Losses disguised as wins evoke the reward-positivity event-related potential in a simulated machine gambling task.

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Abstract

Electronic gambling machines include a suite of design characteristics that may contribute to gambling related harms and require more careful attention of regulators and policymakers. One strategy that has contributed to these concerns is the presentation of "losses disguised as wins" (LDWs), a type of salient losing outcome in which a gambling payout is less than the amount wagered (i.e., a net loss), but is nonetheless accompanied by the celebratory audio-visual stimuli that typically accompanies a genuine win. These events could thereby be mistaken for gains, or otherwise act as a reward signal, reinforcing persistent gambling, despite being a loss. This study aimed to determine whether LDWs evoke a reward positivity component in a task modelled on slot-machine gambling. A prominent account of the reward positivity event-related potential suggests that it is evoked during the positive appraisal of task related feedback, relative to neutral or negative events, or that it is evoked by neural systems that implement the computation of a positive reward prediction error. We recruited 32 individuals from university recruitment pools and asked them to engage in a simple gambling task designed to mimic key features of a slot machine design. The reward positivity was identified using temporospatial principal components analysis. Results indicated a more positive reward positivity following LDWs relative to clear losses, consistent with the theory that LDWs contribute to positive reinforcement of continued gambling, despite being net losses.

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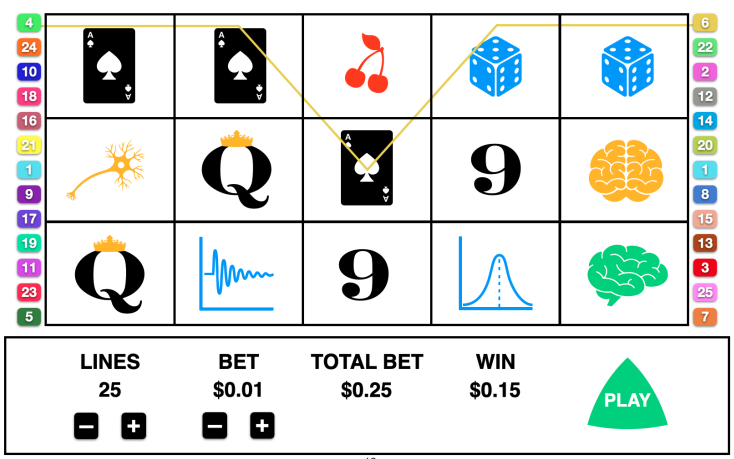

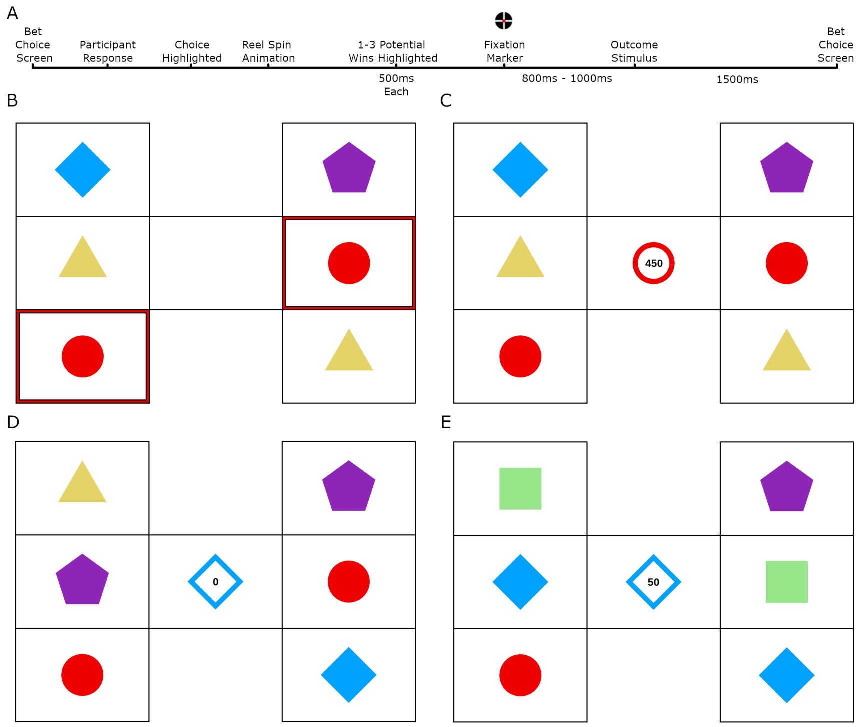

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Losses disguised as wins evoke the reward-positivity event-related potential in a simulated machine gambling task

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Keywords:

Losses disguised as wins; Gambling; Event related potential; Reward positivity; Slot machine; Electronic gambling machines

Abbreviations:

AUD – Australian Dollars

CS – Conditioned Stimuli

EEG – Electroencephalography

EGM – Electronic Gambling Machine

ELPD – Expected Log Pointwise Predictive Density

EOG – Electrooculogram

ERP – Event Related Potential

fMRI – Functional Magnetic Resonance Imaging

HDPI – Highest Density Posterior Interval

Hz – Hertz

ICA – Independent Components Analysis

LDWs – Losses Disguised as Wins

OR – Odds Ratio

OSF – Open Science Framework

PCA – Principal Components Analysis

RewP – Reward Positivity

RPE – Reward Prediction Error

Abstract

Electronic gambling machines include a suite of design characteristics that may contribute to gambling related harms and require more careful attention of regulators and policymakers. One strategy that has contributed to these concerns is the presentation of "losses disguised as wins" (LDWs), a type of salient losing outcome in which a gambling payout is less than the amount wagered (i.e., a net loss), but is nonetheless accompanied by the celebratory audio-visual stimuli that typically accompanies a genuine win. These events could thereby be mistaken for gains, or otherwise act as a reward signal, reinforcing persistent gambling, despite being a loss. This study aimed to determine whether LDWs evoke a reward positivity component in a task modelled on slot-machine gambling. A prominent account of the reward positivity event-related potential suggests that it is evoked during the positive appraisal of task related feedback, relative to neutral or negative events, or that it is evoked by neural systems that implement the computation of a positive reward prediction error. We recruited 32 individuals from university recruitment pools and asked them to engage in a simple gambling task designed to mimic key features of a slot machine design. The reward positivity was identified using temporospatial principal components analysis. Results indicated a more positive reward positivity following LDWs relative to clear losses, consistent with the theory that LDWs contribute to positive reinforcement of continued gambling, despite being net losses.

Declarations

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Conflicts of interest

The authors declare that they have no conflict of interest in relation to the publication of this article.

Dan Myles has received funding from the New South Wales Department of Health, Office of Responsible Gambling which derives resources in part through hypothecated taxes on gambling revenue.

None of the authors have knowingly received direct research funding from the gambling, tobacco, or alcohol industries, nor from any industry-sponsored organisation, or any other commercial entity that may stand to gain or lose financially through the publication of this manuscript. None of the authors have any personal financial interest in these industries.

Availability of data, materials, and analysis scripts

The code necessary to implement the psychtoolbox task used in this experiment has been made available on GitHub. De-identified raw data, processed data, data analysis scripts, and other materials have been made available on the Open Science Framework.

OSF Project: https://osf.io/s8wrb/

GitHub: https://github.com/danmyles/9Line_Slots_Task

Pre-registration:

This study was not pre-registered.

Authors' contributions

Table 1 – Author Contributions Using Contributor Roles Taxonomy

Author	Contribution
Dan Myles	Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.
Stefan Bode	Methodology, Resources, Supervision, Writing – review & editing.
Adrian Carter	Supervision, Writing – review & editing.
Murat Yücel	Supervision, Writing – review & editing.

Ethics approval

This study was performed in line with the principles of the Declaration of Helsinki. Ethics approval was obtained from the University of Melbourne Human Research Ethics Committee (Project ID 20440). A copy of this initial approval, along with relevant documentation was co-registered with the Monash University Human Research Ethics Committee (Project ID: 27157).

Consent to participate

Prior to providing consent participants were presented with a plain language statement describing the study. All participants for whom data were recorded provided explicit consent to participate in the study as described.

Consent for publication

The plain language explanatory statement presented to participants prior to consent included the following specific information about the intention to use of research data in future publications or presentations: "Data will be collated, statistically analysed, and may form part of a research thesis. The results may also be presented at research conferences, presentations or included in a published research journal. Public presentations and publications will only report aggregate and anonymised data and will not identify you personally".

Our explanatory statement also stated the authors' intention to publish open access data: "data will be made available to other researchers via a data repository such as the Open Science Framework or the website of a scientific journal. Data will also be made available to other scientists during the formal peer review process of any findings intended for publication. All data made available to other researchers will be thoroughly anonymised. It will not be possible to identify you personally from any data made available in this way." Participants were also informed in plain language of the potential benefits of open data practices, and that any data made available would be under a Creative Commons Non-Commercial Licence that forbids the use of these data for commercial gain.

Our consent form included specific acknowledgement that participants had read this statement, that they understood that data may be used in research publications and presentations, that data would be made publicly accessible in an anonymous format on an open access database for other researchers to use, and that this data may be used in future research projects.

Introduction

The use and availability of gambling products is positively associated with a long list of social, personal, and economic harms; from addictive gambling, to bankruptcy, loss of employment, financial crime, both perpetrating and experiencing domestic violence, and an increased risk of suicide (Banks, 2017; Dowling et al., 2016; Giovanni et al., 2016; Langham et al., 2016). Products that allow for rapid and continuous wagering—such as electronic gambling machines (EGMs) or live sports betting—appear to inflate the incidence of these harms, or attract disproportionate use among individuals already experiencing harm (Armstrong & Carroll, 2018; Badji et al., 2020; Bischof et al., 2016; Markham et al., 2016). These higher-risk risk products also appear to accelerate the transition to addictive gambling (Breen & Zimmerman, 2002) and account for a greater proportion of individuals seeking treatment for gambling related issues or reporting gambling-related problems (Gainsbury, 2014; Petry, 2003).

A public health approach to addressing gambling harm asserts that any meaningful solution must not only attempt to provide support and treatment to individuals who experience these harms, but also seek to prevent harm from occurring by attending to its determinates. Addressing or preventing these harms requires a broad frame of reference that positions the psychobiology of harmful gambling behaviour within the regulatory, commercial or cultural environments that enable it (Wardle et al., 2019). A key feature of this approach has been to consider how the commercial incentives to design gambling products that maximise profit has also motivated the design of product features that facilitate the initiation and maintenance of addictive behaviour (Schüll, 2012). The higher rates of harm associated with EGMs has been partially attributed to specific product design features thought to influence human cognition and reinforce the extended or repetitive use of these products (Blaszczynski et al., 2015; Livingstone et al., 2019; Yücel et al., 2018). Of particular concern are those features that provide a source of reward while gambling that is incommensurate with their utility, or features that encourage inaccurate appraisals of the structure of a wager and its outcome. One such feature are "losses disguised as wins" (LDWs); a type of gambling event in which a net loss is celebrated in a manner comparable to a genuine win (Dixon et al., 2010).

LDWs are a common event in multiline video slot machines, a prevalent type of EGM. These devices accept simultaneous wagers along numerous "pay-lines", where a pay-line refers to a set positions along the EGM display in which matching symbols will produce a payout (see Figure 1 where a matching outcome has been highlighted along pay-line 6). Like classical slot machines, a winning outcome will occur when a set of matching symbols line up across the centre most position along of each vertical reel (typically pay-line 1). However, these multiline machines will also accept additional and concurrent wagers on an array of different pay-lines, such the outcome displayed below in Figure 1. LDWs occur when a winning outcome on one pay-line fails to win back more than the total stake. In the example displayed in Figure 1 below, a 1c bet was placed across 25 different pay-lines for a total wager of $0.25. The match of three ace of spades symbols has occurred along pay-line 6 and this represents a 15-fold return on the wager. While the exact presentation of these outcomes can differ between jurisdictions (Stevens & Livingstone, 2019), a typical device will prominently display the payout of $0.15 under the text "WIN", highlight the matching symbols with a brief animation of flashing lines, and celebrate the outcome with a short musical fanfare. This sequence of events closely resembles the sequence of events that occurs following a small genuine win, despite the fact it has resulted in a *net-loss* of −\$0.10. Losing pay-lines are not highlighted and the net return is not displayed on the screen of typical devices.

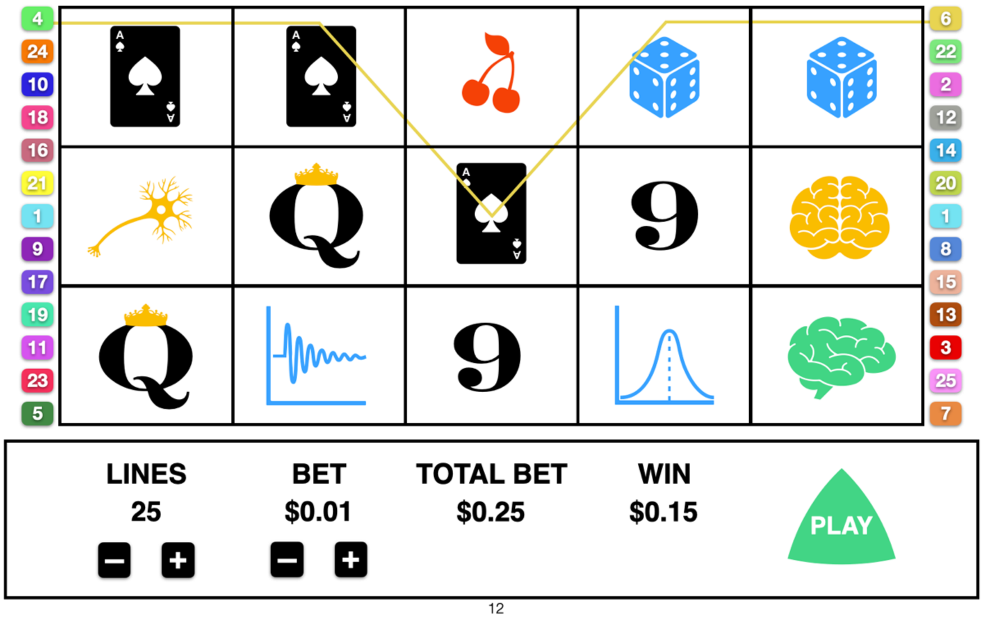

Figure 1 An illustrative example of an LDW. The 1c bet on 25 pay-lines results in a total wager of \$0.25. The match of three ace of spades symbols has occurred along pay-line 6 for a payout of \$0.15. The display of this outcome closely resembles a genuine win, despite the fact it has resulted in a net-loss of −\$0.10.

LDWs could contribute to addictive or harmful use of EGMs in two critical ways. First, by increasing the frequency of LDWs, manufacturers can reduce the probability of clear losses without change to the long-run financial expectation. If LDWs are less aversive than clear losses, this could mitigate extinction effects by reducing the incidence and length of consecutive strings of losses that would otherwise accumulate to dissuade continued wagering (Haw, 2008). Consistent with this concern, Leino et al. (2016) observed that consumers were more likely to terminate a gambling session following a loss than an LDW, a conclusion based on data extracted from 8,636 EGM user accounts provided by a state-owned gambling company in Norway. A second concern is that LDWs may increase the frequency of positive reinforcers while gambling. This may occur firstly because LDWs appear to be commonly mistaken for actual gains. Numerous self-report studies have found that both experienced and novice gambler's overestimate the rate at which they have won more than they wagered when LDWs are present, relative to when they are absent, in realistic simulated EGM gambling scenarios (Dixon et al., 2015; Dixon, Graydon, et al., 2014; Graydon et al., 2017, 2021; Jensen et al., 2013; Myles et al., 2023; Templeton et al., 2015). A further concern is that the celebratory audio-visual stimuli paired with both wins and LDWs may serve as conditioned reinforcers regardless of whether these events are miscategorised as gains (Dixon, Harrigan, et al., 2014). This may enable a second-order random-ratio reinforcement schedule in which behaviour is maintained by two levels of reinforcement (Myles et al., 2019). The first "unit-order" of reinforcement being the frequent presentation of a conditioned reinforcer, in this case LDWs; the second being the relatively rare presentation of larger wins. Second-order schedules are a highly effective technique in separating reward motivated behaviour from the actual presentation of that reward and for increasing resistance to extinction phases (Everitt & Robbins, 2000; Schindler et al., 2002).

Methodologies from cognitive neuroscience could provide an additional line of evidence to complement these behavioural findings and further illuminate whether LDWs contribute to the addictive potential of EGMs (Myles et al., 2019). One promising electroencephalography (EEG) measure of neural activity related to reward or outcome processing is the reward positivity[1] (RewP) event-related potential (ERP) (Holroyd et al., 2008; Holroyd & Coles, 2002; Proudfit, 2015). This component is typically observed as a positive difference in amplitude at frontocentral electrode sites, approximately 200 to 350ms following the presentation of subjectively favourable outcome information, relative to neutral or unfavourable information.

Studies employing concurrent functional magnetic resonance imaging (fMRI) and EEG, or within-subjects EEG-fMRI designs (Becker et al., 2014; Carlson et al., 2011), have demonstrated that the RewP is correlated with metabolic activity in the ventral striatum, as well as medial prefrontal and cingulate regions of the cortex. These cortical regions receive dopaminergic inputs from the ventral striatum and ventral tegmental area and are likely candidates for the primary source of electrical activity measured at the scalp (Hauser et al., 2014; Smith et al., 2015). Together, these regions are also key areas of the brain's reward system, a network of regions thought to implement the computation of reinforcement learning, beginning with the phasic firing of dopamine neurons in the ventral tegmental area and spreading systematically to efferent sites, including but not limited to, the ventral striatum, amygdala, hippocampus, anterior cingulate cortex and medial prefrontal cortex (Montague et al., 1996; Niv, 2009). Decades of research have linked the activity of this system to motivation, addiction and reward processing more generally, and further studies have demonstrated associations with financial gains presented during gambling tasks (Corlett et al., 2022; Fauth-Bühler et al., 2017; Linnet, 2014; Murch & Clark, 2016; Myles et al., 2019; Shao et al., 2013).

The RewP is also reliably associated with the subjective valance attributed to outcomes across a diverse range of tasks (Cockburn & Holroyd, 2018; Glazer et al., 2018; Hajcak et al., 2006; Holroyd et al., 2006; Proudfit, 2015). This valence dependency of the RewP has been reproduced in a large sample of 500 participants (Williams et al., 2021) and in a meta-analysis of 55 experiments involving monetary outcomes (Sambrook & Goslin, 2015). Most relevant to the current study, numerous studies have reported that this measure is sensitive to the distinction between wins and losses in tasks designed to simulate slot-machine gambling (Lole et al., 2013, 2015; Luo et al., 2011).

The primary motivation for this study was to test the theory that slot-machine LDWs are rewarding in a manner comparable to small wins, and unlike losses. To test this hypothesis, we developed a novel computer-based gambling task intended to mimic the key features of how a slot machine displays LDWs. We hypothesised that the LDWs produced by this task would elicit an increase in amplitude

[1] Historically the reward positivity has also been referred to as the feedback related negativity, among other names. We follow Greg Proudfit's (2015) terminology here as this term more accurately describes the measure's specific response to gains and the relative positive difference in amplitude relative to losses.

relative to losses within the time course and topography of the RewP. We further hypothesised that the difference in amplitude between LDWs and losses would exceed any difference between LDWs and small gains.

Methods

Participants

Participants were recruited using flyers placed around University of Melbourne and Monash University campuses, and the online participant recruitment pool provided at both institutions. Inclusion criteria included right-handedness, normal or corrected to normal vision, no history of neurological or psychiatric disorder and limited gambling activity of no more than twice in the previous 12 months. The final sample consisted of 32 individuals, including 22 women, 9 men, and one participant not endorsing a binary gender. Participants were between 18 and 47 years of age, and median age was 23. Twenty-nine participants were currently enrolled to study in a university program, and all 32 participants had completed high school or a tertiary qualification. Participants were informed that they would be paid for any credits remaining at the end of the experiment. In addition, all participants received a fixed participation fee of $10 AUD. This study was performed in line with the principles of the Declaration of Helsinki. Ethics approval was obtained from the University of Melbourne Human Research Ethics Committee (Project ID 20440). A copy of this initial approval, along with relevant documentation was co-registered with the Monash University Human Research Ethics Committee (Project ID: 27157).

Experimental Paradigm

Participants completed a novel computer-based gambling task that was purpose built to mimic essential features of the presentation of LDWs in slot-style EGMs (the "9 Line Slot Task" available at https://github.com/danmyles/9Line_Slots_Task).

The sequence of events presented to participants during each trial is displayed below in Figure 2A. On every trial, participants first made a wager of 90 credits (described below). Following the wager, the task presented an H-shaped grid of 7 rectangles, arranged as two vertical columns either side of a central rectangle. A sequence of events was then presented within this grid beginning with an animation of spinning symbols within the left and right columns intended to resemble slot machine reels. The left reel stopped first, followed by the right reel. Potential pay-line matches were then highlighted sequentially (500 ms), followed by a fixation marker displayed at the centre of the screen for 800–1000 ms (random uniform temporal jitter). The outcome stimulus was then displayed at the fixation point for 1500 ms before continuing to the next trial. No sound was paired with any stimulus to avoid potential confounds due to auditory ERPs. A payout occurred when the outcome stimulus matched symbols in both the left and right columns, allowing for 9 pay-lines (Figure 2B). The numeric payout was immediately displayed within the outcome stimulus (Figure 2D and 2E).

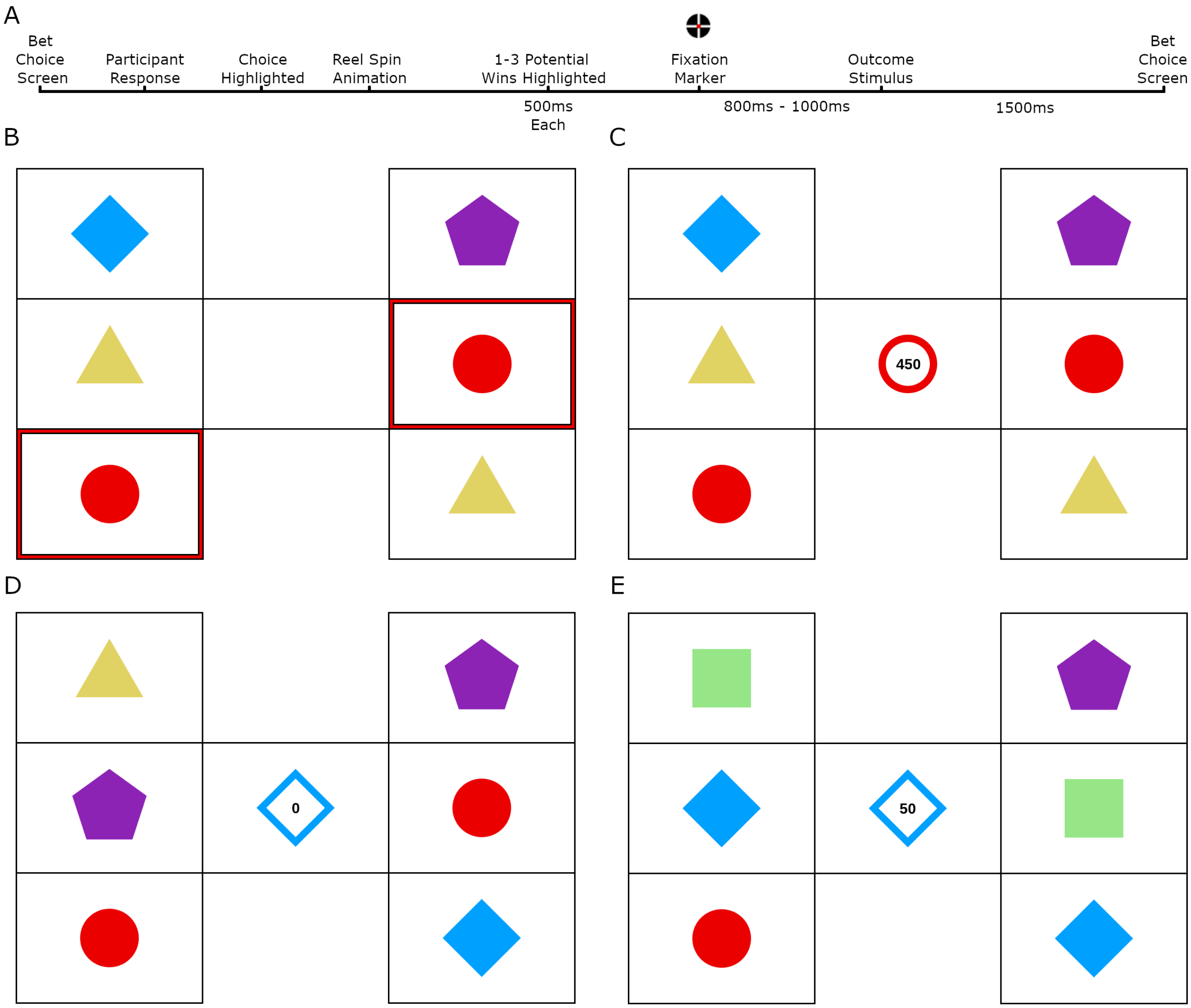

Figure 2 A schematic representation of the 9 Line Slot Task. **A.** Timeline of the sequence of events displayed on each trial. **B.** Screen capture during pay-line highlighting phase. Note that for the combination show here a second highlight would also occur on the yellow triangles. **C.** Screen capture displaying a winning outcome matching on the red circle. **D.** Screen capture displaying a clear loss. **E.** Screen capture displaying an LDW. This outcome matches on the blue diamond and represents a net loss of 40 credits after subtracting the cost of the wager (90 credits).

There were 5 different symbols in total, and the sequence of symbols on each reel was designed so that the same symbol could not appear more than once within the same reel. This design ensured that prior to the presentation of the outcome stimulus, each trial presented between 1 and 3 potential matches, but that no more than a single pay-line could pay out on any one trial. Payouts included two LDWs of 30 (i.e., net −60) or 50 (net −40) credits; two small genuine wins, 130 (net +40) or 150 (net +60) credits; or a larger win of 450 (net +390) credits. Non-matching or losing outcomes were indicated as 0 (net −90) credits.

An active betting choice was presented at the start of each trial, and participants could choose between two alternate gambles, labelled “Blue Game” and “Green Game” displayed either side of the screen. This was primarily intended to provide a sense of control or agency during the experiment as previous work has indicated that RewP amplitudes are attenuated in passive gambling tasks (Mühlberger et al., 2017). Although the influence of the preceding outcome on decision behaviour was considered in an analysis of choice behaviour (see Results). The position of the "Green Game" and "Blue Game" was randomly exchanged between the left or right side of the screen on each trial. This bet choice screen also clearly displayed the cost of each wager (90 credits) and any remaining credits. Participants indicated their choice using a keyboard press and their choice was briefly highlighted with a red rectangle. The outcomes for both the "Green Game" and "Blue Game" were generated using the same process so that each choice had the same negative expected value and frequency of each event type.

For each participant the events corresponding to each betting choice and were randomly sorted into blocks of 30 trials containing exactly 15 losses, 6 LDWs (3 x 30 credits; 3 x 50 credits), 6 small wins (3 x 130 credits; 3 x 150 credits), and 3 large wins. This block design was chosen for methodological and practical reasons. First, to ensure a satisfactory number of repeated observations for each event type for each participant. Second, to prevent a-typical long runs of the same event. Finally, this procedure ensured that each participant's payment would be approximately comparable, that payments could not exceed our available funds, and that losses could not accrue to the extent that they exceeded a participants' starting credits. However, participant choices could produce incomplete final blocks, resulting in a slightly different event frequency for each participant at the conclusion of the experiment.

In total this resulted in 360 trials comprised of approximately 180 losses and 180 "events"; the latter of which included approximately 72 LDWs (36 x 30 credits + 36 x 50 credits), 72 small wins (36 x 130 credits + 36 x 150 credits), and 36 large wins (450 credits). The frequency and magnitude of these payouts delivered a negative expected value, or an average loss of 9 credits per 90 credit wager. This value was based on an analysis of the average house-edge of EGMs in Victoria, Australia (Woolley et al., 2013).

A short screen capture video demonstrating a series of example trials has been included in the supplementary online materials, along with the task instructions presented to participants. OSF link: https://osf.io/s8wrb/

Procedure

All participants were provided with a plain language statement explaining that the purpose of the experiment was to investigate how people observe and understand gambling outcomes using a computer-based gambling task and a non-invasive measure of brain activity. Losses disguised as wins were not explicitly mentioned in this statement as previous behavioural studies have reported that awareness of LDWs may reduce their influence on win-overestimation (Graydon et al., 2017).

Upon entry to the lab participants were provided with an opportunity to sign a written consent form and confirm that they met the study inclusion criteria. Consenting and eligible participants were then fitted with EEG electrodes. Participants were seated in front of a 24.5" 240 Hz LCD monitor (all hardware and software is described on the OSF page). The task was presented in MATLAB (R2022a) using extensions from the Psychophysics Toolbox (PTB-3) (Brainard, 1997). Task instructions were presented on screen while the experimenter remained present to answer questions and confirm participants' understanding. Participants were provided with a starting balance of 20,000 credits and informed that they would be paid for any credits remaining at the end of the experiment (1,000 credits = $1 AUD). During the EEG experiment, participants were presented with a break screen every 60 trials. Median completion time for the gambling task was 52m 0s (min = 44m 1s, max = 1h 11m 51s) and the median duration of each trial was 6.85 seconds.

Following the gambling task participants were directed to complete a short demographic survey. Finally, participants were provided with a plain language debriefing statement explaining that the primary aim of the study and describing LDWs. They were then reimbursed $10 AUD for their time in addition to a payment proportional to the credits remaining at the end of the gambling task (median = $16.74, minimum = $15.90, maximum = $17.27).

EEG recording

EEG was recorded at a sampling rate of 1024 Hz using a BioSemi Active-Two system and Actiview acquisition software. This system employs a common mode sense active electrode and driven right leg passive electrode in place of a traditional ground. Data were recorded from 64 active electrodes positioned in a fabric electrode cap according the 10/20 system and 2 active electrodes were affixed to the left and right mastoid. Concurrent electrooculogram (EOG) was recorded from 4 active electrodes attached above and below the right eye and adjacent to each lateral canthi.

EEG pre-processing

EEG data were pre-processed using the EEGLab v2022.1 toolbox (Delorme & Makeig, 2004), ERPlab v9.00 (Lopez-Calderon & Luck, 2014) and MATLAB 2022a. Data were first down sampled to 256 Hz and band-pass filtered between 0.1 and 30 Hz (ERPLab Butterworth filter, order 2). Remaining line noise was identified and removed using the Cleanline plugin for EEGlab (Mullen, 2012). Ocular artefacts were identified and corrected using independent components analysis (ICA) (EEGlab extended runica algorithm). All data were referenced offline to the right mastoid during pre-processing and re-referenced to the average of both mastoid electrodes following ICA and prior to artefact rejection and averaging. To improve the performance of both the Cleanline algorithm and the ICA, we applied a 1Hz high-pass filter (EEGlab Basic FIR filter new, default settings) to a copy of the dataset prior to each procedure. Signal identified as line noise in this copy of the data was then subtracted from the primary data set and ICA components were copied from the 1Hz filtered data set to the primary dataset, as recommended by Bigdely et al. (2015) and Luck (2022).

Following line noise removal and prior to implementing the ICA, the data were segmented to remove breaks and long periods of non-responding at the bet choice screen (> 5 seconds). Problem electrodes were manually identified and deleted based on persistent discontinuities, excessive noise, or frequent artefacts isolated to single electrodes during the planned epoch period (range = 0 – 8 electrodes deleted, median = 2.5; Fz, FCz and Cz were not affected). Electrodes with low maximum correlations across the whole dataset, or low correlations across 500 randomly selected windows, were scrutinised more closely for deletion, as were electrodes displaying unusual log power spectral density. Finally, segments of data containing large artefacts across multiple electrodes were excluded from the ICA dataset. ICA components were manually identified based on broad scalp topography, temporal association with a bipolar EOG electrode, and with additional support from the IClabel plugin for EEG lab (Pion-Tonachini et al., 2019).

Following the ICA correction, any deleted electrodes were interpolated using spherical spline interpolation. The data were then re-referenced to the average of both mastoid electrodes and segmented into feedback locked epochs, comprising of a 200 ms baseline period and an 800 ms post-feedback interval. We then conducted a semi-automatic artefact detection process. Trials containing eye movements within 200 ms of outcome presentation or containing larger artefacts during the full epoch were rejected. Where artefacts were detected on single electrodes without issues at remaining sites, single trial interpolation of the electrode was employed to prevent unnecessary data loss. Following this process all participant data sets retained greater than 80% of the total trials.

Data reduction

One methodological concern with isolating the RewP is that this component typically exhibits temporal and spatial overlap with the nearby P2 and P3 components (Glazer et al., 2018). One approach to alleviate this concern and to facilitate a data-driven selection of ERP latency is the to use temporospatial principal components analysis (PCA) (Dien, 2012). This approach has been used in numerous recent RewP studies (e.g., Carlson et al., 2011; Foti et al., 2011; Mulligan & Hajcak, 2018; Sambrook & Goslin, 2016), including studies investigating slot-machine style tasks specifically (Lole et al., 2013, 2015).

In the present study we also adopted these procedures. Each participant data set was randomly shuffled and split into two "sessions" containing the same number of each type of payout (±1), before averaging by payout magnitude (0, 30, 50, 130, 150, or 450 credits). This step was performed to enable a varying slopes analysis of the resulting PCA factor. We then conducted a two-step temporospatial PCA using the ERP PCA Toolkit (Dien, 2010b). As outlined in the toolbox guidelines (Dien, 2010a, 2012) we first analysed temporal variation using promax rotation. The data were reduced to 11 temporal factors based on a parallel test, which selects factors with eigenvalues greater than those generated from a random noise data set (Horn, 1965). A separate spatial PCA was then performed for each of these 11 temporal factors using infomax rotation. The ERP PCA Toolkit computes a single parallel test for this second step averaged across all remaining temporal factors, requiring the same number of spatial factors be retained for each temporal factor. This process resulted in a total of 33 temporospatial factors (3 spatial factors for each of the 11 temporal factors).

Collectively all components accounted for 84.3% of the variance in the data, and 8 individual components accounted for greater than 1% unique variance. As the intention of this study was to analyse the RewP component specifically, this component was identified based on latency, temporal position relative to other factors and scalp topography (see Figure 3). The ERP PCA Toolkit facilitates the reconstruction of these factor scores back to the microvolt scale, and these values were used in all following statistical analyses. Further information pertaining to remaining factors explaining > 1% unique variance has been made available in the appendix for interested readers. Two of these resembled a feedback P3 and Late Positive Potential (Glazer et al., 2018). A brief exploratory analysis is reported in the appendix for each of these.

Data Analysis

Additional data processing was performed in *R* (R Core Team, 2022) with support from *data.table* (Dowle & Srinivasan, 2022) and *stringr* (Wickham, 2022) packages. All visualisations were composed using *R* and *ggplot2* (Wickham, 2016) with additional functions from the *cowplot* (Wilke, 2020) and *eegUtils* (Craddock, 2022) packages.

Bayesian Estimation

Parameter estimates for the regression models outlined below were derived using Bayesian estimation. In Bayesian estimation all model parameters are first assigned a prior probability distribution that represents a feasible range of parameter values weighted by a pre-determined probability. These values are then updated using Bayes' rule, to produce a posterior probability distribution for each parameter, such that the continuous range of values for each parameter is weighted to represent the degree to which each value is compatible with the data observed and structural assumptions of a statistical model, including any prior constraints placed on the parameter’s values.

Bayesian estimation enables a proportionate consideration of the full range of uncertainty associated with an estimate because the primary output is a complete posterior distribution, rather than a point estimate, or the results of statistical test which may obscure the extent to which a continuous range of values are consistent with the data. The advantages of estimation over null-hypothesis significance testing are well summarised by Geoff Cumming (2014). For an excellent introduction to Bayesian estimation see McElreath (2020), and for an account of the advantages of Bayesian estimation over ordinary least squares or maximum likelihood estimation, see Kruschke & Liddell (2018).

In this study we used uninformative or mildly regularising priors that set minimal prior constraints on these values (see below for details). These priors did not provide information related to the research hypothesis or prior research. Unless otherwise indicated, posterior point estimates refer to the median of a posterior distribution and these are reported alongside the lower and upper bounds of a 95% highest density posterior interval (HDPI).

All regression models were fit using *brms* (Bürkner, 2017), which provides a convenient interface for specifying Bayesian models in *R* using the *Stan* modelling language (Carpenter et al., 2017). All models were fit with 8 chains, 1,000 warmup draws, and 2,500 post-warmup draws, resulting in a total of 20,000 posterior draws. The reported models all achieved good convergence ($\widehat{R} < 1.01$) and bulk and tail effective sample sizes for all parameter estimates were greater than 1,000 (Vehtari et al., 2021).

Behaviour

Behavioural data from participant decisions to bet on either the Blue Game or Green Game were modelled using logistic regression. The purpose of this analysis was to consider whether there was an influence of the preceding outcome on decision behaviour on the following trial. Outcomes were coded as a binary variable such that `Switch = 1` when the choice on the preceding trial differed from the choice on the subsequent trial. Each preceding event type was assigned a dummy coded predictor (LDW, small win, large win), and varying intercepts and slopes were assigned by participant. The syntax used to model behavioural data is displayed below in Code Block 1. We used a Normal(0, 1.5) prior on the model intercept. This prevents prior density amassing at extreme values close to 0 or 1, but is otherwise approximately flat across the bulk of the probability scale (McElreath, 2020). Very mild regularising Normal(0, 1) priors were set on the dummy coded predictors and any remaining priors were set as explained in the Reward Positivity section below.

```
brm(formula = Switch ~ 1 + LDW + SW + LW + (1 + LDW + SW + LW | id),
    family  = bernoulli(),
    prior   = c(
      prior(normal(0, 1.5), class = "Intercept"),
      prior(normal(0, 1), class = "b"),
      prior(lkj(2), class = "L"),
      prior(exponential(1), class = "sd")),
    etc...)
```

Code Block 1 `brms` syntax used to model behavioural data.

Reward Positivity

The association between payout magnitude (0, 30, 50, 130, 150, or 450 credits) and the RewP amplitude (identified as the temporospatial factor outlined above) was modelled using hierarchical regression. This model structure included an intercept and a set of dummy coded predictors representing each payout amount (30, 50, 130, 150, 450). Both the intercept and slopes were permitted to vary by participant, to accommodate the repeated measures (`brm(formula = Amplitude ~ 1 + payout + (1 + payout | id), etc... )`).

Heterogeneity

The average ERPs used to compute the PCA were derived using a different number of trials for the loss condition (2 sets of 90 trials minus artefact contaminated trials) relative to the other events (2 sets of 18 trials minus artefact contaminated trials). This averaging procedure would produce heteroscedasticity. It is also conceivable that the residual standard deviation may vary across conditions due to some feature of the data generating process. For example, if ERPs in response to LDWs were more variable than those following small gains. To accommodate this, we fit two alternative distributional models to assess the assumption of homogeneity. Distributional models (Bürkner, 2022) allow a linear model to be fit to the residual standard deviation as well as the mean, to explicitly accommodate heterogeneity of variance.

To accommodate heterogeneity due to the averaging method, we estimated residual standard deviation separately for the loss condition and pooled across all remaining conditions in which the outcome was not a loss, to account for the averaging process (i.e., `log(sigma) ~ 1 + event` where `event` is a single dummy coded predictor for any non-loss outcome). To accommodate heterogeneity due to some feature of the data generating process, an alternative model provided a separate estimate of for each trial type to test the assumptions of condition-wise homogeneity (i.e., `log(sigma) ~ 1 + payout`, where payout is as above).

Influential Values

Influential data points were identified during leave-one-out cross validation based on pareto k values greater than 0.7. The original regression model assumed a Gaussian likelihood (i.e., normally distributed residuals). Inspection of the data distribution indicated a small number of extreme scores that would not be well accounted for by thin tails of a Gaussian distribution. To minimise bias due to these influential observations we fit each model again using a robust Student-t likelihood (McElreath, 2020, p. 233).

Model Comparison

The best performing of these robust models was then selected using leave-one-out cross validation which provides an approximate and relative measure of out of sample predictive performance indicated by a reduction in the expected log pointwise predictive density (ELPD) (Vehtari et al., 2017). The distributional model with a single dummy coded predictor across all non-loss payout events was the best performing by this metric, which indicated a substantial improvement relative to the standard homogenous model (ELPD Difference = −10.06, Standard Error = 3.46) and similar or marginally improved performance relative to the full condition-wise model (ELPD Difference = −2.87, SE = 2.40). This model was also felt to best account for the averaging method and regardless estimates for the fixed effects were closely comparable to the more complex model, and so the results of this simpler model are reported in the current paper.

Priors

Prior to analysis all outcome measures were centred relative to the loss condition mean and scaled by the standard deviation of the loss condition. This approach was adopted to aid in setting mild regularising priors on the model intercept. Following model fitting, all posterior estimates were transformed back to the microvolt scale and all estimates are reported on this scale. Accordingly, we used a Normal($\mu = 0$, $\sigma = 0.5$) prior for the model intercept. Fixed effects retained default brms uniform priors. A mild regularising Exponential($\lambda = 1$) prior was set for the standard deviation of parameters varying by participant and LKJ($\eta = 2$) priors were used for correlations between parameters (McElreath, 2020). Robust regression models included a Gamma(3, 1) prior for the Student t normality parameter, ν with a lower bound of 1. This prior was chosen to induce the model towards a more conservative t distribution with fatter tails, whilst excluding distributions for which the mean is undefined. A Normal(e, 2) prior was used for the intercept of the residual error term to centre the prior at 1 following transformation to the unit scale (brms uses a natural log link), and Normal($\mu = 0$, $\sigma = 1$) priors were used for the coefficients.

Results

Behaviour

A varying intercepts Bayesian logistic regression indicated approximately even odds of choosing the "Blue Game" (p = .51, 95% HDPI = [.45, .56]; odds = 1.02, [0.80, 1.27]) relative to the "Green Game" for an average participant. This result was as expected, given the symmetry of the two betting options. We then considered whether the probability of switching between bets would differ following each outcome type. We fit a Bayesian logistic regression that included the preceding event type as a dummy coded predictor (LDW, small win, large win), and varying intercepts and slopes by participant. The results reported in this section indicate the probability of switching bets (p). Odds ratios (OR) and differences in probability estimates are reported for each contrast. All estimates include the lower and upper bounds of a 95% HDPI in square brackets.

The probability of switching bets was higher following losses (p = .33, [.26, .39]) than it was following LDWs (p = .24, [.18, .30]; difference = −.09, [−.13, −.05]; OR = 0.65, [0.53, 0.79]), small wins (p = .18, [.13, .23]; difference = −.15, [−.20, −.10]; OR = 0.45, [0.33, 0.58]), or large wins (p = .19, [.14, .24]; difference = −.14, [−.19, −.08]; OR = 0.48, [0.34, 0.64]). The probability of switching following an LDW was higher than the probability of switching following a small gain (difference = .06, [.02, .10]; OR = 1.45, [1.14, 1.78]). Finally, the odds of switching were approximately even when comparing large wins to small wins (difference = −.01, [−.05, +.03]; OR = 0.94, [0.71, 1.19]).

Event Related Potentials

Reward Positivity

PCA factor TF5/SF1 (Figure 3B) mapped closely onto a large early peak in the difference wave (Figure 3D) derived from the classical grand average ERP (Figure 3C) when contrasting losses against other payout conditions. The latency, frontocentral scalp topography, and temporal position of this factor relative to other factors, resembled the features of the RewP identified using PCA in previous ERP studies of slot machine gambling (Lole et al., 2013), and within-subjects EEG-fMRI designs (Carlson et al., 2011). It was therefore concluded that the PCA had successfully isolated the RewP component. The virtual RewP component and topography of this factor are displayed below in Figure 3 alongside the traditional ERP and difference wave at electrode Fz.

We next considered posterior estimates from the statistical analysis of RewP amplitudes by payout condition. We first compared the average RewP for all payout conditions (i.e, 30, 50, 130, 150, 450 credits) to losses (0 credits). We found that relative to losses, all payout events were associated with a reliable average increase in RewP amplitude, see Table 2. This included the two LDWs of 30 and 50 credits, each of which represented a net loss of 60 and 40 credits respectively, after accounting for the cost of the bet (90 credits). Consistent with our secondary hypothesis we observed that the average RewP amplitudes following each of the LDW outcomes were closer on average to small gains, than they were to losses, see Figure 3 and Table 2.

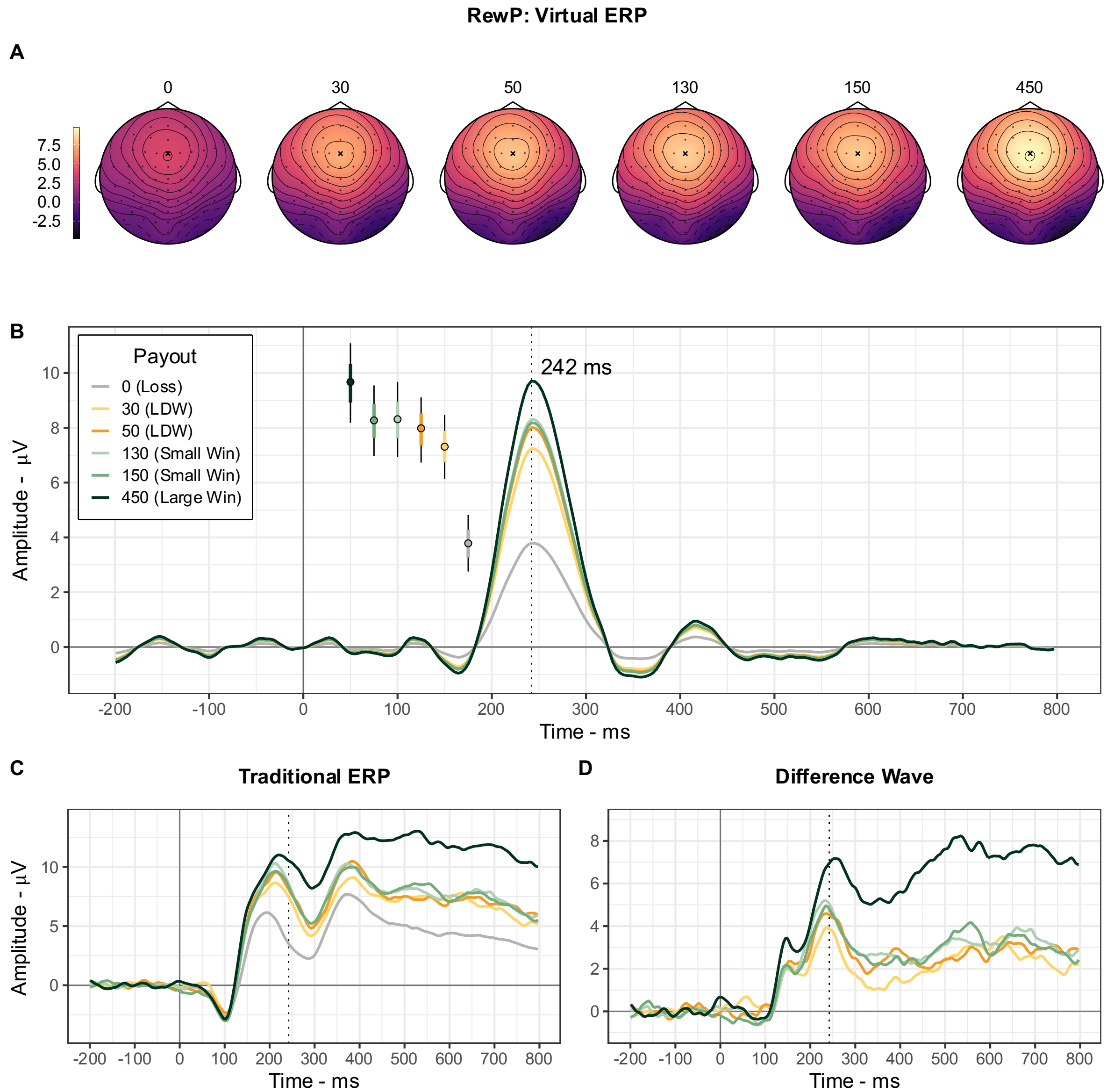

Figure 3 A. Topographic plot for temporospatial factor identified as the RewP. This topographic plot displays factor weight rescaled to amplitude at 242 ms post outcome stimulus for each payout condition. **B.** Virtual ERP for RewP/TF5SF1. The virtual ERP is displayed alongside posterior estimates of the average factor amplitude by payout amount. Error bars indicate 67% and 95% highest density posterior intervals around the mean amplitude estimates. Note that the horizontal position of these point estimates is simply to aid visibility and does not indicate time. **C.** Traditional grand average ERP at Fz. **D.** Difference wave relative to losses at Fz. Dotted vertical line indicates peak latency (242ms) of temporospatial factor TF5SF1, identified as the reward positivity in the present study.

The large gain of 450 credits (net 360) was associated with a substantially more positive RewP, relative to all other events, which may indicate some influence of either novelty or reward magnitude on the RewP amplitude, see Table 2. We also observed evidence of heterogeneity of variance depending on whether the outcome was a loss or payout event, as expected. The residual standard deviation for the RewP was larger (0.87; 95% HDPI = [0.39, 1.29]) across payout conditions (σ_{error} = 2.04 [1.78, 2.32]) relative to the loss condition (σ_{error} = 1.17 [0.81, 1.60]). As outlined in the methods section, this was theorised to be a result of averaging a different number of trials.

Table 2 Posterior estimates for TF5/SF1 (RewP) rescaled to amplitude (microvolts).

	Condition Mean			Contrast vs. Loss		
Payout	50%	2.5%	97.5%	50%	2.5%	97.5%
0 (Loss)	3.78	2.76	4.82	-	-	-
30 (LDW)	7.31	6.13	8.47	3.53	2.83	4.21
50 (LDW)	7.98	6.73	9.11	4.19	3.41	5.01
130 (Small Win)	8.31	6.94	9.68	4.53	3.70	5.39
150 (Small Win)	8.27	6.97	9.55	4.49	3.62	5.34
450 (Large Win)	9.67	8.18	11.08	5.88	4.86	6.95

Payout Contrasts			
Contrast	50%	2.5%	97.5%
50 − 30	0.66	−0.32	1.58
150 − 130	−0.04	−1.08	0.94
130 − 30	1.01	0.06	1.96
150 − 50	0.30	−0.81	1.36
450 − 50	1.68	0.57	2.90
450 − 150	1.39	0.30	2.52

[Table Note] Model estimates for factor TF5/SF1, identified as the RewP component. These intervals represent modelling uncertainty around the estimation of the mean of each condition (left). Contrasts indicate differences between these mean values (centre and right). Contrast estimates indicate a more positive RewP for all events relative to losses (centre panel), and for large gains relative to all other payout events (bottom right). Estimates provided indicate the posterior median (50%) and 95% highest density posterior interval (HDPI).

Discussion

The present study was motivated by a reinforcement learning or reward-processing theory of both the reward positivity (Holroyd & Coles, 2002; Proudfit, 2015) and the contribution of LDWs to persistent gambling (Linnet, 2014; Murch & Clark, 2016; Myles et al., 2019). Based on these background theories we hypothesised that if LDWs, despite being net losses, are in fact rewarding then they should evoke a RewP ERP relative to clear losses, in a manner comparable to small wins. To test this hypothesis, we presented participants with different gambling outcomes (losses, LDWs, small wins, and large wins) in a simplified gambling task designed to mimic essential elements of a slot-machine display. We observed clear evidence that LDWs elicit a more positive RewP relative to clear losses. We also observed that the magnitude of this difference was substantially larger than any difference between LDWs and genuine small wins. Conditional on this motivating theory, these findings are consistent with the concern that LDWs may provide a source of reward while gambling despite being financial losses. These findings are inconsistent with the proposition that LDWs are perceived in a manner that is indistinguishable from clear losses.

As outlined in the introduction, the finding that the RewP is sensitive to a binary assessment of outcome valence is very robust, and has been replicated numerous times in a wide array of reward-processing tasks, as well with meta-analysis and in larger samples (Proudfit, 2015; Sambrook & Goslin, 2015; Williams et al., 2021). A number of studies have reported that the RewP appears to be sensitive only to positively valanced outcomes, and displays little to no distinction between neutral and negative outcomes (Hajcak et al., 2006; Holroyd et al., 2006; Kujawa et al., 2013; Varona-Moya et al., 2015). If so, these findings suggest that LDWs are experienced as a positive outcome, on average, despite being a net loss.

Another prominent account of the RewP has proposed that it provides an index of a positive reward prediction error (RPE), rather than a simple binary assessment the subjective valence of an outcome (Holroyd & Coles, 2002; Sambrook & Goslin, 2015, 2016). An RPE refers to the difference between a predicted reward and the value of an actual outcome. A *positive* RPE occurs when an outcome was better than expected. RPEs are a fundamental variable used to adjust future predictions in reinforcement learning models which describe a computational process by which environmental contingencies that lead to desirable outcomes are learned and used to motivate behavioural patterns that increase the future receipt of these outcomes (Rescorla & Wagner, 1972; Sutton & Barto, 2018). As outlined in the introduction, key aspects of this computational process are believed to be implemented in brain reward regions. This is supported in part by numerous observations that midbrain dopamine neurons display phasic firing patterns that co-occur with reward presentation and conditioned stimuli that predict the future presentation of reward, as well as firing rates that correspond to the relative size of a RPE, or the predicted reward value (Montague et al., 1996; Niv, 2009). These dopaminergic neurons have afferent projections to the ventral striatum, as well as anterior cingulate and medial pre-frontal regions of the cortex; areas positively correlated with the RewP in dual-modality EEG fMRI studies (Becker et al., 2014; Carlson et al., 2011). Additionally, RewP studies employing behavioural reinforcement learning tasks have reported findings broadly consistent with a reinforcement learning model of the RewP (Hoy et al., 2021; Sambrook & Goslin, 2016). If a positive RewP provides an index of positive RPEs, these findings suggest that LDWs may be interpreted as being better than an expected outcome (recall that the objective expected value for each bet on this task was −9 credits) and may therefore have a motivating influence on behaviour, despite being a net loss of either −60 or −40 credits.

In reporting these results we have made comparisons between LDWs and small gains, observing that the difference between these two types of events was much smaller than the difference observed between losses and LDWs. In interpreting these results, it is critical to highlight that the average amplitude of the RewP likely does not scale in a simple linear fashion with the cognitive representation of reward magnitude, given that both the relationship between subjective utility and objective currency values (Kahneman & Tversky, 1979), or between firing rates of dopamine neurons and metric measurements of the volume of appetitive rewards (Eshel et al., 2016; Schultz et al., 2015), typically take on non-linear sigmoidal functions. Moreover, non-linear response functions provide a means to implement unbounded continuous space within physiological constraints (Abbott & Dayan, 2001). We therefore caution that a simple linear interpretation of the observed similarities between LDWs and small gains, relative to losses, may not adequately reflect the cognitive representation of the scale of differences in reward magnitude, or the motivational potency of these outcomes.

The behavioural results observed in the present study are also consistent with the concerns expressed in the introduction that LDWs may mitigate the otherwise aversive influence of losing money on decision making, or result in more favourable appraisals of a gamble, relative to clear losses. In the current study, we observed that participants were more likely to make a switch between the two betting options following a loss than they were following an LDW. A similar, albeit stronger, pattern was observed following clear wins. This result is broadly consistent with behavioural and self-report findings that participants prefer to gamble on multiline slots that present LDWs relative to machines that do not (Graydon et al., 2018), as well observations based on user account data by Leino et al. (2016) that consumers were more likely to terminate a gambling session following a loss, relative to an LDW. The model used to fit the behavioural data in the present study was relatively simple, considering only the influence of the previous trial on subsequent decisions. It also has limited inferential value in the sense that a loss of −40 or −60 credits ought to be appraised more favourably (or less unfavourably) than a loss of −90 credits. Future studies could consider the influence of LDWs on trial-by-trial decision making in more depth by employing computational models of reinforcement learning. Such models (for example, Haines et al., 2018) could provide insight into to whether LDWs influence behaviour in a manner that is consistent with learning an expected value or win frequency that is incommensurate with objective value of the LDW. These models could be further enriched by considering correlations between model parameters, RPEs, and single trial EEG data, as recently reported by Hoy et al., (2021).

While this is, to our knowledge, the first study to examine the RewP in a slot-gambling modality, Peterburs et al. (2013) conducted an ERP study using a card gambling task that included LDW-like events. In this study, an initial stake of either 0 or 50 credits was randomly subtracted from a participant's available funds prior to making a choice between two cards. Following this choice participants were presented with an outcome of either −60, −20, −10, +20, +30, +60, +70, or +100 credits. A key feature of this design was that payouts of 20 or 30 credits would represent a net loss when the stake was 50 credits, but a clear win when the stake was 0. Although the stake by payout interaction effect was not statistically significant, the authors reported follow-up tests and a qualitative interpretation of the ERP waveform that suggested that RewP amplitudes following these payouts were comparable to losses when a bet was placed, but comparable to gains when the bet was free. This set of observations is consistent with the proposal that LDW-like events in this card gambling were subjectively experienced as losses, contrary to the findings reported in the present study.

There are a number of considerations that may explain the apparent incongruity between the results observed by Peterburs et al. (2013), and those observed in the current study. First, as Peterburs et al. (2013) note, LDWs may occur as a result of a combination of factors that were not present in their simple card game, which may have insufficiently represented the deceptive presentation of these events in commercial slot machines. By contrast, the present study attempted to mimic critical visual features of the display of LDWs in a slot machine. Second, the study by Peterburs et al. (2013), and most tasks reported in the RewP literature, are designed to have an overall net even or positive expected value. For example, the task described by Peterburs et al. (2013) had a net-even (0 credit) expected value globally, a positive expected value of +25 credits when the stake was 0 credits, and a negative expected value of −25 credits when the stake was 50 credits. The RewP appears to be sensitive to the global context of the task (Kujawa et al., 2013) in which case it is deviation from the overall expectation is likely to be the important consideration (Sambrook & Goslin, 2016). Experimental designs that involve a positive or net-even expected value may provide very valuable insights into human cognition, but they have limited face value if we are to understand how the structural characteristics of commercial slot machines contribute to their persistent use despite negative consequences. The negative expected value of commercial gambling products is critical to the very real financial harm associated with the persistent use of these products. Experimental designs must reflect this if findings are to have any ecological validity in this context, or policy application to actual gambling products. A casino that offered devices with a positive or net even expected value would no doubt be very popular for the short period of time that it remained open, but such opportunities are rare outside of temporary promotions or inducements to trial new products (Challet-Bouju et al., 2020; Hing et al., 2017). A related concern is that participants must also feel as though they are gambling with and for actual cash. In contrast to the study by Peterburs et al. (2013), the current study design had a negative expected value and participants were paid in cash for any credits remaining at the task conclusion.

One limitation of the present study is that our design did not adhere to the Hillyard principle; the recommendation that sensory features of the outcome stimuli involved in contrasts must be identical, while the design manipulates the task instructions such that the equivalent stimuli come to have a different cognitive representation (Luck, 2014). As a result, it remains possible that the contrasts observed may have occurred partly due to visual properties of the stimuli, or the cognitive representation of the numeric aspects of these stimuli that is unrelated to their reward properties. However, the interpretation of the effect being primarily driven by the reward properties of each outcome is more consistent with the observed behaviour, and with the neural source thought to generate the RewP (Becker et al., 2014; Carlson et al., 2011; Proudfit, 2015). A relative strength of the design reported by Peterburs et al. (2013), enabled such a comparison between genuine wins and LDWs, because the experimental manipulation of the initial stake at the beginning of each trial meant that the same outcome stimulus was compared across conditions. However, the critical comparison to make is not between equal payouts while varying the stake. It is between clearly presented losses and financially equivalent LDWs. Because this concern rests on the very appearance of the outcome stimuli (losses displayed like wins vs. losses displayed like losses), the Hillyard principle cannot be adopted with a pure within-subjects design. An alternative would be to employ between subjects or mixed design which presented instructions intended to intervene on the interpretation of LDWs. This approach was used in a behavioural study reported by Graydon et al (2017). In this study, participants were randomly assigned to view a brief educational animation either explaining LDWs or control condition explaining an unrelated feature of EGM design. The authors reported that participants exposed to the LDW video provided a more accurate estimates of the win rate following the session, relative to the control condition. These findings suggest that simply making a participant aware of the LDW feature may be sufficient to disrupt it. A similar design could be employed as a follow-up to the present study to determine whether knowledge of LDWs attenuated the RewP, a comparison which would minimise potential confounds of any non-reward related representation of the stimulus itself. The estimates, and data, provided by the present study will facilitate the simulation or power analysis necessary for a registered report of this proposed design.

Our results resemble findings from a broader literature concerning the influence of near miss events during slot machine gambling or other tasks. A near miss is another type of salient gambling loss that is presented in such a manner so as to appear as though it came close to being a win (Harrigan, 2008). The paradigmatic example is when only two of the three jackpot symbols necessary for a large win occur along the pay-line during EGM gambling. A number of ERP studies have reported a more positive RewP following near-misses relative to losses (Lole et al., 2013, 2015; Luo et al., 2011). Similarly, fMRI studies have observed increased metabolic activity following near-miss events relative to clear losses in the ventral striatum and anterior insula, regions also recruited in response to clear gains (Clark et al., 2009). Along with behavioural and self-report evidence, this has been interpreted as evidence of the potential for near misses to motivate continued gambling despite the financial loss. We have made a comparable interpretation here; however, we would add that the results observed suggest that the relative magnitude of the RewP following LDWs observed in this study substantially outstrips those differences observed between losses and near misses in previous studies, which may be reason for additional concern. Relevant here is that the present design always cued a minimum of 1 potential matching pay-line prior to any loss (see Figure 2B). This was necessary to avoid any reward anticipation effects occurring more frequently prior to LDWs, relative to losses in which no match was possible. Considering the literature on near misses suggests they may have some motivational potential; our design would have resulted in a more conservative comparison between LDWs and losses that always included key features of the presentation of a near miss.

Our interpretation of the present findings is predicated on reward processing theories of the RewP. In our view this theory is the most theoretically sound given current evidence, as well as being the consensus view of most scientists working in this field (Cockburn & Holroyd, 2018; Glazer et al., 2018; Proudfit, 2015). However, this interpretation is offered alongside the caveat that alternate theories of the RewP have been proposed. For example, some researchers have contended that the RewP is an index of the subjective *salience* of an event, rather than being exclusively or predominately sensitive to reward, such that aversive stimuli can also elicit a RewP relative to neutral stimuli under certain conditions (Hager et al., 2022; Talmi et al., 2013). However, this alternative account of the RewP is contrary to other findings concerning aversive stimuli (Heydari & Holroyd, 2016). And PCA studies have typically reported the RewP to be primarily driven by *positive* reward prediction errors, rather than an unsigned salience prediction error (Sambrook & Goslin, 2016).

Aspects of the theory used to motivate the present study make testable predictions about the recruitment of reward-related brain regions that could be exposed to further challenge using fMRI, which has a more precise spatial resolution than EEG. The task designed for the present study could be easily adapted for this purpose. We also argued that second order reinforcement schedules are a potential process by which LDWs could reinforce persistent gambling. Previous studies have considered the influence of win-paired conditioned stimuli (CS) on risky betting and punishment insensitivity (Barrus & Winstanley, 2016; Cherkasova et al., 2018), and numerous animal studies have employed such schedules in the study of drug-motivated behaviour (Everitt & Robbins, 2000; Schindler et al., 2002). However, to our knowledge the relative efficacy of a reinforcement schedule that includes occasional win-*associated* CS paired with the absence of any payout, or a net-negative payout, in place of what would otherwise be a clear loss, has not yet been directly assessed against a schedule in which the CS only co-occurs with a payout in a gambling modality. One promising avenue to pursue this would be an adaptation of the rat gambling task (Winstanley et al., 2011). This approach would also enable more invasive intervention on, or measurement of, brain structures argued to be at play in our preliminary conclusion.

Conclusions and Significance

This study was motivated by a theory that posited that LDWs are rewarding in a manner comparable to small wins, despite being a net loss. Based on this theory, we argued that LDWs should elicit neural activity associated with reward processing. To test this, we measured the reward-positivity (RewP) event related potential, a widely used EEG measure that is sensitive to positively valanced and rewarding outcomes. Consistent with our predictions, we observed that relative to clear losses, LDWs were associated with a more positive RewP. These results support a key premise of a more general theory that LDWs, by rewarding financial losses, increase the frequency of positive reinforcers while gambling, without substantial change to the financial expectation of a gambling product. This would result in a concomitant disruption of extinction effects that may occur during longer strings of losses. Based on a reinforcement learning or operant conditioning theory of persistent or harmful gambling, this suggests that LDWs may contribute to the likelihood or intensity of habitual gambling behaviour. If this theory is sound, it has important implications for the design of slot machines and the regulation of the gambling industry. Considered alongside accumulating behavioural evidence that LDWs appear to result in mistaken appraisals of gambling events, LDWs represent a reasonable target for regulatory strategies to mitigate harmful gambling, or erroneous gambling cognition. One potential solution would be to introduce regulatory guidelines to mandate that EGM displays must clearly indicate the net return to the consumer. Future studies should consider whether a proportionate intervention of this nature is sufficient to alleviate these concerns which may help to guide evidence-based harm-minimisation policy.

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