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EXCITED AND AROUSED: THE PREDICTIVE IMPORTANCE OF SIMPLE CHOICE PROCESS METRICS

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Excited and aroused: The predictive importance of simple choice process metrics*

Abstract: We conduct a lottery experiment to assess the predictive importance of simple choice process metrics (SCPMs) in forecasting risky 50/50 gambling decisions using different types of machine learning algorithms as well as traditional choice modeling approaches. The SCPMs are recorded during a fixed pre-decision phase and are derived from tracking subjects' eye movements, pupil sizes, skin conductance, and cardiovascular and respiratory signals. Our study demonstrates that SCPMs provide relevant information for predicting gambling decisions, but we do not find forecasting accuracy to be substantially affected by adding SCPMs to standard choice data. Instead, our results show that forecasting accuracy highly depends on differences in subject-specific risk preferences and is largely driven by including information on lottery design variables. As a key result, we find evidence for dynamic changes in the predictive importance of psychophysiological responses that appear to be linked to habituation and resource-depletion effects. Subjects' willingness to gamble and choice-revealing arousal signals both decrease as the experiment progresses. Moreover, our findings highlight the importance of accounting for previous lottery payoff characteristics when investigating the role of emotions and cognitive bias in repeated decision-making scenarios.

Key words: Repeated decision making; Eye-tracking; Psychophysiological responses; Machine learning; Forecasting

JEL: C44, C45, C53, D81, D87, D91

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1 Introduction

Tracking choice process data (CPD) often allow a better understanding to be reached of the relevant decision factors and reasoning steps underlying a resolution procedure that cannot be derived only from standard choice data (Bernheim, 2009; Fehr & Rangel, 2011; Krajbich et al., 2014; Nicholas, 2009). For instance, eye-tracking data can be used to identify distinct attention patterns during the information acquisition process (Reutskaja et al., 2011) and detect the emergence of competing behavioral strategies (Knoepfle et al., 2009; Schulte-Mecklenbeck et al., 2011). Similarly, emotions and

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visceral factors can substantially influence the decision-making process (Bellemare et al., 2019; Heilman et al., 2010; Kliger et al., 2012; Levav & McGraw, 2009; Loewenstein, 1999), and a growing number of studies demonstrate that tracking CPD linked to emotional and cognitive states can yield novel insights into economics research (Adam et al., 2015; Breaban & Noussair, 2018; Daly et al., 2009; Hattke et al., 2019; Hobson et al., 2012; Hytönen et al., 2014).

There is an increasing interest in evaluating the predictive importance of CPD in modeling economic decisions (Clithero, 2018b; Huseynov et al., 2019; Krol & Krol, 2017; Sundararajan et al., 2017). As an example, Imai et al. (2019) show that accounting for hypothetical purchase lookup patterns can improve out-of-sample predictions for real purchases. Likewise, neurological CPD have been demonstrated to reveal consumer preferences in passive product viewing and non-choice experiments (Lusk et al., 2016; Smith et al., 2014). However, the vast majority of studies that evaluate out-of-sample choice predictions using CPD includes information that is not accessible before a decision has been executed (Clithero, 2018a; Huseynov et al., 2019; Krol & Krol, 2019; Sundararajan et al., 2017) or focus on individual but often complex types of CPD that are expensive to collect, such as neuroimaging measures (Knutson et al., 2007; Levy et al., 2011).

In contrast to existing research, in this study, we investigate the feasibility of predicting real decisions on the basis of simple choice process metrics (SCPMs) that we derive from various types of CPD that are recorded during a fixed pre-decision phase. To this end, we conduct a simple lottery experiment and evaluate conventional choice modeling approaches in addition to various machine learning (ML) methods for forecasting risky gambling decisions on the basis of combinations of the following input categories: lottery design variables, socioeconomic characteristics, past gambling behavior, and SCPMs derived from tracking gaze-path, pupil size, blood volume pulse, heart rate, respiration, skin temperature, and skin conductance responses.

First, we employ a descriptive and regression-based analysis and test different hypotheses linked to gambling behavior, lotteries' payoff structures, attention, and emotional arousal. In the second step, we investigate different statistical and ML methods' out-of-sample choice forecasting capabilities, including linear (e.g., elastic net regression), non-linear (e.g., artificial neural networks), and tree-based ensemble algorithms (e.g., random forest), and compare the models' forecasting performances for selected SCPM distributions to further investigate the hypotheses that we test in the first step. Last, to complement our analysis, we examine the extent to which choice-revealing information associated with individual SCPMs may already be covered by standard behavioral economics data.

Forecasting human decisions is difficult; not only can risk preferences considerably differ across individuals (Kliger & Levy, 2002), but numerous factors can impact choices in various and interdependent ways (Kleinberg et al., 2018; Loewenstein, 1999; Makridakis & Taleb, 2009). Many studies that analyze economic decisions focus on in-sample-based hypotheses tests and often use (generalized) linear parametric models that require non-linear effects and variable interactions to be explicitly specified. Conversely, in this paper, we focus on out-of-sample predictions, and based on the complex relationship between decision making, CPD, and emotional and cognitive processes (Alós-Ferrer, 2018; Giacomantonio et al., 2018; Hytönen et al., 2014), we investigate different ML algorithms that can be applied in high-dimensional data structures, automatically select important predictors, and account for the potential existence of higher-order interactions and non-linear dependencies without the need for pre-specification. In addition to often yielding more accurate out-of-sample predictions than conventional parametric approaches (Mullainathan & Spiess, 2017), these abilities make ML methods promising tools to evaluate behavioral models of choice because they can aid in identifying relevant decision factors (Camerer, 2018) and provide upper bounds for evaluating the predictive power of a theory (Peysakhovich & Naecker, 2017).

Similar to, e.g., Peysakhovich & Naecker (2017), Kleinberg et al. (2018), and Camerer (2018), we posit that using data-driven ML techniques to analyze systems that are complex by nature, such as the link between cognitive and emotional processes, can yield valuable insights into systematic patterns in human decision making. In particular, we aim to stimulate the existing discussion on using CPD to develop improved economic models of decision making and choice prediction (Bernheim, 2009; Camerer et al., 2018; Clithero, 2018a; Fehr & Rangel, 2011; Huseynov et al., 2019; Imai et al., 2019; Krol & Krol, 2019; Lo & Repin, 2002) and novel ways for eliciting preferences that do not rely on standard choice data or observing real decisions (Chen & Fischbacher, 2016; Lusk et al., 2016; Pozharliev et al., 2015; Smith et al., 2014; Telpaz et al., 2015). Furthermore, by investigating the extent to which previous choices and their outcomes affect subsequent gambling decisions, our study contributes to the broad literature on behavioral bias and affective processes in repeated decision making (e.g., Coricelli et al., 2005; Guryan & Kearney, 2008; Hytönen et al., 2014; Kostek & Ashrafioun, 2014; Rabin & Vayanos, 2010; Schneider et al., 2016; Thaler & Johnson, 1990).

Comprehensive choice data and information on individuals' reasons for their behavior are often non-existent or not publicly available for analysis, and traditional market research can mislead as a result of consumers' biased perceptions and memories (Poels & Dewitte, 2006). As an example, people tend to alter their verbal responses when reflecting on their purchases to rationalize their behaviors (Reczek et al., 2018), although their decisions are often driven by (subconscious) emotions (Fisher Gardial et al., 2016). Consequently, tracking CPD linked to attentional focus and emotional states is highly valuable to consumer and marketing research (Venkatraman et al., 2015; Wang & Minor, 2008), and various businesses compete on how to best collect and exploit such data to predict and manipulate human behavior (Economist, 2017; Guardian, 2019; Reutskaja et al., 2011).

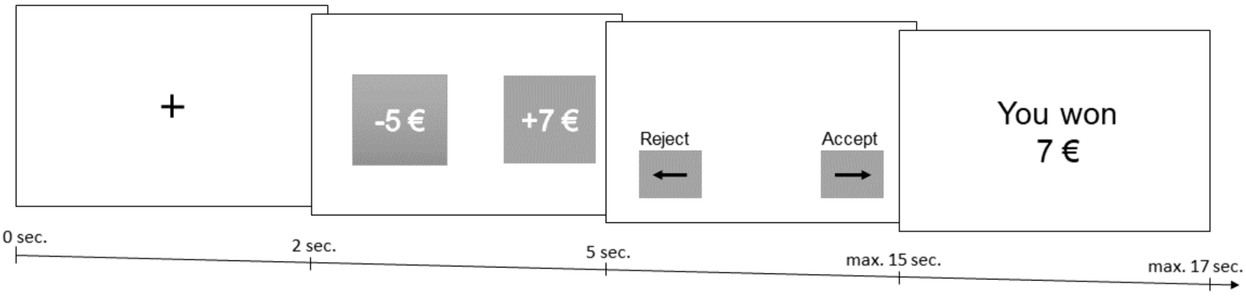
Our empirical results demonstrate that pre-decision SCPMs provide relevant information for forecasting risky gambling decisions; however, we do not find forecasting accuracy to be substantially affected by adding SCPMs to the set of conventional choice predictors. Instead, our results show that forecasting accuracy is largely driven by including information on lotteries' payoff structures and highly depends on differences in individual risk-taking behavior. Specifically, our findings suggest that a large fraction of the choice-revealing information linked to typical arousal measures is already provided by lottery design variables and socioeconomic characteristics, thereby highlighting the existence of complex dependencies associated with SCPMs. As a main result, we find a decreasing willingness to accept lotteries throughout the experiment to be linked to dynamic changes in the predictive power of typical arousal measures as well as cardiovascular and respiratory signals, indicating the presence of habituation and resource-depletion effects.

The remainder of this paper is structured as follows: Chapter 2 describes the experimental design. In Chapter 3, we survey relevant CPD literature and motivate and describe our hypotheses, variable specifications, and employed methods. Chapter 4 summarizes the results of our descriptive analysis. Chapter 5 shows the results from our regression-based hypotheses tests, and Chapter 6 presents the results of our forecasting analysis of gambling choices and SCPMs. Chapter 7 concludes the study.

2 Experimental setup

Our gambling experiment covers 44 subjects that each played 200 lotteries, thereby resulting in a total of 8800 observations. In each lottery, participants were offered a simple 50/50 gamble that involves a potential gain and a potential loss, and they could decide to either accept or reject the offered lottery. Across lotteries, we manipulated the potential gain and loss (range of gains: +1 EUR to +20 EUR; range of losses -1 EUR to -10 EUR; both in 1 Euro steps; see Appendix, Table A4 for an overview of all considered win-loss-value combinations). During the experiment, subjects were notified when they reached the 67th and 133rd trial and subsequently rested for 30 seconds before continuing with the experiment. The order of the lotteries and the arrangement of the payoff boxes and decision buttons on the screen were randomized for each participant.

Figure 1. Sequence of events and screens for one round of lottery gambling by time



Notes: Sequence of events and screens for one round of lottery gambling by time (seconds). The content of the displayed screens is resized for better readability. A Figure showing the pictures in correct proportions is included in the Appendix, Section 2.1.

The first picture (left) shows a fixation cross and indicates that a lottery will be shown soon. The second picture shows the newly offered lottery for three seconds (pre-decision phase). The third picture shows the arrows that are displayed for a maximum of ten seconds in the decision phase and must be pressed to accept or reject the previously displayed lottery. After a decision has been executed, the realized outcome is displayed; for rejected gambles, the fourth screen is omitted.

All subjects started with an endowment of 10 EUR. At the end of the experiment, one trial was randomly selected for the final payout. If the subject rejected the selected lottery, she kept the initial endowment of 10 EUR. If the subject accepted the lottery, its outcome was realized and added to [subtracted from] the initial endowment for a win [loss]. Detailed descriptions of the experimental design and employed CPD tracking devices are included in the Appendix, Section 2.1.

3 Hypotheses, data, and methods

3.1 Investigated hypotheses

During the experiment, we manipulate the sizes of the potential gains and losses of the displayed lotteries and keep winning and losing probabilities fixed at 50%. This feature allows us to identify the effect of a marginal increase in the potential win [loss] on gambling acceptance. In the prospect theory framework, the value of a lottery is assumed to be concave [convex] for gains [losses] and is generally steeper for losses than for gains (Kahneman & Tversky, 1979). We investigate these assumptions by testing the following two hypotheses.

H1a: Individuals are more likely to accept [reject] a gamble when the potential win [loss] increases.

H1b: The effect of losses is larger than the effect of gains.

Many studies find a strong link between attentional shifts, information processing, learning, strategic behavior, and choice outcomes. Precisely, attention allows for a focus on specific information at the cost of ignoring other information and, in general, people tend to choose the options that receive most of their attention ("gaze bias") (Brocas et al., 2014; Fiedler & Glöckner, 2012; Knoepfle et al., 2009; Reutskaja et al., 2011).

Pachur et al. (2018) show that individual risk parameters (loss-aversion, outcome-sensitivity, and probability-sensitivity) are correlated with the allocation of attention during pre-decisional lottery information processing. Important to our analysis, they find loss-aversion to be associated with the relative attention allocated to potential losses and gains. In our simplified framework involving only 50/50 gambles, these findings translate into the following hypothesis.

H2: Individuals are more likely to accept [reject] a lottery when they allocate more attention toward the potential gain [loss].

Arousal is hypothesized as playing a central role in gambling (Baudinet & Blaszczynski, 2013). Scitovsky (1976) attributes the purchase of lottery tickets to people's search for optimal arousal and considers freely chosen risk as potentially arousing. In line with this hypothesis, Ladouceur et al. (2003) find that the act of gambling is arousing, especially when expecting to win money. Similarly, recent field evidence suggests that lottery participation itself yields utility in advance of observing the outcome as feelings of joy and excitement irrespective of whether the lottery ticket was free or had to be purchased (Burger et al., 2020). These findings motivate our last hypothesis.

H3: High [low] levels of arousal are an indicator of lottery acceptance [rejection].

3.2 Description and motivation of variable specifications

The following section motivates and describes the different sets of predictor variables that we consider in this paper: lottery design variables (*L*), socioeconomic characteristics (*S*), past gambling behavior (*G*), SCPMs derived from psychophysiological signals (*P*), and SCPMs derived from eye movements as measures of visual attention (*A*). A concise overview of all of the variables and their empirical specifications is presented at the end of this section in Table 1.

Lottery design variables

We consider several standard economic decision drivers: a lottery's potential win and loss value and a binary variable to indicate whether the EV is negative. Moreover, deciding on a large number of repeated gambling decisions can be cognitively draining; however, the evidence is mixed and previous research has found both increasing (Bruyneel et al., 2009) and decreasing (Kostek & Ashrafioun, 2014) risk preferences in response to cognitive depletion. During the experiment, subjects were informed when reaching the 67th and 133rd trial. In addition to specifying lottery trial as an integer variable, we include two dummy variables that indicate the corresponding resting periods to capture potential resource-depletion effects. Furthermore, people tend to prefer options displayed on the left side when choosing between two alternatives located next to each other. To account for such a potential "left-hand side" (Lusk et al., 2016) bias, we specify two binary variables that indicate whether the potential win is displayed in the right box (vs. left box) and whether the right arrow (vs. left arrow) has to be pressed to accept the gamble.

Socioeconomics characteristics

We use binary variables to account for the impact of subject-specific effects and socioeconomic characteristics that have frequently been identified as relevant sources of heterogeneity in decision making: gender, age, income, educational background, and highest degree. Women have been found to systematically respond differently to risk than do men; most prominently, women are often reported as having more risk-averse behavior (Croson & Gneezy, 2009). Likewise, various age-related factors exist that can impact risk attitudes (Besedeš et al., 2014); perhaps the most frequently reported age-related stylized fact is that we become more conservative and risk-averse as we age (Ahlfeldt et al., 2019).

The literature on poverty and decision making suggests that people with low relative incomes and education levels may engage in conspicuous consumption behavior to compensate for their lower social status (Veblen, 1899). As an example related to gambling behavior, Haisley et al. (2008) find that lotteries are more attractive to low income households because they provide the rare opportunity to substantially increase their wealth and social status in a short period. Moreover, from a different perspective on social comparison mechanisms, a recent gambling experiment finds that people with higher incomes take higher risks than people with lower incomes, but only if the inequality in relative income levels is known to the participants (Schmidt et al., 2019).

Gambling behavior

We account for previous gambling choices and outcomes by specifying interaction terms between the last preceding five gambling decisions and positive and negative lottery outcomes. Precisely, when considering a sequence of repeated or path-dependent gambling decisions, players' subsequent gambling decisions are likely affected by their previous choices and experiences. As a prominent example, Thaler & Johnson (1990) find that prior gains can increase risk-taking behavior because people seem to treat potential losses differently when facing a recent gambling surplus ("house money effect"); similarly, people tend to take higher risks when they have the chance to be compensated for previous losses ("break-even effect").

In addition, gambling behavior can also be affected by different cognitive sampling biases in the judgment of a series of random process outcomes. In particular, evidence exists that people tend to falsely expect that a sequence of positives [negatives] is proceeded by another positive [negative] outcome ("hot hand fallacy") (Gilovich et al., 1985). In similar ways, spurious positive autocorrelation in observed gambling outcomes may also be attributed to good luck [bad luck] (Guryan & Kearney, 2008). On the other hand, people tend to overestimate the statistical representativeness of small samples and, consequently, often believe that a random sequence should exhibit systematic patterns of reversal after observing a streak of similar outcomes ("gambler's fallacy") (Laplace, 1820; Rabin & Vayanos, 2010).

Last, previous studies also show that emotions can substantially impact risk-taking behavior in repeated decision scenarios. For instance, according to the "mood maintenance hypothesis," a positive affective state decreases the willingness to take risks, whereas a negative affective state increases risk-taking behavior in an attempt to shift toward a more positive affective state (Schneider et al., 2016). Likewise, the experience of winning [losing] can induce positive [negative] emotions that likely affect subsequent gambling decisions (Coricelli et al., 2005).

Psychophysiological reactions and arousal

The different types of psychophysiological reactions analyzed in this study all share established relations with emotional arousal; however, in addition to representing biological health indicators, these variables can also provide information on various other affective and deliberative states. For a general overview on choice process techniques and measures for emotion detection and cognitive process analysis, see, e.g., Kreibig (2010), Schulte-Mecklenbeck et al. (2011), and Potter & Bolls (2012).

Except for skin conductance measures, all of the psychophysiological SCPMs are related to CPD type-specific minimum, maximum, mean, and differences between the minimum and maximum values within the pre-decision phase. Whereas predicting discrete emotions or deriving more complex measures from CPD can provide various information that cannot be derived only from pre-decision SCPMs (Kreibig, 2010), CPD signals can exhibit substantial noise (Sundararajan et al., 2017), emotion detection software can provide misleading information because emotional expressions can vary across a large number of cultural and individual factors (Barrett et al., 2019), and precise measurements often require expensive tracking devices and careful sensor calibration under a controlled (laboratory) environment (Schulte-Mecklenbeck et al., 2011). As a result, no clear consensus exists on the validity and reliability of alternative choice process techniques (Halko & Sääksvuori, 2017; Wang & Minor, 2008).

Skin conductance responses. Skin conductance response (SCR) measures are considered one of the most useful sources of information on sympathetic arousal because electrodermal activity is assumed to be mostly unaffected by parasympathetic influences, in contrast to other psychophysiological reactions (Mauss & Robinson, 2009). Examples for the predictive information associated with SCR data are as follows: SCRs can systematically differ between loss and gain frame decisions (Ring, 2015), evidence exists that SCRs can indicate cheating intentions, such as tax evasion behavior (Coricelli et al., 2010), and SCRs can provide information on the stress level experienced during bureaucratic procedures (Hattke et al., 2019) and signal emotional arousal during auction betting (Astor et al., 2013).

Similar to, e.g., Hattke et al. (2019), Adam et al. (2015), and Coricelli et al. (2010), we include in our analysis information on the number of significant (above threshold) SCRs and the sum of their amplitudes (SCRA) (in microsiemens). Furthermore, SCRs have a delay of approximately one second, and we adjust the time window accordingly (Boucsein, 2012). The remaining CPD considered in our analysis are measured with respect to the first three seconds of lottery information processing.

Cardiovascular and respiratory measures. Changes in the heart rate (HR), blood flow, and respiration can reflect both sympathetic and parasympathetic activity. Activation of the sympathetic nervous system ("fight or flight") usually increases the respiration rate (RSR), HR, blood volume pulse (BVP), and blood pressure. In contrast, a decrease in these measures, in addition to low heart rate variability (HRV), is mainly associated with parasympathetic activity ("rest or digest") (Mauss & Robinson, 2009). However, HR and HRV are affected by different physiological responses, such as respiration and blood pressure. Likewise, body temperature (BT) is regulated by the cardiovascular, integumentary (e.g., skin and sweat glands), respiratory, and muscular systems (Kreibig, 2010).

Both cardiovascular and respiratory signals have been found to provide relevant information on economic behavior. For instance, Ladouceur et al. (2003) find that HR increases before and during gambling trials with high winning expectations. Moreover, there is evidence that HR patterns can reveal emotional states of stress and arousal in competitive environments (Buckert et al., 2017; Halko & Sääksvuori, 2017). Specifically, Adam et al. (2015) find that HR (and SCR) patterns are relevant in understanding the "auction fever" phenomenon—a state of high emotional arousal associated with irrational bids and upward biased auction prices. Likewise, Daly et al. (2009) find HRV and blood pressure to be related to systematic differences in financial discounting patterns, and the findings of Falk et al. (2018) suggest that unhealthy HRV patterns can be related to unfair payment. As one of the few existing examples of economics studies that exploit a larger mix of physiological measures, Lo & Repin (2002) provide evidence for a strong link between emotions, SCRs, HR, BVP, BT, RSRs, and stock trading behavior.

We include SCPMs for HR (in beats per minute). Thus, our specification of HR variables also implicitly captures information on HRV. Moreover, similar to Lo et al. (2002), in addition to specifying BVP (as a % change), we include individual SCPMs for BVP amplitude (BVPA) that we derive from the BVP raw signals (in millivolts). Precisely, BVP measures changes in blood volume in the arteries and capillaries, and BVPA indicates relative blood flow. Similarly, in addition to specifying RSR (in beats per minute), we include information on subjects' chest or abdominal respiration depth (RSD) (raw signal, in millivolts) that is used to compute RSR. Last, we include SCPMs for finger temperature (in C°) as BT variables.

Pupil dilation and constriction. Another widely used measure of arousal can be derived from tracking changes in pupil size (PS), which correspond to either sympathetic (dilation) or parasympathetic (constriction) activity. Precisely, PS adapts to differences in light conditions, luminance, and brightness to optimize information capacity while protecting the retina; moreover, pupils can also dilate in response to various physiological phenomena, including stress, mental effort, arousal, and pain (Wang et al., 2010). As examples, pupil dilation can indicate deceptive and dishonest behaviors in sender-receiver games (Hochman et al., 2016; Wang et al., 2010), PS has been found to be correlated with the expected values of risky gambling offers (Fiedler & Glöckner, 2012), and pupil dilation can signal product purchases (Huseynov et al., 2019). Similar to, e.g., Wang et al. (2010), Fiedler & Glöckner (2012), and Huseynov et al. (2019), we include SCPMs for the mean of both pupils' sizes (in mm).

Eye movements and attention

Eye- and mouse-tracking are the most predominant process techniques for assessing visual attention, but other CPD, such as SCRs, PS, and cardiovascular measures, can also provide information on attention (Poels & Dewitte, 2006; Potter & Bolls, 2012; Venkatraman et al., 2015). Yet, attention is affected by both somatic (voluntary) and autonomic activity, and psychophysiological processes are linked to various emotional and cognitive states. Consequently, it is important to acknowledge the existence of different potential sources of variations in CPD when analyzing alternative measures of attention and arousal. Therefore, many researchers argue for combining different types of CPD to improve the identification and interpretation of emotional and cognitive responses (Daly et al., 2009; Kreibig, 2010; Mauss & Robinson, 2009; Potter & Bolls, 2012).

Simple lookup pattern metrics, such as gaze-dwell time and the number of fixations per option, have frequently been identified as relevant choice predictors (Fiedler & Glöckner, 2012; Imai et al., 2019; Krajbich et al., 2010; Krol & Krol, 2019; Stewart et al., 2016). In addition, tracking more subtle measures, such as the tempo, duration, and latency of rapid eye movements (saccades), can provide further exploitable information on choice processes and their outcomes (Schulte-Mecklenbeck et al., 2011). However, identifying relevant saccade changes requires eye-tracking devices with appropriately high sampling rates. Conversely, standard web and smartphone cameras—which can be used to record eye movements, facial expressions, as well as cardiovascular and respiratory measures—record at video sampling frequencies of 30 fps. Analogously, in this study, we record subjects' eye movements and PS with 30 Hz (for details, see Appendix, Section 2.1). As a result, we derive all of the attention variables from unprocessed eye-position data and do not attempt to analyze differences in saccades and fixations. Furthermore, because we conduct a simple and repetitive 50/50 gambling task, we desist from investigating more complex metrics, such as distance and similarity measures between individual gaze-paths.

The SCPMs that we derive from tracking subjects' eye movements during lottery information acquisition include the time that they spent looking at the win and loss boxes. In addition, we include several variables to account for simple lookup pattern characteristics: the number of times that a subject switched between looking at the win and loss boxes (integer) and two binary variables to indicate whether a subject looked first at the win box and at the left box.

Table 1. Description of included predictor variables

# Vs	*Lottery design* (L)
2	Potential win and loss value (EUR)
1	Expected value < 0 (binary)
1	Lottery trial (integer)
3	Lottery trial: 1 to 67, 68 to 133, and 134 to 200 (binary)
1	Potential win is displayed on the right box (binary)
1	Accept the displayed lottery by pressing the right arrow (binary)
# Vs	*Socioeconomic* (S)
44	Subject-specific effects (binary)
5	Highest education: GCSE, Vocational baccalaureate diploma, A-levels, Bachelor, Master or higher (binary)
4	Educational background: Psychology, Economics, NA, other (binaries)
3	Income level: income $\leq$ 800 EUR, 800 EUR $<$ income $\leq$ 1200 EUR, 1200 EUR $<$ income (binary)
3	Age group: age $\leq$ 25, 25 $>$ age $<$ 33, age $\geq$ 33 (binary)
1	Gender: female (binary)
# Vs	*Gambling behavior* (G)
5	Interaction terms between lagged decisions: 1, 1x2, …, 1x2x3x4x5 (binary)
5	Interaction terms between lagged decision and positive outcome: 1, …, 5 (binary)
5	Interaction terms between lagged decision and negative outcome: 1, …, 5 (binary)
# Vs	*Psychophysiological reactions* (P)
1	Significant skin conductance responses (SCRs) (integer)
1	Sum of SCR-amplitudes of significant SCRs (microsiemens)
4	Blood volume pulse (as % change)
4	Blood volume pulse amplitude (millivolts)
4	Chest or abdominal breathing depth (millivolts)
4	Respiration rate (breathes per min)
4	Heart rate (beats per min)
4	Finger temperature (°C)
4	Pupil size (mm)
# Vs	*Attention* (A)
2	Time spent on fixating win [loss] box (sec)
2	Looked first at left [win] box (binary)
1	Number of times switched between boxes (integer)

Notes: This table shows the number (# Vs) and descriptions of all included predictor variables. Except for skin conductance data, all physiological (P) variables relate to minimum, maximum and mean values and the difference between minimum and maximum values. We aggregate several age, educational and income groups because there is not much variation in the data.

We encode factor variables as dummy variables and specify 119 predictors. Then, we exclude the most frequently observed level for each category as the corresponding reference group. This encoding results in a total of 112 predictors: 36 numeric and 76 binary variables. In our data cleaning process, we exclude 220 observations because they include information on past gambling behavior and 82 observations because of missing eye-tracking data, which can occur when the recording device loses track of the eyes. The final dataset includes 8498 records. A detailed description of the empirical specifications and summary statistics are presented in the Appendix, Section 2.

3.3 Description of forecasting methods

The different model types that we evaluate in the course of our forecasting analyses correspond to four general modeling frameworks: naïve, generalized linear, non-linear, and tree-based ensemble methods. Specifically, in addition to two simple benchmark models, logistic regression and linear elastic net regression (Elastic net) (Zou & Hastie, 2005), we evaluate several popular ML methods that can automatically account for potentially complex non-linear dependencies and higher-order interactions without the need for pre-specification: support vector machines (SVM) (Cortes & Vapnik, 1995), feed-forward artificial neural networks (ANN) (Rosenblatt, 1961), random forests (RF) (Breiman, 2001), and tree-based gradient boosting machines (GBM) (Friedman, 2002).

The ML and forecasting literature mainly focuses on model generalizability and primarily judges the predictive capabilities of algorithms based on how well they perform on unseen or future observations (test data). To this extent, ML algorithms include model-specific hyperparameters that control the trade-off between functional flexibility and over-fitting on the training data (“bias-variance trade-off”) by minimizing a model’s out-of-sample prediction error with respect to some loss function. We follow standard practice and determine sensitive hyperparameter values using a cross-validation-based systematic grid-search using 80% of the observations for model training. The remaining 20% of the observations are used as test data for the model evaluation (see Section 6.1 for details). A general overview of ML concepts is provided by, e.g., Mullainathan & Spiess (2017) and Varian (2014). For detailed information on the ML techniques employed in this study, see, e.g., Hastie et al. (2009).

Elastic net is an algorithm that performs both regularization and variable selection by combining the lasso and ridge regression penalty terms to constrain the size of the estimated predictor variables’ coefficients. Elastic net is especially useful when confronted with a large set of potentially relevant predictor variables because it can automatically identify less important predictors and shrink their coefficients toward or near zero (Zou & Hastie, 2005). However, in contrast to the other ML methods evaluated in our analysis, the linear Elastic net framework requires explicitly specifying variable interaction effects and non-linear functional relationships.

The standard SVM for binary classification tasks partitions the parameter space by attempting to find optimal hyperplanes for linearly separable patterns that maximize the margin between two classes in a local area and simultaneously minimize the total error under tolerance. In addition, using the kernel trick allows the SVM to account for relevant non-linear dependencies and variable interactions by transforming the data to higher-dimensional spaces (Cortes & Vapnik, 1995; Hastie et al., 2009). In our analysis, we use a radial basis function kernel (squared exponential kernel) that is often considered to be more flexible than, e.g., polynomial kernels, because its function space can provide a greater variety of high-dimensional transformations (Efron & Hastie, 2016).

The functioning of ANN resembles the idea of how neural neurons process and exchange information. In general, an ANN can be described as a highly parameterized model that is built from different layers of neurons (nodes) connected with each other. Each node receives an input, performs a computation that typically involves weighting signals obtained from its connections with nodes from the previous layer, and transmits signals to nodes in the next layer. The last (output) layer of the ANN finally combines the received signals to derive a prediction. The learning and prediction process of a neural network involves mapping the predictors to the outcome by a series of simple data transformations and evaluation of feedback signals, which allows an ANN to identify and learn the form of highly complex decision boundaries (Hastie et al., 2009). In this study, we use non-linear sigmoid activation functions to construct a basic multi-layer perceptron ANN comprised of one input, one hidden, and one output layer.

The general idea of the RF ensemble method is to train many deep decision trees (complex models) and reduce the variance associated with each of the trees by averaging their predictions. A core element of RF is that the individual decision tree models are decorrelated by growing them on the basis of different bootstrap samples of the training data (“bagging”). In addition to bagging, the RF method further decorrelates the individual trees by only selecting a random subset of predictors as potential candidate variables any time a node is split in the tree-building process (Breiman, 2001). In this study, we evaluate RFs grown from standard classification and regression trees (CART) and use the Gini entropy measure as the evaluation metric in the RF training process.

In contrast to the RF technique, boosting is an ensemble method that creates a complex model from a number of weaker models (e.g., shallow decision trees) in a sequential way. Precisely, boosting methods first train a series of models in an iterative process in which each consecutive model learns from the prediction errors made by the previous one and then combine the individual models’ estimates to derive a final prediction. However, similar to bagging, we employ a generalized boosted modeling framework using decision trees as base learners that are grown from different random samples of the training data (Friedman, 2002).

In addition to automatically accounting for the potential existence of complex non-linear functional relationships and higher order interactions, RF and GBM are considered to be less sensitive to variable transformations, robust to the inclusion of non-relevant predictors, require little hyperparameter tuning, and perform well in high-dimensional data settings (Hastie et al., 2009). As a result, these "off-the-shelf" methods have frequently been found to yield accurate out-of-sample predictions in numerous classification and regression problems (Efron & Hastie, 2016; Kleinberg et al., 2018; Lessmann & Voß, 2017; Mueller, 2020).

Furthermore, simple heuristics and statistical decision rules can often explain a large share of the heterogeneity in individual decision making and have been demonstrated to outperform advanced and knowledge-intensive methods in various forecasting domains (Goldstein & Gigerenzer, 2009). Similar to Stahl (2018), who evaluates lottery choices on the basis of judgmental heuristics, we discuss our empirical findings relative to two simple decision rules. The first predicts all test records as the most frequent class observed in the training data (not-played). We describe this naïve forecast as a risk-averse decision rule (RDR) because the most risk-averse behavior is to reject all lotteries to receive the 10 EUR endowment as a final payout. The second benchmark can be described as a simple statistical decision rule (SDR) that classifies gambling decisions according to a lottery's expected value (EV). According to this SDR, we predict lotteries with EV < 0 as not-played and lotteries with EV ≥ 0 as played, thereby maximizing the final expected payout.

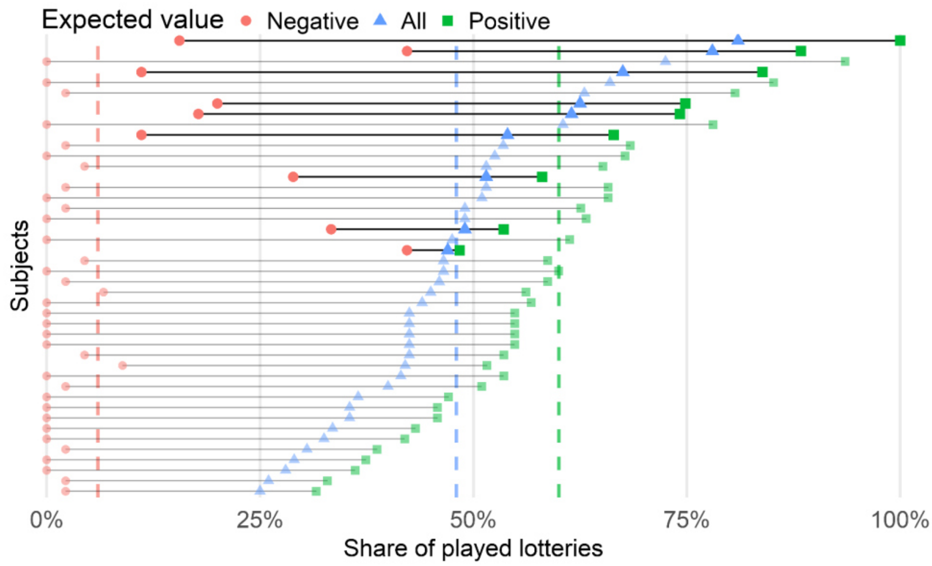
4 Descriptive analysis

In this chapter, we summarize the main findings from our descriptive analysis and present selected pieces of analysis. The comprehensive results are provided in the Appendix, Section 3.

4.1 Gambling choices, lottery payoff structure, and socioeconomic characteristics

Figure 2 shows the relative share of the number of played lotteries for each of the 44 individual subjects for all 200 lotteries: 155 lotteries with positive expected values (EV ≥ 0) and 45 lotteries with negative expected values.[1] The mean EV over all lotteries is 2.50 EUR (SD=3.30), the mean EV for negative expected value lotteries (NEVL) is –1.90 EUR (Min=–4.50, Max=–0.50, SD=1.20), and the mean EV for positive expected value lotteries (PEVL) is 3.80 EUR (Min=0.00, Max=9.50, SD=2.50).

Figure 2. Share of played lotteries by subject and lotteries' expected values



Notes: This figure shows the share of played lotteries by subject and the lotteries' expected values (EV) and is based on 8800 gambling decisions. Each of the 44 subjects decided on 200 lotteries: 155 with positive expected values (PEV) and 45 with negative expected values (NEV). Subjects that play five or more NEV lotteries are highlighted (bold). Dashed lines correspond to mean shares of played lotteries by EV. Subjects are ordered according to the highest share of the played lotteries (All).

The mean subject plays 48% of all lotteries, but there is high heterogeneity in the individual shares of played lotteries across subjects and within and between NEVL and PEVL. Twenty-one subjects do not play any NEVL, and 14 subjects play one to four NEVL. The remaining nine subjects play five or more NEVL. In contrast to an average share of played NEVL of 6%, the average share of played PEVL is 60%, and no strict decision boundary is identified that can be used to classify subjects as risk averse for playing PEVL. The distribution of the share of played PEVL is much smoother across individuals compared with NEVL. On average, though, subjects are more inclined to accept a gamble as its expected value increases for both NEVL and PEVL. The mean difference in predicted probabilities

[1] There are ten lotteries with an EV = 0. In our analysis, we distinguish between negative and non-negative EV lotteries. For clarity, in the further course of this paper, we refer to the lotteries with an EV≥ 0 as positive EV lotteries.

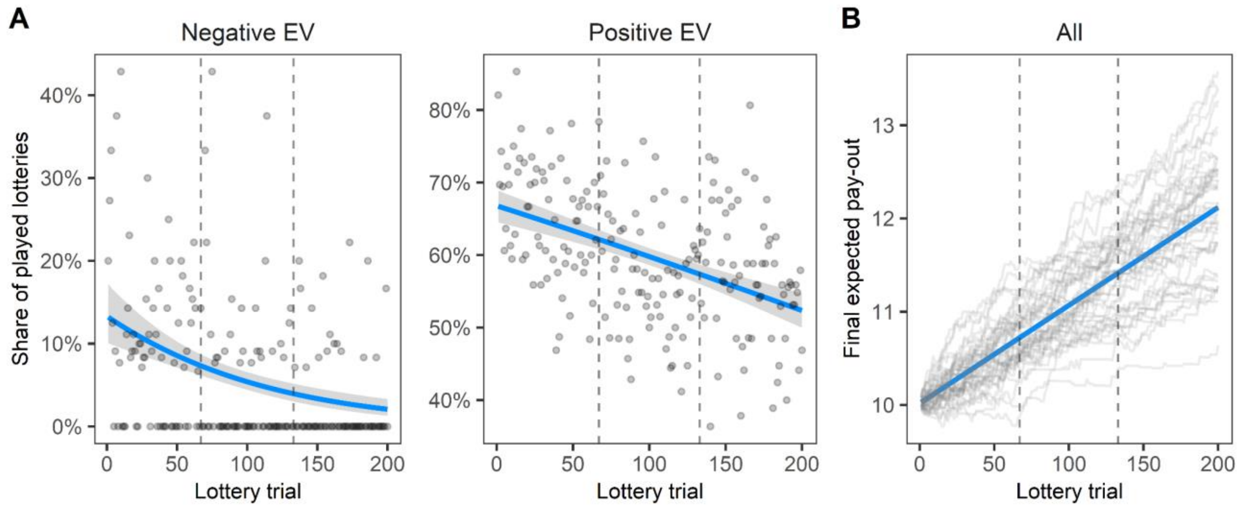
that we derive from fitting a simple logistic regression is 7.26% per one Euro increase in a lottery's EV (see Appendix, Section 3.1).

Although we do not find a significant difference between the mean share of accepted gambles across all lotteries by men (48.3%) and women (46.8%), women play approximately 50% more NEVL as men (7.6% and 5%), and men play slightly more PEVL than women (60.9% and 58.2%). Likewise, we do not find large differences between the share of accepted lotteries among the three income groups across all lotteries (48.8% vs. 47.6% vs. 45.6%). However, the highest income group plays the smallest share of PEVL (56.4 vs. 60.1% and 61.1%) and the largest share of NEVL (8.2% vs. 6.4% and 4.6%). Hence, for NEVL [PEVL], we find a positive [negative] correlation between income and the share of accepted lotteries. Because a large intersection exists between income and age groups, the differences in risk-taking preferences between members of the lower and higher income groups are similar to the differences between younger and older subjects (see Appendix, Section 3.2).

4.2 Sequential gambling choices and lottery outcomes

Figure 3 panel A shows the mean share of accepted NEVL and PEVL by trial. Panel B shows subjects' individual expected final payoffs with respect to all 200 lottery decisions, incorporating all previous choices and outcomes at each trial, and assuming that all subsequent lotteries are rejected. For both NEVL and PEVL, subjects' willingness to gamble decreases as the experiment progresses, though, all subjects could increase their final expected payout to exceed the initial 10 Euro endowment.

Figure 3. Expected payout and relative share of subjects that played lotteries by lottery trial



Notes: Panel A shows the mean share of played positive and negative expected value (EV) lotteries across subjects by lottery trial. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 with EV≥0 and 45 with EV<0. Panel B shows subjects' expected final payouts (solid gray lines) with respect to all 200 lottery decisions, including all previous choices and outcomes at each lottery trial and assuming that all subsequent lotteries are rejected. Solid black lines correspond to weighted logistic (panel A) and simple linear (panel B) regression curves. 95% confidence intervals are indicated by gray-shaded areas. Dashed lines indicate the 67th and 133rd trials.

First, we consider the impact of the last accepted lottery outcome on subjects' next consecutive choice across all lotteries. In line with the break-even and house-money effects, subjects are more inclined to gamble after a prior loss or win than after a prior lottery rejection. On the other hand, in contrast to prior losses or small to moderate wins, large prior wins appear to decrease the willingness to accept the next gamble beyond 50%. Taking into account a prior lottery's EV, we find that subjects' motivation to gamble increases by the amount they won in previously accepted NEVL, whereas losing NEVL and PEVL or winning PEVL decreases a subject's propensity to accept the next lottery in proportion to the amount that was lost/won. Hence, having previously won NEVL seems to particularly stimulate consecutive gambling activity. Although it is unclear why subjects engage in such gambling behavior, this phenomenon may be attributed to the resulting excitement and arousal experienced by winning unfavorable lotteries (NEVL). In contrast, a decreased propensity to gamble after larger losses may be attributed to negative emotions in reaction to losing and regretting the previous gamble. In line with this potential explanation, the effect of losing unfavorable lotteries is twice as large as the effect of losing favorable lotteries.

Regarding sequential choice behavior, we find gambling [non-gambling] streaks to increase the probability to accept [reject] the next lottery. Substantiating previous evidence on the hot hand effect and the gambler's fallacy, both positive and negative outcome streaks increase the willingness to accept the next consecutive lottery. The detailed results of our analysis of sequential choices and previous outcomes are presented in the Appendix, Section 3.3.

4.3 Lottery design, lookup patterns, and psychophysiological responses

Subjects first look at the left box in 73.0% across all lotteries and accept 48.5% [45.6%] of the trials during which they first looked at the win [loss] (Table A14). Hence, accounting for the location of the win box also captures information on subjects' tendency to play a higher share of lotteries for which they first looked at the win. However, we do not find strong evidence for a "left-hand side" bias. Furthermore, subjects looked at least once at each payoff box in 98% of all trials, and subjects switched between looking at the win and loss boxes 2-3 times in approximately 67% of all trials (see Appendix, Section 3.4.).

An analysis of SCPM correlations reveals complex dependencies across and within different types of CPD, and we find PS and several *A* SCPMs to significantly correlate with lottery payoff variables (see Appendix, Sections 3.5 and 3.6). Moreover, we use OLS to regress lottery trial on individual SCPMs (standard errors clustered at the subject level) and find that typical indicators of arousal, such as the number of significant SCRs and PS responses, are alleviated over time. This finding indicates that subjects become habituated to the gambling experience. Conversely, we find significant positive coefficient estimates for BT and many cardiovascular and respiratory SCPMs (Table A16). Consequently, we also find that several SCR and PS metrics are negatively correlated with BT, and many PS SCPMs are negatively correlated with several cardiovascular and respiratory measures (Figure A5).

5 Multiple regression-based hypothesis tests

In this section, we use the binary gambling choice y as the outcome ($y = 1$ for played) and summarize the results of logistic regression models that account for subject fixed effects. Precisely, each model includes subject-specific dummy variables, and we cluster standard errors at the subject level. Detailed results are presented in the Appendix, Section 4.

H1: On the basis of the *L* data, we find that larger potential gains increase subjects' willingness to gamble ($\beta = 0.33$, $p < 0.01$, Table A17). The average marginal effect across potential win values is 0.037; i.e., if the win value increases by 1 Euro, the predicted probability for lottery acceptance on average increases by 3.7%. The reverse holds true for losses (β = –0.68, $p < 0.01$, Table A17). The corresponding average marginal effect is –0.078; thus, the effect is significantly larger for losses than for gains ($p < 0.01$). In line with our hypothesis linked to lottery payoff characteristics, extending the *L* data by the set of *SGPA* variables does not change these results; the win and loss value coefficients remain highly significant and are of near identical magnitude (Table A19).

H2: We evaluate individual *A* SCPMs regressions and find that the propensity to accept a displayed lottery significantly increases in the time that subjects allocate to the win (β = 0.37, $p < 0.01$, Table A17). Conversely, when using the full set of *A* variables or controlling for the *LSGP* variables, the effect becomes insignificant ($p > 0.1$, Tables A17 and A19). In contrast, the effect of losses is significantly different from zero for both *A* (β = –0.43, $p < 0.01$, Table A17) and *LSGPA* (β = –0.31, $p < 0.05$, Table A19).

H3: Estimating separate regressions for assessing the effect of individual *P* SCPMs on gambling decisions reveals that most SCR and PS variables show significant and positive coefficient estimates, whereas the estimates for minimum, maximum, and mean BT are significantly negative (Table A18). However, on the basis of the *LSGPA* data, the only significant *P* coefficients are the number of significant SCRs (β = 0.12, $p < 0.1$, Table A19) and subjects' mean PS (β = 1.55, $p < 0.01$, Table A19).

When interpreting these results, it is important to acknowledge that several *A* and *P* SCPMs are significantly correlated with the set of lottery design variables, and our evaluation of different model specifications shows that controlling for the *LSG* variables can substantially affect individual SCPM coefficient estimates. As an example, subjects' BT increases during the experiment; thus, both a lottery trial and BT can capture subjects' decreasing willingness to accept gambles over time (see Table A20). Precisely, a lottery trial can provide information on cognitive depletion associated with extended periods of gambling, and higher ambient and body temperatures have also been linked to resource-depletion effects and decreasing risk preferences. For instance, Cheema & Patrick (2012) find that warmer temperatures increase heuristic information processing and decrease a subject's willingness to accept complex lottery gambles. Likewise, our descriptive analysis shows that PS and SCRs are negatively correlated with lottery trial; therefore, we expect their estimated effects to be more [less] pronounced during the earlier [later] lottery trials. Comparing individual regressions for the first and second half of the trials supports this hypothesis: the coefficient estimate (SD in parentheses) for the PS mean decreases from 2.00 (0.416) to 1.85 (0.497), and the estimated effect of the number of significant SCRs decreases from 0.19 (0.078) to 0.07 (0.069) (Table A20).

Furthermore, similar to the inherent dependency between BT regulation and the cardiovascular and respiratory systems and the correlations between *P* SCPMs and lottery design variables, our findings show that a lottery's potential win [loss] is positively correlated with the time that subjects spent looking at it and, in general, spending more time looking at the win [loss] decreases the time that subjects can spend looking at the loss [win]. As a result, the coefficient for the time allocated to the win becomes statistically significant when excluding the win value and/or the time that subjects look at the loss but is insignificant otherwise (Table A17). In contrast, the win and loss value estimates derived from various logistic model specifications are all highly significant and of similar magnitude.

6 Out-of-sample performance evaluation

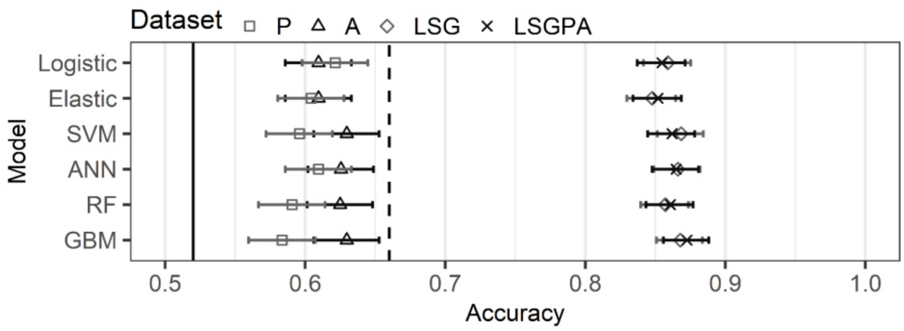
6.1 Forecasting risky gambling choices

For our algorithmic modeling approach, let us consider a function $f_i(\cdot)$ that relates the gambling choice *Y* to a predictor-set D_i with *i* = {*P, A, LSG, LSGPA*}. The objective is to identify well-approximating functional relationships that relate the specified predictor-sets to the decision outcome by learning and identifying systematic choice patterns from the training data. In the following, we focus on a visual inspection and discussion of selected forecasting results. Detailed results for hyperparameter tuning and out-of-sample performance are included in the Appendix, Section 5.

We use subjects as strata in both randomly selecting 80% of the cleaned data as a training sample and tuning models' hyperparameters via 10-fold stratified cross validation (CV) on the basis of the training sample. The remaining 20% of the data are used as a hold-out test set to produce reasonable accuracy estimates. This sampling procedure utilizes 6810 observations for model training and 1688 observations for model testing. Moreover, we include subject-specific dummy variables in each of the evaluated data sets (*P*, *A*, *LSG*, *LSGPA*), and since the average share of played lotteries is relatively balanced, we use classification accuracy to assess models' predictive capabilities in the model training process. Furthermore, we set the cut-off value for classifying a record as played to a predicted probability of 50%, and we separately center and scale all numeric predictors with respect to the corresponding 10 training CV fold-sets and the test records.

For all of the results reported in this study, we set the models' hyperparameters to the values that yield the highest mean CV accuracies. Figure 4 shows the out-of-sample classification accuracy for the 1688 records included in the test data.

Figure 4. Out-of-sample classification accuracy for playing a 50/50-gamble



Notes: Out-of-sample accuracy for playing a 50/50 gamble. Test [training] data consist of 1688 [6810] records and the models' hyperparameters are chosen as the values that yield the highest mean 10-fold CV accuracy using subjects as strata. We evaluate logistic (Logistic) and penalized regression models (Elastic), support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and gradient boosting machines (GBM) on the basis of psychophysiological (*P*) and attention (*A*) choice-process data; lottery design, socioeconomic characteristics, and information on past gambling behavior (*LSG*); and a full model that is comprised of all input categories (*LSGPA*). The error bars correspond to 95% confidence intervals. The solid line is a naïve forecast that yields a test data accuracy of 52% by predicting all records as not-playing, and the dashed line is a second naïve forecast that results in an accuracy of 66% by predicting a lottery choice with EV<0 as not-playing and with EV≥0 as played.

The solid [dashed] line indicates the RDR [SDR] forecast that results in a test accuracy of 52% [66%]. The best out-of-sample accuracy for *P* is observed with 62% (Logistic), for *A* with 63% (SVM, ANN, RF, GBM), for *LSG* with 87% (SVM, ANN, GBM), and for *LSGPA* with 87% (GBM). Hence, forecasting accuracy is largely driven by including information on standard choice predictors, such as lotteries' payoff structures, and we do not find the additional *P* and *A* SCPMs to significantly affect forecasting accuracy when added to the *LSG* variables. Precisely, for the Elastic net and RF and GBM models, the *LSGPA* results are slightly more accurate than the corresponding *LSG* results; the reverse holds true for the Logistic, SVM, and ANN models. Moreover, we do not find a dominant approach among the linear, non-linear, and tree-based ML algorithms. Comparing forecasting accuracy in terms of different predictive measures and evaluating subject-model-specific accuracy results further substantiate these findings (see Appendix, Section 5.4).

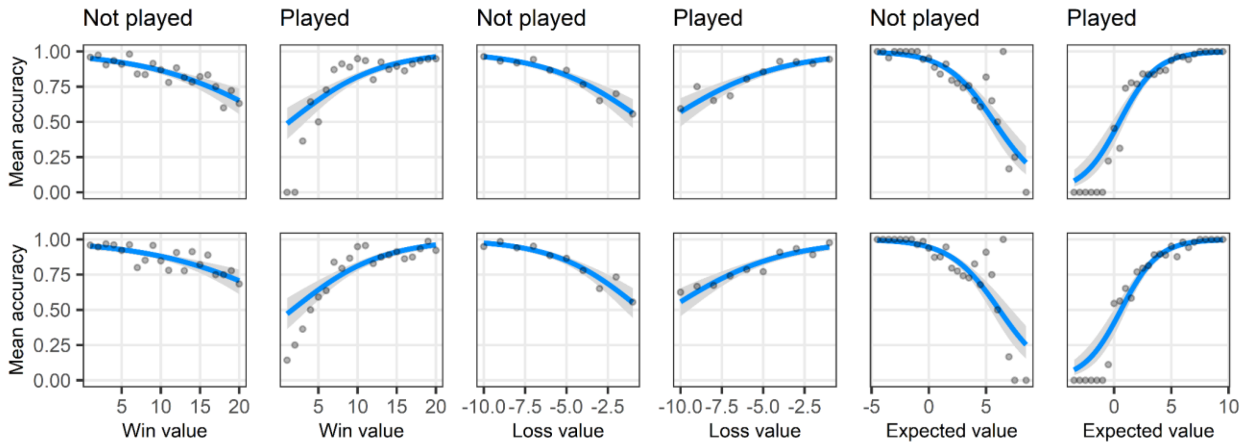
Concerning the predictions derived from the *P* data, all models yield very similar CV accuracy results. However, when considering the out-of-sample *P* data evaluation, the SVM, RF, and GBM perform significantly worse, the Elastic net and ANN test accuracy results do not differ much from their CV results, whereas the standard logistic regression accuracy improves by 2 %-points. Hence, it appears that the more data-driven ML methods tend to overfit on the *P* SCPM patterns observed in the training data, and these methods are likely to require a larger training data set to appropriately capture and approximate the complex relationships between gambling choices, lottery design, and SCPMs.

All ML model predictions derived from the *A* data are more accurate than the predictions based on the *P* data. In comparison to the generalized linear models (Logistic and Elastic), our results demonstrate that the more data-driven ML methods (SVM, ANN, RF, and GBM) better utilize the information provided by subjects' individual lookup patterns (*A*) and produce more accurate predictions on the basis of *LSG* and *LGSPA*. To further investigate potentially relevant interactions between individual *A* SCPMs, we evaluate the Elastic net model on the basis of an extended predictor-set. Using the standard *A* data, the Elastic net approach results in a test accuracy of 60.96%, and adding pairwise interactions between the *A* SCPMs and subject-specific interactions results in a test accuracy of 63.03%. This increase in forecasting accuracy suggests that relevant dependencies exist between the *A* SCPMs and subject-specific lookup patterns that, in addition to the more data-driven ML methods, can also be captured by linear penalized modeling approaches.

H1: Regarding our hypotheses related to lottery payoff characteristics, in Figure 5, we separately present the GBM out-of-sample mean accuracy results for *LSG* (upper panel) and *LSGPA* (lower panel) by lotteries' win, loss, and expected values for rejected (Not played) and accepted (Played) lotteries.[2] Hence, for rejected [accepted] gambles, the reported mean accuracy results correspond to the mean specificity [sensitivity].

[2] The predictor-set-specific forecasts are based on the models that show the highest test data classification accuracy. A general comparison of the different models' forecasting results is provided in the Appendix, Section 5.

Figure 5. Out-of-sample classification accuracy by lottery design variables

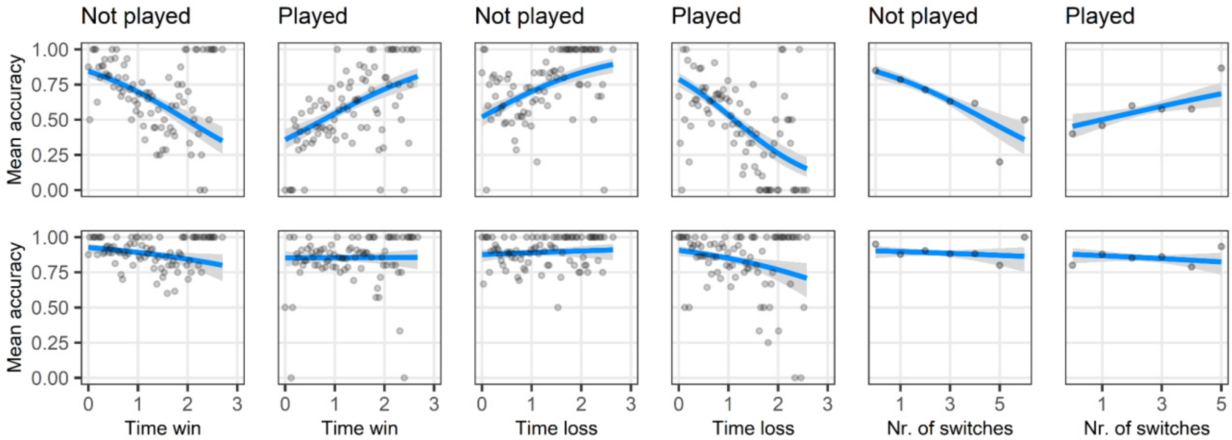


Notes: Out-of-sample mean accuracy results for playing a 50/50 gamble by lotteries' win, loss and expected values for rejected and accepted lotteries. Predictions are derived from gradient boosting (GBM) classification based on lottery design variables, subjects' socioeconomic characteristics and past gambling behavior (*LSG*) (upper panel) and on *LSG* extended by psychophysiological responses and attention metrics (*LSGPA*) (lower panel). Solid lines correspond to logistic regressions weighted by the number of observations per win, loss, and expected value. 95% confidence intervals are indicated by grey-shaded areas.

The solid lines in Figure 5 correspond to weighted logistic regressions that highlight the strong nonlinear relationship between gambling decisions and lotteries' payoff structure: the higher [lower] a lottery's win [loss] value, the more accurate the forecast becomes for games predicted as played [not played]. The same pattern holds for a lottery's EV, and the corresponding logistic regression curves show a strong link between correct predictions and large [small] EVs for accepted [rejected] lotteries. Likewise, we do not observe many correct predictions for the share of rejected PEVL with an EV > 5 or the share of accepted NEVL. Although the forecasting accuracy for the GBM model only marginally improves when adding the *PA* SCPMs to the *LSG* data (see Figure 4), extending the set of standard choice predictors by the *PA* variables appears to worsen the GBM predictions for NEVL but slightly improves the GBM predictions for both rejected and accepted PEVL.

H2: Continuing with our analysis of lookup patterns, in Figure 6, we show the GBM out-of-sample mean accuracy results based on *A* (upper panel) and *LSGPA* (lower panel) by the time that subjects look at the win and loss boxes and the number of box switches.

Figure 6. Out-of-sample classification accuracy by attention metrics

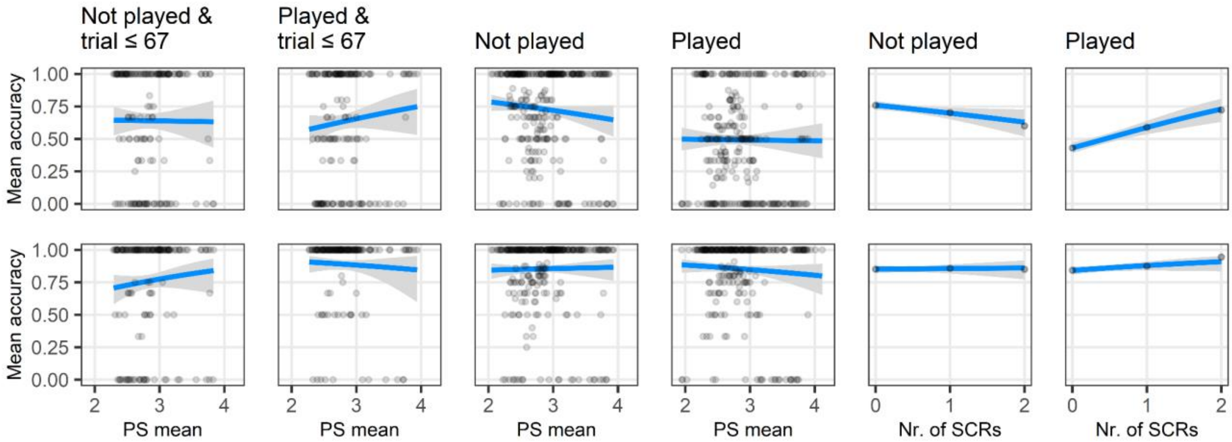


Notes: Out-of-sample mean accuracy results for playing a 50/50 gamble by the time that subjects spent looking at a lottery's win and loss box, and the number of box switches for rejected and accepted lotteries. Predictions are derived from gradient boosting (GBM) classification based on attention metrics (*A*) (upper panel) and on *A* extended by lottery design variables, subjects' socioeconomic characteristics, past gambling behavior, and psychophysiological response metrics (*LSGPA*) (lower panel). Solid lines correspond to logistic regressions weighted by the number of observations per time win, time loss, and box switches. 95% confidence intervals are indicated by grey-shaded areas.

The predictions based on *A* (upper panel) substantiate the results from our in-sample-based analysis: the longer [shorter] the time that subjects look at the win, and the shorter [longer] the time that subjects look at the loss, the more accurate the RF's forecast becomes for games that are predicted as played [not played]. Furthermore, for accepted games, we do not find a strong relationship between the number of box switches and the mean accuracy results obtained from *A* when compared with the results for the time that subjects spent looking at the win and loss boxes, but we find that increasing numbers of box switches are associated with a decreasing share of correct predictions for rejected games. However, when comparing the *A* and *LSGPA* predictions (lower panel), the *A* predictors do not vary much with respect to the consistently high forecasting accuracy results obtained from *LSGPA*.

H3: Concerning gambling choices and arousal, in Figure 7, we present the logistic regression out-of-sample mean accuracy results for *P* (upper panel) and *LSGPA* (lower panel) by mean PS and the number of significant SCRs and mean PS only for early lottery trials (trial ≤ 67).

Figure 7. Out-of-sample classification accuracy by arousal metrics



Notes: Out-of-sample mean accuracy results for playing a 50/50 gamble by mean pupils size (PS) and the Nr. of significant skin conductance responses (SCRs) for rejected and accepted lotteries. Predictions are derived from logistic regression based on psychophysiological response metrics (*P*) (upper panel) and on *P* extended by lottery design variables, subjects' socioeconomic characteristics, past gambling behavior, and attention metrics (*LSGPA*) (lower panel). Solid lines correspond to logistic regressions weighted by the number of observations per PS mean and the number of significant SCRs. 95% confidence intervals are indicated by grey-shaded areas.

We find that forecasting accuracy increases with mean PS for accepted gambles for the early lottery trials of the experiment and decreases with mean PS for rejected gambles when considering all lottery trials. In contrast, average accuracy does not vary much across mean PS for accepted lotteries across all trials and mean PS for rejected lotteries during earlier trials. Similar to PS changes, a higher [smaller] number of significant SCRs indicates higher [lower] forecasting accuracy. However, whereas PS changes and SCRs both decrease over time, the association between SCRs and forecasting accuracy appears to persist throughout the entire experiment. Nonetheless, although forecasting accuracy appears not to largely vary by PS, these results do not imply that PS data do not provide valuable information for predicting gambling choices. In particular, the coefficient estimates for the number of significant SCRs and PS mean derived from differently specified logistic effects regression models are all statistically significant and in line with our *P* CPD-related main hypothesis—higher arousal levels signal upcoming lottery acceptance.

For the *LSGPA* predictions (lower panel), forecasting accuracy does not vary much across SCRs when compared with the *P* forecast; however, we still find that forecasting accuracy increases with the number of significant SCRs. Moreover, we find a reversed pattern for the relationship between forecasting accuracy and PS for the early lottery trials and slightly decreasing mean accuracy results for increasing PS mean values for accepted lotteries.

6.2 Forecasting simple choice process data metrics

In this section, we analyze the extent to which the choice-revealing information provided by the *A* and *P* SCPMs may already be captured by lottery-design variables and socioeconomic characteristics because only marginal differences exist between the model-specific *LSG* und *LSGPA* forecasting results, and many of the *A* and *P* SCPMs significantly correlate with the *LS* data. To this end, we evaluate forecasting CPD type-specific mean values on the basis of the *LS* input categories using RF and Elastic net regression without including information on subjects' gambling choices and outcomes.[3] The corresponding CV and out-of-sample results are reported in Table 2.

Table 2. Choice process data metrics forecasting results

Cross-validation results			Out-of-sample evaluation results		
Outcome	R2 - Elastic	R2 - RF	Outcome	R2 - Elastic	R2 - RF
Time win	18.28%	34.43%	Time win	18.39%	35.27%
Time loss	18.78%	35.14%	Time loss	16.49%	34.17%
Nr. of switches	26.56%	30.31%	Nr. of switches	28.99%	33.40%
HR mean	86.15%	89.23%	HR mean	86.88%	89.92%
BVP mean	93.14%	93.83%	BVP mean	92.83%	93.58%
BVPA mean	85.05%	91.02%	BVPA mean	85.47%	91.06%
RSR mean	20.49%	20.97%	RSR mean	21.67%	21.01%
RSD mean	99.10%	99.51%	RSD mean	99.14%	99.52%
BT mean	76.90%	99.54%	BT mean	77.18%	99.62%
PS mean	92.89%	94.56%	PS mean	93.58%	95.15%

Notes: Accuracy reported in terms of R-squared values. Test [training] data consist of 1688 [6810] records, and the models' hyperparameters are chosen as the values that yield the highest mean 10-fold CV accuracy in terms of RMSE using subjects as strata. We evaluate linear penalized regression models (Elastic) and random forest regression (RF) on the basis of lottery design and socioeconomic characteristics (*LS*) for predicting the time that subjects look at the win and loss, the Nr. of box switches, and mean values for subjects' blood volume pulse (BVP), BVP amplitude (BVPA), respiration rate (RSR), respiration depth (RSD), heart rate (HR), body temperature (BT), and pupil size (PS).

Except for RSR, both Elastic net and RF produce fairly accurate forecasts for the mean *P* CPD values (BVP, BVPA, RSD, HR, BT, and PS) but low accuracy results for RSR mean. Similar to RSR, both models produce less accurate forecasts for the *A* SCPM; the corresponding Elastic net [RF] out-of-sample R-squared results range from 16.5% [33.4%] to 29.0% [35.3]. RF outperforms Elastic net for each SCPM except the RSR mean, and the largest differences between the Elastic net and RF test data results

[3] To regress individual *P* SCPMs on the *LS* predictor-set, we use the same model training procedure and set of hyperparameter values as for forecasting gambling choices, but instead of classification accuracy, we use the resulting root mean squared error (RMSE) to fit the models' hyperparameter values. For the RF training process, we use the weighted variance measure as the splitting criterion.

are observed for mean BT (77.2% vs. 99.6%) and the time spent looking at the loss (16.5% vs. 34.2%) and the win (18.4% vs. 35.3%) boxes.

A potential explanation for the rather low accuracy results for the *A* SCPMs is the likely existence of interdependent relationships between gambling choices, lookup patterns, and lottery attributes.[4] Moreover, we evaluate forecasting the number of significant SCRs using a multi-classification approach that distinguishes between 0, 1, and 2 or more significant SCRs: both the Elastic net and RF models yield 99.82% accurate predictions on the test data. Hence, in contrast to the simple lookup pattern metrics, RF and Elastic net produce highly accurate forecasts for the two arousal measures that we identified as relevant choice predictors: Mean PS and the number of significant SCRs.

7 Conclusions

This study demonstrates that pre-decisional attention and arousal metrics can effectively be used to forecast risky gambling decisions, but we do not find that SCPMs substantially impact forecasting accuracy when added to the standard choice-modeling data. In addition to subject-specific risk preferences, we find that forecasting accuracy is mainly driven by including information on lottery design variables. In general, our study highlights the importance of accounting for various correlations and causal dependencies between gambling choices, lottery design, and *A* and *P* CPD. However, the existence of these complex relationships makes it difficult to isolate effects attributable to individual SCPMs, and our findings suggest that a large proportion of the choice-revealing information associated with simple arousal metrics can already be captured by standard choice predictors.

One of our key results is that subjects' decreasing willingness to accept lotteries throughout the experiment is linked to the predictive importance of typical indicators of arousal and cardiovascular and respiratory measures. For instance, we observe smaller PS changes and lower frequencies of significant SCRs in the later stages of the experiment; conversely, subjects show higher levels of arousal in the early stages of the experiment when the gambling experience is still new and exciting. In addition to such habituation effects, we find that subjects' skin temperature and their tendency to reject lotteries consistently increases as the experiment progresses, thereby supporting

[4] For a detailed discussion on interdependencies between eye movements and choices, see, e.g., Shimojo et al. (2003) and Stewart et al. (2016).

previous findings on potential resource-depletion effects. Furthermore, our analysis of subsequent gambling behavior highlights the importance of accounting for individual payoff characteristics of previously offered lotteries when investigating cognitive bias and the role of emotions in winning and losing in repeated gambling decision scenarios.

As a final remark, albeit our data include 200 lottery decisions per subject, we emphasize that with 44 subjects, our results are based on a rather limited sample of individuals. Consequently, in our forecasting analysis, we use information on all subjects in both the training and the test data. Whereas our findings provide new insights into the predictive importance of CPD, we conduct a simple and repetitive lottery gambling experiment and restrict our analysis to pre-decisional attention and psychophysiological SCPMs that are exclusively recorded using low-cost tracking devices. Based on the numerous available CPD tracking methods, modeling strategies, and experimental designs, we consider our study to be one of many necessary pieces of research in the course of assessing the relevance of CPD to better understand and predict human preferences and behaviors.

References

Adam, M. T. P., Krämer, J., & Müller, M. B. (2015). Auction Fever! How Time Pressure and Social Competition Affect Bidders' Arousal and Bids in Retail Auctions. *Journal of Retailing*, *91*(3), 468–485.

Ahlfeldt, G. M., Maennig, W., & Mueller, S. Q. (2019). The generation gap in direct democracy. *CEPR Discussion Paper*, 1–43.

Alós-Ferrer, C. (2018). A Review Essay on «Social Neuroscience»: Can Research on the Social Brain and Economics Inform Each Other? *Journal of Economic Literature*, *56*(1), 234–264.

Astor, P. J., Adam, M. T. P., Jähnig, C., & Seifert, S. (2013). The Joy of Winning and the Frustration of Losing: A Psychophysiological Analysis of Emotions in First-Price Sealed-Bid Auctions. *Journal of Neuroscience, Psychology, and Economics*, *6*(1), 14–30.

Barrett, L. F., Adolphs, R., Marsella, S., Martinez, A. M., & Pollak, S. D. (2019). Emotional Expressions Reconsidered: Challenges to Inferring Emotion From Human Facial Movements. *Psychological Science in the Public Interest*, *20*(1), 1–68.

Baudinet, J., & Blaszczynski, A. (2013). Arousal and Gambling Mode Preference: A Review of the Literature. *Journal of Gambling Studies*, *29*(2), 343–358.

Bellemare, C., Sebald, A., & Suetens, S. (2019). Guilt aversion in economics and psychology. *Journal of Economic Psychology*, *73*(452), 52–59.

Bernheim, B. D. (2009). On the potential of neuroeconomics: A critical (but hopeful) appraisal. *American Economic Journal: Microeconomics*, *1*(2), 1–41.

Besedeš, T., Deck, C., & Sarangi, S. (2014). Age Effects and Heuristics in Decision Making. *Review of Economics and Statistics*, *94*(2), 580–595.

Boucsein, W. (2012). *Electrodermal activity* (2nd ed.). Ney York: Springer.

Breaban, A., & Noussair, C. N. (2018). Emotional State and Market Behavior. *Review of Finance*, *22*(1), 279–309.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Brocas, I., Carrillo, J. D., Wang, S., & Camerer, C. F. (2014). Imperfect choice or imperfect attention? Understanding strategic thinking in private information games. *Review of Economic Studies*, *81*(3), 944–970.

Bruyneel, S. D., Dewitte, S., Franses, P. H., & Dekimpe, M. G. (2009). I felt low and my purse feels light: depleting mood regulation attempts affect risk decision making. *Journal of Behavioral Decision Making*, *22*, 153–170.

Buckert, M., Schwieren, C., Kudielka, B. M., & Fiebach, C. J. (2017). How stressful are economic competitions in the lab? An investigation with physiological measures. *Journal of Economic Psychology*, *62*, 231–245.

Burger, M. J., Hendriks, M., Pleeging, E., & van Ours, J. C. (2020). The joy of lottery play: evidence from a field experiment. *Experimental Economics*, (https://doi.org/10.1007/s10683-020-09649-9), 1–18.

Camerer, C. F. (2018). Artificial intelligence and behavioral economics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The Economics of Artificial Intelligence: An Agenda* (pp. 1–33). University of Chicago Press.

Camerer, C. F., Nave, G., & Smith, A. (2018). Dynamic Unstructured Bargaining with Private Information: Theory, Experiment, and Outcome Prediction via Machine Learning. *Management Science*, *65*(4).

Cheema, A., & Patrick, V. M. (2012). Influence of warm versus cool temperatures on consumer choice: A resource depletion account. *Journal of Marketing Research*, *49*(6), 984–995.

Chen, F., & Fischbacher, U. (2016). Response time and click position: cheap indicators of preferences. *Journal of the Economic Science Association*, *2*(2), 109–126.

Clithero, J. A. (2018a). Improving out-of-sample predictions using response times and a model of the decision process. *Journal of Economic Behavior and Organization*, *148*, 344–375.

Clithero, J. A. (2018b). Response times in economics: Looking through the lens of sequential sampling models. *Journal of Economic Psychology*, *69*, 61–86.

Coricelli, G., Critchley, H. D., Joffily, M., Doherty, J. P. O., Sirigu, A., & Dolan, R. J. (2005). Regret and its avoidance: a neuroimaging study of choice behavior. *Nature Neuroscience*, *8*, 1255–1262.

Coricelli, G., Joffily, M., Montmarquette, C., & Villeval, M. C. (2010). Cheating, emotions, and rationality: An experiment on tax evasion. *Experimental Economics*, *13*(2), 226–247.

Cortes, C., & Vapnik, V. (1995). Support-Vector Networks. *Machine Learning*, *20*, 273–297.

Croson, R., & Gneezy, U. (2009). Gender Differences in Preferences. *Journal of Economic Literature*, *47*(2), 448–474.

Daly, M., Delaney, L., & Harmon, C. P. (2009). Psychological and Biological Foundations of Time Preference: Evidence from a Day Reconstruction Study with Biological Tracking. *Journal of the European Economic Association*, *7*(2–3), 659–669.

Economist. (2017, June 8). Body language: How retailers are watching shoppers' emotions.

Efron, B., & Hastie, T. (2016). *Computer Age Statistical Inference*. *Institute of Mathematical Statistics Monographs*. New York: Cambrdige University Press.

Falk, A., Kosse, F., Menrath, I., Verde, P. E., & Siegrist, J. (2018). Unfair pay and health. *Management*

Science, *64*(4), 1477–1973.

Fehr, E., & Rangel, A. (2011). Neuroeconomic Foundations of Economic Choice - Recent Advances. *Journal of Economic Perspectives*, *25*(4), 3–30.

Fiedler, S., & Glöckner, A. (2012). The dynamics of decision making in risky choice: An eye-tracking analysis. *Frontiers in Psychology*, *3*(OCT), 1–18.

Fisher Gardial, S., Clemons, D. S., Woodruff, R. B., Schumann, David, W., & Burns, M. J. (2016). Comparing Consumers Recall of Prepurchase and Postpurchase Product Evaluation Experiences. *Journal of Consumer Research*, *20*(4), 548–560.

Friedman, J. H. (2002). Stochastic gradient boosting. *Computational Statistics and Data Analysis*, *38*(4), 367–378.

Giacomantonio, M., Jordan, J., Federico, F., van den Assem, M. J., & van Dolder, D. (2018). The evil eye: Eye gaze and competitiveness in social decision making. *European Journal of Social Psychology*, *48*(3), 388–396.

Gilovich, T., Vallone, R., & Tversky, A. (1985). The Hot Hand. *Cognitive Psychology*, *17*, 295–314.

Goldstein, D. G., & Gigerenzer, G. (2009). Fast and frugal forecasting. *International Journal of Forecasting*, *25*(4), 760–772.

Guardian. (2019, August 17). AI can read your emotions. Should it?, pp. 1–8.

Guryan, J., & Kearney, M. S. (2008). Gambling at lucky stores: Empirical evidence from state lottery sales. *American Economic Review*, *98*(1), 458–473.

Haisley, E., Loewenstein, G., & Romel, M. (2008). Subjective Relative Income and Lottery Ticket Purchases. *Journal of Behavioral Decision Making*, *21*, 283–295.

Halko, M. L., & Sääksvuori, L. (2017). Competitive behavior, stress, and gender. *Journal of Economic Behavior and Organization*, *141*(396), 96–109.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The Elements of Statistical Learning* (2nd ed.). New York: Springer.

Hattke, F., Hensel, D., & Kalucza, J. (2019). Emotional Responses to Bureaucratic Red Tape. *Public Administration Review*, *80*(1), 53–63.

Heilman, R. M., Crișan, L. G., Houser, D., Miclea, M., & Miu, A. C. (2010). Emotion Regulation and Decision Making Under Risk and Uncertainty. *Emotion*, *10*(2), 257–265.

Hobson, J. L., Mayew, W. J., & Venkatachalam, M. (2012). Analyzing Speech to Detect Financial Misreporting. *Journal of Accounting Research*, *50*(2), 349–392.

Hochman, G., Glöckner, A., Fiedler, S., & Ayal, S. (2016). "I can see it in your eyes": Biased Processing and Increased Arousal in Dishonest Responses. *Journal of Behavioral Decision Making*, *29*(2–3), 322–335.

Huseynov, S., Kassas, B., Segovia, M. S., & Palma, M. A. (2019). Incorporating biometric data in models of consumer choice. *Applied Economics*, *51*(14), 1514–1531.

Hytönen, K., Baltussen, G., van den Assem, M. J., Klucharev, V., Sanfey, A. G., & Smidts, A. (2014). Path dependence in risky choice: Affective and deliberative processes in brain and behavior. *Journal of Economic Behavior and Organization*, *107*(PB), 566–581.

Imai, T., Kang, M. J., & Camerer, C. F. (2019). When the eyes say buy: visual fixations during hypothetical consumer choice improve prediction of actual purchases. *Journal of the Economic Science Association*, *5*(1), 112–122.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk.

Econometrica, *47*(2), 263–292.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J., & Mullainathan, S. (2018). Human decisions and machine predictions. *Quarterly Journal of Economics*, *133*(1), 237–293.

Kliger, D., Gurevich, G., & Haim, A. (2012). When chronobiology met economics: Seasonal affective disorder and the demand for initial public offerings. *Journal of Neuroscience, Psychology, and Economics*, *5*(3), 131–151.

Kliger, D., & Levy, O. (2002). Risk Preferences Heterogeneity: Evidence from Asset Markets. *Review of Finance*, *6*(3), 277–290.

Knoepfle, D. T., Tao-yi Wang, J., & Camerer, C. F. (2009). Studying learning in games using eye-tracking. *Journal of the European Economic Association*, *7*(2–3), 388–398.

Knutson, B., Rick, S., Wimmer, G. E., Prelec, D., & Loewenstein, G. (2007). Neural Predictors of Purchases. *Neuron*, *53*(1), 147–156.

Kostek, J., & Ashrafioun, L. (2014). Tired Winners: The Effects of Cognitive Resources and Prior Winning on Risky Decision Making. *Journal of Gambling Studies*, *30*(2), 423–434.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298.

Krajbich, I., Oud, B., & Fehr, E. (2014). Benefits of neuroeconomic modeling: New policy interventions and predictors of preference. *American Economic Review: Papers & Proceedings*, *104*(5), 501–506.

Kreibig, S. D. (2010). Autonomic nervous system activity in emotion: A review. *Biological Psychology*, *84*(3), 394–421.

Krol, M., & Krol, M. (2017). A novel approach to studying strategic decisions with eye-tracking and machine learning. *Judgment and Decision Making*, *12*(6), 596–609.

Krol, M., & Krol, M. (2019). Simple Eye Movement Metrics Can Predict Future Decision Making Performance: the Case of Financial Choices. *Judgment and Decision Making*, *14*(3), 223–233.

Ladouceur, R., Sévigny, S., Blaszczynski, A., O'Connor, K., & Lavoie, M. E. (2003). Video lottery: Winning expectancies and arousal. *Addiction*, *98*(6), 733–738.

Laplace, P. (1820). *Philosophical Essays on Probabilities*. (F. W. Truscott & F. L. Emory, Eds.). New York: Dover.

Lessmann, S., & Voß, S. (2017). Car resale price forecasting: The impact of regression method, private information, and heterogeneity on forecast accuracy. *International Journal of Forecasting*, *33*(4), 864–877.

Levav, J., & McGraw, A. P. (2009). Emotional accounting: How feelings about money influence consumer choice. *Journal of Marketing Research*, *46*(1), 66–80.

Levy, I., Lazzaro, S. C., Rutledge, R. B., & Glimcher, P. W. (2011). Choice from non-choice: Predicting consumer preferences from blood oxygenation level-dependent signals obtained during passive viewing. *Journal of Neuroscience*, *31*(1), 118–125.

Lo, A. W., & Repin, D. V. (2002). The psychophysiology of real-time financial risk processing. *Journal of Cognitive Neuroscience*, *14*(3), 323–339.

Loewenstein, G. (1999). Emotions in Economic Theory and Economic Behavior. *American Economic Review*, *90*(2), 256–260.

Lusk, J. L., Crespi, J. M., McFadden, B. R., Cherry, J. B. C., Martin, L., & Bruce, A. (2016). Neural antecedents of a random utility model. *Journal of Economic Behavior and Organization*, *132*, 93–103.

Makridakis, S., & Taleb, N. (2009). Living in a world of low levels of predictability. *International Journal of Forecasting*, *25*(4), 840–844.

Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. *Cognition and Emotion*.

Mueller, S. Q. (2020). Pre- and within-season attendance forecasting in Major League Baseball: a random forest approach. *Applied Economics*, *52*(41), 4512–4528.

Mullainathan, S., & Spiess, J. (2017). Machine Learning: An Applied Econometric Approach. *Journal of Economic Perspectives*, *31*(2), 87–106.

Nicholas, a. J. (2009). Generational Perceptions : Workers And Consumers. *Journal of Business & Economics Research*, *7*(10), 47–52.

Pachur, T., Schulte-Mecklenbeck, M., Murphy, R. O., & Hertwig, R. (2018). Prospect theory reflects selective allocation of attention. *Journal of Experimental Psychology: General*, *147*(2), 147–169.

Peysakhovich, A., & Naecker, J. (2017). Using methods from machine learning to evaluate behavioral models of choice under risk and ambiguity. *Journal of Economic Behavior and Organization*, *133*, 373–384.

Poels, K., & Dewitte, S. (2006). How to Capture the Heart? Reviewing 20 Years of Emotion Measurement in Advertising. *Journal of Advertising Research*, *46*(1), 18–37.

Potter, R. F., & Bolls, P. D. (2012). *Psychophysiological Measurement and Meaning: Cognitive and Emotional Processing of Media*.

Pozharliev, R., Verbeke, W. J. M. I., Van Strien, J. W., & Bagozzi, R. P. (2015). Merely being with you increases my attention to luxury products: Using EEG to understand consumers' emotional experience with luxury branded products. *Journal of Marketing Research*, *52*(4), 546–558.

Rabin, M., & Vayanos, D. (2010). The gambler's and hot-hand fallacies: Theory and applications. *Review of Economic Studies*, *77*(2), 730–778.

Reczek, R. W., Irwin, J. R., Zane, D. M., & Ehrich, K. R. (2018). That's Not How I Remember It: Willfully Ignorant Memory for Ethical Product Attribute Information. *Journal of Consumer Research*, *45*(1), 185–207.

Reutskaja, E., Nagel, R., Camerer, C. F., & Rangel, A. (2011). Search Dynamics in Consumer Choice under Time Pressure: An Eye-Tracking Study. *American Economic Review*, *101*(2), 900–926.

Ring, P. (2015). The framing effect and skin conductance responses. *Frontiers in Behavioral Neuroscience*, *9*(188), 1–7.

Rosenblatt, F. (1961). *Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms*. Washington DC: Spartan Books.

Schmidt, U., Neyse, L., & Aleknonyte, M. (2019). Income inequality and risk taking: the impact of social comparison information. *Theory and Decision*, *87*(3), 283–297.

Schneider, S., Kauffman, S., & Ranieri, A. (2016). The effects of surrounding positive and negative experiences on risk taking. *Judgment and Decision Making*, *11*(5), 424–440.

Schulte-Mecklenbeck, M., Kühberger, A., & Ranyard, R. (Eds.). (2011). *A Handbook of Process Tracing Methods for Decision Research*. New York: Psychology Press.

Scitovsky, T. (1976). *The Joyless Economy. An Inquiry into Human Satisfaction and Consumer Dissatisfaction. Oxford University Press*.

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, *6*(12), 1317–1322.

Smith, A., Douglas Bernheim, B., Camerer, C. F., & Rangel, A. (2014). Neural activity reveals preferences without choices. *American Economic Journal: Microeconomics*, *6*(2), 1–36.

Stewart, N., Hermens, F., & Matthews, W. J. (2016). Eye Movements in Risky Choice. *Journal of Behavioral Decision Making*, *29*(2–3), 116–136.

Sundararajan, R. R., Palma, M. A., & Pourahmadi, M. (2017). Reducing brain signal noise in the prediction of economic choices: A case study in neuroeconomics. *Frontiers in Neuroscience*, *11*, 1–13.

Telpaz, A., Webb, R., & Levy, D. J. (2015). Using EEG to predict consumers' future choices. *Journal of Marketing Research*, *52*(4), 511–529.

Thaler, R., & Johnson, E. J. (1990). Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice. *Management Science*, *36*(6), 643–660.

Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives*, *28*(2), 3–28.

Veblen, T. (1899). *The theory of the leisure class*. New York: McMillan.

Venkatraman, V., Dimoka, A., Pavlou, P. A., Vo, K., Hampton, W., Bollinger, B., ... Winer, R. S. (2015). Predicting advertising success beyond traditional measures: New insights from neurophysiological methods and market response modeling. *Journal of Marketing Research*, *52*(4), 436–452.

Wang, J. T., Spezio, M., & Camerer, C. F. (2010). Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games. *American Economic Review*, *100*(3), 984–1007.

Wang, Y. J., & Minor, M. S. (2008). Validity, Reliability, and Applicability of Psychophysiological Techniques in Marketing Research. *Psychology & Marketing*, *25*(2), 197–232.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic-net. *Journal of the Royal Statistical Society*, *67*(2), 301–320.

Excited and aroused: The predictive importance of simple choice process metrics

Appendix

1 Introduction

This online appendix provides additional information on the experimental design and empirical specifications and complements the main text by providing detailed results for the descriptive analysis, our regression-based hypothesis tests, and our forecasting analysis of gambling choices and SCPMs. Furthermore, although this Appendix is not meant to stand alone, we note that it replicates some text and results from the main paper to ensure clarity.

2 Data and experimental design

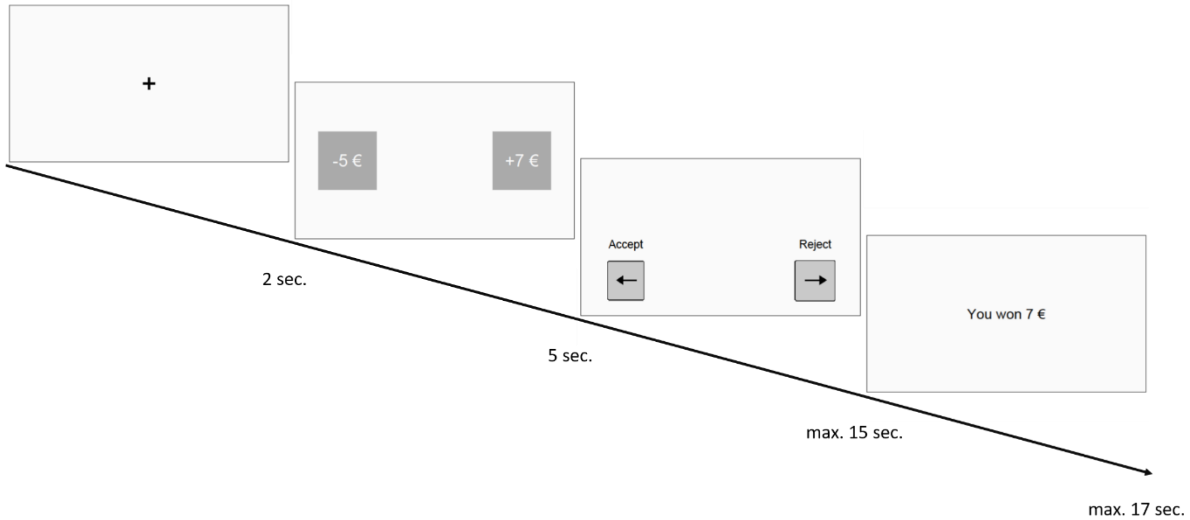
In this section, we provide additional information on the experimental design, the data cleaning process, variable specifications, and summary statistics.

2.1 Experimental design

The experiment was conducted between 2018.07.23 and 2018.08.08 at the Psychology Department of Kiel University, Germany. After the experimenter instructed the subjects, they received documents including general information on the experimental design, informed consent, a worksheet to generate a personal code, and a survey that included questions on socioeconomic characteristics such as age, gender, educational background, and income levels.

We recruited 44 participants (mean age=28 years, SD=4) from the general population of Kiel, Germany, through online advertisements. All subjects gave written informed consent and could decide to discontinue participation at any time. The risk task consisted of 200 consecutive trials. In each trial, participants were offered a 50/50 gamble that involved a potential gain and a potential loss. Across lotteries, we manipulated the potential gain and loss (range of gains: +1 EUR to +20 EUR; range of losses –1 EUR to –10 EUR; both in 1 Euro steps). Participants could accept or reject the offered lottery by pressing a button (left or right arrow) but could not execute their final gambling choices during the first three seconds that a lottery was displayed. Subjects received immediate feedback about the outcome of a lottery if it was accepted. During the experiment, subjects were notified when they reached the 67th and 133rd trial and subsequently rested for 30 seconds before they continued with the experiment. The order of the lotteries and the arrangement of the payoff boxes and decision buttons on the screen were randomized for each participant.

Figure A1. Sequence of events and screens for one round of lottery gambling by time



Notes: Sequence of events and screens for one round of lottery gambling by time (seconds). All of the pictures of the screens are displayed in correct proportions.

The first picture (left) shows a fixation cross and indicates that a lottery will be shown soon. The second picture shows the newly offered lottery for three seconds (pre-decision phase). The third picture shows the arrows that must be pressed to accept or reject the previously displayed lottery for a maximum of ten seconds in the decision phase. After a decision has been executed, the realized outcome is displayed; for rejected gambles, the fourth screen is omitted.

At the beginning of the experiment, subjects were seated in front of a 24" computer screen with a resolution of 1920 x 1080 (Acer XB240H), and different sensors were attached to their bodies. First, subjects were asked to place their heads in the corresponding headrest to adjust the eye-tracking sensors (Tobii Pro X2-30; Tobii AB) for recording gaze focus and pupils' sizes via infrared light reflected by the cornea. Then, the remaining sensors were placed to assess different physiological signals with a 16-channel bioamplifier (Nexus-16; Mind Media B.V.).[1] At first, a breast strap was attached to the thorax to assess breathing movement. Skin conductance was measured using two disposable electrodes that were attached to the distal phalange of the index and middle fingers of the non-dominant hand. Blood volume pulse (BVP) was measured using a photoplethysmographic sensor placed at the annular finger. Heart rate (HR) is computed from the BVP raw signal by detecting and counting the peaks of the BVP waveform to determine the inter-beat interval. A thermistor was taped to the auricular finger to monitor skin temperature. Blood volume pulse was sampled with 128 Hz, and eye movements and pupil size were sampled at a rate of 30 Hz. All remaining CPD was recorded with 32 Hz. We used the software package Psychtoolbox-3 implemented in MATLAB R2016a (MathWorks Inc., United States) to present the visual stimuli. The software used to record, process, filter, and remove artifacts from the raw CPD signals are Biotrace (Mind Media B.V.), Ledalab, Tobii Pro Eye Tracker Manager, and Tobii Pro SDK (Tobii AB).

The lottery gambling experiment started after we ensured a successful calibration of all sensors. The first screen was a welcome page. Again, subjects were presented with concise instructions for the lottery gambling experiment. Then, subjects were asked to start the experiment by pressing the space-bar and deciding on three test trials. After subjects were asked if they had any remaining questions, they were shielded from acoustic disturbances with ear protectors, and the actual experiment started. After deciding on 200 lottery trials, the experiment was finished, sensors were removed, and subjects received their final payouts.

All subjects started with an endowment of 10 EUR. At the end of the experiment, one trial was randomly selected for the final payout. If the subject rejected the selected lottery, she kept the initial endowment of 10 EUR. If the subject accepted the lottery, its outcome was realized and added to [subtracted from] the initial endowment in the case of a win [loss] outcome.

2.2 Data cleaning and variable specifications

From the total sample of 8800 observations, we discard the first five lottery decision for each of the 44 subjects because we include information on preceding choices and outcomes. We also exclude

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[1] The bioamplifier and corresponding software make use of bandpass filters and noise reduction functions (e.g., rectification and smoothing), and automatically amplify the recorded physiological signals to maximize their informational content.

an additional 82 observations because of missing eye-tracking data, which can occur when the recording device loses track of the eyes. The cleaned dataset includes 8498 records.

In Table A1, we present the variables' empirical specifications by predictor-set and groups, together with distributional summary statistics. Moreover, whereas the P and A predictor-sets do not contain any information related to lottery design variables, such as displayed win and loss values, we note for A that we implicitly include the side of the computer screen (left vs. right) on which a lottery's win and loss values are displayed in specifying subjects' lookup patterns.

Table A1. Predictor variable specifications and summary statistics

Variable	Predictor-set	Variable group	Description	Min	Max	Mean	SD
played	Outcome	Economic decision	Played vs. not played (binary)	0	1	0.47	0.5
win_value	LSG, LSGPA	Win and loss values (L)	Potential win (EUR)	1	20	10.49	5.77
loss_value	LSG, LSGPA	Win and loss values (L)	Potential loss (EUR)	-10	-1	-5.51	2.86
neg_exp_value	LSG, LSGPA	Win and loss values (L)	Expected value < 0	0	1	0.23	0.42
trial	LSG, LSGPA	Trial (L)	Lottery trial (numeric)	6	200	102.79	56.18
trial_D1_1_67	LSG, LSGPA	Trial (L)	Lottery trial 1 to 67 (binary)	0	1	0.32	0.47
trial_D2_68_133*	LSG, LSGPA	Trial (L)	Lottery trial 68 to 133 (binary)	0	1	0.34	0.47
trial_D3_134_200	LSG, LSGPA	Trial (L)	Lottery trial 134 to 200 (binary)	0	1	0.34	0.47
win_right	LSG, LSGPA	Left vs. right (L)	Potential win is displayed on the right box (binary)	0	1	0.5	0.5
accept_right	LSG, LSGPA	Left vs. right (L)	Accept by pressing the right arrow (binary)	0	1	0.49	0.5
quali_D1_abi*	LSG, LSGPA	Socioeconomic (S)	Highest education: A-levels (binary)	0	1	0.43	0.5
quali_D2_bach	LSG, LSGPA	Socioeconomic (S)	Highest education: Bachelor (binary)	0	1	0.25	0.43
quali_D3_real	LSG, LSGPA	Socioeconomic (S)	Highest education: GCSE (binary)	0	1	0.11	0.32
quali_D4_master	LSG, LSGPA	Socioeconomic (S)	Highest education: Master or similar degree (binary)	0	1	0.16	0.36
quali_D5_fachabi	LSG, LSGPA	Socioeconomic (S)	Highest education: "Fachabitur" (binary)	0	1	0.04	0.2
educ_D1_psy*	LSG, LSGPA	Socioeconomic (S)	Educational background: Psychology (binary)	0	1	0.16	0.36
educ_D2_eco	LSG, LSGPA	Socioeconomic (S)	Educational background: Economics/Business (binary)	0	1	0.16	0.36
educ_D3_na	LSG, LSGPA	Socioeconomic (S)	Educational background: NA (binary)	0	1	0.09	0.29
educ_D4_other	LSG, LSGPA	Socioeconomic (S)	Educational background: Other (binary)	0	1	0.59	0.49
income_D1	LSG, LSGPA	Socioeconomic (S)	Income level <= 800 EUR (binary)	0	1	0.36	0.48
income_D2*	LSG, LSGPA	Socioeconomic (S)	Income level > 800 EUR & < 1200 EUR (binary)	0	1	0.41	0.49
income_D3**	LSG, LSGPA	Socioeconomic (S)	Income level >= 1200 EUR (binary)	0	1	0.23	0.42
female_D1	LSG, LSGPA	Socioeconomic (S)	Gender: Male vs. Female (binary)	0	1	0.46	0.5
age_D1_19_25	LSG, LSGPA	Socioeconomic (S)	Age group: 19 to 25 years (binary)	0	1	0.32	0.47
age_D2_26_32*	LSG, LSGPA	Socioeconomic (S)	Age group: 26 to 32 years (binary)	0	1	0.57	0.49
age_D3_33_39	LSG, LSGPA	Socioeconomic (S)	Age group: 33 to 39 years (binary)	0	1	0.11	0.31
played_lag_1*	LSG, LSGPA	Gambling behavior (G)	lagged 1 played (binary)	0	1	0.48	0.5

Variable	Predictor-set	Variable group	Description	Min	Max	Mean	SD
played_lag_1_2	LSG, LSGPA	Gambling behavior (G)	lagged 1 x 2 played (binary)	0	1	0.25	0.43
played_lag_1_2_3	LSG, LSGPA	Gambling behavior (G)	lagged 1 x 2 x 3 played (binary)	0	1	0.14	0.35
played_lag_1_2_3_4	LSG, LSGPA	Gambling behavior (G)	lagged 1 x 2 x 3 x 4 played (binary)	0	1	0.09	0.28
played_lag_1_2_3_4_5	LSG, LSGPA	Gambling behavior (G)	lagged 1 x 2 x 3 x 4 x 5 played (binary)	0	1	0.06	0.23
lag1_pos_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 1 positive outcome: played & won money (binary)	0	1	0.23	0.42
lag2_pos_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 2 positive outcome: played & won money (binary)	0	1	0.23	0.42
lag3_pos_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 3 positive outcome: played & won money (binary)	0	1	0.23	0.42
lag4_pos_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 4 positive outcome: played & won money (binary)	0	1	0.23	0.42
lag5_pos_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 5 positive outcome: played & won money (binary)	0	1	0.23	0.42
lag1_neg_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 1 negative outcome: played & lost money (binary)	0	1	0.24	0.43
lag2_neg_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 2 negative outcome: played & lost money (binary)	0	1	0.24	0.43
lag3_neg_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 3 negative outcome: played & lost money (binary)	0	1	0.24	0.43
lag4_neg_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 4 negative outcome: played & lost money (binary)	0	1	0.24	0.43
lag5_neg_outcome	LSG, LSGPA	Gambling behavior (G)	Lag 5 negative outcome: played & lost money (binary)	0	1	0.25	0.43
TTP_nSCR	P, LSGPA	Skin conductance (P) SCR	No. of significant skin conductance responses (SCRs) (integer)	0	3	0.38	0.53
TTP_AmpSum	P, LSGPA	Skin conductance (P) SCR	Sum of the significant SCR amplitudes (microsiemens)	0	3.95	0.1	0.27
BVP_max	P, LSGPA	Blood volume pulse (P)	Blood volume pulse: maximum (relative (%) changes)	-13.9	221.43	76.8	38.25
BVP_min	P, LSGPA	Blood volume pulse (P)	Blood volume pulse: minimum (relative (%) changes)	-153.23	-14.61	-49.87	21.15
BVP_mean	P, LSGPA	Blood volume pulse (P)	Blood volume pulse: mean (relative (%) changes)	-46.89	1.14	-16.66	9.46
BVP_delta**	P, LSGPA	Blood volume pulse (P)	Difference BVP min and max (relative (%) changes)	19.03	347.05	126.67	55.23
BVP_Amp_max	P, LSGPA	Blood volume pulse (P)	Blood volume pulse amplitude: maximum (millivolts)	14.33	247.1	104.19	43.74
BVP_Amp_min	P, LSGPA	Blood volume pulse (P)	Blood volume pulse amplitude: minimum (millivolts)	11.68	210.87	83.9	37.01
BVP_Amp_mean	P, LSGPA	Blood volume pulse (P)	Blood volume pulse amplitude: mean (millivolts)	13.36	229.88	94.16	40.47
BVP_Amp_delta**	P, LSGPA	Blood volume pulse (P)	Difference BVP amplitude max and min (millivolts)	1.23	85.29	20.3	10.03
RSD_max	P, LSGPA	Respiration (P)	Respiration depth: mean (mm)	910.29	1236.95	1065.77	69.31
RSD_min	P, LSGPA	Respiration (P)	Respiration depth: minimum (mm)	900.72	1223.58	1051.48	68.4
RSD_mean	P, LSGPA	Respiration (P)	Respiration depth: maximum (mm)	904.86	1230.71	1057.35	68.69
RSD_delta**	P, LSGPA	Respiration (P)	Difference: RSD max and min (mm)	0.8	124.09	14.29	10.92
RSP_rate_max	P, LSGPA	Respiration (P)	Respiration rate: maximum (breathes per min)	4.45	60	20.5	7.64
RSP_rate_min	P, LSGPA	Respiration (P)	Respiration rate: minimum (breathes per min)	4.28	58.18	16.12	4.46

Variable	Predictor-set	Variable group	Description	Min	Max	Mean	SD
RSP_rate_mean	P, LSGPA	Respiration (P)	Respiration rate: mean (breathes per min)	4.45	58.18	18.32	5.6
RSP_rate_delta**	P, LSGPA	Respiration (P)	Difference: RSP rate max and min (breathes per min)	0	48.47	4.38	6.66
HR_max	P, LSGPA	Heart rate (P)	Heart rate: maximum (beats per min)	48.01	128.01	83.56	12.42
HR_min	P, LSGPA	Heart rate (P)	Heart rate: minimum (beats per min)	42.67	123.87	76.74	11.78
HR_mean	P, LSGPA	Heart rate (P)	Heart rate: mean (beats per min)	46.66	125.91	80.18	12.07
HR_delta**	P, LSGPA	Heart rate (P)	Difference: Heart rate max and min (beats per min)	0	39.1	6.82	4.07
Temp_max	P, LSGPA	Body temperature (P)	Finger temperature: maximum (°C)	32.02	36.78	35.81	0.65
Temp_min	P, LSGPA	Body temperature (P)	Finger temperature: minimum (°C)	32.02	36.77	35.8	0.65
Temp_mean	P, LSGPA	Body temperature (P)	Finger temperature: mean (°C)	32.02	36.77	35.81	0.65
Temp_delta**	P, LSGPA	Body temperature (P)	Difference: Finger temperature max and min (°C)	0	0.14	0.01	0.01
t1_pupil_avg_lr_min	P, LSGPA	Pupil size (P)	Average pupil size: minimum (mm)	1.36	3.97	2.48	0.35
t1_pupil_avg_lr_max	P, LSGPA	Pupil size (P)	Average pupil size: maximum (mm)	2.27	6.43	3.06	0.36
t1_pupil_avg_lr_mean	P, LSGPA	Pupil size (P)	Average pupil size: mean (mm)	1.95	4.11	2.77	0.33
t1_delta_pupil_avg_lr**	P, LSGPA	Pupil size (P)	Average pupil size: difference max min (mm)	0.17	4.4	0.58	0.26
t1_time_none	A, LSGPA	Gaze (A)	Time not spent on fixating boxes (sec)	0.03	2.82	1.06	0.57
t1_time_win	A, LSGPA	Gaze (A)	Time spent on fixating win (sec)	0.03	2.73	0.94	0.54
left_box_first	A, LSGPA	Gaze (A)	First box looked at: left box (vs. right box) (binary)	0	1	0.73	0.44
win_box_first	A, LSGPA	Gaze (A)	First box looked at: win box (vs. loss box) (binary)	0	1	0.55	0.5
nr_switches	A, LSGPA	Gaze (A)	Number of times switched between boxes (integer)	1	7	2.36	1

Notes: Summary statistics are computed on the basis of the cleaned data sample that includes 8498 observations. We include subject-specific dummy variables in all predictor-sets that we evaluate in our forecasting analyses (summary statistics omitted for brevity). Initially, we specify 119 predictor variables and encode factor variables as dummy variables. To this end, we exclude the most frequently observed level for each category as corresponding reference groups (indicated with *). This encoding results in a total number of 112 predictors (36 numeric and 76 binary variables). ** indicates variables that we omit in our regression analyses because of multi-collinearity. For our forecasting analyses, we use QR decomposition to control for multi-collinearity issues with respect to each of the individual four predictor-sets. Furthermore, the number of significant skin conductance response peaks (amplitude threshold of ≥ 0.01 microsiemens) and the sum of their amplitudes are computed from standard trough-to-peak (TTP) analysis (details can be found on www.ledalab.de).

3 Descriptive analysis

In this section, we provide the detailed results of our descriptive analyses that are omitted from the main text for brevity.

3.1 Gambling choices and lottery pay off structure

Tables A2, A3, and A4 show the frequencies of the absolute and relative numbers of played lotteries by lotteries' win and loss values, as well as by win-loss and expected value combinations. We find that the propensity to accept a displayed lottery increases for larger win values; conversely, the propensity to accept a gamble decreases as the loss value increases. The mean difference in the predicted probabilities derived from estimating simple logistic regressions of the playing decision on the displayed win [loss] value across all lotteries is 3.63% [–7.63%] per one Euro increase. Hence, the absolute magnitude of the effect of a one Euro increase in the loss value on accepting a lottery is more than twice as large (in absolute terms) as the effect of a one Euro increase in the win value. Similarly, we find that subjects' propensity to accept a displayed lottery increases with its EV. The corresponding mean difference in predicted probabilities from a simple logistic regression for a one Euro increase in a lottery's EV is 7.26%.

Table A2. Cross-tabulation for gambling decision by lotteries' win and loss values

Variable	Played (=1) x Negative expected value (=1)						
	0.0	1.0	% played	0.1	1.1	% played	Total
Win							
1	29 (1.1%)	15 (0.4%)	34.1%	376 (20.2%)	20 (16.4%)	5.1%	440 (5.0%)
2	57 (2.1%)	31 (0.8%)	35.2%	330 (17.8%)	22 (18.0%)	6.3%	440 (5.0%)
3	81 (2.9%)	51 (1.3%)	38.6%	292 (15.7%)	16 (13.1%)	5.2%	440 (5.0%)
4	109 (4.0%)	67 (1.6%)	38.1%	246 (13.2%)	18 (14.8%)	6.8%	440 (5.0%)
5	123 (4.5%)	97 (2.4%)	44.1%	207 (11.1%)	13 (10.7%)	5.9%	440 (5.0%)
6	135 (4.9%)	129 (3.2%)	48.9%	164 (8.8%)	12 (9.8%)	6.8%	440 (5.0%)
7	165 (6.0%)	143 (3.5%)	46.4%	122 (6.6%)	10 (8.2%)	7.6%	440 (5.0%)
8	191 (6.9%)	161 (4.0%)	45.7%	83 (4.5%)	5 (4.1%)	5.7%	440 (5.0%)
9	205 (7.5%)	191 (4.7%)	48.2%	38 (2.0%)	6 (4.9%)	13.6%	440 (5.0%)
10	214 (7.8%)	226 (5.6%)	51.4%	0 (0.0%)	0 (0.0%)		440 (5.0%)
11	208 (7.6%)	232 (5.7%)	52.7%	0 (0.0%)	0 (0.0%)		440 (5.0%)
12	191 (6.9%)	249 (6.1%)	56.6%	0 (0.0%)	0 (0.0%)		440 (5.0%)
13	165 (6.0%)	275 (6.8%)	62.5%	0 (0.0%)	0 (0.0%)		440 (5.0%)
14	157 (5.7%)	283 (7.0%)	64.3%	0 (0.0%)	0 (0.0%)		440 (5.0%)
15	142 (5.2%)	298 (7.3%)	67.7%	0 (0.0%)	0 (0.0%)		440 (5.0%)
16	141 (5.1%)	299 (7.3%)	68.0%	0 (0.0%)	0 (0.0%)		440 (5.0%)
17	125 (4.5%)	315 (7.7%)	71.6%	0 (0.0%)	0 (0.0%)		440 (5.0%)
18	120 (4.4%)	320 (7.9%)	72.7%	0 (0.0%)	0 (0.0%)		440 (5.0%)
19	105 (3.8%)	335 (8.2%)	76.1%	0 (0.0%)	0 (0.0%)		440 (5.0%)
20	88 (3.2%)	352 (8.7%)	80.0%	0 (0.0%)	0 (0.0%)		440 (5.0%)
Loss							
-10	344 (12.5%)	140 (3.4%)	28.9%	370 (19.9%)	26 (21.3%)	6.6%	880 (10.0%)
-9	377 (13.7%)	151 (3.7%)	28.6%	338 (18.2%)	14 (11.5%)	4.0%	880 (10.0%)
-8	366 (13.3%)	206 (5.1%)	36.0%	288 (15.5%)	20 (16.4%)	6.5%	880 (10.0%)
-7	365 (13.3%)	251 (6.2%)	40.7%	249 (13.4%)	15 (12.3%)	5.7%	880 (10.0%)
-6	341 (12.4%)	319 (7.8%)	48.3%	204 (11.0%)	16 (13.1%)	7.3%	880 (10.0%)
-5	253 (9.2%)	451 (11.1%)	64.1%	172 (9.3%)	4 (3.3%)	2.3%	880 (10.0%)
-4	215 (7.8%)	533 (13.1%)	71.3%	125 (6.7%)	7 (5.7%)	5.3%	880 (10.0%)
-3	187 (6.8%)	605 (14.9%)	76.4%	74 (4.0%)	14 (11.5%)	15.9%	880 (10.0%)
-2	175 (6.4%)	661 (16.2%)	79.1%	38 (2.0%)	6 (4.9%)	13.6%	880 (10.0%)
-1	128 (4.7%)	752 (18.5%)	85.5%	0 (0.0%)	0 (0.0%)		880 (10.0%)
N	2751	4069		1858	122		8800

Notes: Share of played lotteries by win and loss values. Each of the 44 subjects decided on 200 lotteries: 155 with positive expected values and 45 with negative expected values.

Table A3. Cross-tabulation for expected values and corresponding share of played lotteries

Expected value	Not played	Played	% played	Total
-4.5	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
-4	83 (1.8%)	5 (0.1%)	5.7%	88 (1.0%)
-3.5	127 (2.8%)	5 (0.1%)	3.8%	132 (1.5%)
-3	170 (3.7%)	6 (0.1%)	3.4%	176 (2.0%)
-2.5	210 (4.6%)	10 (0.2%)	4.5%	220 (2.5%)
-2	251 (5.4%)	13 (0.3%)	4.9%	264 (3.0%)
-1.5	292 (6.3%)	16 (0.4%)	5.2%	308 (3.5%)
-1	324 (7.0%)	28 (0.7%)	8.0%	352 (4.0%)
-0.5	358 (7.8%)	38 (0.9%)	9.6%	396 (4.5%)
0	354 (7.7%)	86 (2.1%)	19.5%	440 (5.0%)
0.5	347 (7.5%)	93 (2.2%)	21.1%	440 (5.0%)
1	311 (6.7%)	129 (3.1%)	29.3%	440 (5.0%)
1.5	286 (6.2%)	154 (3.7%)	35.0%	440 (5.0%)
2	245 (5.3%)	195 (4.7%)	44.3%	440 (5.0%)
2.5	219 (4.8%)	221 (5.3%)	50.2%	440 (5.0%)
3	196 (4.3%)	244 (5.8%)	55.5%	440 (5.0%)
3.5	166 (3.6%)	274 (6.5%)	62.3%	440 (5.0%)
4	140 (3.0%)	300 (7.2%)	68.2%	440 (5.0%)
4.5	129 (2.8%)	311 (7.4%)	70.7%	440 (5.0%)
5	107 (2.3%)	333 (7.9%)	75.7%	440 (5.0%)
5.5	93 (2.0%)	303 (7.2%)	76.5%	396 (4.5%)
6	58 (1.3%)	294 (7.0%)	83.5%	352 (4.0%)
6.5	40 (0.9%)	268 (6.4%)	87.0%	308 (3.5%)
7	26 (0.6%)	238 (5.7%)	90.2%	264 (3.0%)
7.5	14 (0.3%)	206 (4.9%)	93.6%	220 (2.5%)
8	12 (0.3%)	164 (3.9%)	93.2%	176 (2.0%)
8.5	4 (0.1%)	128 (3.1%)	97.0%	132 (1.5%)
9	2 (0.0%)	86 (2.1%)	97.7%	88 (1.0%)
9.5	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
N	4609 (100%)	4191 (100%)		8800 (100%)

Notes: Share of played lotteries by win and loss values. Each of the 44 subjects decided on 200 lotteries: 155 with positive expected values and 45 with negative expected values.

Table A4. Cross-tabulations for win and loss value combinations and corresponding share of played lotteries

Win X Loss	Not played	Played	% played	Total
1.-10	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
2.-10	40 (0.9%)	4 (0.1%)	9.1%	44 (0.5%)
3.-10	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
4.-10	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
5.-10	40 (0.9%)	4 (0.1%)	9.1%	44 (0.5%)
6.-10	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
7.-10	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
8.-10	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
9.-10	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
10.-10	40 (0.9%)	4 (0.1%)	9.1%	44 (0.5%)
11.-10	39 (0.8%)	5 (0.1%)	11.4%	44 (0.5%)
12.-10	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
13.-10	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
14.-10	34 (0.7%)	10 (0.2%)	22.7%	44 (0.5%)
15.-10	31 (0.7%)	13 (0.3%)	29.5%	44 (0.5%)
16.-10	27 (0.6%)	17 (0.4%)	38.6%	44 (0.5%)
17.-10	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
18.-10	24 (0.5%)	20 (0.5%)	45.5%	44 (0.5%)
19.-10	24 (0.5%)	20 (0.5%)	45.5%	44 (0.5%)
20.-10	21 (0.5%)	23 (0.5%)	52.3%	44 (0.5%)
1.-9	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
2.-9	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
3.-9	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
4.-9	44 (1.0%)	0 (0.0%)	0.0%	44 (0.5%)
5.-9	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
6.-9	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
7.-9	40 (0.9%)	4 (0.1%)	9.1%	44 (0.5%)
8.-9	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
9.-9	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
10.-9	39 (0.8%)	5 (0.1%)	11.4%	44 (0.5%)
11.-9	36 (0.8%)	8 (0.2%)	18.2%	44 (0.5%)
12.-9	36 (0.8%)	8 (0.2%)	18.2%	44 (0.5%)
13.-9	36 (0.8%)	8 (0.2%)	18.2%	44 (0.5%)
14.-9	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
15.-9	32 (0.7%)	12 (0.3%)	27.3%	44 (0.5%)
16.-9	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
17.-9	26 (0.6%)	18 (0.4%)	40.9%	44 (0.5%)
18.-9	26 (0.6%)	18 (0.4%)	40.9%	44 (0.5%)
19.-9	22 (0.5%)	22 (0.5%)	50.0%	44 (0.5%)
20.-9	20 (0.4%)	24 (0.6%)	54.5%	44 (0.5%)
1.-8	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
2.-8	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
3.-8	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
4.-8	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
5.-8	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
6.-8	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
7.-8	40 (0.9%)	4 (0.1%)	9.1%	44 (0.5%)
8.-8	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
9.-8	37 (0.8%)	7 (0.2%)	15.9%	44 (0.5%)
10.-8	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
11.-8	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
12.-8	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
13.-8	28 (0.6%)	16 (0.4%)	36.4%	44 (0.5%)
14.-8	35 (0.8%)	9 (0.2%)	20.5%	44 (0.5%)
15.-8	28 (0.6%)	16 (0.4%)	36.4%	44 (0.5%)
16.-8	24 (0.5%)	20 (0.5%)	45.5%	44 (0.5%)
17.-8	20 (0.4%)	24 (0.6%)	54.5%	44 (0.5%)
18.-8	21 (0.5%)	23 (0.5%)	52.3%	44 (0.5%)

Win X Loss	Not played	Played	% played	Total
19.-8	17 (0.4%)	27 (0.6%)	61.4%	44 (0.5%)
20.-8	14 (0.3%)	30 (0.7%)	68.2%	44 (0.5%)
1.-7	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
2.-7	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
3.-7	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
4.-7	39 (0.8%)	5 (0.1%)	11.4%	44 (0.5%)
5.-7	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
6.-7	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
7.-7	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
8.-7	37 (0.8%)	7 (0.2%)	15.9%	44 (0.5%)
9.-7	37 (0.8%)	7 (0.2%)	15.9%	44 (0.5%)
10.-7	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
11.-7	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
12.-7	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
13.-7	23 (0.5%)	21 (0.5%)	47.7%	44 (0.5%)
14.-7	22 (0.5%)	22 (0.5%)	50.0%	44 (0.5%)
15.-7	20 (0.4%)	24 (0.6%)	54.5%	44 (0.5%)
16.-7	25 (0.5%)	19 (0.5%)	43.2%	44 (0.5%)
17.-7	16 (0.3%)	28 (0.7%)	63.6%	44 (0.5%)
18.-7	19 (0.4%)	25 (0.6%)	56.8%	44 (0.5%)
19.-7	19 (0.4%)	25 (0.6%)	56.8%	44 (0.5%)
20.-7	10 (0.2%)	34 (0.8%)	77.3%	44 (0.5%)
1.-6	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
2.-6	41 (0.9%)	3 (0.1%)	6.8%	44 (0.5%)
3.-6	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
4.-6	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
5.-6	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
6.-6	36 (0.8%)	8 (0.2%)	18.2%	44 (0.5%)
7.-6	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
8.-6	36 (0.8%)	8 (0.2%)	18.2%	44 (0.5%)
9.-6	36 (0.8%)	8 (0.2%)	18.2%	44 (0.5%)
10.-6	29 (0.6%)	15 (0.4%)	34.1%	44 (0.5%)
11.-6	29 (0.6%)	15 (0.4%)	34.1%	44 (0.5%)
12.-6	27 (0.6%)	17 (0.4%)	38.6%	44 (0.5%)
13.-6	20 (0.4%)	24 (0.6%)	54.5%	44 (0.5%)
14.-6	16 (0.3%)	28 (0.7%)	63.6%	44 (0.5%)
15.-6	15 (0.3%)	29 (0.7%)	65.9%	44 (0.5%)
16.-6	12 (0.3%)	32 (0.8%)	72.7%	44 (0.5%)
17.-6	14 (0.3%)	30 (0.7%)	68.2%	44 (0.5%)
18.-6	13 (0.3%)	31 (0.7%)	70.5%	44 (0.5%)
19.-6	11 (0.2%)	33 (0.8%)	75.0%	44 (0.5%)
20.-6	9 (0.2%)	35 (0.8%)	79.5%	44 (0.5%)
1.-5	44 (1.0%)	0 (0.0%)	0.0%	44 (0.5%)
2.-5	44 (1.0%)	0 (0.0%)	0.0%	44 (0.5%)
3.-5	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
4.-5	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
5.-5	34 (0.7%)	10 (0.2%)	22.7%	44 (0.5%)
6.-5	35 (0.8%)	9 (0.2%)	20.5%	44 (0.5%)
7.-5	31 (0.7%)	13 (0.3%)	29.5%	44 (0.5%)
8.-5	32 (0.7%)	12 (0.3%)	27.3%	44 (0.5%)
9.-5	24 (0.5%)	20 (0.5%)	45.5%	44 (0.5%)
10.-5	21 (0.5%)	23 (0.5%)	52.3%	44 (0.5%)
11.-5	19 (0.4%)	25 (0.6%)	56.8%	44 (0.5%)
12.-5	9 (0.2%)	35 (0.8%)	79.5%	44 (0.5%)
13.-5	9 (0.2%)	35 (0.8%)	79.5%	44 (0.5%)
14.-5	7 (0.2%)	37 (0.9%)	84.1%	44 (0.5%)
15.-5	5 (0.1%)	39 (0.9%)	88.6%	44 (0.5%)
16.-5	9 (0.2%)	35 (0.8%)	79.5%	44 (0.5%)
17.-5	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
18.-5	6 (0.1%)	38 (0.9%)	86.4%	44 (0.5%)
19.-5	5 (0.1%)	39 (0.9%)	88.6%	44 (0.5%)

Win X Loss	Not played	Played	% played	Total
20.-5	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
1.-4	42 (0.9%)	2 (0.0%)	4.5%	44 (0.5%)
2.-4	43 (0.9%)	1 (0.0%)	2.3%	44 (0.5%)
3.-4	40 (0.9%)	4 (0.1%)	9.1%	44 (0.5%)
4.-4	35 (0.8%)	9 (0.2%)	20.5%	44 (0.5%)
5.-4	32 (0.7%)	12 (0.3%)	27.3%	44 (0.5%)
6.-4	26 (0.6%)	18 (0.4%)	40.9%	44 (0.5%)
7.-4	28 (0.6%)	16 (0.4%)	36.4%	44 (0.5%)
8.-4	22 (0.5%)	22 (0.5%)	50.0%	44 (0.5%)
9.-4	14 (0.3%)	30 (0.7%)	68.2%	44 (0.5%)
10.-4	7 (0.2%)	37 (0.9%)	84.1%	44 (0.5%)
11.-4	10 (0.2%)	34 (0.8%)	77.3%	44 (0.5%)
12.-4	7 (0.2%)	37 (0.9%)	84.1%	44 (0.5%)
13.-4	7 (0.2%)	37 (0.9%)	84.1%	44 (0.5%)
14.-4	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
15.-4	5 (0.1%)	39 (0.9%)	88.6%	44 (0.5%)
16.-4	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
17.-4	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
18.-4	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
19.-4	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
20.-4	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
1.-3	39 (0.8%)	5 (0.1%)	11.4%	44 (0.5%)
2.-3	35 (0.8%)	9 (0.2%)	20.5%	44 (0.5%)
3.-3	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
4.-3	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
5.-3	31 (0.7%)	13 (0.3%)	29.5%	44 (0.5%)
6.-3	17 (0.4%)	27 (0.6%)	61.4%	44 (0.5%)
7.-3	15 (0.3%)	29 (0.7%)	65.9%	44 (0.5%)
8.-3	14 (0.3%)	30 (0.7%)	68.2%	44 (0.5%)
9.-3	10 (0.2%)	34 (0.8%)	77.3%	44 (0.5%)
10.-3	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
11.-3	6 (0.1%)	38 (0.9%)	86.4%	44 (0.5%)
12.-3	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
13.-3	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
14.-3	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
15.-3	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
16.-3	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
17.-3	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
18.-3	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
19.-3	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
20.-3	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
1.-2	38 (0.8%)	6 (0.1%)	13.6%	44 (0.5%)
2.-2	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
3.-2	33 (0.7%)	11 (0.3%)	25.0%	44 (0.5%)
4.-2	23 (0.5%)	21 (0.5%)	47.7%	44 (0.5%)
5.-2	20 (0.4%)	24 (0.6%)	54.5%	44 (0.5%)
6.-2	13 (0.3%)	31 (0.7%)	70.5%	44 (0.5%)
7.-2	8 (0.2%)	36 (0.9%)	81.8%	44 (0.5%)
8.-2	9 (0.2%)	35 (0.8%)	79.5%	44 (0.5%)
9.-2	6 (0.1%)	38 (0.9%)	86.4%	44 (0.5%)
10.-2	5 (0.1%)	39 (0.9%)	88.6%	44 (0.5%)
11.-2	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
12.-2	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
13.-2	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
14.-2	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
15.-2	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
16.-2	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
17.-2	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
18.-2	4 (0.1%)	40 (1.0%)	90.9%	44 (0.5%)
19.-2	1 (0.0%)	43 (1.0%)	97.7%	44 (0.5%)
20.-2	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)

Win X Loss	Not played	Played	% played	Total
1.-1	29 (0.6%)	15 (0.4%)	34.1%	44 (0.5%)
2.-1	24 (0.5%)	20 (0.5%)	45.5%	44 (0.5%)
3.-1	15 (0.3%)	29 (0.7%)	65.9%	44 (0.5%)
4.-1	18 (0.4%)	26 (0.6%)	59.1%	44 (0.5%)
5.-1	6 (0.1%)	38 (0.9%)	86.4%	44 (0.5%)
6.-1	8 (0.2%)	36 (0.9%)	81.8%	44 (0.5%)
7.-1	7 (0.2%)	37 (0.9%)	84.1%	44 (0.5%)
8.-1	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
9.-1	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
10.-1	0 (0.0%)	44 (1.0%)	100.0%	44 (0.5%)
11.-1	1 (0.0%)	43 (1.0%)	97.7%	44 (0.5%)
12.-1	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
13.-1	1 (0.0%)	43 (1.0%)	97.7%	44 (0.5%)
14.-1	3 (0.1%)	41 (1.0%)	93.2%	44 (0.5%)
15.-1	1 (0.0%)	43 (1.0%)	97.7%	44 (0.5%)
16.-1	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
17.-1	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
18.-1	0 (0.0%)	44 (1.0%)	100.0%	44 (0.5%)
19.-1	0 (0.0%)	44 (1.0%)	100.0%	44 (0.5%)
20.-1	2 (0.0%)	42 (1.0%)	95.5%	44 (0.5%)
N	4609 (100%)	4191 (100%)		8800 (100%)

Notes: Share of played lotteries by win and loss value combinations. Each of the 44 subjects decided on 200 lotteries: 155 with positive expected values and 45 with negative expected values.

3.2 Gambling choices and socioeconomic characteristics

In Tables A5 and A6, we show the frequencies and shares of played lotteries by socioeconomic characteristics across all lotteries and individually for NEVL and PEVL. We find that the group of relatively older subjects plays a larger share of lotteries than the two groups of relatively younger subjects (51.7% vs. 46.8% and 47.7%). Specifically, comparing gambling behavior across NEVL and PEVL reveals that the oldest group of subjects plays a substantially larger share of NEVL than the younger groups (18.2% vs. 3.2% and 5.4%).

Regarding differences between the share of accepted lotteries with respect to subjects' educational backgrounds, we find that subjects with a psychological educational background play the smallest share of lotteries (41.2%) and, moreover, accept a significantly lower share of NEVL than the other groups (0.3% vs. 7.6%, 7.2%, and 7.2%). Concerning differences in gambling behavior across groups of subjects with different highest degrees, we find that subjects with A levels ("Abitur") play the relative largest share of lotteries, whereas subjects with "Fachabitur" play the lowest share of lotteries (49.9% vs. 38.0%). Furthermore, we find that subjects with A levels play the largest share of PEVL (62.5%), and subjects with "Fachabitur" play the smallest share of PEVL (48.7%) and NEVL (1.1% vs. 6.1%, 6.3%, and 7.6%).

Although we do not find large differences between the share of accepted lotteries among the three income groups across all lotteries (47.6% vs. 48.8% vs. 45.6%), the group of subjects with the highest relative income plays the smallest share of PEVL (56.4 vs. 60.1% and 61.1%) but the largest share of NEVL (8.2% vs. 6.4% and 4.6%). Hence, for NEVL [PEVL], we find a positive [negative] correlation between income and the share of accepted lotteries. Because a large intersection exists between income and age groups, the differences in risk taking between lower and higher income levels are similar to the differences between younger and older subjects.

Last, we do not find a significant difference between the mean share of accepted lotteries by men (48.3%) and women (46.8%) but find women to play around 50% more NEVL than men (5.0% vs. 7.6%) and men to play slightly less PEVL than women (58.2% vs. 60.9%).

Table A5. Frequency table for specified socioeconomic characteristics by gambling decision

Variable	Not played	Played	% played	All	p-value
Gender					0.170
Male	2482 (53.9%)	2318 (55.3%)	48.3%	4800 (54.5%)	
Female	2127 (46.1%)	1873 (44.7%)	46.8%	4000 (45.5%)	
Age					0.017
19-25 years	1464 (31.8%)	1336 (31.9%)	47.7%	2800 (31.8%)	
26-32 years	2662 (57.8%)	2338 (55.8%)	46.8%	5000 (56.8%)	
33-39 years	483 (10.5%)	517 (12.3%)	51.7%	1000 (11.4%)	
Income					0.068
<=800 EUR	1676 (36.4%)	1524 (36.4%)	47.6%	3200 (36.4%)	
801-1200 EUR	1844 (40.0%)	1756 (41.9%)	48.8%	3600 (40.9%)	
>1200 EUR	1089 (23.6%)	911 (21.7%)	45.6%	2000 (22.7%)	
Educational Background					< 0.001
Psychology	823 (17.9%)	577 (13.8%)	41.2%	1400 (15.9%)	
Economics	705 (15.3%)	695 (16.6%)	49.6%	1400 (15.9%)	
NA	319 (6.9%)	481 (11.5%)	60.1%	800 (9.1%)	
Other	2762 (59.9%)	2438 (58.2%)	46.9%	5200 (59.1%)	
Highest degree					< 0.001
A levels	1905 (41.3%)	1895 (45.2%)	49.9%	3800 (43.2%)	
Bachelor	1133 (24.6%)	1067 (25.5%)	48.5%	2200 (25.0%)	
GCSE	506 (11.0%)	494 (11.8%)	49.4%	1000 (11.4%)	
Master	817 (17.7%)	583 (13.9%)	41.6%	1400 (15.9%)	
Fachabitur	248 (5.4%)	152 (3.6%)	38.0%	400 (4.5%)	
N	4609	4191		8800	

Notes: Share of played lotteries by subjects' socioeconomic characteristics and lotteries' expected values (EV). Each of the 44 subjects decided on 200 lotteries: 155 with positive EVs and 45 with negative EVs. Reported p-values correspond to chi-square association tests.

Table A6. Frequency table for socioeconomic characteristics by lottery decision and lotteries' expected values

Variable	Played (=1) x Negative expected value lottery (=1)						
	0.0	1.0	% played	0.1	1.1	% played	All
Gender							0.015
Male	1456 (52.9%)	2264 (55.6%)	60.9%	1026 (55.2%)	54 (44.3%)	5.0%	4800 (54.5%)
Female	1295 (47.1%)	1805 (44.4%)	58.2%	832 (44.8%)	68 (55.7%)	7.6%	4000 (45.5%)
Age							< 0.001
19-25 years	854 (31.0%)	1316 (32.3%)	60.6%	610 (32.8%)	20 (16.4%)	3.2%	2800 (31.8%)
26-32 years	1598 (58.1%)	2277 (56.0%)	58.8%	1064 (57.3%)	61 (50.0%)	5.4%	5000 (56.8%)
23-39 years	299 (10.9%)	476 (11.7%)	61.4%	184 (9.9%)	41 (33.6%)	18.2%	1000 (11.4%)
Income							0.014
<=800 EUR	989 (36.0%)	1491 (36.6%)	60.1%	687 (37.0%)	33 (27.0%)	4.6%	3200 (36.4%)
801-1200 EUR	1086 (39.5%)	1704 (41.9%)	61.1%	758 (40.8%)	52 (42.6%)	6.4%	3600 (40.9%)
>1200 EUR	676 (24.6%)	874 (21.5%)	56.4%	413 (22.2%)	37 (30.3%)	8.2%	2000 (22.7%)
Educ. background							< 0.001
Psychology	509 (18.5%)	576 (14.2%)	53.1%	314 (16.9%)	1 (0.8%)	0.3%	1400 (15.9%)
Economics	414 (15.0%)	671 (16.5%)	61.8%	291 (15.7%)	24 (19.7%)	7.6%	1400 (15.9%)
NA	152 (5.5%)	468 (11.5%)	75.5%	167 (9.0%)	13 (10.7%)	7.2%	800 (9.1%)
Other	1676 (60.9%)	2354 (57.9%)	58.4%	1086 (58.4%)	84 (68.9%)	7.2%	5200 (59.1%)
Highest degree							< 0.001
A levels	1104 (40.1%)	1841 (45.2%)	62.5%	801 (43.1%)	54 (44.3%)	6.3%	3800 (43.2%)
Bachelor	668 (24.3%)	1037 (25.5%)	60.8%	465 (25.0%)	30 (24.6%)	6.1%	2200 (25.0%)
GCSE	298 (10.8%)	477 (11.7%)	61.5%	208 (11.2%)	17 (13.9%)	7.6%	1000 (11.4%)
Master	522 (19.0%)	563 (13.8%)	51.9%	295 (15.9%)	20 (16.4%)	6.3%	1400 (15.9%)
"Fachabitur"	159 (5.8%)	151 (3.7%)	48.7%	89 (4.8%)	1 (0.8%)	1.1%	400 (4.5%)
N	2751	4069		1858	122		8800

Notes: Share of played lotteries by subjects' socioeconomic characteristics and lotteries' expected values (EV). Each of the 44 subjects decided on 200 lotteries: 155 with positive EVs and 45 with negative EVs. Reported p-values correspond to chi-square association tests.

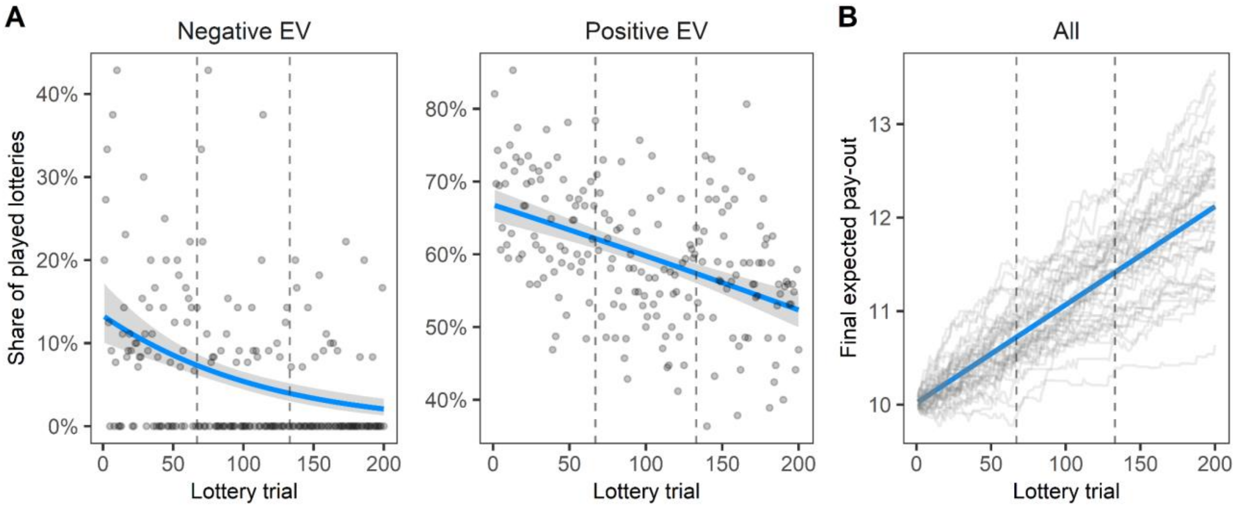
3.3 Sequential choices and gambling outcomes

In the following section, we conduct a descriptive analysis of the impact of previous gambling decisions and their outcomes on subjects' subsequent gambling behavior.

Panel A in Figure A2 shows the mean share of accepted NEVL and PEVL by lottery trial and highlights that subjects' willingness to gamble decreases as the experiment progresses; the mean difference in predicted probabilities derived from regressing the gambling decision on lottery trial is –0.066%. The corresponding mean difference for playing NEVL [PEVL] is –0.056% [–0.072%]. Panel B shows subjects' individual expected final payoffs with respect to all 200 lottery decisions, incorporating all previously accepted and non-accepted gambles and their corresponding outcomes at each lottery trial, and assuming that all subsequent lotteries are rejected. Whereas subjects' gambling activity substantially decreases in the course of the experiment, all subjects could increase their final expected payoffs to exceed the initial 10 Euro endowment. The mean expected final payoff after the 200th trial is 12.12 EUR, the overall minimum is 9.77 EUR, and the overall maximum is 13.58 EUR.

Furthermore, playing all PEVL and no NEVL would have maximized the (expected) final expected payout with 12.91 EUR.

Figure A2. Expected payout and relative share of subjects that played lotteries by trial



Notes: Panel A shows the mean share of played positive and negative expected value (EV) lotteries across subjects by lottery trial. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 with EV≥0 and 45 with EV<0. Panel B shows subjects' expected final payouts (solid gray lines) with respect to all 200 lottery decisions, including all previous choices and outcomes at each lottery trial, and assuming that all subsequent lotteries are rejected. Solid black lines correspond to weighted logistic (panel A) and linear (panel B) regression curves. 95% confidence intervals are indicated by gray-shaded areas. Dashed lines indicate the 67th and 133rd trials.

3.3.1 Last previous choice

First, we tabulate the last gambling decision and its outcome by the current gambling decisions and the share of accepted lotteries across all lotteries in Table A7.

On average, after having accepted [rejected] the last lottery, subjects tend to accept [reject] the next consecutive lottery as well; the corresponding share of accepted lotteries is 51.9% [43.5%]. Depending on the outcome of previously accepted gambles, the corresponding share ranges from 78.6% (1 EUR) to 48.6% (20 EUR) for prior gains and from 50.4% (–1 EUR) to 67.9% (–10 EUR) for prior losses. On the one hand, in line with the break-even and house-money effects, subjects are more inclined to gamble after a prior loss or win than after a prior lottery rejection. On the other hand, in contrast to prior losses or small to moderate wins, large prior wins appear to decrease the willingness to accept the next gamble beyond 50%.

Table A7. Cross-tabulation for the share of accepted gambles by last gambling choice and outcome

Variable	Not played	Played	% played	All
Last choice				
Not played	2588 (56.3%)	1992 (47.9%)	43.5%	4580 (52.3%)
Played	2010 (43.7%)	2166 (52.1%)	51.9%	4176 (47.7%)
Last Outcome				
-10	27 (0.6%)	57 (1.4%)	67.9%	84 (1.0%)
-9	30 (0.7%)	46 (1.1%)	60.5%	76 (0.9%)
-8	44 (1.0%)	65 (1.6%)	59.6%	109 (1.2%)
-7	61 (1.3%)	66 (1.6%)	52.0%	127 (1.5%)
-6	74 (1.6%)	83 (2.0%)	52.9%	157 (1.8%)
-5	106 (2.3%)	141 (3.4%)	57.1%	247 (2.8%)
-4	141 (3.1%)	147 (3.5%)	51.0%	288 (3.3%)
-3	153 (3.3%)	164 (3.9%)	51.7%	317 (3.6%)
-2	169 (3.7%)	175 (4.2%)	50.9%	344 (3.9%)
-1	193 (4.2%)	196 (4.7%)	50.4%	389 (4.4%)
1	3 (0.1%)	11 (0.3%)	78.6%	14 (0.2%)
2	7 (0.2%)	11 (0.3%)	61.1%	18 (0.2%)
3	15 (0.3%)	18 (0.4%)	54.5%	33 (0.4%)
4	11 (0.2%)	33 (0.8%)	75.0%	44 (0.5%)
5	18 (0.4%)	29 (0.7%)	61.7%	47 (0.5%)
6	45 (1.0%)	35 (0.8%)	43.8%	80 (0.9%)
7	34 (0.7%)	35 (0.8%)	50.7%	69 (0.8%)
8	41 (0.9%)	45 (1.1%)	52.3%	86 (1.0%)
9	35 (0.8%)	53 (1.3%)	60.2%	88 (1.0%)
10	46 (1.0%)	60 (1.4%)	56.6%	106 (1.2%)
11	65 (1.4%)	56 (1.3%)	46.3%	121 (1.4%)
12	48 (1.0%)	53 (1.3%)	52.5%	101 (1.2%)
13	66 (1.4%)	68 (1.6%)	50.7%	134 (1.5%)
14	62 (1.3%)	71 (1.7%)	53.4%	133 (1.5%)
15	78 (1.7%)	66 (1.6%)	45.8%	144 (1.6%)
16	86 (1.9%)	70 (1.7%)	44.9%	156 (1.8%)
17	85 (1.8%)	72 (1.7%)	45.9%	157 (1.8%)
18	82 (1.8%)	77 (1.9%)	48.4%	159 (1.8%)
19	94 (2.0%)	77 (1.9%)	45.0%	171 (2.0%)
20	91 (2.0%)	86 (2.1%)	48.6%	177 (2.0%)
Not played	2588 (56.3%)	1992 (47.9%)	43.5%	4580 (52.3%)
N	4598	4158		8756

Notes: This table reports the share of played lotteries, and absolute and relative frequencies for the last and current gambling choices. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV ≥ 0) and 45 negative expected value lotteries (NEVL). We exclude the first observation for assessing the impact of the last previous gambling decision, resulting in 8756 observations.

To further assess the impact of the last lottery decision and outcome, we first use simple logistic regression models to estimate the effect of having played the last lottery and the effect of an increase of one Euro for previous wins and previous losses on the probability to accept the lottery under a decision. Regarding the impact of having played the last previous lottery, the difference in predicted probabilities derived from a fitted logistic model equals 8.37%. Specifically, the logistic regression results suggest that having played the previous lottery (out of 199 possible lotteries decisions) on average increases a subject's propensity to accept the current lottery under a decision from 43.49% to 51.86%. Concerning the outcomes of the set of last previous lotteries played, the mean difference in predicted probabilities for a previous win is –0.81% per one Euro increase in the previous gain and –1.34% per one Euro increase in the previous loss.

A different picture emerges when distinguishing between the impacts of previously played lotteries with positive and negative EVs. For previously accepted NEVL, the mean difference in predicted probabilities derived from a fitted logistic regression model equals 1.15% per a one Euro increase in the win value for positive outcomes and –2.22% per a one Euro increase in the loss value for NEVL with negative outcomes. Conversely, for previously played PEVL, the corresponding mean difference is –0.66% for positive outcomes and –1.00% for negative outcomes. Hence, in general, having won or lost a large amount in the last previous lottery decreases a subject's propensity to reject the next consecutive lottery. For PEVL, the impact of previously accepted lotteries with negative outcomes is approximately one-third higher than for previously accepted PEVL with positive outcomes. In contrast, higher loss values of previously accepted NEVL with positive outcomes appear to increase a subject's propensity to accept the next offered lottery.

Our findings suggest that having previously won unfavorable lotteries with large potential losses seems to foster consecutive gambling activity. However, why subjects appear to engage in such gambling behavior is unclear. This phenomenon may be attributed to the resulting excitement and arousal experienced by winning NEVL. In contrast, a decreased propensity to gamble after a large loss may be attributed to negative emotions in reaction to losing and regretting the previous gamble. In line with this potential explanation, the effect of lost NEVL is approximately twice as large as the effect of lost PEVL.

3.3.2 Gambling and non-gambling streaks

Next, we report the detailed results for analyzing the impact of previous gambling and non-gambling streaks on subsequent gambling behavior. In this context, we note that we do not include the last lottery decision (200th trial) for calculating the number of playing and outcome streaks because we are interested in assessing the impact of gambling and outcome streaks on the next consecutive gambling decision. Similarly, we do not include the first lottery decision (1st trial) to evaluate the impact of previous decisions on the next consecutive gambling choices.

First, in Tables A8 and A9, we cross-tabulate the number of gambling streaks by the next consecutive lottery decision on the basis of all lotteries and separately for NEVL and PEVL.

Table A8. Cross-tabulation for the share of played lotteries by playing streaks

Variable	Not played	Played	% played	All	p-value
Gambling Streak (num)	0.87 (1.44)	1.31 (2.00)		1.08 (1.75)	< 0.001
Gambling Streak					< 0.001
0	2608 (56.6%)	2036 (48.6%)	43.8%	4644 (52.8%)	
1	1074 (23.3%)	944 (22.5%)	46.8%	2018 (22.9%)	
2	454 (9.9%)	485 (11.6%)	51.7%	939 (10.7%)	
3	238 (5.2%)	246 (5.9%)	50.8%	484 (5.5%)	
4	91 (2.0%)	154 (3.7%)	62.9%	245 (2.8%)	
5	53 (1.1%)	101 (2.4%)	65.6%	154 (1.8%)	
6	31 (0.7%)	70 (1.7%)	69.3%	101 (1.1%)	
7	21 (0.5%)	49 (1.2%)	70.0%	70 (0.8%)	
8	17 (0.4%)	32 (0.8%)	65.3%	49 (0.6%)	
9	11 (0.2%)	21 (0.5%)	65.6%	32 (0.4%)	
10	11 (0.2%)	53 (1.3%)	82.8%	64 (0.7%)	
N	4609	4191		8800	

Notes: This table reports the mean and standard deviations (in brackets) as well as the share of played lotteries, absolute and relative frequencies for playing streaks by gambling decision. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV ≥ 0) and 45 negative expected value lotteries (NEVL), resulting in 8800 observations. Reported p-values correspond to chi-square association tests for multilevel factor variables and Kruskal-Wallis tests for numeric variables.

Table A9. Cross-tabulation for playing streaks by gambling decision and lotteries' expected value

Gambling	Played (=1) X Negative expected value lottery (=1)						
Streak	0.0	1.0	% played	0.1	1.1	% played	All
Numeric	0.78 (1.31)	1.28 (1.96)		1.00 (1.61)	2.53 (2.91)		1.08 (1.75)
Factor							
0	1607 (58.4%)	2001 (49.2%)	55.5%	1001 (53.9%)	35 (28.7%)	3.4%	4644 (52.8%)
1	642 (23.3%)	917 (22.5%)	58.8%	432 (23.3%)	27 (22.1%)	5.9%	2018 (22.9%)
2	269 (9.8%)	468 (11.5%)	63.5%	185 (10.0%)	17 (13.9%)	8.4%	939 (10.7%)
3	124 (4.5%)	233 (5.7%)	65.3%	114 (6.1%)	13 (10.7%)	10.2%	484 (5.5%)
4	49 (1.8%)	149 (3.7%)	75.3%	42 (2.3%)	5 (4.1%)	10.6%	245 (2.8%)
5	21 (0.8%)	97 (2.4%)	82.2%	32 (1.7%)	4 (3.3%)	11.1%	154 (1.8%)
6	12 (0.4%)	64 (1.6%)	84.2%	19 (1.0%)	6 (4.9%)	24.0%	101 (1.1%)
7	9 (0.3%)	46 (1.1%)	83.6%	12 (0.6%)	3 (2.5%)	20.0%	70 (0.8%)
8	10 (0.4%)	29 (0.7%)	74.4%	7 (0.4%)	3 (2.5%)	30.0%	49 (0.6%)
9	5 (0.2%)	19 (0.5%)	79.2%	6 (0.3%)	2 (1.6%)	25.0%	32 (0.4%)
10	3 (0.1%)	46 (1.1%)	93.9%	8 (0.4%)	7 (5.7%)	46.7%	64 (0.7%)
N	2751	4069		1858	122		8800

Notes: This table reports the mean and standard deviation (in brackets) as well as the share of played lotteries, absolute and relative frequencies for playing streaks by gambling decision and lotteries' expected values (positive vs. negative). The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV ≥ 0) and 45 negative expected value lotteries (NEVL), resulting in 8800 observations.

Table A8 indicates that, on average, subjects' propensity to play lotteries increases with the number of consecutive accepted lotteries, i.e., playing more lotteries in a sequence increases the probability of extending a gambling streak. The corresponding mean difference in predicted probabilities derived from fitting a simple logistic regression model is 3.41%. Table A9 shows that this pattern also holds true when distinguishing between the impact of gambling streaks on playing NEVL and PEVL; the corresponding mean differences in predicted probabilities for one additional played game within a streak for playing NEVL is 4.36% and, thus, slightly higher than the corresponding mean difference of 3.23% for playing PEVL.

Next, in Tables A10 and A11, we present the cross-tabulations for the number of non-gambling streaks by the next consecutive lottery decision on the basis of all lotteries and separately for NEVL and PEVL. Similar to the results of gambling streaks, subjects' propensity to reject the next lottery increases with the number of previously rejected consecutive lotteries. In general, our results reflect subjects' stronger inclination to play PEVL than NEVL. The corresponding mean differences in predicted probabilities derived from separate logistic regressions for playing the next consecutive lottery are –2.73% (all lotteries), –0.62% (NEVL), and –3.39% (PEVL).

Table A10. Cross-tabulation for the share of played lotteries by non-playing streaks

Variable	Not played	Played	% played	All	p-value
Non-playing streak (num)	1.52 (2.29)	1.05 (1.66)		1.30 (2.03)	< 0.001
Non-playing streak					< 0.001
0	2035 (44.2%)	2207 (52.7%)	52.0%	4242 (48.2%)	
1	1052 (22.8%)	954 (22.8%)	47.6%	2006 (22.8%)	
2	583 (12.6%)	462 (11.0%)	44.2%	1045 (11.9%)	
3	341 (7.4%)	239 (5.7%)	41.2%	580 (6.6%)	
4	207 (4.5%)	132 (3.1%)	38.9%	339 (3.9%)	
5	126 (2.7%)	77 (1.8%)	37.9%	203 (2.3%)	
6	76 (1.6%)	49 (1.2%)	39.2%	125 (1.4%)	
7	46 (1.0%)	29 (0.7%)	38.7%	75 (0.9%)	
8	31 (0.7%)	15 (0.4%)	32.6%	46 (0.5%)	
9	24 (0.5%)	7 (0.2%)	22.6%	31 (0.4%)	
10	17 (0.4%)	7 (0.2%)	29.2%	24 (0.3%)	
11	10 (0.2%)	7 (0.2%)	41.2%	17 (0.2%)	
12	9 (0.2%)	1 (0.0%)	10.0%	10 (0.1%)	
13	52 (1.1%)	5 (0.1%)	8.8%	57 (0.6%)	
N	4609	4191		8800	

Notes: This table reports the mean and standard deviation (in brackets) as well as the share of played lotteries, absolute and relative frequencies for non-playing streaks by gambling decision. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV ≥ 0) and 45 negative expected value lotteries (NEVL), resulting in 8800 observations. Reported p-values correspond to chi-square association tests for individual multilevel factor variables and Kruskal-Wallis tests for numeric variables.

Table A11. Cross-tabulation for non-playing streaks by gambling decision and lotteries' expected value

Non-playing streak	Played (=1) x Negative expected value lottery (=1)						
	0.0	1.0	% played	0.1	1.1	% played	All
Numeric	1.64 (2.42)	1.07 (1.66)		1.34 (2.07)	0.63 (1.63)		1.30 (2.03)
Factor							
0	1165 (42.3%)	2118 (52.1%)	64.5%	870 (46.8%)	89 (73.0%)	9.3%	4242 (48.2%)
1	616 (22.4%)	937 (23.0%)	60.3%	436 (23.5%)	17 (13.9%)	3.8%	2006 (22.8%)
2	362 (13.2%)	454 (11.2%)	55.6%	221 (11.9%)	8 (6.6%)	3.5%	1045 (11.9%)
3	221 (8.0%)	236 (5.8%)	51.6%	120 (6.5%)	3 (2.5%)	2.4%	580 (6.6%)
4	123 (4.5%)	131 (3.2%)	51.6%	84 (4.5%)	1 (0.8%)	1.2%	339 (3.9%)
5	79 (2.9%)	76 (1.9%)	49.0%	47 (2.5%)	1 (0.8%)	2.1%	203 (2.3%)
6	50 (1.8%)	48 (1.2%)	49.0%	26 (1.4%)	1 (0.8%)	3.7%	125 (1.4%)
7	36 (1.3%)	28 (0.7%)	43.8%	10 (0.5%)	1 (0.8%)	9.1%	75 (0.9%)
8	21 (0.8%)	15 (0.4%)	41.7%	10 (0.5%)	0 (0.0%)	0.0%	46 (0.5%)
9	16 (0.6%)	7 (0.2%)	30.4%	8 (0.4%)	0 (0.0%)	0.0%	31 (0.4%)
10	10 (0.4%)	7 (0.2%)	41.2%	7 (0.4%)	0 (0.0%)	0.0%	24 (0.3%)
11	6 (0.2%)	7 (0.2%)	53.8%	4 (0.2%)	0 (0.0%)	0.0%	17 (0.2%)
12	7 (0.3%)	1 (0.0%)	12.5%	2 (0.1%)	0 (0.0%)	0.0%	10 (0.1%)
13	39 (1.4%)	4 (0.1%)	9.3%	13 (0.7%)	1 (0.8%)	7.1%	57 (0.6%)
N	2751	4069		1858	122		8800

Notes: This table reports the mean and standard deviation (in brackets) as well as the share of played lotteries, absolute and relative frequencies for non-playing streaks by gambling decision and lotteries' expected values (positive vs. negative). The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV ≥ 0) and 45 negative expected value lotteries (NEVL), resulting in 8800 observations.

3.3.3 Gambling streaks with only negative and positive outcomes

In the next step of our analysis of sequential gambling decisions, we analyze the cross-tabulations for gambling streaks with only negative and positive outcomes by subsequent lottery decisions across all lotteries and separately for NEVL and PEVL in Tables A12 and A13, respectively. We find that both gambling streaks with only positive or negative outcomes increase subjects' propensity to accept the next consecutive lottery. The mean difference in the predicted probabilities derived from logistic regressions for playing a lottery per one additional played game in a previous playing streak with positive [negative] outcomes is 2.96% [4.55%]. The corresponding mean difference for playing PEVL is 3.14% [4.42%] and for playing NEVL is 2.63% [6.20%]. Hence, these findings are in line with two frequently reported cognitive biases: the hot hand effect of gambling streaks with positive outcomes and the gambler's fallacy for gambling streaks with negative outcomes. Moreover, the effect of playing NEVL after gambling streaks with only positive or only negative outcomes is larger than the corresponding effects for playing PEVL.

Table A12. Cross-tabulation for the share of played lotteries by streaks of played lotteries with positive and negative outcomes

Variable	Not played	Played	% played	All	p-value
PO streak (num)	0.28 (0.60)	0.33 (0.67)		0.30 (0.64)	0.003
PO streak					0.002
0	3598 (78.1%)	3170 (75.6%)	46.8%	6768 (76.9%)	
1	802 (17.4%)	758 (18.1%)	48.6%	1560 (17.7%)	
2	150 (3.3%)	196 (4.7%)	56.6%	346 (3.9%)	
3	49 (1.1%)	46 (1.1%)	48.4%	95 (1.1%)	
4	7 (0.2%)	14 (0.3%)	66.7%	21 (0.2%)	
5	3 (0.1%)	7 (0.2%)	70.0%	10 (0.1%)	
NO streak (num)	0.28 (0.62)	0.38 (0.76)		0.33 (0.69)	< 0.001
NO streak					< 0.001
0	3611 (78.3%)	3051 (72.8%)	45.8%	6662 (75.7%)	
1	754 (16.4%)	824 (19.7%)	52.2%	1578 (17.9%)	
2	191 (4.1%)	219 (5.2%)	53.4%	410 (4.7%)	
3	45 (1.0%)	66 (1.6%)	59.5%	111 (1.3%)	
4	5 (0.1%)	19 (0.5%)	79.2%	24 (0.3%)	
5	2 (0.0%)	5 (0.1%)	71.4%	7 (0.1%)	
6	0 (0.0%)	4 (0.1%)	100.0%	4 (0.0%)	
7	0 (0.0%)	2 (0.0%)	100.0%	2 (0.0%)	
8	1 (0.0%)	1 (0.0%)	50.0%	2 (0.0%)	
N	4609	4191		8800	

Notes: This table reports the mean and standard deviations (in brackets) as well as the share of played lotteries, absolute and relative frequencies for playing-outcome by gambling decision. We consider positive outcome (PO) streaks and negative outcome (NO) streaks. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV ≥ 0) and 45 negative expected value lotteries (NEVL), resulting in 8800 observations. Reported p-values correspond to chi-square association tests for multilevel factor variables and Kruskal-Wallis tests for numeric variables.

Table A13. Cross-tabulation for the share of played negative and positive expected value lotteries by streaks of played lotteries with positive and negative outcomes

Outcome	Played (=1) x Negative expected value lottery (=1)						
Streak	0.0	1.0	% played	0.1	1.1	% played	All
Pos. (num)	0.27 (0.58)	0.33 (0.67)		0.30 (0.64)	0.43 (0.77)		0.30 (0.64)
Pos							
0	2152 (78.2%)	3086 (75.8%)	58.9%	1446 (77.8%)	84 (68.9%)	5.5%	6768 (76.9%)
1	491 (17.8%)	730 (17.9%)	59.8%	311 (16.7%)	28 (23.0%)	8.3%	1560 (17.7%)
2	77 (2.8%)	190 (4.7%)	71.2%	73 (3.9%)	6 (4.9%)	7.6%	346 (3.9%)
3	27 (1.0%)	43 (1.1%)	61.4%	22 (1.2%)	3 (2.5%)	12.0%	95 (1.1%)
4	3 (0.1%)	13 (0.3%)	81.3%	4 (0.2%)	1 (0.8%)	20.0%	21 (0.2%)
5	1 (0.0%)	7 (0.2%)	87.5%	2 (0.1%)	0 (0.0%)	0.0%	10 (0.1%)
Neg. (num)	0.25 (0.57)	0.38 (0.76)		0.33 (0.67)	0.57 (0.83)		0.33 (0.69)
Pos							
0	2202 (80.0%)	2978 (73.2%)	57.5%	1409 (75.8%)	73 (59.8%)	4.9%	6662 (75.7%)
1	429 (15.6%)	790 (19.4%)	64.8%	325 (17.5%)	34 (27.9%)	9.5%	1578 (17.9%)
2	95 (3.5%)	210 (5.2%)	68.9%	96 (5.2%)	9 (7.4%)	8.6%	410 (4.7%)
3	21 (0.8%)	60 (1.5%)	74.1%	24 (1.3%)	6 (4.9%)	20.0%	111 (1.3%)
4	2 (0.1%)	19 (0.5%)	90.5%	3 (0.2%)	0 (0.0%)	0.0%	24 (0.3%)
5	2 (0.1%)	5 (0.1%)	71.4%	0 (0.0%)	0 (0.0%)		7 (0.1%)
6	0 (0.0%)	4 (0.1%)	100.0%	0 (0.0%)	0 (0.0%)		4 (0.0%)
7	0 (0.0%)	2 (0.0%)	100.0%	0 (0.0%)	0 (0.0%)		2 (0.0%)
8	0 (0.0%)	1 (0.0%)	100.0%	1 (0.1%)	0 (0.0%)	0.0%	2 (0.0%)
N	2751	4069		1858	122		8800

Notes: This table reports the mean and standard deviations (in brackets) as well as the share of played lotteries, absolute and relative frequencies for playing-outcome streaks specified as factor variable by gambling decision. We consider positive outcome (PO) streaks and negative outcome (NO) streaks. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 positive expected value lotteries (PEVL) (EV $\geq$ 0) and 45 negative expected value lotteries (NEVL), resulting in 8800 observations.

3.4 Gambling choices, lottery design, and eye movements

Table A14 shows a cross-tabulation for gambling decisions, the share of played lotteries by lookup patterns metrics, and the arrangement of lotteries' payoff and decision boxes across all lotteries.

Table A14. Cross-tabulation for gambling decisions by measures of visual attention and lottery display variables

Variable	Level	Not played	Played	% played	Total	p-value
Time win	Numeric	1.006 (0.576)	1.117 (0.573)		1.059 (0.577)	< 0.001
Time loss	Numeric	0.986 (0.572)	0.876 (0.512)		0.934 (0.547)	< 0.001
Time none	Numeric	7.008 (0.645)	7.007 (0.630)		7.007 (0.638)	0.6
Left box first	0	1160 (25.9%)	1138 (28.4%)	49.5%	2298 (27.0%)	0.01
	1	3324 (74.1%)	2876 (71.6%)	46.4%	6200 (73.0%)	
Win box first	0	2061 (46.0%)	1729 (43.1%)	45.6%	3790 (44.6%)	0.007
	1	2423 (54.0%)	2285 (56.9%)	48.5%	4708 (55.4%)	
LBF x WBF	0.0	497 (11.1%)	429 (10.7%)	46.3%	926 (10.9%)	0.002
	1.0	1564 (34.9%)	1300 (32.4%)	45.4%	2864 (33.7%)	
	0.1	663 (14.8%)	709 (17.7%)	51.7%	1372 (16.1%)	
	1.1	1760 (39.3%)	1576 (39.3%)	47.2%	3336 (39.3%)	
Win right	0	2257 (50.3%)	2005 (50.0%)	47.0%	4262 (50.2%)	0.724
	1	2227 (49.7%)	2009 (50.0%)	47.4%	4236 (49.8%)	
Accept right	0	2233 (49.8%)	2036 (50.7%)	47.7%	4269 (50.2%)	0.395
	1	2251 (50.2%)	1978 (49.3%)	46.8%	4229 (49.8%)	
WR x AR	0.0	1101 (24.6%)	1045 (26.0%)	48.7%	2146 (25.3%)	0.121
	1.0	1132 (25.2%)	991 (24.7%)	46.7%	2123 (25.0%)	
	0.1	1156 (25.8%)	960 (23.9%)	45.4%	2116 (24.9%)	
	1.1	1095 (24.4%)	1018 (25.4%)	48.2%	2113 (24.9%)	
Left box last	0	2557 (57.0%)	2299 (57.3%)	47.3%	4856 (57.1%)	0.816
	1	1927 (43.0%)	1715 (42.7%)	47.1%	3642 (42.9%)	
Win box last	0	2264 (50.5%)	1685 (42.0%)	42.7%	3949 (46.5%)	< 0.001
	1	2220 (49.5%)	2329 (58.0%)	51.2%	4549 (53.5%)	
LBL x WBL	0.0	1320 (29.4%)	1002 (25.0%)	43.2%	2322 (27.3%)	< 0.001
	1.0	944 (21.1%)	683 (17.0%)	42.0%	1627 (19.1%)	
	0.1	1237 (27.6%)	1297 (32.3%)	51.2%	2534 (29.8%)	
	1.1	983 (21.9%)	1032 (25.7%)	51.2%	2015 (23.7%)	
Box switches (num)	Numeric	2.269 (1.050)	2.366 (1.032)		2.315 (1.042)	< 0.001
Box switches	1	980 (21.9%)	776 (19.3%)	44.2%	1756 (20.7%)	< 0.001
	2	1684 (37.6%)	1461 (36.4%)	46.5%	3145 (37.0%)	
	3	1167 (26.0%)	1200 (29.9%)	50.7%	2367 (27.9%)	
	4	470 (10.5%)	429 (10.7%)	47.7%	899 (10.6%)	
	5-7	183 (4.1%)	148 (3.7%)	44.7%	331 (3.9%)	
N		4484	4014		8498	

Notes: Our experiment includes 44 subjects that each decided on 200 lotteries: 155 with positive expected values (PEVL) and 45 with negative expected values (NEVL), resulting in 8800 observations. The presented statistics are computed on the basis of the cleaned data sample that comprises 8498 observations (see Section 2.2). Reported p-values correspond to chi-square association tests for binary variables and Kruskal-Wallis tests for numeric variables.

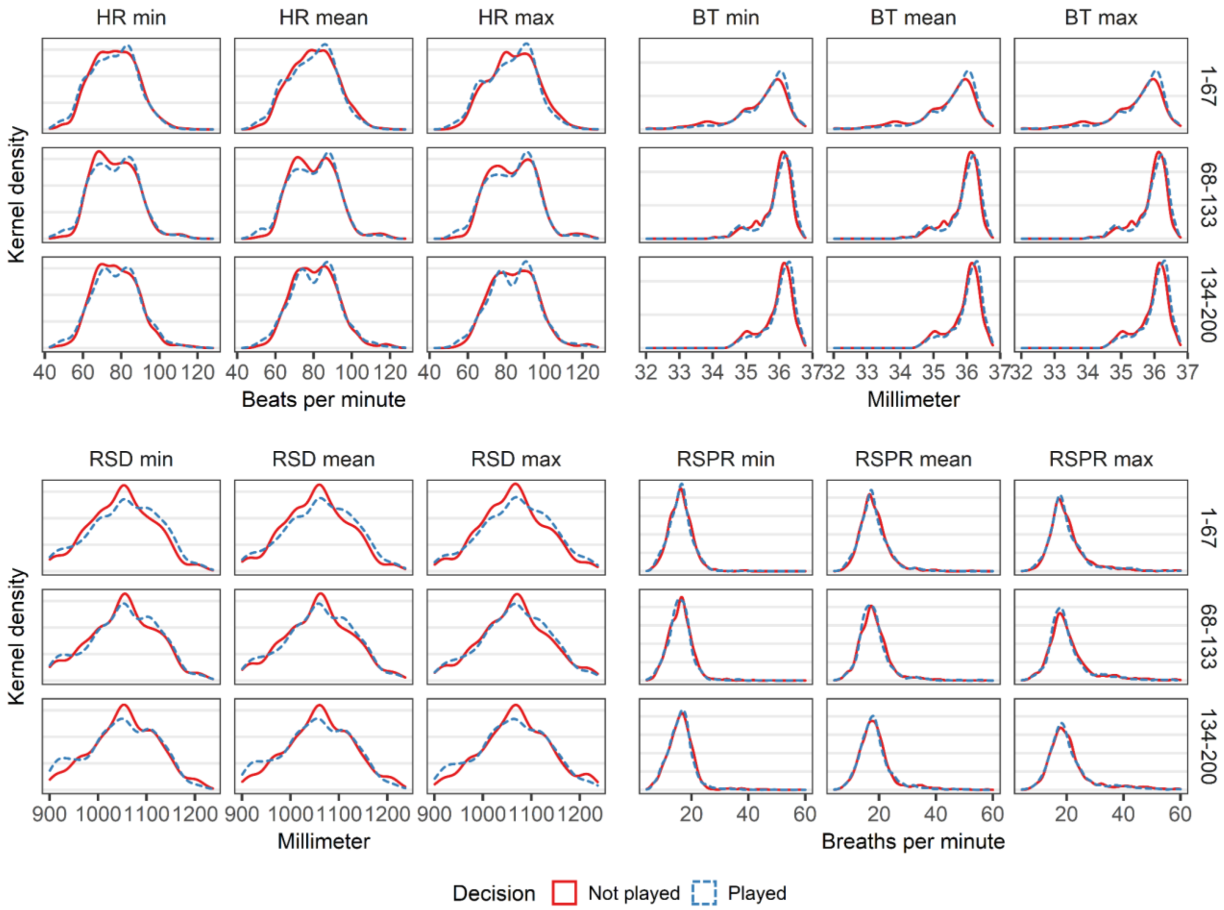
On average, subjects spent more time looking at the win [loss] value when accepting [rejecting] a displayed lottery. In contrast, the time that subjects do not look at the two payoff boxes is not significantly different for accepted and rejected lotteries. With respect to differences in the sequence of lookup patterns, subjects first look at the left payoff box in 73.0% of all trials and accept 48.5%

[45.6%] of the trials during which they first looked at the win [loss]. Hence, the information on which side of the screen the win box is displayed also captures information on subjects' tendency to play a higher share of lotteries for which they first looked at the win box. However, no evidence exists for a simple left-hand-side bias. We find subjects that play the highest share of lotteries for games in which the win value is displayed at the right box, and subjects first looked at the win box (51.7% vs. 47.2%, 46.3%, 45.4%). Moreover, although subjects accept 51.2% [42.7%] of the trials during which they looked last at the win [loss] box and 51.2% [42.7%] of the trials during which they last looked at the left [right] box, they look last at the win [left] box in 51.2% [47.1%] of all trials. In this context, subjects switched between looking at the win and loss boxes 2-3 times in approximately 67% of all trials.

3.5 Gambling choices and psychophysiological reactions

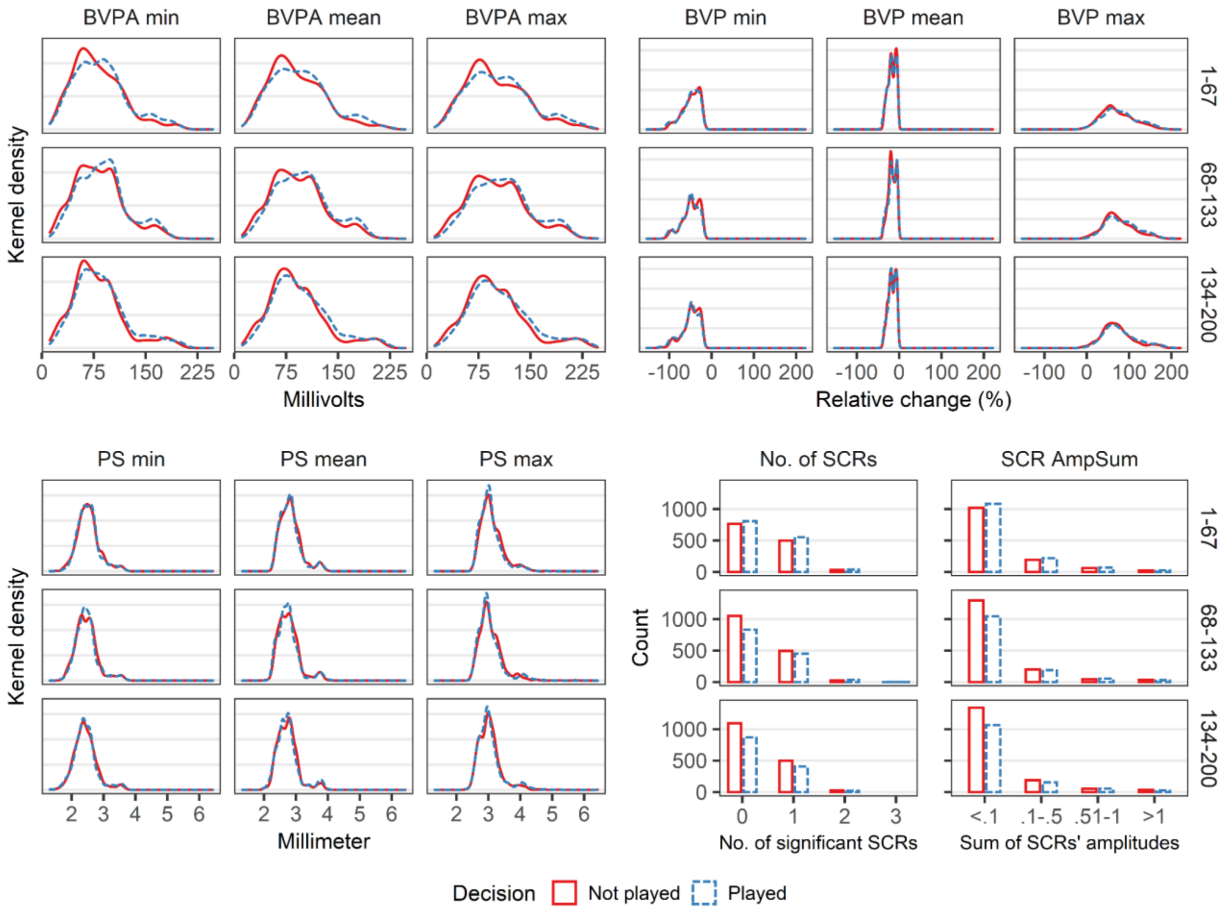
Figures A3 and A4 show kernel density estimates and absolute frequencies for CPD type-specific minimum, mean, and maximum values by lottery trial for accepted and rejected lotteries. A casual inspection of Figures A3 and A4 show relevant differences in SCPM distributions between accepted and rejected lotteries over time. For instance, the first third of the trials display more significant SCRs for accepted gambles than rejected gambles; however, this pattern appears to reverse during the experiment. Hence, we find that the number of significant SCRs decreases as the experiment progresses, which indicates that arousal and excitement levels decrease over time. Similarly, Figure A3 shows that subjects' BT increases over time, which may be attributed to emotional and cognitive depletion.

Figure A3. Kernel density estimates of psychophysiological responses I



Notes: Kernel density estimations of minimum, mean, and maximum values for heart rate (HR), body temperature (BT), respiration depth (RSD), and respiration rate (RSR) by gambling decision and lottery trial. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 with positive expected values (EV ≥ 0) and 45 negative expected values (EV<0), resulting in 8800 observations. The presented density estimates are computed on the basis of the cleaned data sample that comprises 8498 observations.

Figure A4. Kernel density estimates of psychophysiological responses II



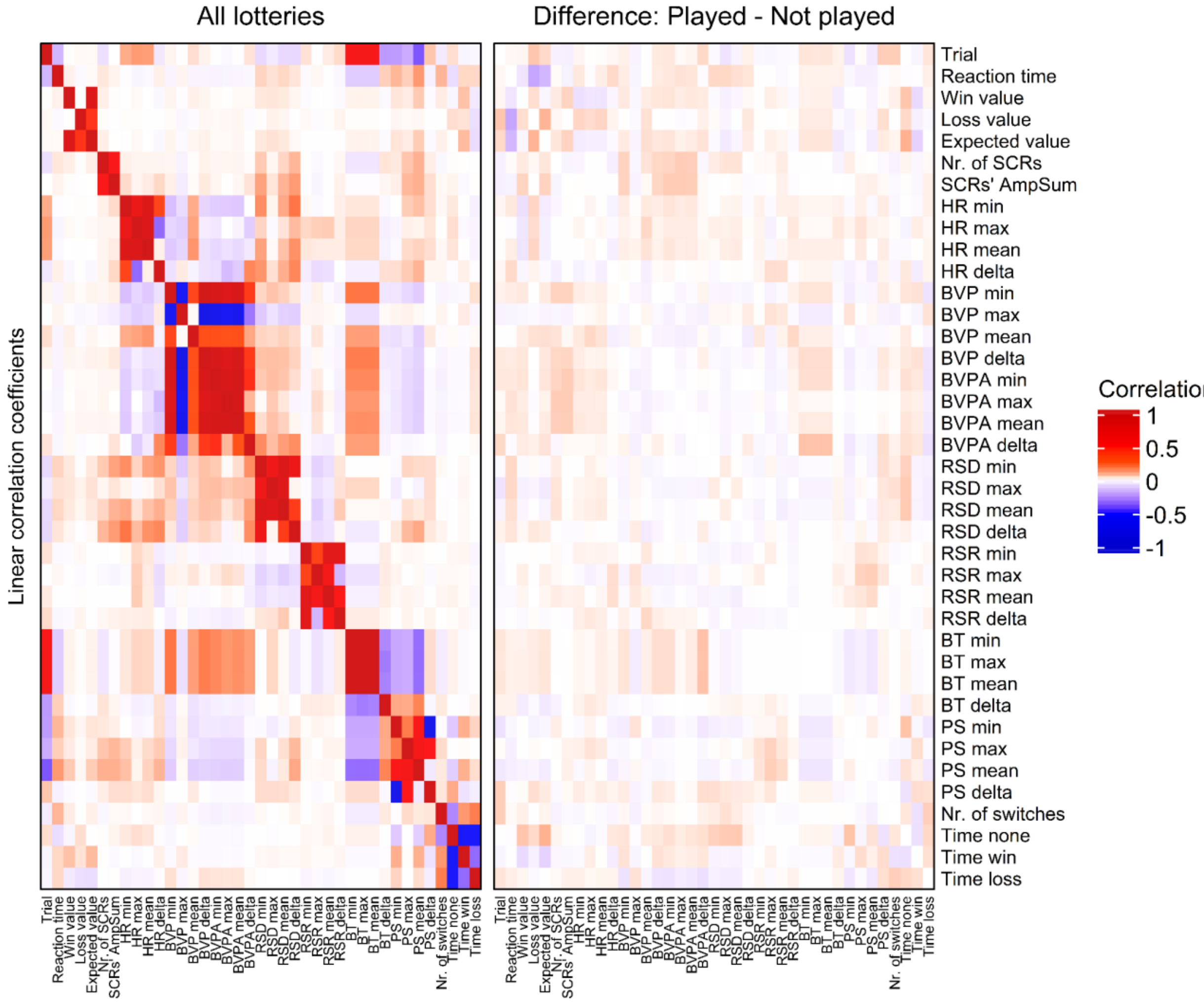
Notes: Kernel density estimations and relative frequency distributions of minimum, mean, and maximum values for blood volume pulse amplitude (BVPA), blood volume pulse (BVP), pupil size (PS), and the number of significant skin conductance responses (SCRs) and the sum of the significant SCRs' amplitudes by gambling decision and lottery trial. The experiment includes data on 44 subjects who decided on 200 lotteries: 155 with positive expected values (EV ≥ 0) and 45 negative expected values (EV<0), resulting in 8800 observations. The presented statistics are computed on the basis of the cleaned data sample that comprises 8498 observations.

3.6 Correlations between choice process data and lottery design

First, in Figure A5, we present two heat maps to illustrate linear correlations among SCPMs, between SCPMs and lottery design variables, and reaction time.[2]

[2] At the end of this section, we provide a brief analysis of the time that subjects require to reach a final decision.

Figure A5. Linear correlation coefficients



Notes: This figure shows the linear correlations between simple choice process metrics (SCPMs), reaction time and lotter design variables for all lottery decisions (left panel) as well as the difference in the corresponding correlation coefficients between accepted and rejected gambles (right panel). The experiment includes data on 44 subjects who decided on 200 lotteries: 155 PEV (EV ≥ 0) and 45 with negative expected values (EV<0), resulting in 8800 observations. The presented statistics are computed on the basis of the cleaned data sample that comprises 8498 observations. The included SCPMs are derived from various psychophysiological responses and lookup pattern metrics: the number of significant skin conductance responses (SCRs) and the sum of their amplitudes (SCR AS), heart rate (HR), blood volume pulse (BVP), blood volume pulse amplitude (BVPA), respiration depth (RSD), respiration rate (RSR), body temperature (BT), and pupil size (PS), as well as the number of times that subjects switch between looking at the two payoff boxes, the time that subjects look at the win box (Time win), at the loss box (Time loss), and at neither of the two payoff boxes (Time none).

The left panel of Figure A5 shows the linear Pearson correlation coefficients on the basis of the cleaned data sample. Regarding CPD type-specific SCPM correlations, the corresponding heat map substantiates the descriptive results presented in Figure A3: the BT SCPMs are positively correlated with lottery trial, i.e., subjects' BT increases during the experiment. Likewise, Figure A5 also shows that the number of significant SCRs decreases over time and, consequently, further indicates that the number of significant SCRs (and their sum of amplitudes) is negatively correlated with the BT variables. Similar to the correlations between the SCR and BT SCPMs, many PS SCPMs are also negatively correlated with lottery trial and BT measures as well as with BVP, BVPA, and SCPMs. In addition, we also find several HR SCPMs to be negatively correlated with BVP and BVPA variables and the RSD SCPMs to be negatively correlated with BVP maximum and several RSR SCPMs. Furthermore, HR delta, which can be interpreted as an HRV measure, is also negatively correlated with lottery trial.

Similar to the differences in the distribution of SCPMs presented in Figures A3 and A4, the right panel of Figure A5 shows a heat map that illustrates the differences between the linear correlations of accepted and rejected gambles. Concisely, we see that there exist systematic differences in the SCPM correlation structures for accepted and rejected gambles. To provide some examples, we find relatively large differences for the correlations among the SCR, BVP, and BVPA variables, between BVPA delta and the BT SCPMs, and between the PS SCPMs minimum and lottery trial.

In the second step of our analysis of SCPM correlations, in Table A15, we present inverse variance inflation factors (VIFs) on the basis of different combinations of SCPMs derived from standard OLS regressions while excluding perfect multi-collinear predictors.

Table A15. Inverse variance inflation factors for simple lookup measures and psychophysiological response metrics for predicting risky gambling choices

	(1)	(2)	(3)	(4)	(5)
Variable	1/VIF	1/VIF	1/VIF	1/VIF	1/VIF
HR min	0.027**	0.027**			
HR max	0.022**	0.022**			
HR mean	0.008***	0.008***	0.885	0.876	0.128*
BVP min	0.058**	0.059**			
BVP max	0.028**	0.029**			
BVP mean	0.159*	0.159*	0.658	0.643	0.061**
BVPA min	0.013**	0.013**			
BVPA max	0.007***	0.007***			
BVPA mean	0.004***	0.004***	0.697	0.694	0.124*
RSD min	0.002***	0.002***			
RSD max	0.003***	0.003***			
RSD mean	0.001***	0.001***	0.930	0.902	0.008***
RSR min	0.388*	0.388*			
RSR max	0.218*	0.218*			
RSR mean	0.136*	0.136*	0.984	0.983	0.778
BT min	< .001	< .001			
BT max	< .001	< .001			
BT mean	< .001	< .001	0.769	0.762	0.219*
PS min	0.189*	0.191*			
PS max	0.167*	0.172*			
PS mean	0.078**	0.079**	0.761	0.749	0.062**
Nr. of SCRs	0.731	0.732	0.738	0.736	0.686
SCR AmpSum	0.724	0.728	0.738	0.731	0.647
Time win	0.710			0.775	0.488*
Time loss	0.691			0.750	0.481*
Left box first	0.959			0.967	0.768
Win box first	0.990			0.992	0.761
Nr. of switches	0.859			0.888	0.658
Controls	-	-	-	-	Yes
N	8498	8498	8498	8498	8498

Notes: The presented inverse variance inflation factors (1/VIF) are derived from predicting risky 50/50 lottery gambling decision on the basis of different combinations of simple choice process metrics that relate to various psychophysiological reactions and lookup patterns, including heart rate (HR), blood volume pulse (BVP), blood volume pulse amplitude (BVPA), respiration depth (RSD), respiration rate (RSR), body temperature (BT), pupil size (PS), the number of significant skin conductance responses (SCRs) and the sum of their amplitudes (SCR AS), as well as the number of times that subjects switched between looking at the two boxes, the time that subjects look at the win box (time win) and at the loss box (time loss), and whether subjects first looked at the left box and whether they first looked at the win box. As additional control variables, Model (5) includes subject-specific dummy variables and all the lottery design variables, socioeconomic characteristics, and past gambling behavior and experiences (for an overview of variable specifications, see Table A1, Section 2.2). * $1/VIF < 0.5$, ** $1/VIF < 0.1$, *** $1/VIF < 0.01$

We consider CPD type-specific minimum, maximum, and mean values. Consequently, many highly collinear *P* SCPMs exist. Restricting the *P* SCPMs to mean values appears to largely eliminate these multi-collinearity issues. We note that the individual *A* [*LSG*] predictor-sets do not contain any variables with an inverse VIF < 0.8 [0.2]. Likewise, combining the *A* and *P* mean SCPMs (Model 4) does not produce any inverse VIF < 0.6. However, extending model (4) by the *LSG* predictors and subject-specific dummy variables (model (5)) results in new multi-collinearity issues with respect to both the predictors included in the *LSG* set and the *A* and *P* SCPMs—intuitively, physiological responses can systematically vary by individual subjects and/or socioeconomic characteristics, such as age and gender.

Third, we further investigate the extent to which SCPMs and lottery design variables are linearly correlated and provide in Table A16 the resulting coefficient estimates obtained from individual simple OLS regressions of the lotteries' win, loss, and expected values on the *A* and *P* SCPMs. In each regression, standard errors are clustered at the subject level.

Regarding relevant linear correlations between a lottery's win value and SCPMs, we find significant positive effects for PS min and PS mean and for the time that subjects spent looking at the win box. Moreover, we find a significant negative effect of the time that subjects look at the loss box. All other estimated SCPM coefficients are not significantly different from zero.

Regressing the lottery's loss value on individual SCPMs shows (weakly) significant negative effects for RSR delta and the time that subjects look at the win and the time that subjects did not look at either the win or the loss box. Last, we find a significant positive effect of the time that subjects allocate to a potential loss. All remaining coefficients are not significantly different from zero.

Similar to the results for using the win value as an outcome, for the expected value regressions, we find a (weakly) significant positive effects for PS min and mean, and a significant positive [negative] effect of the time that subjects spent looking at the win [loss] value. Furthermore, we find weakly significant positive coefficient estimates for BT minimum, maximum, and mean.

Table A16. Linear regression coefficient estimates for predicting lottery design variables on the basis of simple choice process metrics

Variable	(1-34) Win value		(35-68) Loss value		(69-102) Exp. value		(103-136) Trial	
HR min	0.0015	(0.0024)	-0.0002	(0.0011)	0.0008	(0.0013)	0.2158**	(0.0975)
HR max	-0.0005	(0.0024)	0.0002	(0.0010)	-0.0003	(0.0012)	0.1287	(0.0949)
HR mean	0.0001	(0.0023)	0.0004	(0.0011)	-0.0002	(0.0012)	0.1836*	(0.0979)
HR delta	-0.0169	(0.0153)	0.0036	(0.0050)	-0.0103	(0.0081)	-0.6096**	(0.2311)
BVP min	-0.0007	(0.0009)	0.0008	(0.0005)	-0.0008	(0.0005)	-0.0446	(0.0510)
BVP max	0.0006	(0.0007)	-0.0002	(0.0004)	0.0004	(0.0004)	0.0193	(0.0373)
BVP mean	0.0011	(0.0020)	0.0008	(0.0010)	0.0002	(0.0012)	0.0492	(0.0655)
BVP delta	0.0004	(0.0004)	-0.0002	(0.0002)	0.0003	(0.0002)	0.0158	(0.0238)
BVPA min	-0.0003	(0.0008)	-0.0003	(0.0003)	0.0000	(0.0005)	0.0055	(0.0356)
BVPA max	0.0000	(0.0006)	-0.0002	(0.0003)	0.0001	(0.0003)	0.0109	(0.0311)
BVPA mean	0.0001	(0.0007)	-0.0002	(0.0003)	0.0002	(0.0004)	0.0090	(0.0338)
BVPA delta	0.0037	(0.0045)	0.0008	(0.0025)	0.0015	(0.0027)	0.1323	(0.1269)
RSR min	-0.0024	(0.0116)	0.0061	(0.0046)	-0.0043	(0.0066)	0.0103	(0.2220)
RSR max	-0.0102	(0.0071)	-0.0034	(0.0034)	-0.0034	(0.0039)	0.3054***	(0.1053)
RSR mean	-0.0117	(0.0109)	-0.0011	(0.0047)	-0.0053	(0.0058)	0.3089*	(0.1642)
RSR delta	-0.0124	(0.0080)	-0.0072*	(0.0039)	-0.0026	(0.0043)	0.3978***	(0.0930)
RSD min	0.0002	(0.0002)	-0.0000	(0.0001)	0.0001	(0.0001)	0.0007	(0.0067)
RSD max	0.0003	(0.0002)	0.0000	(0.0001)	0.0001	(0.0001)	-0.0010	(0.0067)
RSD mean	0.0002	(0.0002)	-0.0000	(0.0001)	0.0001	(0.0001)	-0.0004	(0.0068)
RSD delta	0.0030	(0.0032)	0.0016	(0.0013)	0.0007	(0.0017)	-0.0662	(0.0914)
BT min	0.0791	(0.0549)	-0.0285	(0.0357)	0.0538*	(0.0300)	29.6105***	(4.5146)
BT max	0.0775	(0.0552)	-0.0291	(0.0353)	0.0533*	(0.0301)	29.5120***	(4.5250)
BT mean	0.0782	(0.0551)	-0.0287	(0.0355)	0.0535*	(0.0300)	29.5615***	(4.5196)
BT delta	-9.7252	(6.2179)	-1.9076	(3.7635)	-3.9088	(3.3441)	-1333.7571***	(164.1119)
PS min	0.2140*	(0.1250)	-0.0405	(0.0526)	0.1273*	(0.0643)	-18.3388***	(5.5495)
PS max	0.1183	(0.1066)	-0.0036	(0.0562)	0.0610	(0.0624)	-10.8617***	(3.8910)
PS mean	0.2797**	(0.1048)	-0.0120	(0.0418)	0.1458**	(0.0545)	-18.8473***	(6.1567)
PS delta	-0.1583	(0.2402)	0.0645	(0.1152)	-0.1114	(0.1367)	12.2202*	(6.6583)
Nr. of SCRs	0.188	(0.134)	-0.026	(0.068)	0.107	(0.081)	-7.607***	(1.787)
SCR AmpSum	0.237	(0.296)	0.163	(0.149)	0.037	(0.161)	0.025	(3.071)
Time win	0.729***	(0.167)	-0.164**	(0.065)	0.447***	(0.091)	-2.518	(2.056)
Time loss	-0.543***	(0.157)	0.417***	(0.064)	-0.480***	(0.092)	-1.875	(2.178)
Time none	-0.198	(0.132)	-0.173***	(0.056)	-0.013	(0.084)	3.441	(2.457)
Box switches	0.117	(0.073)	0.010	(0.038)	0.053	(0.042)	-2.671**	(1.254)
N	8498		8498		8498		8498	

Notes: The presented coefficient estimates result from 136 individual OLS regressions. The corresponding outcomes are a lottery's win value (1-34), loss value (35-68), expected value (69-102), and trial (103-136). Constant terms' coefficient estimates are omitted for brevity. The simple choice process metrics are derived from various psychophysiological responses and lookup patterns, including heart rate (HR), blood volume pulse (BVP), blood volume pulse amplitude (BVPA), respiration depth (RSD), respiration rate (RSR), body temperature (BT), and pupil size (PS), the number of significant skin conductance responses (SCRs) and the sum of their amplitudes (SCR AmpSum), as well as the number of times that subjects switched between looking at the win and loss boxes (box switches), and the time that subjects spend looking at the win box (time win), at the loss box (time loss), and at neither of the two payoff boxes (time none). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Standard errors (in parentheses) are clustered at the subject level.

Moreover, the individual OLS regression results for lottery trial presented in Table A16 substantiate the correlation patterns shown in Figure A4: The coefficient estimates for HR delta, BT delta, PS min, max, and mean, number of significant SCRs, and number of box switches are significantly negative.

Conversely, we find significant positive coefficient estimates for HR min and HR mean, RSR max, mean, and delta, BT min, max, and mean, and PS delta. Hence, some psychophysiological reactions associated with sympathetic activity and arousal, e.g., pupil dilation and increasing numbers of significant SCRs, are stronger at the beginning of the experiment when the repetitive gambling experience is still new and exciting. Conversely, we find significant positive coefficient estimates for BT as well as for several cardiovascular and respiratory SCPMs, which can reflect stress and resource depletion (Cheema & Patrick, 2012; Halko & Sääksvuori, 2017). Consequently, we also find several SCR and PS metrics to be negatively correlated with BT measures. Furthermore, many PS SCPMs are negatively correlated with several cardiovascular and respiratory measures (see Figure A4).

Last, although this study focuses on the predictive importance of CPD, we also briefly investigate how long subjects are required to execute their decision after the first three seconds of lottery information processing. On the basis of the uncleaned data sample that comprises 8800 observations, the mean reaction time (RT) is 0.667 seconds (SD=0.518), the minimum is 0.001, the maximum is 7.341, the median is 0.529, and the first and third quartiles are 0.386 and 0.752, respectively. Most importantly, all subjects executed their final decisions within the required 10-second period; after this period, the experiment software would had automatically and randomly decided to accept or reject the offered lottery. Moreover, the left panel of Figure A4 shows that RT is slightly positively correlated with a lottery's (absolute) win, loss, and expected value, which may indicate that subjects take more time reaching a final decision when relatively higher stakes are at play. Similarly, the right panel of Figure A4 shows that, on average, the correlation between lottery design variables and RT is slightly higher for rejected than accepted gambles. Furthermore, RT is negatively correlated with lottery trial, which may indicate that subjects experience cognitive depletion and, consequently, more frequently choose the risk-averse alternative as the experiment progresses.

4 Multiple regression-based analysis and hypotheses testing

In this section, we present the detailed results of our regression-based hypotheses tests that were omitted from the main text for brevity. We estimate logistic regression models with subject fixed effects using the binary gambling choice y as an outcome ($y = 1$ for played). To this end, in each model, we include subject-specific dummy variables and, in addition, cluster standard errors at the subject level. For our regression-based analysis and hypotheses testing, we use Stata (Statacorp, 2017).

Table A17. Logistic regression results for predicting gambling choices on the basis of lottery design characteristics and attention variables

	(1)		(2)		(3)		(4)	
	L1		L2		L3		L4	
Win value	0.3278***	(0.0407)	0.3278***	(0.0407)	0.1985***	(0.0157)		
Loss value	-0.6769***	(0.0835)	-0.6770***	(0.0835)			-0.4204***	(0.0337)
Trial	-0.0060***	(0.0009)	-0.0060***	(0.0009)				
Win right	0.0225	(0.1239)						
Accept right	0.9542***	(0.0835)						
Constant	-0.5913*	(0.3116)	-0.5781**	(0.2864)	-3.0277***	(0.1970)	1.3788***	(0.1534)

	(5)		(6)		(7)		(8)	
	A1		A2		A3		A4	
Time win	0.1451	(0.1351)	0.1933	(0.1313)	0.3672***	(0.0803)		
Time loss	-0.3875***	(0.1351)	-0.3107**	(0.1260)			-0.4311***	(0.0724)
Left box first	-0.0075	(0.0636)						
Win box first	0.1695***	(0.0631)						
Nr. of switches	0.1171**	(0.0551)						
Constant	-0.7805***	(0.2308)	-0.6558***	(0.2377)	-1.1141***	(0.0858)	-0.3487***	(0.0617)

	(9)		(10)		(11)		(12)	
	LA1		LA2		LA3		LA4	
Win value	0.3266***	(0.0405)	0.3262***	(0.0405)				
Loss value	-0.6745***	(0.0837)	-0.6760***	(0.0835)	-0.4241***	(0.0338)	-0.4215***	(0.0337)
Trial	-0.0060***	(0.0009)	-0.0059***	(0.0009)	-0.0037***	(0.0007)	-0.0037***	(0.0007)
Time win	0.1241	(0.1233)	0.2324**	(0.0955)	0.3032**	(0.1435)		
Time loss	-0.1962	(0.1246)			-0.1519	(0.1255)	-0.3419***	(0.0780)
Constant	-0.5098	(0.3690)	-0.8098**	(0.3262)	1.5998***	(0.2877)	2.0809***	(0.1631)
N	8498		8498		8498		8498	

Notes: Dependent variable is gambling decision. We account for subject fixed effects by including subject-specific dummy variables in all models (coefficients omitted for brevity). Standard errors (in parentheses) are clustered at the subject level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results presented in Table A17 are in line with our hypotheses related to lotteries' payoff structure. First, individuals are more likely to accept [reject] a gamble when the win [loss] value increases (*H1a*). The average marginal effect estimate on the basis of model (1) across potential win [loss] values is 0.0367 [–0.0777]. Second, the effect of an additional one Euro increase in the loss value is significantly larger than a one Euro increase in the win value (p<0.001) (*H1b*).

Moreover, the results in Table A17 (model (7) and (8)) also support our attention-related hypothesis: individuals are more likely to accept [reject] a lottery when allocating more attention to the potential gain [loss] (*H2*). However, when including both the time spent looking at the win and loss values, only one of both coefficient estimates remains significantly different from zero (model (5-8)). Furthermore, when using the information on both *L* data and *A* SCPMs, Table A17 shows that the coefficient estimates for the time spent looking at the win and loss values become insignificant. However, the coefficient for the time spent looking at the win value becomes significant when excluding a lottery's potential win and/or the time spent looking at the loss value (model (9-12)). These results reflect the inherent correlation between *A* SCPMs and their relationship with lottery payoff structure variables: the win value is positively [negatively] correlated with the time spent looking at the win [loss] value, the loss value is negatively [positively] correlated with time spent looking at the win [loss] value, and spending more time looking at the win [loss] value decreases the time that is left for looking at the loss [win] value.

In Table A18, we present the results for individual logistic regression models on the basis of psychophysiological SCPMs and—controlling for subject fixed effects—to investigate our last hypothesis: High levels of arousal are an indicator of lottery acceptance (*H3*).

Table A18. Logistic regression results for predicting gambling choices on the basis of simple choice process metrics derived from psychophysiological responses

	(1-7) Min		(8-14) Max		(15-21) Mean		(22-28) Delta	
HR	-0.0011	(0.0049)	-0.0013	(0.0056)	-0.0028	(0.0053)	-0.0003	(0.0071)
BVP	-0.0079*	(0.0046)	0.0019	(0.0015)	-0.0001	(0.0103)	0.0018	(0.0012)
BVPA	0.0005	(0.0016)	0.0004	(0.0015)	0.0011	(0.0015)	0.0002	(0.0039)
RSR	-0.0016	(0.0064)	-0.0038	(0.0034)	-0.0027	(0.0054)	-0.0039	(0.0032)
RSD	0.0063	(0.0049)	0.0066**	(0.0029)	0.0070*	(0.0037)	0.0058**	(0.0027)
BT	-0.1849***	(0.0615)	-0.1857***	(0.0619)	-0.1854***	(0.0617)	3.2890	(2.6399)
PS	0.5885***	(0.1561)	0.5138**	(0.2483)	1.9863***	(0.3738)	-0.1102	(0.1481)
N	8498		8498		8498		8498	

	(29) SCR1		(30) SCR2		(31) SCR3	
Nr. of SCRs	0.1312**	(0.0602)	0.1375**	(0.0550)		
SCR AmpSum			-0.0273	(0.1346)	0.1039	(0.1372)
N	8498		8498		8498	

Notes: Dependent variable is gambling decision. The presented coefficient estimates result from regressing the gambling decision on individual simple choice process metrics (SCPMs), i.e., 115 regressions in total. In addition to a CPD-type specific SCPMs (e.g., HR Min), each model includes subject specific dummy variables and a constant (coefficients omitted for brevity). The SCPMs relate to minimum (1-28), maximum (29-56), and mean values (57-84), as well as the difference between maximum and minimum values (85-112), and are derived from different psychophysiological responses: heart rate (HR), blood volume pulse (BVP), blood volume pulse amplitude (BVPA), respiration depth (RSD), respiration rate (RSR), body temperature (BT), and pupil size (PS). Models (113-115) are based on SCPMs that are derived from skin conductance responses (SCRs): the number of significant SCRs and the sum of the significant SCRs' amplitudes (SCR AmpSum). Standard errors (in parentheses) are clustered at the subject level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results presented in Table A18 show that high levels of arousal measured by SCRs and PS indicate lottery acceptance. In addition, higher [lower] BT levels significantly indicate a lower [higher] propensity to accept lotteries. Furthermore, only RSD max, mean, and delta show a slightly significant and positive coefficient estimate, and BVP min shows a weakly significant negative estimate. All other SCPM coefficient estimates are not significantly different from zero.

In Table A19, we show logistic regression results based on different predictor-set combinations: *LSG*, *LSGA*, *LSGP*, and *LSGPA*. However, we desist from estimating time-invariant socioeconomic characteristics in favor of controlling for subject fixed effects and clustering standard errors at the subject level. In this context, except for the two SCR variables, we further note that, in Table A19, we restrict the set of *P* SCPMs to mean values to mitigate multi-collinearity issues (for details, see our VIF analysis in Section 3.5).

Table A19. Logistic regression results for predicting gambling choices on the basis of varying data sets

	(1) LSG		(2) LSGA		(3) LSGP		(4) LSGAP	
Win value	0.3300***	(0.0404)	0.3283***	(0.0402)	0.3289***	(0.0403)	0.3274***	(0.0402)
Loss value	-0.6817***	(0.0825)	-0.6788***	(0.0827)	-0.6835***	(0.0828)	-0.6804***	(0.0830)
Trial	-0.0058***	(0.0009)	-0.0058***	(0.0009)	-0.0049***	(0.0011)	-0.0049***	(0.0011)
Win right	0.0217	(0.1251)	0.0063	(0.1106)	0.0215	(0.1254)	0.0069	(0.1104)
Accept right	0.9323***	(0.1009)	0.7181***	(0.1390)	1.8041	(1.3911)	1.5267	(1.3975)
Lag1-2 played	0.0729	(0.1426)	0.0761	(0.1428)	0.0717	(0.1472)	0.0738	(0.1468)
Lag1-3 played	0.1047	(0.1710)	0.1038	(0.1734)	0.0995	(0.1678)	0.0951	(0.1706)
Lag1-4 played	0.1388	(0.2637)	0.1472	(0.2682)	0.1322	(0.2595)	0.1448	(0.2647)
Lag1-5 played	0.3183	(0.3022)	0.3103	(0.3014)	0.3170	(0.2971)	0.3082	(0.2975)
Lag1 PO	-0.2696	(0.1847)	-0.2811	(0.1849)	-0.2607	(0.1955)	-0.2675	(0.1954)
Lag2 PO	0.0434	(0.1678)	0.0424	(0.1682)	0.0463	(0.1721)	0.0473	(0.1725)
Lag3 PO	-0.1709*	(0.1027)	-0.1731*	(0.1032)	-0.1731*	(0.1021)	-0.1735*	(0.1026)
Lag4 PO	0.0350	(0.0844)	0.0327	(0.0844)	0.0389	(0.0830)	0.0365	(0.0829)
Lag5 PO	0.1642*	(0.0896)	0.1645*	(0.0888)	0.1651*	(0.0909)	0.1662*	(0.0900)
Lag1 NO	0.0636	(0.1779)	0.0639	(0.1772)	0.0739	(0.1846)	0.0746	(0.1834)
Lag2 NO	0.0146	(0.1606)	0.0148	(0.1602)	0.0141	(0.1647)	0.0149	(0.1639)
Lag3 NO	0.0696	(0.1105)	0.0621	(0.1117)	0.0654	(0.1104)	0.0567	(0.1116)
Lag4 NO	0.0250	(0.0923)	0.0302	(0.0927)	0.0294	(0.0931)	0.0340	(0.0937)
Lag5 NO	0.1560*	(0.0947)	0.1605*	(0.0947)	0.1548	(0.0946)	0.1600*	(0.0946)
Time win			0.0920	(0.1281)			0.0381	(0.1323)
Time loss			-0.2594**	(0.1300)			-0.3104**	(0.1294)
Left box first			0.0034	(0.0930)			-0.0043	(0.0908)
Win box first			0.0755	(0.0938)			0.0756	(0.0911)
Nr. of switches			0.1078*	(0.0551)			0.1161**	(0.0545)
HR mean					-0.0000	(0.0083)	-0.0018	(0.0081)
BVP mean					-0.0038	(0.0137)	-0.0039	(0.0135)
BVPA mean					0.0003	(0.0032)	0.0008	(0.0031)
RSR mean					0.0000	(0.0069)	-0.0019	(0.0068)
RSD mean					0.0045	(0.0092)	0.0044	(0.0092)
BT mean					0.0395	(0.1532)	0.0509	(0.1515)
PS mean					1.4785***	(0.3844)	1.5462***	(0.4001)
Nr. of SCRs					0.1132	(0.0708)	0.1177*	(0.0698)
Constant	-0.6524*	(0.3558)	-0.6718	(0.4386)	-10.7935	(9.0162)	-11.0066	(9.0605)
N	8498		8498		8498		8498	

Notes: Dependent variable is gambling decision. We account for subject fixed effects by including subject-specific dummy variables in all models (coefficients omitted for brevity). Simple choice process metrics (SCPMs) are derived from different types of eye movements and psychophysiological responses, including heart rate (HR), blood volume pulse (BVP), blood volume pulse amplitude (BVPA), respiration depth (RSD), respiration rate (RSR), body temperature (BT), pupil size (PS), and significant skin conductance responses (Nr. of SCRs). Standard errors (in parentheses) are clustered at the subject level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A19 shows that the coefficient estimates for the lottery design variables on the basis of *LSG*, *LSGA*, *LSGP*, and *LSGPA* change only marginally when compared with the individual *L* regression results presented in Table A17. Whereas the estimated coefficient for the time that subjects spent looking at the loss value is significantly negative when controlling for the *LSG* or *LSGP* variables (model (2) and (4)), the effect is of less magnitude than the corresponding estimate obtained from the individual regressions shown in Table A17. Moreover, the corresponding estimates for the time spent looking at the win value become insignificant after controlling for the full set of *LSGA* or *LSGP* variables. Similar to the estimates of the *A* predictors, the estimated effect of the number of significant SCRs is only weakly significant when controlling for the *LSGA* variables (model (3) and (4)). Conversely, PS is highly significant across both model specifications ((3) and (4)).

To further investigate the extent to which controlling for lottery design variables affects selected SCPM coefficient estimates, in Table A20, we show additional logistic regression results for BT mean, PS mean, and the number of significant SCRs.

Table A20. Logistic regression results for predicting gambling choices on the basis of lottery design variables and selected psychophysiological choice process metrics

	(1) Played		(2) Played		(3) Played		(4) Played	
Trial	-0.0060***	(0.0011)	-0.0028***	(0.0006)				
Win value	0.3278***	(0.0407)			0.3229***	(0.0402)		
Loss value	-0.6770***	(0.0835)			-0.6659***	(0.0829)		
BT mean	-0.0058	(0.1596)	0.0341	(0.0621)	-0.4775***	(0.1467)	-0.1854***	(0.0617)
Constant	-0.3736	(5.6477)	-1.6634	(2.1708)	15.7791***	(5.2216)	5.8455***	(2.1903)
N	8498		8498		8498		8498	

	(5) Played		(6) Played		(7) Played		(8) Played	
PS mean	1.9943***	(0.4158)			1.8454***	(0.4970)		
Nr. of SCRs			0.1900**	(0.0777)			0.0664	(0.0688)
Constant	-5.5817***	(1.0877)	-0.3987***	(0.0120)	-5.7739***	(1.2550)	-1.1418***	(0.0167)
Trial	<= 100		<= 100		> 100		> 100	
N	4132		4132		4366		4366	

Notes: Dependent variable is gambling decision. We account for subject fixed effects by including subject-specific dummy variables in all models (coefficients omitted for brevity). Choice process metrics are derived from different psychophysiological responses: body temperature (BT), pupil size (PS), significant skin conductance responses (Nr. of SCRs). Standard errors (in parentheses) are clustered at the subject level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Our correlation analysis in Section 3.5 (Table A16) shows that lottery trial is positively correlated with standard BT measures (min, max, and mean), and the results presented in Table A20 suggest that both lottery trial and BT capture information on subjects' decreasing propensity to accept gambles as the experiment progresses. However, whereas the lottery trial coefficient remains significant across various model specifications (Tables A17, A19, and A20), the BT mean coefficient estimate is only significantly different from zero when excluding lottery trial (Tables A18 and A20).

5 Detailed results for forecasting gambling choices

5.1 Implementation

We use R (R Core Team, 2020) and RStudio (RStudio Team, 2020) for the main computations and graphics in this paper. For the generalized linear methods employed in this study we use the R-package *glmnet* (Friedman et al., 2010), for support vector machines we use *kernlab* (Karatzoglou et al., 2004), for neural network models we use *nnet* (Venables & Ripley, 2002), for random forests we use *ranger* (Wright & Ziegler, 2017), and for stochastic gradient boosting machines we use *gbm* (Greenwell et al., 2018). We use *caret* (Kuhn, 2018) for model training and model evaluation. Moreover, we use *tidyverse* (Wickham et al., 2019; 2020), *circlize* (Gu et al., 2014), *RColorBrewer* (Neuwirth, 2014), and *complexHeatmap* (Gu et al., 2016), *visreg* (Breheny & Burchett, 2017), *svglite* (Wickham et al., 2020), *rsvg* (Ooms, 2020), *gridExtra* (Auguie, 2017), *ggimage* (Yu, 2020), *ggpubr* (Kassambara, 2020), *egg* (Auguie, 2019), and *arsenal* (Heinzen et al., 2020) for data manipulations and creating the tables and figures that are included this study. Furthermore, we use *doParrallel* (Calaway et al., 2017) for multicore processing where applicable.

5.2 Data splitting and model training strategy

We use subjects as strata in both randomly selecting 80% of the cleaned data as a training sample and tuning models' hyperparameters via 10-fold stratified cross validation on the basis of the training sample. The remaining 20% of the data are used as a hold-out test set to produce reasonable accuracy estimates. This sampling procedure utilizes 6810 observations for model training and 1688 observations for model testing. We use classification accuracy as a metric to assess models' predictive capabilities in the model training process because the average share of played lotteries is relatively balanced. Moreover, we set the cut-off value for classifying a record as played to a predicted probability of 50%, and we separately center and scale all numeric predictors with respect to the corresponding 10 training CV fold-sets and the test data.

In Table A21 we separately summarize the distribution of gambling choices by lotteries' expected values for each data sample: the full data, the cleaned data (100%), the training data (80%), and the test data (20%).

Table A21. Distribution of risky choices by data sample and lotteries' expected values

Data: Full sample	All	PEV	NEV
Not played	4609 (52.4%)	2751 (40.3%)	1858 (93.8%)
Played	4191 (47.6%)	4069 (59.7%)	122 (6.2%)
N	8800	6820	1980

Data: Cleaned	All	PEV	NEV
Not played	4484 (52.8%)	2677 (40.7%)	1807 (94.2%)
Played	4014 (47.2%)	3902 (59.3%)	112 (5.8%)
N	8498	6579	1919

Data: Training	All	PEV	NEV
Not played	3602 (52.9%)	2125 (40.5%)	1477 (94.1%)
Played	3208 (47.1%)	3116 (59.5%)	92 (5.9%)
N	6810	5241	1569

Data: Test	All	PEV	NEV
Not played	882 (52.3%)	552 (41.3%)	330 (94.3%)
Played	806 (47.7%)	786 (58.7%)	20 (5.7%)
N	1688	1338	350

Notes: The experiment data covers 44 subjects that each were offered 200 lotteries with 50/50 outcome probabilities: 155 with positive expected values (PEV) (EV≥0) and 45 with negative expected values (NEV).

In Table A22, we provide an overview of the models and the corresponding model hyperparameters evaluated in this study using a systematic grid search. Except for the two naïve forecasting methods, we evaluate all models on the basis of four differently specified predictor-sets. Furthermore, for our forecasting analysis, we individually control for multi-collinearity by QR decomposition for each predictor-set.

Table A22. Summary of evaluated forecasting methods and tested hyper parameters

Method	Hyperparameters	Tested values
Naïve		
Risk-averse decision rule	-	-
Statistical decision rule	-	-
Generalized linear		
Logistic regression	-	-
Penalized regression	Alpha	$0, 0.1, 0.2, \dots, 1$
	Lambda	$0.01, 0.025, 0.05, 0.1, 0.15$
Non-linear		
Support vector machine	Kernel	$Radial\ basis$
(SVM)	Cost	$1, 2, \dots, 10$
	Inverse kernel width (sigma)	$0.01, 0.025, 0.05, 0.1, 0.15$
Artificial neural network	Activation function	$Sigmoid$
(ANN)	No. of nodes in the hidden layer	$1, 2, \dots, 10$
	Weight decay	$0.1, 0.2, \dots, 0.5$
Tree-based ensemble		
Random forest (RF)	Splitting rule	$Gini$
	No. of ensembled trees	1500
	Min. no. of samples in each leaf	$1, 5, 10, 20, 40$
	No. of predictors in each split	$\lvert D_i \rvert(0.1, 0.2, 0.4, 0.8, 1)$
Gradient boosting ma-	Interaction depth	$5, 10, 20, 40$
(GBM)	No. of ensembled trees	$20, 40, 80, 160$
	Shrinkage	$0.1, 0.4, 0.7, 1$
	Min. no. of samples in each leaf	$10, 40, 70, 100$

Notes: $\lvert D_i \rvert$ refers to the number of predictors for predictor-set i with i ={*P*, *A*, *LSG*, *LSGPA*}. Except for the two naïve forecasting methods, we evaluate all models on the basis of four differently specified predictor-sets, resulting in 1750 individual model specifications.

5.3 Cross validated accuracy results

Table A23 shows the selected models' hyperparameters according to the highest 10-fold CV mean accuracy. All other models' hyperparameter values are set to their default values (detailed information can be found in the corresponding R package documentation). However, we note that we evaluate the model performance on the same left-out CV observations for each round of CV.

Table A23. Selected model hyperparameters according to highest mean 10-fold CV accuracy

Model: Elastic	*Dataset*			
Hyperparameter	P	A	LSG	LSGPA
Alpha	0.0	0.0	0.4	0.8
Lambda	0.01	0.01	0.025	0.01
CV Accuracy	0.61	0.60	0.85	0.85

Model: SVM	*Dataset*			
Hyperparameter	P	A	LSG	LSGPA
Kernel	Radial	Radial	Radial	Radial
Sigma	0.01	0.15	0.01	0.01
Cost	10	5	7	3
Accuracy	0.60	0.66	0.87	0.87

Model: ANN	*Dataset*			
Hyperparameter	P	A	LSG	LSGPA
Activation function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
No. of neurons in the hidden layer	1	9	7	7
Weight decay	0.4	0.4	0.5	0.5
Accuracy	0.60	0.65	0.87	0.87

Model: RF	*Dataset*			
Hyperparameter	P	A	LSG	LSGPA
Splitting rule	Gini	Gini	Gini	Gini
No. of ensembled trees	1500	1500	1500	1500
Min. no. of samples in each leaf node	1	10	5	1
No. of predictors considered in each split	7	5	50	18
Accuracy	0.60	0.64	0.86	0.87

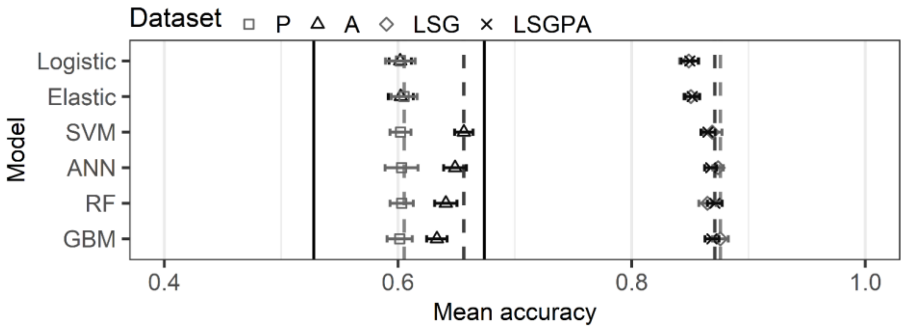
Model: GBM	*Dataset*			
Hyperparameter	P	A	LSG	LSGPA
Shrinkage	0.1	0.1	0.1	0.1
Interaction depth	5	10	40	40
Min. no. of samples in each leaf node	40	10	10	10
No. of ensembled trees	160	80	160	160
Accuracy	0.60	0.63	0.88	0.87

Notes: We determined models' hyperparameters via a systematic-grid search using 10-fold mean CV accuracy with subjects as strata. Training data include 6810 observations (80%) that are randomly drawn from the cleaned data using subjects as strata. We evaluate logistic and penalized linear regression models (Elastic), support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and tree-based gradient boosting machines (GBM) on the basis of psychophysiological (*P*) and attention (*A*) choice-process predictors; lottery-design, socioeconomic characteristics, and information on past gambling behavior (*LSG*); and a full-model that is comprised of all input categories (*LSGPA*).

For all consecutive results reported in our study, we set the models' hyperparameters to the values that yield the highest mean 10-fold CV accuracies.

Figure A7 shows the 10-fold CV accuracy results by model and predictor-set.

Figure A7. 10-fold Cross validation classification accuracy for playing a 50/50-gamble



Notes: Mean 10-fold CV accuracy on the basis of 6810 observations for playing a 50/50-gamble with one potential loss- and one win-outcome using subjects as strata in the random sampling process. We evaluate logistic (Logistic) and penalized linear regression models (Elastic), support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and tree-based gradient boosting machines (GBM) on the basis of psychophysiological (*P*) and attention (*A*) choice-process predictors; lottery-design, socioeconomic characteristics, and information on past gambling behavior (*LSG*); and a full-model that is comprised of all input categories (*LSGPA*). Error bars correspond to 95% confidence intervals with respect to the 10 CV fold-sets. The dashed lines correspond to the models that achieves the highest mean CV accuracy with respect to the different predictor-sets. The first solid line is a naïve forecast benchmark that yields a training data accuracy of 53% by predicting all records as not-playing, and the second solid line is a naïve forecast that yields an accuracy of 67% by predicting a lottery with EV<0 as not-playing and with EV≥0 as played.

Table A24 shows the differences in models' CV accuracy estimates together with pairwise t-tests for detecting significant differences on the basis of Bonferroni-adjusted p-values.

Table A24. Models' differences in mean 10-fold CV accuracies and pairwise t-test results

Data: P	Accuracy	Logistic	Elastic	SVM	ANN	RF	GBM
Logistic	0.60		-0.003	0.000	-0.001	-0.001	0.001
Elastic	0.61	1.000		0.003	0.002	0.002	0.004
SVM	0.60	1.000	1.000		-0.001	-0.001	0.001
ANN	0.60	1.000	1.000	1.000		0.000	0.002
RF	0.60	1.000	1.000	1.000	1.000		0.002
GBM	0.60	1.000	1.000	1.000	1.000	1.000	

Data: A	Accuracy	Logistic	Elastic	SVM	ANN	RF	GBM
Logistic	0.60		0.000	-0.054	-0.047	-0.039	-0.031
Elastic	0.60	1.000		-0.054	-0.047	-0.039	-0.031
SVM	0.66	0.000	0.000		0.007	0.015	0.023
ANN	0.65	0.000	0.000	1.000	0.008	0.008	0.016
RF	0.64	0.000	0.000	0.061	1.000		0.008
GBM	0.63	0.002	0.001	0.003	0.428	0.546	

Data: LSG	Accuracy	Logistic	Elastic	SVM	ANN	RF	GBM
Logistic	0.85		-0.002	-0.020	-0.025	-0.016	-0.027
Elastic	0.85	1.000		-0.018	-0.023	-0.014	-0.025
SVM	0.87	0.000	0.007		-0.005	0.004	-0.007
ANN	0.87	0.000	0.000	1.000		0.009	-0.002
RF	0.86	0.033	0.045	1.000	0.885		-0.011
GBM	0.88	0.001	0.004	1.000	1.000	0.325	

Data: LSGPA	Accuracy	Logistic	Elastic	SVM	ANN	RF	GBM
Logistic	0.85		-0.002	-0.016	-0.018	-0.021	-0.019
Elastic	0.85	1.000		-0.014	-0.016	-0.019	-0.017
SVM	0.87	0.050	0.023		-0.002	-0.006	-0.003
ANN	0.87	0.005	0.004	1.000		-0.004	-0.001
RF	0.87	0.001	0.011	1.000	1.000		0.002
GBM	0.87	0.009	0.006	1.000	1.000	1.000	

Notes: Mean 10-fold CV accuracy differences using 6810 observations for playing a 50/50-gamble with one potential loss- and one win-outcome using subjects as strata. The upper triangle shows the pair-wise estimates of accuracy differences between models, and the lower triangle shows the Bonferroni adjusted p-values for pairwise t-tests for detecting differences between models' accuracies with H_0 as a difference of zero. We evaluate logistic (Logistic) and penalized linear regression models (Elastic), support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and tree-based gradient boosting machines (GBM) on the basis of psychophysiological (*P*) and attention (*A*) choice-process predictors; lottery-design, socioeconomic characteristics, and information on past gambling behavior (*LSG*); and a full-model that is comprised of all input categories (*LSGPA*). Model hyperparameters are selected via a systematic grid-search based on 10-fold CV.

5.4 Out-of-sample forecasting results

The detailed out-of-sample results for all models, predictor-sets, and predictive classification measures are reported in Table A25.

Table A25. Model out-of-sample performance metrics over all lotteries

Measure	Logistic	Elastic	SVM	ANN	RF	GBM	Data
Accuracy	0.62	0.60	0.60	0.61	0.59	0.58	P
Lower accuracy	0.60	0.58	0.57	0.59	0.57	0.56	P
Upper accuracy	0.64	0.63	0.62	0.63	0.61	0.61	P
Sensitivity	0.49	0.44	0.49	0.47	0.48	0.46	P
Specificity	0.74	0.75	0.69	0.73	0.69	0.69	P
Positive predicted value	0.62	0.61	0.59	0.61	0.58	0.57	P
Negative predicted value	0.62	0.60	0.60	0.61	0.60	0.59	P
Balanced accuracy	0.62	0.60	0.60	0.61	0.59	0.58	P

Measure	Logistic	Elastic	SVM	ANN	RF	GBM	Data
Accuracy	0.61	0.61	0.63	0.63	0.63	0.63	A
Lower accuracy	0.59	0.59	0.61	0.60	0.60	0.61	A
Upper accuracy	0.63	0.63	0.65	0.65	0.65	0.65	A
Sensitivity	0.51	0.47	0.56	0.57	0.54	0.56	A
Specificity	0.70	0.74	0.69	0.67	0.70	0.69	A
Positive predicted value	0.60	0.61	0.62	0.61	0.62	0.62	A
Negative predicted value	0.61	0.61	0.64	0.64	0.63	0.64	A
Balanced accuracy	0.61	0.61	0.63	0.63	0.63	0.63	A

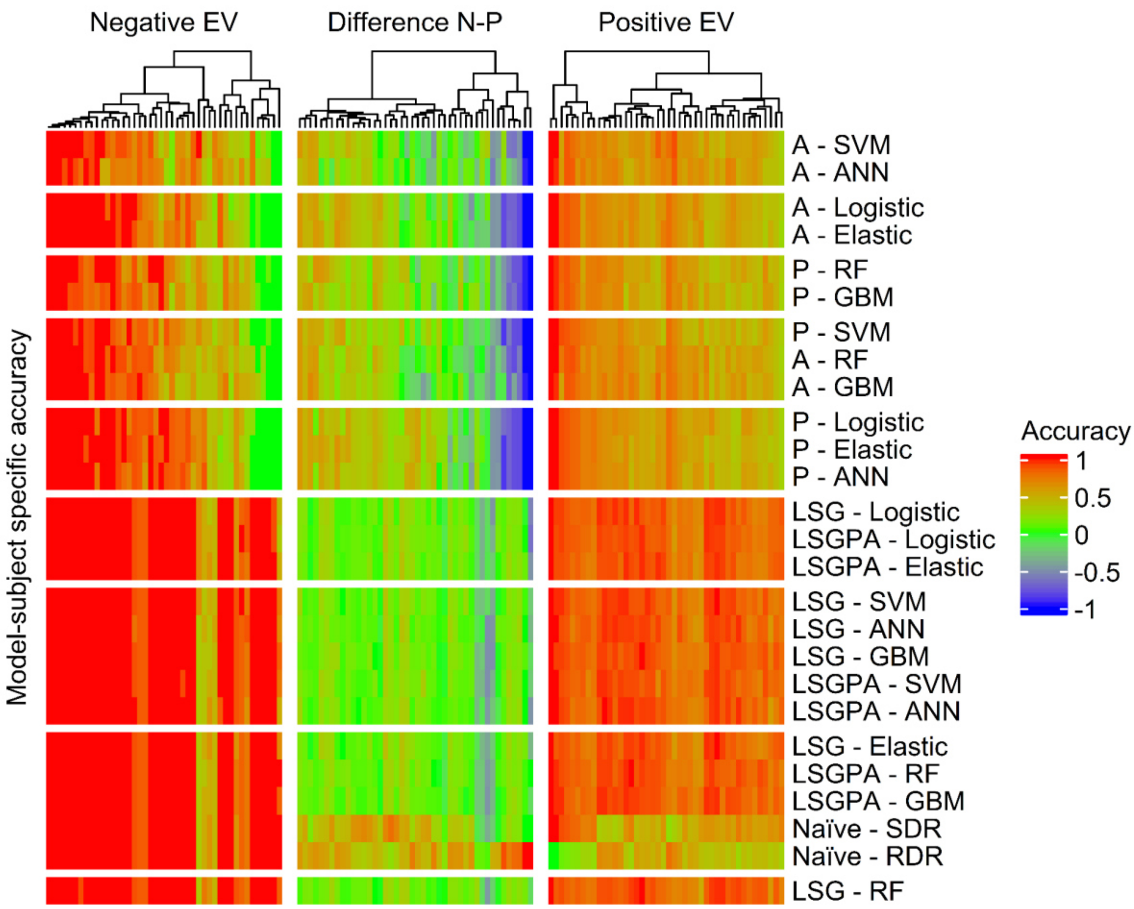
Measure	Logistic	Elastic	SVM	ANN	RF	GBM	Data
Accuracy	0.86	0.85	0.87	0.87	0.86	0.87	LSG
Lower accuracy	0.84	0.83	0.85	0.85	0.84	0.85	LSG
Upper accuracy	0.88	0.86	0.88	0.88	0.87	0.88	LSG
Sensitivity	0.86	0.84	0.87	0.86	0.85	0.86	LSG
Specificity	0.86	0.86	0.87	0.87	0.86	0.87	LSG
Positive predicted value	0.85	0.84	0.86	0.85	0.85	0.86	LSG
Negative predicted value	0.87	0.85	0.88	0.88	0.87	0.88	LSG
Balanced accuracy	0.86	0.85	0.87	0.87	0.86	0.87	LSG

Measure	Logistic	Elastic	SVM	ANN	RF	GBM	Data
Accuracy	0.85	0.85	0.86	0.86	0.86	0.87	LSGPA
Lower accuracy	0.84	0.83	0.84	0.85	0.84	0.86	LSGPA
Upper accuracy	0.87	0.87	0.88	0.88	0.88	0.89	LSGPA
Sensitivity	0.86	0.85	0.87	0.87	0.86	0.85	LSGPA
Specificity	0.85	0.86	0.86	0.86	0.86	0.89	LSGPA
Positive predicted value	0.84	0.84	0.84	0.85	0.84	0.87	LSGPA
Negative predicted value	0.87	0.86	0.88	0.88	0.88	0.87	LSGPA
Balanced accuracy	0.85	0.85	0.86	0.86	0.86	0.87	LSGPA

Notes: Out-of-sample accuracy for playing a 50/50 gamble. Test [training] data consist of 1688 [6810] records and the models' hyperparameters are chosen as the values that yield the highest mean 10-fold CV accuracy using subjects as strata. We evaluate two naïve benchmark forecasts (RDR and SDR), logistic (Logistic) and penalized linear regression models (Elastic), support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and tree-based gradient boosting machines (GBM) on the basis of psychophysiological (*P*) and attention (*A*) choice-process data; lottery-design, socioeconomic characteristics, and information on past gambling behavior (*LSG*); and a full-model is comprised of all input categories (*LSGPA*). Models' hyperparameters were determined via a systematic grid-search using 10-fold CV and subjects as strata.

To assess the importance of CPD on forecasting risky choices for NEVL and PEVL across models' test results by individual subjects, in Figure A8, we present the predictor-set- and subject-specific out-of-sample accuracy results for NEVL, PEVL, and the difference between NEVL and PEVL. To highlight differences across subjects' accuracy results, we separately use a hierarchical k-means clustering approach with respect to the corresponding subject-model-specific accuracy results for NEVL, PEVL, and the difference between NEVL and PEVL.

Figure A8. Out-of-sample classification accuracy for playing a 50/50-gamble for individual subjects by method and lotteries' expected values



Notes: Out-of-sample accuracy results for 44 subjects for negative expected value lotteries (NEVL) positive expected value lotteries (PEVL), and the difference between NEVL and PEVL for playing a 50/50 gamble. Test [training] data consist of 1688 [6810] records and the models' hyperparameters are chosen as the values that yield the highest mean 10-fold CV accuracy using subjects as strata. In this Figure, we use k-means clustering to highlight differences across subjects-model-specific accuracy results across PEVL, NEVL and differences between NEVL and PEVL results. We evaluate logistic and penalized linear regression models (Elastic), support vector machines (SVM), artificial neural networks (ANN), random forests (RF), and gradient boosting machines (GBM) on the basis of psychophysiological (*P*) and attention (*A*) choice-process predictors; lottery-design, socioeconomic characteristics, and information on past gambling behavior (*LSG*); and a full-model that comprises all input categories (*LSGPA*). RDR is naïve forecast that predicts all records as not-playing, and SDR results from predicting a lottery with NEV (EV<0) as not-playing and PEV (EV≥0) as played.

Figure A8 supports our previous findings with respect to systematic differences in models' forecasting capabilities between subject-specific NEVL and PEVL choices. The corresponding subjects are characterized by the large differences within their NEVL results (red vs. green) and between their NEVL and PEVL results (red vs. blue). For example, the *A*-Logistic, *A*-Elastic, *P*-Logistic, *P*-Elastic, and *P*-ANN result in more 100% accurate forecasts for individual subjects for NEVL than all other *A* and *P* model-predictor-set combinations. In addition, they are the model-predictor-set combinations that show the highest number of subject-specific forecast differences between NEVL and PEVL (blue shaded areas). For *LSG* and *LSGPA*, both provide information on lotteries' payoff structures, and all evaluated forecasting methods produce accurate forecasts for the vast majority of subjects, especially for NEVL. Concisely, in contrast to PEVL, many subjects strictly reject NEVL, although a small number of subjects play a relatively large share of NEVL. As a result, for the vast majority of subjects, classification accuracy for the predictor-sets that include information on the lotteries' payoff structure is substantially higher for NEVL when compared with PEVL.

References

Auguie, B. (2017). gridExtra: Miscellaneous Functions for "Grid" Graphics. *R Package Version 2.3*.

Auguie, B. (2019). egg: Extensions for "ggplot2": Custom Geom, Custom Themes, Plot Alignment, Labelled Panels, Symmetric Scales, and Fixed Panel Size. *R Package Version 0.4.5*.

Breheny, P., & Burchett, W. (2017). Visualization of Regression Models Using visreg. *R Package Version 2.7.0. The R Journal*, *9*(2), 65–71.

Calaway, R., Corporation, M., Weston, S., & Tenenbaum, D. (2017). "doParallel": foreach parallel adaptor for the parallel package. *R Package Version 1.0.11*.

Cheema, A., & Patrick, V. M. (2012). Influence of warm versus cool temperatures on consumer choice: A resource depletion account. *Journal of Marketing Research*, *49*(6), 984–995.

Friedman, J. H., Hastie, T., & Tibshirani, R. (2010). Regularization Paths for Generalized Linear Models via Coordinate Descent. *R Package Version 4.0-2. Journal of Statistical Software*, *3*(1), 1–22.

Greenwell, B., Boehmke, B., Cunningham, J., & Developers, G. (2018). gbm: Generalized Boosted Regression Models. *R Package Version 2.1.5*.

Gu, Z., Eils, R., & Schlesner, M. (2016). Complex heatmaps reveal patterns and correlations in multidimensional genomic data. *Bioinformatics*, *32*(18), 2847–2849.

Gu, Z., Gu, L., Eils, R., Schlesner, M., & Brors, B. (2014). Circlize implements and enhances circular visualization in R. *R Package Version 0.4.10. Bioinformatics*, *30*(19), 2811–2812.

Halko, M. L., & Sääksvuori, L. (2017). Competitive behavior, stress, and gender. *Journal of Economic Behavior and Organization*, *141*(396), 96–109.

Heinzen, E., Sinnwell, J., Atkinson, E., Gunderson, T., & Dougherty, G. (2020). arsenal: An Arsenal of "R" Functions for Large-Scale Statistical Summaries. *R Package Version 3.4.0*.

Karatzoglou, A., Smola, A., Hornik, K., & Zeileis, A. (2004). kernlab - An S4 Package for Kernel Methods in R. *R Package Version 0.9-29. Journal of Statistical Software*, *11*(9), 1–20.

Kassambara, A. (2020). ggpubr: "ggplot2" Based Publication Ready Plots. *R Package Version 0.4.0*.

Kuhn, M. (2018). caret: Classification and Regression Training. R package version 6.0-73. *Contributions from Jed Wing, Steve Weston, Andre Williams, Chris Keefer, Allan Engelhardt, Tony Cooper, Zachary Mayer, Brenton Kenkel, the R Core Team, Michael Benesty, Reynald Lescarbeau, Andrew Ziem, Luca Scrucca, Yuan Tang, Can Candan and Tyler Hunt*.

Neuwirth, E. (2014). RColorBrewer: ColorBrewer palettes. *R Package Version 1.1-2*, https://cran.R-project.org/package=RColorBrewer.

Ooms, J. (2020). rsvg: Render SVG Images into PDF, PNG, PostScript, or Bitmap Arrays. *R Package Version 2.1*.

R Core Team. (2020). R: A Language and Environment for Statistical Computing. *R Foundation for Statistical Computing (Version 4.0.2 and 4.0.0)*.

Statacorp. (2017). *StataCorp. Stata Statistical Software: Release 15*.

Venables, W. N., & Ripley, B. D. (2002). *Modern Applied Statistics with S. Fourth Edition* (R Package). New York: Springer.

Wickham, H., Averick, M., Bryan, J., Chang, W., D'Agostino McGowan, L., François, R., … Yutani, H. (2019). Welcome to the tidyverse. *R Package Version 1.3.0. Journal of Open Source Software*, *4*(43), 1686.

Wickham, H., Lionel, H., Pedersen, T. L., Luciani, T. J., Decorde, M., & Lise, V. (2020). svglite: An "SVG" Graphics Device. *R Package Version 1.2.3.2*.

Wright, M. N., & Ziegler, A. (2017). ranger: A Fast Implementation of Random Forests for High Dimensional Data in C++ and R. *R Package Version 0.12.1. Journal of Statistical Software*, *77*(1), 1–17.

Yu, G. (2020). ggimage: Use Image in "ggplot2." *R Package Version 0.2.8*.

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