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Gambling on Smartphones: A Study of a Potentially Addictive Behaviour in a Naturalistic Setting

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Keywords

Gambling · Addiction · Mobile phone · App · Behaviour

Abstract

Smartphone users engage extensively with their devices, on an intermittent basis for short periods of time. These patterns of behaviour have the potential to make mobile gambling especially perseverative. This paper reports the first empirical study of mobile gambling in which a simulated gambling app was used to measure gambling behaviour in phases of acquisition and extinction. We found that participants showed considerable perseverance in the face of continued losses that were linearly related to their prior engagement with the app. Latencies between gambles were associated with the magnitude of reinforcement; more positive outcomes were associated with longer breaks between play and a greater propensity to end a gambling session. Greater latencies were associated with measurements of problem gambling, and perseverance with gambling-related cognitions and sensation-seeking behaviour.

Introduction

Mobile gambling is an emerging activity that has the potential to profoundly affect people's behaviour. There is evidence that certain schedules of reward common in gambling are particularly resistant to extinction [1]. Gambling disorder is the only behavioural addiction currently recognized by the American Psychiatric Association [2]. Models of Gambling Disorder emphasize the role of operant and classical conditioning in the transition towards addictive behaviour [3]. There is always a concern with new technologies that these introduce new activities or media that are potentially harmful (e.g., social media, gaming), or enable existing activities of societal concern (gambling, pornography) to become easier to access. However, research studying the effects of new technology and their potential for addiction is limited; currently research has focused on self-report data [4, 5] or on markers of harm that are contrived or inappropriately translated from other addictions [6]. This paper reports a study designed to observe mobile gambling on a specifically designed app, written and delivered to par-

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ticipants' phones in order to observe their behaviour over a period of several weeks.

Mobile gambling is increasingly becoming popular worldwide. Although it is restricted alongside online gambling in some jurisdictions, the mobile gambling market is likely to continue showing considerable growth [7]. Evidence from gambling regulators shows that mobile gambling is often conducted by younger adults, who are more vulnerable to addiction [8]. The most common form of mobile gambling is sports betting; live action betting is heavily promoted on mobile gambling apps in areas where gambling regulation is more permissive [9], despite its relationship with gambling related harm [10]. There are additional issues concerning the integration between gambling and forms of gaming on social media and mobile phones [11]. As there is a continuing trend towards the liberalisation of Internet gambling laws worldwide, understanding the risks associated with mobile gambling is both timely and necessary.

Mobile technology involves short, interspersed bouts of interaction that have been compared to snacking [12]. The behavioural literature has identified that increases in the latency between reinforcements is associated with increased acquisition of learned behaviours [1, 13], as well as non-reinforcing events (i.e., near-misses) that have structural and aesthetic similarities to wins [14, 15]. When applied to gambling's random ratio schedule of reinforcement, there is the potential for an additive risk of harm. What differentiates mobile gambling from other new gambling technologies is its associative basis; whereas it has been shown that the primary risk of internet gambling is to people already addicted to gambling, mobile gambling's behavioural profile suggests a risk towards a wider proportion of the population [16]. However, there is little extant literature on mobile gambling, and no direct research studying the behaviour of the individual while gambling on a mobile phone. One of the aims of this study is to begin to answer these questions empirically.

These types of actions imply that the role of timing is especially important for mobile gambling. The literature has examined the role of post reinforcement pauses (PRPs), showing that gamblers take longer to initiate another gamble after a win relative to a loss [17–21]. This is a general associative phenomenon, sensitive to the rate of reinforcement on many different schedules of reinforcement [22], and the magnitude of reinforcement [18], with greater positive reinforcement associated with longer delays. Changes in PRP affect perseverance at gambling when reinforcement is suppressed [1], for instance when gamblers are exposed to an unavoidable string of losses.

Mobile apps have been used in health research to deliver interventions to change behaviour, including chronic illnesses (i.e., obesity, diabetes), and psychiatric conditions [23]. Many make use of functions such as self-monitoring and recording, goal-setting and context sensitive functionality alongside a component to induce behaviour change. Others have more explicitly used or enhanced psychological therapies, such as being used to supplement and record data alongside a cognitive behavioural therapy intervention for insomnia [24]. Although these studies often collect a wide variety of self-report data on health behaviours, they typically do not measure the behaviour itself. Mobile phones have the potential to be used as a tool to measure and understand behaviour, building on the extensive behavioural and cognitive gambling research that has been conducted in the laboratory; their use in providing translational research in gambling is particularly valuable.

In this study, we examined how participants interacted with a simulated gambling game on their smartphones. The game had a fixed rate of reinforcement on a random ratio schedule with multiple levels of reward. After a period of engagement with the app, the participants were placed into extinction, during which time it was no longer possible to win any more money. Participants were given a free choice, as they could choose not to engage with the app. Contextual information about app use and location was collected during the course of the study. In addition, behavioural and location (GPS) data were taken each time a gamble was made. Interactions were primarily through touch and tapping the smartphone screen. While this does not cover the entire range of interactions a smartphone allows, it does not appreciably differ from the interactions utilised by commercial gambling apps [16].

We predict that higher levels of engagement with the app will be associated with greater perseverance in extinction (i.e., continued gambling when it is no longer possible to win money). This allows us to test an associative account of gambling and addiction assumed but rarely tested in almost every model of problem gambling, in the context of a mobile phone. A more nuanced prediction is the relationship between the magnitude of a win and the need to play again. A common design principle in mobile gaming and gambling is that small wins, near misses and losses encourage greater levels of engagement. Mobile games superficially appear to be relatively benign because their payoffs are often trivial, but we predict this actually

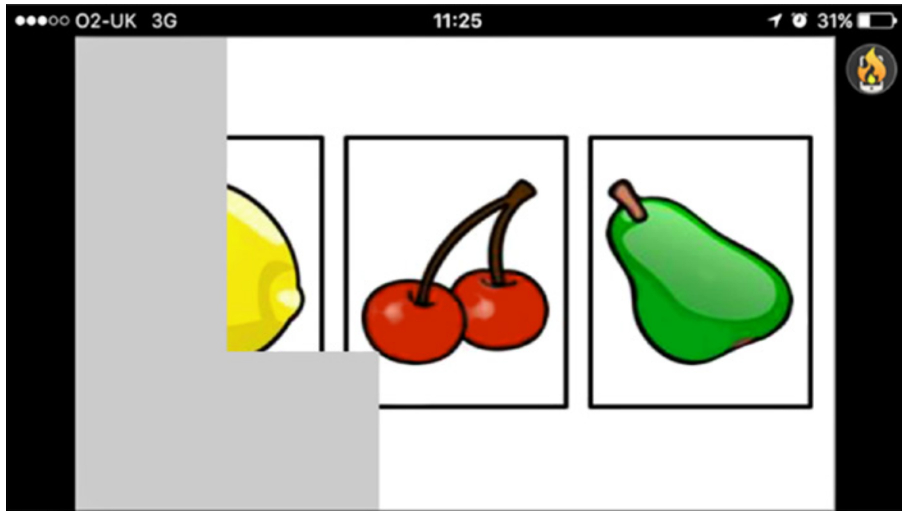

Fig. 1. Screenshot of the app.

makes them more addictive. We test this by comparing the PRP between plays with different outcomes. We predict that larger magnitudes of reinforcement are associated with a greater delay between gambles, and an increased disposition to cease gambling prematurely. One further, open, question concerns the interaction between different patterns of wins and losses and individual differences related to gambling behaviour (e.g., impulsivity, gambling cognitions).

Method

Participants

Thirty student participants were recruited from the University of Nottingham community. Of these, 18 were female and 12 were male, with a mean age of 24.167 (SD 3.55, range 20–37) at pre-test. Sixty per cent had gambled in the past year, which is representative of gambling behaviour in these demographic groups [25]. In order to be included in the study, participants had to own a mobile phone that could download and run the software. Two participants did not complete the follow-up, and in one further case, the participants' phone was destroyed during the experimental period. Participants were reimbursed based on their in-game performance, which was the amount of money in their bank at the end of the study. Ethical clearance was obtained from the School of Psychology, University of Nottingham Ethics Committee prior to data collection; all participants gave their informed consent.

Stimuli

The stimuli for the app study consisted of 19 different scratchcard style games (Fig. 1). These involved 3 different icons placed beneath a grey overlay. There were 5 different types of outcome (lemon, cherry, pear, orange, lucky 7 – in order of payout). Five cards had a winning outcome. Four had a near miss outcome, counterbalanced so that in half the stimuli the near miss was XXO, and in half OXX because participants could remove the overlay in either direction. Previous studies of scratchcard gambling have instructed participants to reveal the card from left to right [19, 20]. The remaining 10 cards were losses. Wins were set at 30%. Once the outcome was decided, each card had an equal chance of being drawn. The near-miss rate was effectively set at 20% (4/14 multiplied by 0.7). Participants had a visual display of the total money they had won on the app, which could be positive or negative, and was wagered when they played the app. The app was delivered using AppFurnace and written in JavaScript.

Measures

At the beginning and the end of the study we asked participants to complete a battery of psychometric assessments measuring constructs directly relevant to gambling and problem gambling. Depression, and positive and negative affect were assessed using the Beck Depression Inventory [26] and the Positive and Negative Affect Scale [27] (with a state frame), as negative reinforcement (i.e., gambling to escape) is thought to be a causal factor in problem gambling development [3]. Constructs related to risk taking and impulsivity were measured using the Sensation Seeking Scale Form-V (SSS-V) [28] and the Barratt Impulsiveness Scale -11 [29]. Problem gambling and gambling cognitions were measured using the Problem Gambling Severity Index [30] and the Gambling Related Cognitions Scale [31]. In addition, we also asked questions about gambling behaviour: types of game played, levels of expenditure, frequency of access and modality of use. At the end of the study, a series of open-ended questions were given to participants about their experiences with the app, reflections on their own behaviour, the contexts in which they gambled and whether they noticed any changes in the app or their behaviour as the study progressed.

A range of behavioural measures were collected over the course of the study. The amount of gambling in acquisition, in extinction and within each session was collected. The app also includes timing information that allows the exploration of the relationship between delays in play and gambling outcomes. For the predictive analyses, we derived measures of perseverance and latency. Perseverative gambling was modelled using a binary variable to capture the last gamble within an instance of play (i.e., break in daily play of >240 s, including stopping completely for the day), except where participants had reached the upper limit. The time each gamble was initiated was recorded for each trial (in hours, minutes, and seconds). Latency (amount of time spent in gamble, plus PRP until the next gamble commenced) was computed for each trial.

Contextual data, concerning location, activity and other app usage (before, and intended after using the app) was collected via a series of self-report questions. GPS co-ordinates were recorded from the phone each time a gamble was placed. Participants had to explicitly opt-in to the recording of these data, and were informed they could change the settings on their phone to prevent the app from recording these data.

Procedure

Participants first completed the questionnaires (order: Gambling Questions, PGSI, GRCS, Barratt Impulsiveness Scale, Beck Depression Inventory, PANAS (state), SSS-V) and a computerised contingency judgement task that probed the illusion of control, a cognitive bias in gambling [32]. These were completed in laboratory settings in the School of Psychology at The University of Nottingham. Then, while still in the lab, participants were instructed how to install the gambling app onto their phone. The participants were then given instructions about how the game worked, specifically on how to uncover the scratchcard and how to upload data.

After leaving the laboratory, participants were allowed to engage with the app freely, and were not instructed to gamble at any specific rate. The app itself however had a pre-specified upper limit, preventing users from playing more than 100 times per day (resetting at 12.01 a.m. GMT every day). Participants engaged with the app in this phase of the experiment for approximately 6 weeks from the start of the study.

Participants were asked 3 questions on the first gamble of each day, or if they resumed play after 2 or more hours: their current location, what types of app they had used prior to opening the gambling app (categorized as game, news, web, sports, work, music, social media, or other kind of app), and which kinds of app they were planning to use after they had finished playing the gambling game. After this was completed they were presented with the scratchcard overlay.

After the study had progressed for 6 weeks, the app was programmed so that it was no longer possible for participants to win any further money. At this point, the participants entered the extinction period and their perseverative gambling behaviour was measured. After approximately 2 weeks had elapsed, participants were then invited back into the lab, and asked to complete the same series of questionnaires and the contingency judgement task. They then were fully debriefed as to the purpose of the study, and reimbursed for their participation.

Statistical Modelling

The effects of gambling outcomes on perseverance and timing on gamble level data were tested using mixed effects models. This approach was taken because the trial data were clustered and likely highly correlated within each participant. Logistic and linear mixed models were used for the perseverance and latency data respectively. However, the same strategy was taken – to begin by looking at the effects of the kinds of outcome (i.e., near-miss, win), before expanding the models to look at the effects of different kinds of near-miss and different magnitudes of reinforcement.

Random intercepts were estimated for each participant and random slopes for each participant for each type of outcome. Random slopes were estimated as it has been previously shown that mixed models that only estimate random intercepts are associated with a substantial type I error rate [33]. Modelling random slopes has the effect of reducing the number of degrees of freedom. However, the addition of random slopes meant some models did not converge. However, the non-convergent models do not differ from the less complex models that are reported, and do converge.

Modelling was conducted using the "lme4" package in *R* [34], and interpretation was guided using the "lmertest" package [35]. This is because when *t* values from a linear mixed model are assumed to be normally distributed, there is a tendency to increase the probability of identifying a false positive [33]. The mixed effects model was estimated using a restricted maximum likelihood. Significance was assessed using an ANOVA model with Satterwaite's approximate for the degrees of freedom for each effect. This has been shown to demonstrate acceptable levels of type 1 error, even with relatively small sample sizes [36]. Cases were not analysed if they were the final gamble within a session (as PRP could not be calculated) or a substantial latency between gambles (>60 s) was observed. These exceptions combined removed a small (n = 1,055) number of trials from analysis.

Results

Behaviour

A total of 45,750 gambles were recorded over the course of the study from the 29 participants who either (a) could be followed up (n = 28) or (b) could not be followed up but had uploaded data (n = 1), distributed over 642 gambling days. The use of the app varied between participants; there was evidence that engagement with the app was bimodally distributed; 4 participants gambled fewer than 100 times, including 2 who did not engage with the app. In a small number of cases (n = 4), the participant had stopped gambling before reaching extinction. In these instances, the participant was asked to play on the app immediately prior to the debrief session. The data from these gambles are not included in the reported statistics. The number of gambles ranged from 0 to 3,467 and the median number of gambles was 1,474. The payout rate during was 30.2%. The distribution of payouts was uniformly spread between the 5 outcomes. Near misses occurred 20.22% of the time, evenly distributed between XXO and OXX outcomes (10.27 vs. 9.95%). The average reimbursement was GBP34.50, ranging from GBP0.10 to GBP93.00. Because the game itself was random the payouts varied but correlated strongly with engagement (r = 0.96). Despite this, there were a number of instances in which participants with similar levels of reimbursement differed in their engagement with the app.

Table 1. Counts and percentages of decisions made to continue gambling or not, split by outcome

Outcome	Continued gambling or maximum number of plays reached	Stopped early	Early stops, %
Loss	22,822	301	1.30
Near miss	9,135	114	1.23
OXX near miss	4,495	58	1.27
XXO near miss	4,640	56	1.19
Win:	13,091	283	2.12
10p	2,594	47	1.78
15p	2,727	41	1.48
20p	2,582	51	1.94
25p	2,572	63	2.39
30p	2,616	81	3.00

There are 4 cases with missing data on the outcome variable. Data: all observations.

Table 2. Mixed effect logistic regression model of the predictors of stopping play, with random intercepts (for each participant) and slopes (for each outcome for each participant)

Effect	*b*	SD/SE	95% CI	*z*	*p* value
Random coefficients					
Intercept	0.965	0.983			
Near miss	0.113	0.335			
Win	1.165	1.079			
Fixed effects					
Intercept	–4.111	0.201	–4.50 to 3.72	–20.486	<0.001***
Near miss	–0.113	0.148	–0.40 to 0.18	–0.761	0.447
Win	0.562	0.231	0.11 to 1.01	2.434	0.015*

* $p < 0.05$, *** $p < 0.001$.
0 = participant gambled again, 1 = participant did not. Thus, positive coefficients indicate an increased likelihood to stop gambling early.

Perseverance

Participants on average gambled 58 times in the extinction period (SD 49.91). This increased to 65.57 (SD 48.08) when we excluded the participants who had ceased playing the app before the extinction period began. The median number of gambles in extinction was 40, and ranged from 0 to 177.

Initially, a linear regression model was estimated to examine the effects of prior gambling behaviour on gambling in extinction. Two participants whose data were analysed at a trial level were excluded from this analysis; in one case, the participant's phone was destroyed during the experimental period, and in the second, the participant could not be followed up. The number of gambles made during acquisition predicted the number of gambles during extinction ($b = 0.0214$, SE = 0.008, $t = 2.728$, $p = 0.0117$, multiple $R^2 = 0.237$, adjusted $R^2 = 0.205$)[1].

Table 1 shows how the decision to stop early is made based on outcome. Despite losses occurring far more frequently than wins, there were almost as many decisions made to stop gambling early after a win, as after a loss. Mixed effect modelling of this confirmed (Tables 2, 3) that participants were relatively more likely to stop playing after a win. Decomposing this effect by looking at the different types of near miss and magnitudes of reinforcement (although the model did not converge) indicated that this effect is driven by the 2 winning cards with the highest magnitude of reinforcement (which paid GBP 0.25 and 0.30 respectively).

[1] Intercept – $b = 22.124$, SE = 15.78, $t = 1.402$, $p = 0.174$.

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Table 3. Mixed effect logistic regression model of the predictors of stopping play, with random intercepts for each participant and random slopes for each type of outcome for each participant

Effect	Estimate	SE	95% CI	z	p value
Random coefficients					
Intercept	0.962	0.981			
OXX near miss	0.124	0.352			
XXO near miss	0.205	0.452			
10p win	1.646	1.283			
15p win	1.497	1.224			
20p win	1.488	1.220			
25p win	1.427	1.195			
30p win	1.133	1.064			
Fixed effects					
Intercept	–4.114	0.201	–4.51 to 3.72	–20.439	<0.001***
OXX near miss	–0.046	0.182	–0.40 to 0.31	–0.251	0.802
XXO near miss	–0.179	0.203	–0.58 to 0.22	0.881	0.378
10p win	0.251	0.316	–0.37 to 0.87	0.793	0.428
15p win	0.051	0.317	–0.57 to 0.67	0.162	0.871
20p win	0.485	0.288	–0.08 to 1.05	1.686	0.092
25p win	0.764	0.283	0.21 to 1.32	2.703	0.006**
30p win	0.932	0.251	0.44 to 1.42	3.721	<0.001***

** $p < 0.01$, *** $p < 0.001$.

0 = participant gambled again, 1 = participant did not. Positive coefficients indicate an increased likelihood to stop gambling early. Please note this model failed to converge. The random intercept model, which did converge, is reported in the online suppl. Table S1. The only difference is in the random intercept model. 20p wins are also associated with an increased likelihood to stop gambling.

Table 4. Descriptive statistics for latencies (in seconds)

Outcome	Mean latency	SD
Loss	5.78	2.11
Near miss	5.82	2.18
R-L near miss	5.80	2.17
L-R near miss	5.85	2.19
Win:	5.89	2.18
10p win	5.83	2.16
15p win	5.91	2.12
20p win	5.93	2.21
25p win	5.83	2.16
30p win	5.97	2.23

Data is from PRPs less than 15 s (n = 43,676).
PRPs, post reinforcement pauses.

Timing

Table 4 reports the effect of gambling outcomes on latency, with initial analysis showing that PRPs differed as a function of outcome (F [2, 21.564] = 9.4985, p = 0.001). To decompose this effect further, the mixed effect model was expanded to study the different types of outcome (magnitude of win, direction of near miss) in further detail. This model failed to converge. In addition, an examination of the regression diagnostics showed that the residuals were not normally distributed and that might be driven by the presence of outliers. Further examination of these revealed that trials with latencies greater than 15 s (n = 1,019) appeared to be driving this effect; the models were a poor fit for these values and the majority had substantial residuals (>10 s). This might mean that a generalized linear model is more appropriate [37]. This was attempted using a negative binomial model (online suppl. Table S2, S3; for all online suppl. material, see www.karger.com/doi/10.1159/000495663). Although the expanded model did not converge again, these findings were the same – greater delays between plays after a win.

The models were refitted only using data with latencies between gambles of 15 s or less. Differences between the 15 and 60 s models were minor. The effect of outcome was still observed (F [2, 9.6562] = 14.475, p = 0.001). Furthermore, modelling with only these data produced a full-outcome mixed effect model that converged. Using the full range of outcomes, a main effect of outcome persisted (F [7, 28.135] = 4.3088, p = 0.002), with wins showing a greater latency relative to losses, and the extent of this latency being contingent upon the magnitude of the reward.

Table 5. Linear mixed effect model regressing time on gamble plus post reinforcement pause on the type of outcome (all trials with a PRP ≤15 s). For each participant, random intercepts and random slopes were estimated

Effect	*b*	SE	95% CI	*t*	*p* value
Random coefficients					
Intercept	2.789	1.670			
Near miss	0.005	0.073			
Win	0.009	0.096			
Fixed effects					
Intercept	6.285	0.320	5.66–6.91	19.67	<0.001***
Near miss	0.054	0.028	0.00–0.11	1.97	0.0821
Win	0.148	0.028	0.09–0.20	5.36	<0.001***

PRP, post reinforcement pause. *** $p < 0.001$.

Table 6. Mixed effect model further decomposing the effect of different types of outcome on time in gamble plus post reinforcement pause, on trials with a PRP ≤15 s. random intercepts were estimated for each participant, and random slopes for each type of outcome for each participant were also modelled

Effect	*b*	SE	95% CI	*t*	*p* value
Random coefficients					
Intercept	2.763	1.662			
OXX near miss	0.003	0.051			
XXO near miss	0.035	0.188			
10p win	0.010	0.100			
15p win	0.009	0.092			
20p win	0.005	0.070			
25p win	0.025	0.158			
30p win	0.091	0.302			
Fixed effects					
Intercept	6.279	0.318	5.66 to 6.90	19.749	<0.001***
OXX near miss	0.022	0.031	–0.04 to 0.08	0.715	0.4775
XXO near miss	0.111	0.049	0.02 to 0.21	2.291	0.040*
10p win	0.099	0.043	0.02 to 0.18	2.319	0.030*
15p win	0.134	0.041	0.05 to 0.21	3.299	0.002**
20p win	0.163	0.041	0.08 to 0.24	3.994	<0.001***
25p win	0.124	0.050	0.03 to 0.22	2.463	0.024*
30p win	0.285	0.073	0.14 to 0.43	3.930	0.002**

PRP, post reinforcement pause. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The mixed effects models (Tables 5, 6) consistently show that participants take longer to initiate the next gamble for outcomes that are not an unambiguous loss. There is a greater delay for wins than for losses, which mirrors the findings of the effect of post-reinforcement pause in the literature. Further examination of the different types of outcome indicates there is some evidence that classic (XXO) near misses are associated with an intermediate latency between gambles, but not for right to left (OXX) near misses. The models consistently show that the size of the coefficient increases with the magnitude of reward. This is also represented in Figure 2, which was prepared using the "ggplot2" package [38].

Individual Differences and Individual Gambling Behaviour

Indices of the degree of variance explained at the participant level, such as the intraclass coefficient, indicated around 40–55% of the variance was explained at the level of the individual. Thus, we examined the rela-

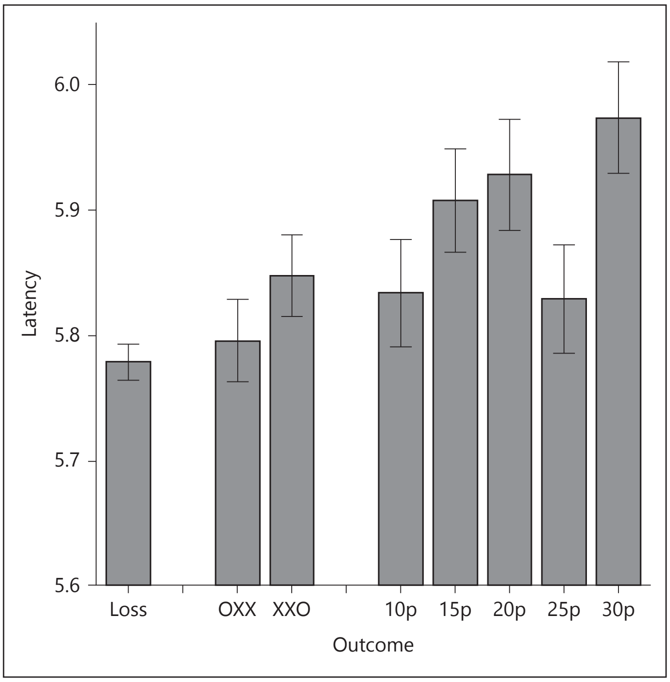

Fig. 2. Latencies (in seconds) between gambles for each type of outcome (p = pence), with error bars plotted as the SE of the mean.

tionship between the parameters in the mixed effect models and measured individual differences. The descriptive statistics is reported in online supplementary Tables S4 and S5. These show considerable stability between pre- and post-tests. As these statistics identified minimal difference between pre- and post-tests, we correlated pre-test measurements against the aforementioned random effects.

The results of this analysis show that problem gambling severity (albeit at sub clinical or "at-risk" levels) was correlated with a greater PRP, with higher PGSI scores associated with greater pauses for classic near-miss and 4 of the 5 winning outcomes in Table 7). In addition, PGSI score was correlated with a greater propensity to end a gambling session early, but was unrelated to any specific outcome. Both the GRCS and the SSS-V were associated with ceasing or continuing to gamble respectively. People displaying more gambling-related biases were more likely to end a gambling session, but were more likely to carry on playing after a near miss and more likely to stop after a win. The opposite was true for respondents with a higher SSS-V score; they were less likely to stop playing in a session, less likely to stop playing after a win, but more likely to stop after a near miss.

Contextual Behaviour

In the Supplementary Materials, we also report how behaviour changed over the course of the app (online suppl. Fig. S1), variation across different kinds of location (online suppl. Table S6), and whether participants reported engagement with other apps before or after using the simulated gambling app (online suppl. Table S7, S8).

Discussion

When exposed to a simulated gambling game on their smartphones, participants showed evidence of considerable persistence in the face of losses. During a pre-programmed extinction period of unavoidable losses, most participants continued to return for multiple days of play. Participants had greater latencies between their gambles after a win relative to other outcomes and the size of this effect increased in line with the magnitude of reinforcement (Fig. 2). Individual variations in behaviour appeared to be affected by sub-clinical problem gambling, gambling cognitions and sensation-seeking.

This raises important implications for the development and design of games, especially on mobile phones where a subset of mobile games show convergence with gambling activities. It is possible that reinforcement and latency can be fine-tuned by designers to elicit the desired behaviour by users, even in the face of unsuccessful, frustrating outcomes. These implications are particularly exacerbated in mobile gambling, where latencies punctuate periods of reinforcement both (a) as part of the nature of smartphone use [16] and (b) directly under the control of the designer using mechanisms to space out reinforcements.

The mixed effect modelling identified that a significant amount of variance in gambling behaviours was explained at the individual level. In turn, problem gambling, gambling-related cognitions and sensation seeking were associated with this individual variance. This raises the possibility of using temporal information as a marker for identifying problematic gambling behaviours. However, this study only looked at gamblers who were classed by the PGSI as not being at risk of gambling. While it may be possible to use temporal data to identify potentially problematic behaviour, it may be less useful when modelling gambling addiction, as people with a gambling addiction show blunted psychophysiological reactions to wins and losses [39].

We found that lower probability outcomes were associated with greater latencies between gambles [40], but un-

Table 7. Correlations between random effects from mixed effect models and measures of individual difference at pre-test

	PGSI	GRCS	BIS-11	BDI	PA	NA	SSS-V
T – RI	0.33~	0.17	–0.05	0	–0.08	–0.05	–0.15
T – RS – NM	0.35~	0.08	–0.22	0	0.09	–0.04	–0.16
T – RS – W	0.35~	0.2	0	0.06	–0.08	–0.01	–0.14
O – RI	0.39*	0.45*	0.04	0.27	0	–0.05	–0.33~
O – RS – NM	–0.33~	–0.39*	0.16	–0.13	0.04	–0.07	0.37*
O – RS – W	0.14	0.52*	0.04	0.17	–0.04	0	–0.42*
T – RI	0.32	0.16	–0.05	–0.01	–0.08	–0.06	–0.15
T – RS – NM – OXX	0.17	–0.07	–0.25	0.07	0.26	0.07	–0.02
T – RS – NM – XXO	0.64*	0.26	–0.2	0.18	0.12	0.1	–0.24
T – RS – W – 10	0.53*	0.32	–0.02	0.21	0	0.12	–0.21
T – RS – W – 15	0.44*	0.22	–0.08	0.07	–0.02	0.01	–0.18
T – RS – W – 20	0.45*	0.37~	0.08	0.4*	–0.04	0.26	–0.23
T – RS – W – 25	0.17	0.19	0.15	0.04	–0.14	0.01	–0.07
T – RS – W – 30	0.63*	0.33~	–0.1	0.25	0.05	0.14	–0.25
O – RI	0.39*	0.46*	0.01	0.27	–0.01	–0.05	–0.35~
O - RS – NM – OXX	–0.21	–0.28	0.39*	–0.01	0.09	–0.06	0.32~
O – RS – NM – XXO	–0.17	–0.33~	0.31	–0.04	0.1	–0.06	0.41*
O – RS – W – 10	0.05	0.41*	0.17	0.15	–0.02	–0.01	–0.34~
O – RS – W – 15	0.18	0.52*	–0.05	0.15	–0.06	0.01	–0.44*
O – RS – W – 20	0.2	0.5*	0.06	0.2	–0.03	–0.02	–0.41*
O – RS – W – 25	0.08	0.46*	0.08	0.14	–0.04	0	–0.39*
O – RS – W – 30	0.15	0.5*	0.09	0.18	–0.03	–0.01	–0.39*

T, Timing; O, Outcome; RI, Participant random intercept; RS, participant random slope; NM, near miss (either classic [XXO] or non class [OXX]); W, win (with value in pence).

The random effects are taken from the following: timing – Tables 5 and 6, outcome – Tables 2 and 3.

BIS-11, Barratt impulsiveness scale; BDI, Beck depression inventory; SSS-V, sensation seeking scale form-V. * $p < 0.05$, ~ $p < 0.10$.

like previous studies also found a small effect of win size on latency, most likely observed due to the very large number of trials. We found some evidence for the effects of near-misses on subsequent latencies as well. Left to right (classic) near misses were associated with an increased latency interposed between wins and losses. Studies of the post-reinforcement pause have identified mixed findings. Some have found no or limited evidence for an effect [18, 19], whereas others have found that near-misses are perceived intermediately between wins and losses [20, 41]. The findings of this study suggest evidence for the latter, despite findings on scratchcard play thus far have been equivocal [19, 20]. Studies in the area have previously instructed participants to remove the overlay from their scratchcard in a specific manner (left to right) [19, 20], which we find corroborating evidence for. It should be noted that the effect size observed in these data is likely to be underestimated, potentially because of the modality (i.e., interactions afforded by smartphones or the app itself), the type of game (scratchcards versus slot machines), the aforementioned measurement or the means of aggregation (trial-by-trial versus mean latencies per participant).

There was also evidence for a second type of PRP; participants tended to prematurely cease gambling after a win, which correlated with the magnitude of reinforcement. People were equally likely to stop after a win than a loss, despite losses being almost twice as likely to occur. This raises an interesting hypothesis concerning the big win and gambling addiction. Recent models have argued that the effect of the big win is due to the effect of statistically improbable wins leading to a qualitatively distinct categorisation of the big win to typical gambling experiences, meaning it is particularly resistant to extinction [42]. The data in this study raises the possibility that, instead, big wins are associated with gambling problems because gamblers may not experience the mundane, frustrating and ultimately unsuccessful outcomes of gambling after their big win.

It is necessary to consider the boundaries on these findings. There has been considerable focus on the effects of technology on behaviour, including addiction. These findings ought to be restricted to gambling but the findings from this study outline a pathway to consider how mobile phone use moderates the relationship between individuals and addictive behaviour. The effect of smartphone use in the context of other behaviours is of great interest, but the study of addiction in this area suffers from a failure to identify whether general smartphone use or specific behaviours should be the focus of attention, and the lack of a rigorous analysis of the behaviours in question [6]. There are some limitations to this study. The range of cues associated with the game itself was relatively restricted; gambling games tend to have richer environments than other games. The game was designed so that there was a positive expected value in the long run, even if each individual trial participant was more likely to lose. Data from gambling machines suggest that larger wins are associated with shorter gambling sessions [43], but an increased likelihood of gambling on the next play [44], thus emphasising the need to validate these results with games more overtly similar to other forms of gambling to confirm the generalisability of this approach. Giving users free gambles at the beginning of the experiment might help in this regard; betting companies frequently offer free bets at enhanced odds, and mobile games with stamina systems are designed for a larger bout of play at the beginning of the experience. While we have associated some phenomena in this study (i.e., PRPs, near-misses) with problematic behaviour, there are multiple interpretations of the mechanisms underlying them, and further research is required to tease out the relationship between these factors and harm. Moreover, because it was a community, student sample, scores on some of the scales (i.e., PGSI, GRCS) were highly skewed by the lack of respondents with greater gambling problems. This also limits the extent to which the study can be generalised to pathological levels of harm, although the population is likely to be more representative of mobile gamblers as a whole. Further validation, including the behavioural measures, in a clinical sample would be beneficial. Although this population may be demographically more similar to mobile gamblers, their gambling intensity is relatively low.

In conclusion, this paper reports an experimental study of mobile gambling behaviour in a naturalistic setting. Participants showed considerable engagement with the app. Engagement with the app while there was a chance of winning predicted perseverative play during the extinction phase when there was none. Larger rewards predicted longer latencies between gambles and the propensity for players to prematurely end a gambling session. This study signposts the potential that smartphones have in studying the relationship between technology and addictive behaviour, both for collecting data and as a possible risk factor for harm.

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Authors Contribution

All authors contributed to the design of the study and the analytic approach. The first author collected, collated and analysed the data, and wrote the first draft of the manuscript. All authors made critical comments and approved of the final version of the manuscript.

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