be distinguished with higher sensitivity than can be achieved by performance. The IGT places subjects in a cognitive situation that generates a specific brain activity known to be different between GD and healthy subjects. Brevers et al. formulated a hypothesis that a hypersensitivity to gain causes altered decision making in the IGT in GD, translating hypersensitivity of the reward system (Brevers, Koritzky, Bechara, & Noël, 2014).

Neuroimaging performed during IGT showed contradictory results regarding the neural bases of decisional alterations in GD. If some showed hypersensitivity to gain (Oberg, Christie, & Tata, 2011), others found that this hypersensitivity was found for the loss (Linnet, Peterson, Doudet, Gjedde, & Møller, 2010). Some methodological differences notably in choice of sample, such as GD severity or favorite gambling activity, would be the cause of these differences (Brevers, Bechara, Cleeremans, & Noël, 2013; Wiehler & Peters, 2015). For example, Online Poker Players are a specific population whose poker training could attenuate impaired IGT performances and information processing (Giustiniani et al., 2024). However, even in absence of impaired IGT performances, Poker players with GD showed an imbalance in neural activity with an increase in the striatum (impulsive system) and a decrease in the prefrontal region (reflective system) (Brevers et al., 2016). In addition, Brevers et al., observed a positive correlation between the problem gambling severity score and ventral striatal activation, suggesting that this activity could be a good indicator of the GD severity (Brevers et al., 2016). If its specific brain activity is also identified in problematic gamblers compared to recreational, this could be exploited in the future as a biomarker of the problematic gambling risk. As brain structures involved in emotion, conflict monitoring, working memory and motor response inhibition (Bechara & Damasio, 2005) have been identified, and they were activated in a very short space of time, this makes it difficult to properly identify the dynamics of the dysfunctional processes. Methods like electroencephalography (EEG) allow an accurate assessment of the time course of neural activation during this process (Giustiniani, Gabriel, Nicolier, Monnin, & Haffen, 2015). The outcome processing is made up of numerous stages which differ from each other in their latency of onset, and which can be altered independently of each other, thus revealing a different dysfunction depending on whether it is early or late (Giustiniani et al., 2024; Oberg et al., 2011). However, classical event-related potential analyzes target certain electrodes and time windows of interest based on previous literature. We hereby propose to use high-density EEG and functional microstate analysis methods that take advantage of the large number of electrodes at its disposal, at least 64. Microstate analysis of EEG is a powerful, inexpensive, and clinically translatable neurophysiological method to study and assess global functional states of the brain in healthy volunteers and patients (Khanna, Pascual-Leone, Michel, & Farzan, 2015). The functional states are assessed by recording topographies of electric potentials with multichannel EEG over the scalp, and considering their stability over time. Microstate analysis has been used in a large number of studies to characterize

neuropsychiatric disorders (see (Chivu, Pascal, Damborská, & Tomescu, 2024) for a review in the evaluation of mood and anxiety disorders). The microstate analysis minimizes user-dependent biases and a priori assumptions by selecting topographic maps that remain stable for a certain duration. Thus, different topographic maps reflect different configurations of electric sources in the brain, which could be extracted and analyzed. Finally, surface neural activity recording allows, thanks to the source localization, identification of the brain structure involved in its generation (Chabin, Pazart, & Gabriel, 2022). The application of this technique will enable us to better understand the neural temporal pathway taken during a decision, and to compare what is different or not between gamblers with and without risk of problematic gambling, in the outcome processing.

In summary, our study is in the exploratory stage, for which the main objective was to determine whether neural responses generated during the IGT performance were different depending on the severity levels of problematic gambling in the gambler's population. For this purpose, we established a relatively homogeneous population of Online Poker Players, divided into two groups (Low-Risk and Problem Gambling) determined by their CPGI, with the objective of comparing the different configurations of electric sources generated during the completion of the IGT. Impulsivity, known to influence the IGT performance and to be present at a high level in the GD population, was controlled to avoid interpretation biases (Grassi et al., 2015; Logge, Morley, Haber, & Baillie, 2023; Ochoa et al., 2013). We tested the hypothesis that the "problem gambling" group would show different brain activity related to outcomes processing than the one with low risk.

METHODS

Participants and recruitment

Forty male volunteers over 18 years old were recruited to participate in the current study; all of them were right-handed and had normal or corrected-to-normal vision. For the recruitment of the gamblers, we focused on the specific online poker population with communication and an advertisement displayed in the local press (Besançon; France). The advertisement asked for participants who "played poker online" to participate in our study.

Participants were divided into two groups according to their severity levels of problematic gambling, as assessed by the Canadian Problem Gambling Index (CPGI) (Ladouceur, Sylvain, Botin, & Doucet, 2000; Petry, Zajac, & Ginley, 2018). Twenty participants were assigned to the Low-Risk group (LR group) if their CPGI score was below 3, and twenty to the Problem Gambling group (PG group) if their CPGI score was greater than or equal to 3. Sample size estimation was based on the neuronal activity measured in one of our previous studies (Giustiniani et al., 2015), where a difference of 1.348 ± 1.365 μV between a gain and a loss was found in the group of subjects developing a favorable strategy. A difference of 0.259 ± 0.867 was observed in the undecided group. We hypothesized that these differences would be the same between the high-risk online gambling addiction group and the low-risk online gambling addiction group, with $\alpha = 0.05$ and power = 80%.

No participants had any previous medical history of psychiatric disorders, substance abuse, alcohol abuse, neurological diseases, traumatic brain injury, or stroke, nor were any participants taking any medication at the time of the study.

Prior to participating in the study, participants received information regarding the aims and procedures of the experiment and gave their written informed consent to participate. All participants received €85 at the end of the experiment in compensation.

Clinical and psychometric measures

Each participant received a hetero-evaluation by a psychiatric addictologist confirming the absence of non-inclusion criteria, and determining the presence of a GD according to the DSM-5 (American Psychiatric Association, 2013). Then, volunteers received several self-assessments to check that the group's personality profile, drinking and smoking habits, and sociodemographic data were equivalent, and could not constitute bias. As tobacco and alcohol consumption were not excluded, their level of consumption was verified by the Alcohol Use Disorder Identification Test (AUDIT) (Saunders, Aasland, Babor, de la Fuente, & Grant, 1993) and the Fagerström Test (Meneses-Gaya, Zuardi, Loureiro, & Crippa, 2009).

The Barratt Impulsiveness Scale (BIS-10) was employed to control the impulsivity and its subcomponents (cognitive (BIS-CI), motor (BIS-MI) and non-planning (BIS-NPI)) (Bouvard, 2009). The BIS/BAS ("Behavioral Inhibition System" and "Behavioral Approach System"), which evaluates the appetitive and aversive motivation, is composed of three sub-categories of the BAS, the Drive (BAS-D), the Fun Seeking (BAS-FS) and the Reward Responsiveness (BAS-RR) (Smillie, Jackson, & Dalgleish, 2006).

Experimental tasks, the Iowa Gambling Task (IGT)

The virtual IGT used in this study is an electronic version of the IGT, adapted for the study of ERPs and the analysis of brain activity sources (Giustiniani et al., 2015). The aim of the task is to win as much money as possible by making successive selections between four decks.

The composition of decks, values, and schedules of reward/punishment were predetermined identically to the original form of the IGT. While the back of each deck looked identical, they differed in composition. Decks A and B were the disadvantageous decks; they provided immediate rewards, but in the long run yielded major economic losses. Decks C and D were the advantageous decks; they provided frequent small wins and smaller long-term penalties, which resulted in long-term gain. The subjects were not informed of the number of trials they would be playing. To adapt the IGT to our French population, the money used to play was

converted from US Dollars to Euros. At the beginning of the IGT, participants received a virtual loan of €2,000 (Bechara et al., 1994; Giustiniani et al., 2015).

A few changes had to be made to adapt the original IGT task to work with the EEG, such as increasing the number of trials to 200, and the delay between the choice and displaying the result (see (Giustiniani et al., 2015) for a complete description of modifications).

EEG recording

EEG signals were recorded using a 256 channel Geodesic Sensor Net (Electrical Geodesics Inc.; EGI, Eugene, OR) during the IGT. Continuous recordings were performed with a high-pass set at 0.1 Hz and a sampling rate of 1,000 Hz. All channels were referenced to the vertex (Cz) and collected with a high impedance amplifier (Net Amp 300 amplifier, Electrical Geodesics) using Net Station 4.5 software (Electrical Geodesics). Data were continuously recorded at a sampling rate of 1,000 Hz. Subjects were instructed to limit body movements, eye blinks, and muscular contractions during task selection and reward feedback (Giustiniani et al., 2015).

Data analysis

Behavioral data analysis. The 200 trials of the task were divided into 10 blocks of 20 trials. The individual net score was calculated by subtracting the number of disadvantageous decks from the number of advantageous decks obtained for each block. We evaluated the adherence to a strategy, also called rigidity score, by calculating how many times the same deck had been chosen (Cabeza et al., 2019).

EEG data analysis. Microstate analysis was performed using Cartool Software 3.551. Raw EEG data were re-referenced offline to a common average reference. Data were bandpass filtered between 1 and 30 Hz (Butterworth), and a notch filter fixed at 50 Hz was applied to remove environmental artifacts.

The main interval of interest in the IGT came following the reward screen. Epochs of 700 ms (100 ms prior to reward feedback – 600 ms following reward feedback) were extracted from the raw data and analyzed, with a baseline correction applied prior to feedback on the onset of the feedback (100–0 ms). A semi-automatic artifact rejection method was used, with a fixed criterion of ±100 μV. Remaining epochs were visually inspected, manually removing any containing blinks, eye movements, or other sources of transient noise from the analysis. Electrodes with an aberrant signal (e.g., excessive noise due to malfunctioning or a bad signal during data collection) were interpolated using a 3-dimensional spline algorithm.

A microstate analysis was performed to determine whether the four conditions (win or loss in the IGT for LR-group and PG-group) differ in global electric fields (Michel & Murray, 2012). The spatiotemporal segmentation was performed on the group-averaged responses from the displayed result to 600 ms after for each condition. Changes in electric fields occur when the configuration of the underlying generator has changed and suggest the activation of different brain networks. A k-means cluster analysis on topographic dissimilarities was applied to determine which topographic template ('map') best explains the participants' neural responses to each experimental condition. This iterative procedure started with an initial guess of maps and terminated when successive iterations differ negligibly. This automatically resulted in a certain number of topography maps that best represent the whole data set.

Following the microstate procedure, one type of analysis was then performed: a fitting procedure comparing the group-averaged data with the scalp topography of ERPs at the individual level. For each condition of each subject, we could then extract various parameters, such as the number of time frames for the maximum global field power (TFmaxGFP), the mean GFP, and the maximum GFP (maxGFP) for each map (Khanna et al., 2015).

Finally, a source localization procedure was also performed by using a distributed linear inverse solution based on a local auto-regressive average (Loreta) model for the maps resulting from the segmentation analysis and showing differences between LR-group and PG-group. These source estimations were computed from the averages of ERPs at all 256 electrodes into a solution space represented by a 3D grid composed of 5,018 nodes. These 5,018 nodes were selected from a grid equally distributed over the gray matter of the average brain provided by the Montreal Neurological Institute.

Statistical analysis. Statistics were performed with Statistica (StatSoft Europe, Hamburg, Germany) and R 3.4.1 (R Development Core Team) software. For the psychometric statistics, *t*-test was used to test potential differences in psychometric scale between the two groups.

A behavioral analysis was performed on the subjects' performances. Net scores obtained for each block were submitted to a General Linear Model (GLM), with the factor group (LR or PG), and the blocks as repeated measures (1–10). If significant, a post hoc Bonferroni test was used to assess the differences. A *t*-test was used to assess potential differences in IGT performance between the two groups. To determine whether there was a relationship between decision-making in the IGT and gambling habits, we performed a Pearson two-tailed correlation between net score during the conceptual phase and CPGI score on the whole group.

In the fitting procedure, each topographic maps, or cluster, were analyzed separately. The topographic maps specific to either group (LR-group versus PG-group) or results were analyzed with a second GLM, including Group × Results. The dependent variables were the number of time frames for the max GFP, the mean GFP, and the maxGFP. For both GLMs, a Bonferroni post hoc correction was applied when necessary.

Ethics

All methods were performed in accordance with the relevant guidelines and regulations and all methods were approved

by the Ethics Committee of Besançon University Hospital (authorized by the General Health Administration (ANSM 2016-A00870-51)), and were carried out in accordance with the protocol and with principles set out in the Declaration of Helsinki.

The study was registered on ClinicalTrials.gov (NCT02873572).

RESULTS

Sociodemographic and psychometric data

Concerning the sociodemographic data, the PG group appears to have less graduates than the LR group. No significant psychometric variations were observed between the two groups in the BIS-10, BIS/BAS, AUDIT and Fagerström test (Table 1).

Behavioral results in the IGT

An increase of performances was observed, subjects playing more and more advantageous cards during the IGT ($F_{(9.342)} = 6.1869$; $p < 0.001$). *Post-hoc* analysis revealed that the net score on blocks 4 to 10 was significantly superior to the first block ($p < 0.05$) (Fig. 1).

We observed the worst performance on the IGT for the PG group, but this was not significantly different from the LR group. No correlation was found between CPGI and final or total net score.

Microstate analysis

The microstate segmentation on the grand mean data revealed five different clusters, or topographic maps, best representing the EEG dataset. The result of the microstate analysis is shown in Fig. 2. One topographic map, time window 1 [TW1], was observed in the loss condition between 150 and 175 ms after the outcome for both groups, whereas it was displayed in the win condition only for the PG group. Another topographic map (Time window 5: TW5) was selected as a period of interest close to P300, in the period that occurs between 290 and 440 ms after the outcome, known to reflect cognitive processes related to the outcome evaluation (Giustiniani et al., 2015).

The cluster maps from the microstate segmentation were then fitted to the individual ERPs of each subject and each condition. For TW1, an interaction was found between the outcome and the number of time frames for the maximum Global Field Power ($F(1,38) = 4.12$, $p = 0.049$), as well as between the outcome and the mean Global Field Power (mean GFP: $F(1,38) = 5.63$; $p = 0.02$). A win resulted in a reduction of TFmaxGFP ($p = 0.04$) and meanGFP (mean GFP, $p = 0.03$) in the LR group only (Fig. 3). A negative correlation between the meanGFP and the rigidity score was observed (Spearman $\rho = -0.355$, $p = 0.024$).

For TW5, the time frame of the peak of GFP (TFmaxGFP) for the loss condition showed no differences in the PG group compared to the LR group (TFmax GFP: $F(1,38) = 4.0.5$, $p = 0.051$).

Table 1. Sociodemographic and psychometric data

	LR- group (Low-Risk group) Mean (SD)	AR- group (Problem Gambling group) Mean (SD)	*p-value*
Sociodemographic data			
Age	30.2 (6.35)	29.2 (6.87)	0.6185
Partnership (%)	25%	55%	0.053
Employment status (%)			0.33
• Unemployed	10%	5%	–
• Student	35%	25%	–
• Employed	55%	70%	–
Children (%)	20%	45%	0.091
Graduates (%)			0.042
• Less than high school	2 (10%)	5 (25%)	–
• High school graduates	2 (10%)	7 (35%)	–
• College or higher	16 (80%)	8 (40%)	–
Addictive habits			
CPGI	0.95 (0.887)	6.6 (3.50)	<0.0001
DSM-5 (Gambling Disorder)	0.35 (0.671	3.55 (1.70)	<0.0001
AUDIT	6.25 (5.02)	6.55 (3.75)	0.8318
Fagerström	0.95 (1.57)	1.15 (1.79)	0.709
Psychometric data			
BIS total	48.4 (14.2)	49.0 (15.4)	0.8822
• BIS-CI	15.0 (4.87)	17 (6.59)	0.2947
• BIS-NPI	18.2 (6.66)	17.3 (5.10)	0.6158
• BIS-MI	15.0 (7.07)	14.8 (7.64)	0.8981
BIS/BAS	38.4 (3.95)	39.1 (4.23)	0.5656
• BAS-D	9.35 (1.57)	9.85 (2.30)	0.4273
• BAS-FS	12.0 (1.54)	12.0 (1.73)	1
• BAS-RR	17.0 (1.93)	17.3 (1.22)	0.6279
• BIS	19.8 (3.14)	19.6 (2.01)	0.9053

Canadian Problem Gambling Index (CPGI); Alcohol Use Disorder Identification Test (AUDIT); Barratt Impulsiveness Scale (BIS-10): cognitive impulsiveness (CI), motor impulsiveness (MI), and non-planning impulsiveness (NPI); BIS/BAS: BIS "Behavioral Inhibition System" and BAS "Behavioral Approach System", Drive (BAS-D), Fun Seeking (BAS-FS) and Reward Responsiveness (BAS-RR).

Source localization

Source localization applied on the TW1 identified Anterior Cingulate Cortex and Temporal regions as generators of this activity. Source localization performed on the TW5 identified the inferior frontal gyri and the right temporal lobe as generators of the neural activity in this time window (Fig. 4).

DISCUSSION

The aim of the current study was to identify differences in neural activity generated during IGT performance between two groups of online poker players, LR group and PG

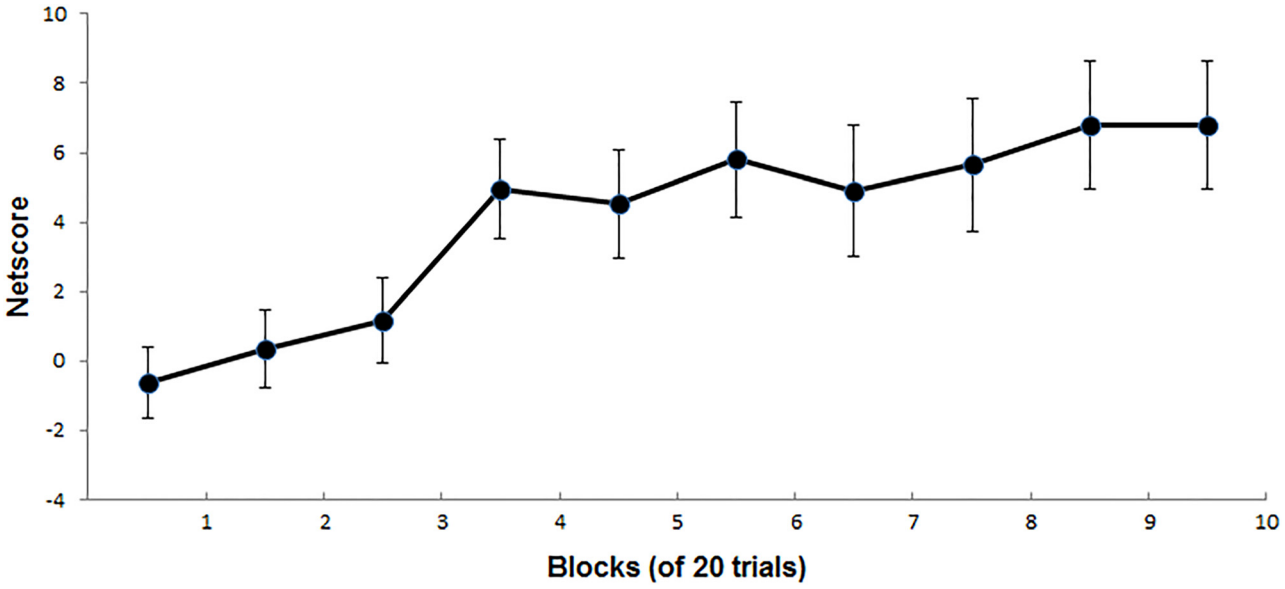

Fig. 1. Behavioral performance in the IGT. Evolution of the net score in each block for the whole group

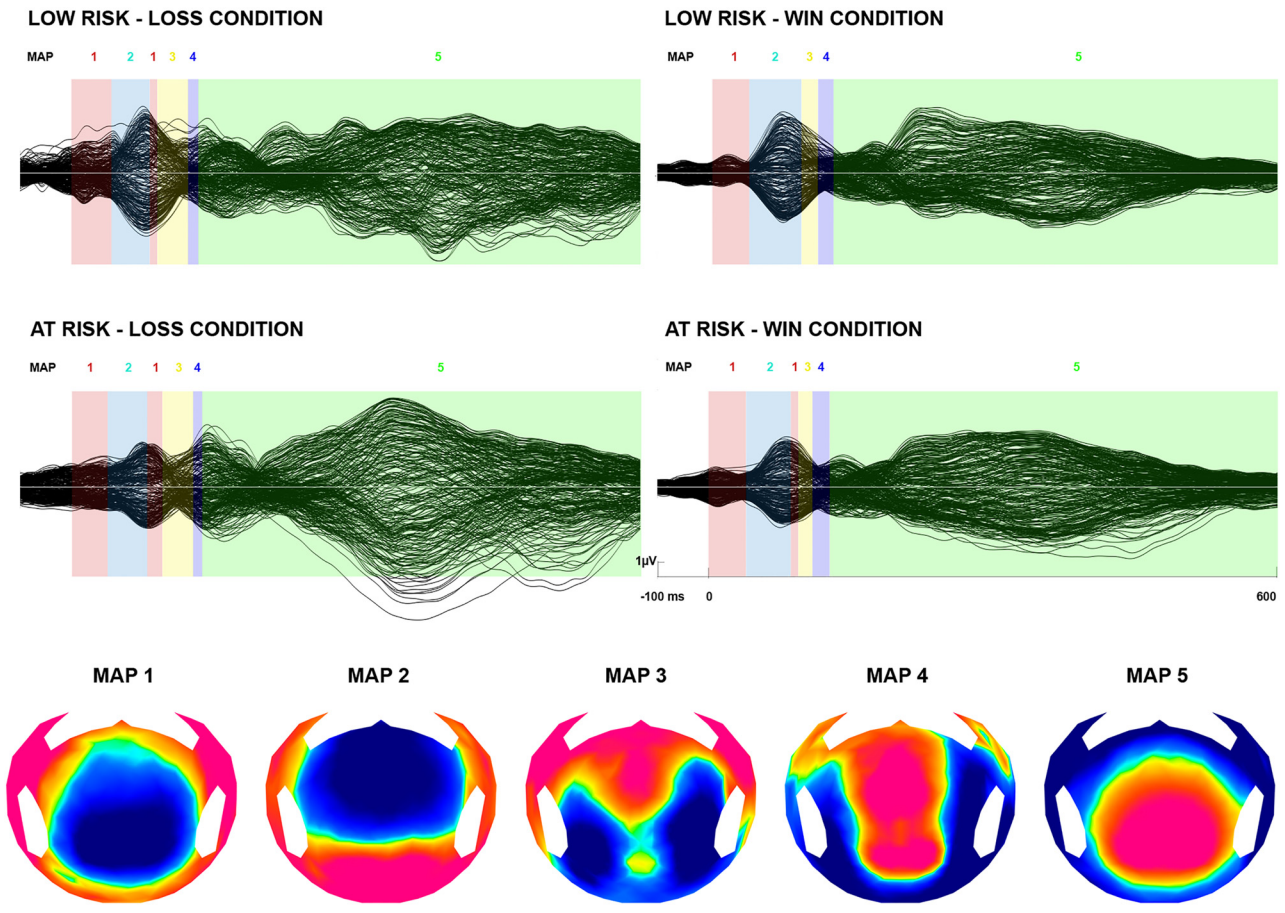

Fig. 2. Top: Microstate analysis for both groups in win and loss conditions. Bottom: topography of the five different maps

group, in order to identify potential biomarkers of the risk of developing GD activity. These two groups did not differ in their personality profiles or in their drinking and smoking habits. We found that the PG group showed a neural activity that testifies to the persistence of gain processing.

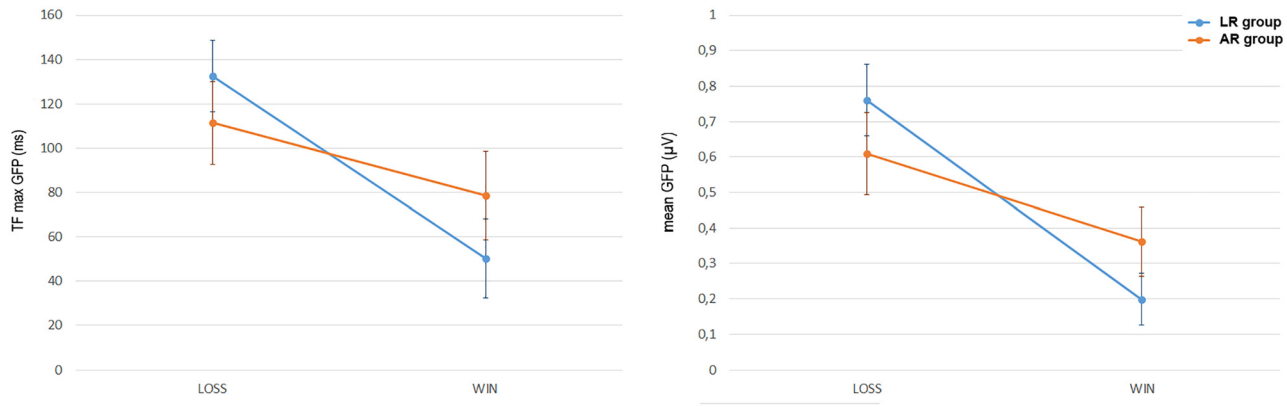

Fig. 3. Differences in time frame of maximum GFP (A) and mean GFP (B) at the time window 150–175 ms (TW1) for the low-risk group and Problem Gambling group

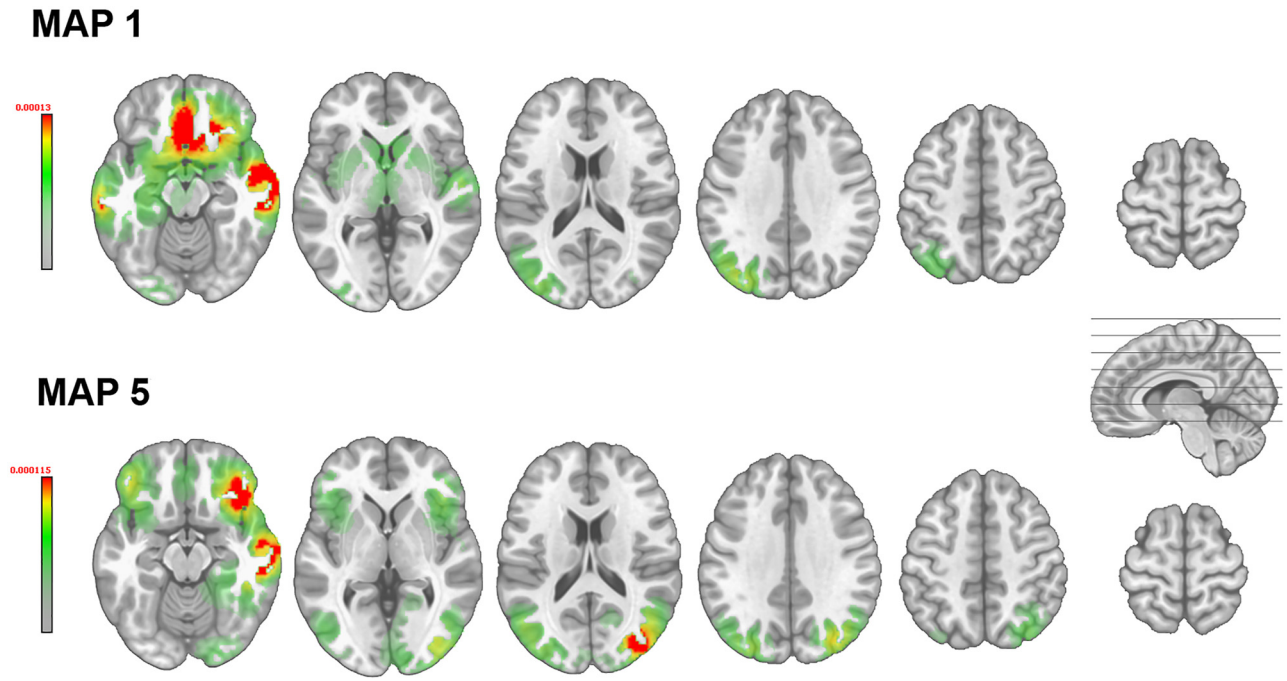

Fig. 4. A/Source localization of the TW1 and TW5 generators

IGT performances

No significant difference in IGT performances were observed between our two groups. Usually, studies which compared behavioral performance compared one clinical population, gambling disorder, to a healthy population (Goudriaan et al., 2005; Oberg et al., 2011). In our study, the population enrolled was not a clinical sample selected from a healthcare center, which is a significant difference from other studies. We can assume that the difference in IGT performance is higher when two opposite groups are compared (GD versus healthy control) (Wiehler & Peters, 2015). IGT performance is influenced by the type of gambling and the severity of the disorder (Brevers et al., 2016; Giustiniani et al., 2024; Wiehler & Peters, 2015). The type of gambling, including Online practice, has a significant impact on behavior. Online gambling in particular engenders a habit of apprehending virtual worlds, so online players are accustomed to making choices and acting in a virtual environment (Brevers et al., 2016; Giustiniani et al., 2024). The absence of a significant difference is probably due to the fact that our two groups are essentially distinguished by their CPGI score.

Early outcome processing

For TW1 early outcome processing, the PG group showed persistent gain processing compared to the LR group. Source localization identified a region encompassing the Anterior Cingulate Cortex (ACC) and the medial frontal lobe, and the temporal lobe as generators.

ACC is well-known to be related to the early outcome processing that reflects an underlying cognitive process

(Bland & Schaefer, 2011; Glazer, Kelley, Pornpattananangkul, Mittal, & Nusslock, 2018). This early activity was previously associated with the reward prediction errors with a phasic activity of the mesencephalic dopamine signaling that tracks violation of reward expectations, and whose activity is localized to striatal reward regions (Glazer et al., 2018). More precisely, the Reinforcement Learning theory states that the neural activity is generated by the disinhibition of neurons in the ACC caused by a phasic decrease in dopaminergic input from striatum when outcomes are worse than expected (Arbel, Hong, Baker, & Holroyd, 2017). The ACC is known to be activated during feedback processing, monitoring, error detection and conflict management (Fellows & Farah, 2005). Neural activity generated by the ACC is recognized to be sensitive of information occurrence (Krigolson, 2018). The latency and the TW1 generators could suggest that this brain activity could be linked to the feedback-related negativity (FRN) (Glazer et al., 2018). In addition, on the TW1, GFP was negatively correlated with their adhesion to a strategy. Moreover, neural activity usually related to this time window is proposed to reflect processes involved in selective attention, executive attention, stimulus classification (Wongupparaj, Sumich, Wickens, Kumari, & Morris, 2018), but above all, its amplitude was correlated to the perception that the outcome was unpredictable (Schuermann, Endrass, & Kathmann, 2012) with a certain degree of uncertainty (Kiat, Straley, & Cheadle, 2016). In the light of these data, we can hypothesize that subjects with low GFP on TW1 would show faster learning skills in the IGT and that consequently the uncertainty phase would be shorter with earlier entry into the conceptual phase of the IGT.

Medial temporal lobe is known to be activated when the outcome is delayed. Its activation allows information to be collected and bound in order to create and store correct associations (Arbel et al., 2017). Thus, in our study, this temporal activation appears to be relevant in regard to our IGT modification for the ERP recording. Indeed, there is a delay between the deck selection and the outcomes displayed that could explain this activation. Moreover, this activity generated after a gain is associated with more errors, a longer learning threshold to reach and to the subjective sensation of a difficulty (Arbel, Goforth, & Donchin, 2013). These could provide another explanation of the negative correlation observation between GFP and rigidity score, for which the lesser reward processing in the LR group could be associated with faster learning.

Generally speaking, all these data point in the direction of gains chasing for the PG group. Chasing, defined as the gambler's willingness to recover from losses, is a central feature of GD. But above all, chasing is a behavioral marker of the risk of transitioning to severe gambling problem (Sleczka & Romild, 2021). For many years, it has also been noted that chasing wins was a driving force and that high-risk online gamblers reported higher chasing wins than chasing losses (Zhang, Rights, Deng, Lesch, & Clark, 2024). Thus, the fact that our "Problem Gambling" online poker players have a higher early win processing than our recreational players seems particularly consistent with these data.

We confirmed that the microstate analysis allowing the recording of brain activity testifying a higher early reward processing in the PG group has already been observed in GDs (Oberg et al., 2011). In addition, we hypothesize that early reward processing could be a neurological marker of chasing wins, a well-known behavioral marker.

Late outcome processing

We failed to observe differences in late outcome processing. Source localization identified the inferior frontal gyrus (IFG) and the right temporal as generators of this TW5. Decision-making activity generated by IGT was associated with activation in prefrontal areas such as the IFG (Brevers et al., 2016). IFG encompasses a part of the orbitofrontal cortex (OFC) well known for its role in decision-making processes (Mavrogiorgou et al., 2017). Indeed, OFC plays a crucial role in the cognitive flexibility and impulsivity control (Barlow et al., 2015). More precisely, IFG activity was associated with GD and the perception of urge to gamble (Goldstein & Volkow, 2011; Goudriaan, de Ruiter, van den Brink, Oosterlaan, & Veltman, 2010). The identification of the right temporal area as generator of the TW5 is consistent with the literature which found that its activity is related to the visuo-spatial memory (Luelsberg et al., 2022), and is in agreement with the theory of emotional asymmetry, in which the right side is related to negative emotion, here the loss (Cui, Chen, Wang, Shum, & Chan, 2013). With regard to the time window and the generators, it is very likely that the observed activity can be associated with a P300 (Polich, 2007). P300 is well known for being engaged in the cognitive task, with attentional, memory and motivational significance (Vuillier, Whitebread, & Szucs, 2015), the absence of statistical difference on the TW5 may reflect a similar interest in its successful completion.

Limits

Our groups appear comparable in many ways, however we observed a difference in the level of graduates with fewer years of study for the PG group, which may have a negative impact on their IGT performance (Davis et al., 2008). In addition, our population showed heterogeneity in risk level in the CPGI, which can have a negative impact on the observation of differences caused by the onset of the disorder. Continuing investigations on a more homogeneous population and comparing gamblers with moderate risk to those with high risk would clarify whether a specific neuronal activity occurs in different stages of severity.

CONCLUSION

Our results are promising in two different ways. From a fundamental point of view, the temporal dynamics view of the EEG allows us to identify brain activity that is associated with reward hypersensitivity, similarly to what has been observed with more complex methods such as fMRI

(Brevers et al., 2016). Future research should focus on reproducibility and on simplifying the procedure to develop a biomarker of GD.

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Conflict of interest: Emmanuel Haffen (EH): I have acted in advisory capacities, carried out clinical studies in relation to drug development; received personal research, study, or travel allowances; given presentations at meetings; and received remuneration for my input from the following pharmaceutical organizations: Janssen, Lundbeck, Otsuka, Neuraxpharm and Ethipharm. I have also held managerial positions at the FondaMental Foundation (Créteil) and the French Association of Biological Psychiatry and Neuropsychopharmacology. The other authors declare no conflict of interest.

Data availability: All data can be provided by Damien Gabriel upon request by e-mail; dgabriel@chu-besancon.fr.

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REFERENCES

American Psychiatric Association (2013). *Manuel diagnostique et statistique des troubles mentaux (DSM-5)*. Elsevier Masson.

Arbel, Y., Goforth, K., & Donchin, E. (2013). The good, the bad, or the useful? The examination of the relationship between the feedback-related negativity (FRN) and long-term learning outcomes. *Journal of Cognitive Neuroscience*, *25*(8), 1249–1260. https://doi.org/10.1162/jocn_a_00385.

Arbel, Y., Hong, L., Baker, T. E., & Holroyd, C. B. (2017). It's all about timing : An electrophysiological examination of feedback-based learning with immediate and delayed feedback. *Neuropsychologia*, *99*, 179–186. https://doi.org/10.1016/j.neuropsychologia.2017.03.003.

Barlow, R. L., Alsiö, J., Jupp, B., Rabinovich, R., Shrestha, S., Roberts, A. C., … Dalley, J. W. (2015). Markers of serotonergic function in the orbitofrontal cortex and dorsal Raphé nucleus predict individual variation in spatial-discrimination serial reversal learning. *Neuropsychopharmacology*, *40*(7), 1619–1630. https://doi.org/10.1038/npp.2014.335.

Bechara, A. (2005). Decision making, impulse control and loss of willpower to resist drugs : A neurocognitive perspective. *Nature Neuroscience*, *8*(11), 1458–1463. https://doi.org/10.1038/nn1584.

Bechara, A., & Damasio, A. R. (2005). The somatic marker hypothesis : A neural theory of economic decision. *Games and Economic Behavior*, *52*(2), 336–372. https://doi.org/10.1016/j.geb.2004.06.010.

Bechara, A., Damasio, A. R., Damasio, H., & Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition*, *50*(1–3), 7–15. https://doi.org/10.1016/0010-0277(94)90018-3.

Bland, A. R., & Schaefer, A. (2011). Electrophysiological correlates of decision making under varying levels of uncertainty. *Brain Research*, *1417*, 55–66. https://doi.org/10.1016/j.brainres.2011.08.031.

Bouvard, M. (2009). *Questionnaires et échelles d'évaluation de la personnalité*. Elsevier Masson.

Brevers, D., Bechara, A., Cleeremans, A., & Noël, X. (2013). Iowa Gambling Task (IGT) : Twenty years after - gambling disorder and IGT. *Frontiers in Psychology*, *4*, 665. https://doi.org/10.3389/fpsyg.2013.00665.

Brevers, D., Koritzky, G., Bechara, A., & Noël, X. (2014). Cognitive processes underlying impaired decision-making under uncertainty in gambling disorder. *Addictive Behaviors*, *39*(10), 1533–1536. https://doi.org/10.1016/j.addbeh.2014.06.004.

Brevers, D., Noël, X., He, Q., Melrose, J. A., & Bechara, A. (2016). Increased ventral-striatal activity during monetary decision making is a marker of problem poker gambling severity. *Addiction Biology*, *21*(3), 688–699. https://doi.org/10.1111/adb.12239.

Cabeza, L., Giustiniani, J., Chabin, T., Ramadan, B., Joucla, C., Nicolier, M., … Peterschmitt, Y. (2019). Modeling decision-making under uncertainty : A direct comparison study between human and mouse gambling data. *bioRxiv*, *570499*. https://doi.org/10.1101/570499.

Chabin, T., Pazart, L., & Gabriel, D. (2022). Vocal melody and musical background are simultaneously processed by the brain for musical predictions. *Annals of the New York Academy of Sciences*, *1512*(1), 126–140. https://doi.org/10.1111/nyas.14755.

Chivu, A., Pascal, S. A., Damborská, A., & Tomescu, M. I. (2024). EEG microstates in mood and anxiety disorders : A meta-analysis. *Brain Topography*, *37*(3), 357–368. https://doi.org/10.1007/s10548-023-00999-0.

Cui, J.-F., Chen, Y.-H., Wang, Y., Shum, D. H. K., & Chan, R. C. K. (2013). Neural correlates of uncertain decision making : ERP evidence from the Iowa gambling task. *Frontiers in Human Neuroscience*, *7*, 776. https://doi.org/10.3389/fnhum.2013.00776.

Davis, C., Fox, J., Patte, K., Curtis, C., Strimas, R., Reid, C., & McCool, C. (2008). Education level moderates learning on two versions of the Iowa Gambling Task. *Journal of the International Neuropsychological Society: JINS*, *14*(6), 1063–1068. https://doi.org/10.1017/S1355617708081204.

Dufour, M., Morvannou, A., Brunelle, N., Kairouz, S., Laverdière, É., Nadeau, L., … Roy, É. (2020). Gambling problem trajectories and associated individuals risk factors : A three-year follow-up study among poker players. *Journal of Gambling Studies*, *36*(1), 355–371. https://doi.org/10.1007/s10899-019-09831-6.

Fellows, L. K., & Farah, M. J. (2005). Is anterior cingulate cortex necessary for cognitive control? *Brain: A Journal of Neurology*, *128*(Pt 4), 788–796. https://doi.org/10.1093/brain/awh405.

Gabellini, E., Lucchini, F., & Gattoni, M. E. (2023). Prevalence of problem gambling : A meta-analysis of recent empirical research (2016-2022). *Journal of Gambling Studies*, *39*(3), 1027–1057. https://doi.org/10.1007/s10899-022-10180-0.

Giustiniani, J., Gabriel, D., Nicolier, M., Monnin, J., & Haffen, E. (2015). Neural correlates of successful and unsuccessful strategical mechanisms involved in uncertain decision-making. *Plos One*, *10*(6), e0130871. https://doi.org/10.1371/journal.pone.0130871.

Giustiniani, J., Nicolier, M., Diwoux, A., Chabin, T., Pazart, L., Haffen, E., & Gabriel, D. (2024). Impact of online poker gambling on behavioural and neurophysiological responses to a virtual gambling task. *Addiction Biology*, *29*(2), e13373. https://doi.org/10.1111/adb.13373.

Glazer, J. E., Kelley, N. J., Pornpattananangkul, N., Mittal, V. A., & Nusslock, R. (2018). Beyond the FRN : Broadening the time-course of EEG and ERP components implicated in reward processing. *International Journal of Psychophysiology: Official Journal of the International Organization of Psychophysiology*, *132*(Pt B), 184–202. https://doi.org/10.1016/j.ijpsycho.2018.02.002.

Goldstein, R. Z., & Volkow, N. D. (2011). Dysfunction of the prefrontal cortex in addiction : Neuroimaging findings and clinical implications. *Nature Reviews. Neuroscience*, *12*(11), 652–669. https://doi.org/10.1038/nrn3119.

Goudriaan, A. E., de Ruiter, M. B., van den Brink, W., Oosterlaan, J., & Veltman, D. J. (2010). Brain activation patterns associated with cue reactivity and craving in abstinent problem gamblers, heavy smokers and healthy controls : An fMRI study. *Addiction Biology*, *15*(4), 491–503. https://doi.org/10.1111/j.1369-1600.2010.00242.x.

Goudriaan, A. E., Oosterlaan, J., de Beurs, E., & van den Brink, W. (2005). Decision making in pathological gambling : A comparison between pathological gamblers, alcohol dependents, persons with tourette syndrome, and normal controls. *Brain Research. Cognitive Brain Research*, *23*(1), 137–151. https://doi.org/10.1016/j.cogbrainres.2005.01.017.

Grassi, G., Pallanti, S., Righi, L., Figee, M., Mantione, M., Denys, D., … Stratta, P. (2015). Think twice : Impulsivity and decision making in obsessive-compulsive disorder. *Journal of Behavioral Addictions*, *4*(4), 263–272. https://doi.org/10.1556/2006.4.2015.039.

Griffiths, M. (2012). An exploratory qualitative study of online poker professional players. *Social Psychological Review*, *14*, 13–25.

Khanna, A., Pascual-Leone, A., Michel, C. M., & Farzan, F. (2015). Microstates in resting-state EEG : Current status and future directions. *Neuroscience and Biobehavioral Reviews*, *49*, 105–113. https://doi.org/10.1016/j.neubiorev.2014.12.010.

Kiat, J., Straley, E., & Cheadle, J. E. (2016). Escalating risk and the moderating effect of resistance to peer influence on the P200 and feedback-related negativity. *Social Cognitive and Affective Neuroscience*, *11*(3), 377–386. https://doi.org/10.1093/scan/nsv121.

Kovács, I., Richman, M. J., Janka, Z., Maraz, A., & Andó, B. (2017). Decision making measured by the Iowa gambling task in alcohol use disorder and gambling disorder : A systematic review and meta-analysis. *Drug and Alcohol Dependence*, *181*, 152–161. https://doi.org/10.1016/j.drugalcdep.2017.09.023.

Krigolson, O. E. (2018). Event-related brain potentials and the study of reward processing : Methodological considerations. *International Journal of Psychophysiology*, *132*, 175–183. https://doi.org/10.1016/j.ijpsycho.2017.11.007.

Ladouceur, R., Sylvain, C., Botin, C., & Doucet, C. (2000). *Le jeu excessif, comprendre et vaincre le gambling (Broché)*. De l'Homme.

Linnet, J., Peterson, E., Doudet, D. J., Gjedde, A., & Møller, A. (2010). Dopamine release in ventral striatum of pathological gamblers losing money. *Acta Psychiatrica Scandinavica*, *122*(4), 326–333. https://doi.org/10.1111/j.1600-0447.2010.01591.x.

Linnet, J., Røjskjaer, S., Nygaard, J., & Maher, B. A. (2006). Episodic chasing in pathological gamblers using the Iowa gambling task. *Scandinavian Journal of Psychology*, *47*(1), 43–49. https://doi.org/10.1111/j.1467-9450.2006.00491.x.

Logge, W. B., Morley, K. C., Haber, P. S., & Baillie, A. J. (2023). Impaired decision-making and skin conductance responses are associated with reward and punishment sensitivity in individuals with severe alcohol use disorder. *Neuropsychobiology*, *82*(2), 117–129. https://doi.org/10.1159/000529156.

Luelsberg, F., Krakau, S., Chaieb, L., Witt, J.-A., von Wrede, R., Fell, J., & Helmstaedter, C. (2022). Neuropsychological features of mind wandering in left-, right- and extra temporal lobe epilepsy. *Seizure*, *95*, 50–55. https://doi.org/10.1016/j.seizure.2021.12.013.

MacKay, T. L., Bard, N., Bowling, M., & Hodgins, D. C. (2014). Do pokers players know how good they are? Accuracy of poker skill estimation in online and offline players. *Computers in Human Behavior*, *31*, 419–424. https://doi.org/10.1016/j.chb.2013.11.006.

Månsson, V., Pettersson, E., Mittendorfer-Rutz, E., Guterstam, J., Berman, A. H., Jayaram-Lindström, N., & Molero, Y. (2023). The risk and development of work disability among individuals with gambling disorder : A longitudinal case–cohort study in Sweden. *Psychological Medicine*, *1–12*. https://doi.org/10.1017/S0033291723003288.

Mavrogiorgou, P., Enzi, B., Klimm, A.-K., Köhler, E., Roser, P., Norra, C., & Juckel, G. (2017). Serotonergic modulation of orbitofrontal activity and its relevance for decision making and impulsivity. *Human Brain Mapping*, *38*(3), 1507–1517. https://doi.org/10.1002/hbm.23468.

Meneses-Gaya, I. C. de, Zuardi, A. W., Loureiro, S. R., & Crippa, J. A. de S. (2009). Psychometric properties of the Fagerström test for nicotine dependence. *Jornal Brasileiro De Pneumologia: Publicacao Oficial Da Sociedade Brasileira De Pneumologia E Tisilogia*, *35*(1), 73–82. https://doi.org/10.1590/s1806-37132009000100011.

Michel, C. M., & Murray, M. M. (2012). Towards the utilization of EEG as a brain imaging tool. *NeuroImage*, *61*(2), 371–385. https://doi.org/10.1016/j.neuroimage.2011.12.039.

Moreau, A., Sévigny, S., Giroux, I., & Chauchard, E. (2020). Ability to discriminate online poker tilt episodes : A new way to prevent excessive gambling? *Journal of Gambling Studies*, *36*(2), 699–711. https://doi.org/10.1007/s10899-019-09903-7.

Oberg, S. A. K., Christie, G. J., & Tata, M. S. (2011). Problem gamblers exhibit reward hypersensitivity in medial frontal

cortex during gambling. *Neuropsychologia*, *49*(13), 3768–3775. https://doi.org/10.1016/j.neuropsychologia.2011.09.037.

Ochoa, C., Alvarez-Moya, E. M., Penelo, E., Aymami, M. N., Gómez-Peña, M., Fernández-Aranda, F., … Jiménez-Murcia, S. (2013). Decision-making deficits in pathological gambling: The role of executive functions, explicit knowledge and impulsivity in relation to decisions made under ambiguity and risk. *The American Journal on Addictions*, *22*(5), 492–499. https://doi.org/10.1111/j.1521-0391.2013.12061.x.

Petry, N. M., Zajac, K., & Ginley, M. K. (2018). Behavioral addictions as mental disorders : To be or not to be? *Annual Review of Clinical Psychology*, *14*, 399–423. https://doi.org/10.1146/annurev-clinpsy-032816-045120.

Polich, J. (2007). Updating P300 : An integrative theory of P3a and P3b. *Clinical Neurophysiology*, *118*(10), 2128–2148. https://doi.org/10.1016/j.clinph.2007.04.019.

Potenza, M. N., Balodis, I. M., Derevensky, J., Grant, J. E., Petry, N. M., Verdejo-Garcia, A., & Yip, S. W. (2019). Gambling disorder. *Nature Reviews Disease Primers*, *5*(1), 1. https://doi.org/10.1038/s41572-019-0099-7.

Saunders, J. B., Aasland, O. G., Babor, T. F., de la Fuente, J. R., & Grant, M. (1993). Development of the alcohol use disorders identification test (AUDIT) : WHO collaborative project on early detection of persons with harmful alcohol consumption–II. *Addiction (Abingdon, England)*, *88*(6), 791–804. https://doi.org/10.1111/j.1360-0443.1993.tb02093.x.

Schuermann, B., Endrass, T., & Kathmann, N. (2012). Neural correlates of feedback processing in decision-making under risk. *Frontiers in Human Neuroscience*, *6*, 204. https://doi.org/10.3389/fnhum.2012.00204.

Sleczka, P., & Romild, U. (2021). On the stability and the progression of gambling problems : Longitudinal relations between different problems related to gambling. *Addiction*, *116*(1), 116–125. https://doi.org/10.1111/add.15093.

Slepian, M. L., Young, S. G., Rutchick, A. M., & Ambady, N. (2013). Quality of professional players' poker hands is perceived accurately from arm motions. *Psychological Science*, *24*(11), 2335–2338. https://doi.org/10.1177/0956797613487384.

Smillie, L. D., Jackson, C. J., & Dalgleish, L. I. (2006). Conceptual distinctions among Carver and White's (1994) BAS scales : A reward-reactivity versus trait impulsivity perspective. *Personality and Individual Differences*, *40*(5), 1039–1050. https://doi.org/10.1016/j.paid.2005.10.012.

Vita, A., Bastiani, L., Turrina, C., Benedetti, E., Bergamini, A., & Molinaro, S. (2021). At-risk gambling in patients with severe psychiatric illness and in community subjects matched for age and sex. *Psychiatry Research*, *304*, 114142. https://doi.org/10.1016/j.psychres.2021.114142.

Vuillier, L., Whitebread, D., & Szucs, D. (2015). ERP evidence of cognitive strategy change in motivational conditions with varying level of difficulty. *Neuropsychologia*, *70*, 126–133. https://doi.org/10.1016/j.neuropsychologia.2015.02.025.

Wiehler, A., & Peters, J. (2015). Reward-based decision making in pathological gambling : The roles of risk and delay. *Neuroscience Research*, *90*, 3–14. https://doi.org/10.1016/j.neures.2014.09.008.

Wongupparaj, P., Sumich, A., Wickens, M., Kumari, V., & Morris, R. G. (2018). Individual differences in working memory and general intelligence indexed by P200 and P300 : A latent variable model. *Biological Psychology*, *139*, 96–105. https://doi.org/10.1016/j.biopsycho.2018.10.009.

Zhang, K., Rights, J. D., Deng, X., Lesch, T., & Clark, L. (2024). Between-session chasing of losses and wins in an online eCasino. *Journal of Behavioral Addictions*, *13*(2), 665–675. https://doi.org/10.1556/2006.2024.00022.