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Could the provision of multiple game themes be a neglected gambling product structural characteristic? Results of an online simulated gambling task

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ABSTRACT

Previous research has indicated that several gambling product features, such as slot games' fast potential speed of play, are potentially harmful 'structural characteristics'. However, we know of little empirical research exploring whether the provision of multiple themes for slot games could be considered another relevant structural characteristic. We therefore explored this game feature in a simulated online experiment ($N = 990$). Compared to the provision of only a single game theme, providing multiple themes could lead to greater persistence among all gamblers (H1), could increase persistence among those at most risk of harm (H2), could influence persistence or lead to switching during periods of losses (H3), or influence participants' desire to play again (H4). However, this experiment yielded either largely null (H1, H2, H4) or contradictory results (H3), where participants were found to be more likely to persist after losses than after wins. In conclusion, the present study's predictions were not supported, meaning that there was no evidence that multiple themes affected slot behavior in this task.

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Introduction

Gambling products that enable fast and continuous gambling are generally seen as being the most harmful (Allami et al., 2021). Modern slot machine games are often considered to be the exemplar harmful gambling product, whether they are delivered in land-based venues via electronic gambling machines (EGMs; Dixon et al., 2018; Livingstone et al., 2008; Schüll, 2012), or provided online via online slots (Forrest et al., 2022). A fast potential speed of play is just one of slot games' 'structural characteristics' which can encourage persistent and therefore harmful gambling (Griffiths, 1993), along with other notable features of their resulting payoffs such as 'near-misses' (Clark, Lawrence, et al.,

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2009) and 'losses-disguised-as-wins' (Dixon et al., 2010). However, there is one noticeable feature of modern slot games and related virtual casino products for which we know of little previous research on: The practice of providing multiple-themed games. Existing research suggests that gamblers have little conscious awareness of slot game themes (Chen et al., 2013). However, gamblers' self-reports may not necessarily predict their behavior, and we know of little experimental research investigating game themes (Paliwal et al., 2014). One observational audit study of online roulette games found an average of 14 themes across 26 major operators, including for example, 'Frankie Dettori's jackpot roulette', 'diamond bet roulette', and 'Superman roulette' (Newall, Walasek, et al., 2022). A similarly wide range of themes can be observed when browsing through slot games on any gambling machine or gambling website. Scratchcards are another gambling product which is frequently delivered through multiple distinct themes, and an anecdotal account from a gambling industry insider suggests that this practice boosts sales (Nibert, 2000). Further investigation of gambling game themes therefore appears justified, and in particular slot game themes, given the unique harms of this product.

Although there is limited research on the effect of multiple gambling themes on online gambling behavior, there is an experimental literature that has examined the effects of concurrently presented slot machines, where gamblers have the choice to play on two or more machines. These paradigms aim to model the characteristics of environments such as casinos or gambling halls. Like online gambling, gamblers are presented with a wide variety of slot machine games with different themes, structural characteristics, features of play, and the choice to persist with the current machine or switch to another. The majority of findings demonstrate that participants are sensitive to the behavioral and structural characteristics between games, preferring to play on games that have a higher rate of reinforcement (Coates & Blaszczynski, 2013; M. R. Dixon et al., 2006), which has been observed in casino choice allocation (Hu & Shoemaker, 2024). There is a clear preference for games in which features such as near-misses (MacLin et al., 2007), gambling-related cues (Spetch et al., 2020) and free spins or bonus plays (Taylor et al., 2017) are present. Machine preference is also sensitive to non-payout contingencies (Hoon et al., 2019), such as verbal information (e.g. comments from other players) or from the content of the theme itself (e.g. favorite film, color, or celebrity). However, the majority of this literature has looked at simulations that principally differ in terms of these structural characteristics. Therefore, the isolation of different game themes appears to be a largely novel game feature for experimental research to explore, whether these themes are explored within the context of EGMs or online slots.

EGMs and other slots-based games are also consistently linked with the risk of experiencing gambling harms (Browne et al., 2023; Dowling et al., 2005). In addition to the high speed of play and event frequency in these games, which allow for rapid gambling and losses (Harris & Griffiths, 2018), structural features that promote continued engagement despite ongoing losses, such as the aforementioned 'near-misses' (i.e. results on the reels that suggest a gambler 'almost' won, such as through the reels being just one position away from a winning line) and losses-disguised-as-wins ('LDWs'; i.e. spins resulting in a payoff, but one that is lower than the amount staked) are of particular concern. These features can recruit similar reward pathways in the brain to actual wins (Clark, Liu, et al., 2009) and can increase gambling intentions and enjoyment (Clark et al., 2012; Sharman et al., 2015), but are associated with cognitive distortions that are risk factors for gambling harms, such as win-overestimation (Myles et al., 2023) and the illusion of control (Harrigan et al., 2014; Ndukaihe & Awo, 2023).

Indeed, the Great British regulator, the Gambling Commission, recently enacted stricter regulations to make online slots 'safer by design' (Gambling Commission, 2021). These regulations aim to reduce the harms inherent from online slots by regulating certain structural characteristics, specifically by reducing the speed of play, and by removing features that exploit cognitive distortions such as LDWs. If the provision of multiple gambling themes were shown to similarly encourage persistent and harmful gambling, then this could be another structural characteristic that the Gambling Commission and other regulators might want to consider regulating.

Despite the broad extent of previous research on gambling product structural characteristics, one recent study produced results that challenge the central role of structural characteristics in influencing gambler behavior (Auer & Griffiths, 2022). This study used behavioral data from an online operator spanning over 40,000 gamblers, across six types of casino game. However, the eight structural characteristics that could be defined from the data explained only 7.7% of the variance in a measure of gambling persistence – the total number of bets made (Auer & Griffiths, 2022). This suggests that these structural characteristics were not a major determinant of gambling behavior, since 92.3% of the variance remained unexplained. However, these findings could understate the importance of structural characteristics in determining gambling behavior if new relevant structural characteristics can be found, such as the importance of game themes. Furthermore, a structural characteristic might have minimal levels of impact on gamblers overall, but have an outsized negative impact on gamblers suffering from elevated levels of gambling harm. This rationale was used to remove the relatively high-price £10 scratchcards from the Great British gambling market in 2019, which were found to be bought disproportionately by gamblers experiencing harm (iGB Editorial Team, 2019). Research should therefore continue investigating new potential gambling structural characteristics and their impacts across different groups of gamblers.

Cognitive psychology research on the 'win-stay/lose-shift' (WSLS) heuristic also appears relevant to the provision of multiple themes for gambling products. In experimental contexts, risky choice behavior can often be accurately modeled by assuming that agents decide to persist with options that yield wins, while shifting away from options after losses (Nowak & Sigmund, 1993). Because any wins on a slot game are due to short-term luck, with losses being the long-run likely outcome (Harrigan & Dixon, 2009; Woolley et al., 2013), it does not make sense to continue gambling on a given slot game just because it has recently yielded a win. But if gamblers do follow a WSLS strategy, which has been shown to fit behavior in other domains (Worthy et al., 2013), then the provision of multiple themes may well lead to increases in gambling persistence, as gamblers shift between multiple games, despite each game offering similar prospects of long-run losses.

Finally, any potential increases in gambling persistence could be due to a greater enjoyment derived from the product that is being gambled on more (Stewart & Zack, 2008). Therefore, it is important to also test for this simpler explanation when considering any experimental manipulation which alters a gambling game structural characteristic.

We therefore planned an online experiment which isolated the factor of providing multiple slot game themes. Participants were presented with an opportunity to voluntarily engage in a slot game. Participants could freely choose to refuse to play on the slot game at all and therefore earn a guaranteed bonus, or risk some of that bonus by risking it on a spin of the slot game. As follows previous gambling research using simulated gambling tasks (Byrne & Russell, 2020; Ladouceur et al., 2003; Rockloff et al., 2015), this game involved a preset sequence of pay-offs, which did not vary between the experimental conditions and which therefore effectively controlled for other relevant structural characteristics such as the frequency of near-misses. This sequence involved periods of wins but an overall losing pattern, as in real gambling games, which resulted in a complete loss of the gambling budget after 100 trials. This task therefore served as a test of gambling persistence.

Participants were randomly assigned to either a 'multiple theme' condition, which allowed them to switch the slot game across four visually-distinct themes; or to a 'single theme' condition where one of the four themes was randomly selected. It was hypothesized that gamblers would persist longer in the multiple theme condition than in the single theme condition (H1). It was also hypothesized (H2) that any greater persistence in the multiple theme condition would be especially felt by participants suffering from greater levels of gambling harm, as measured by the Problem Gambling Severity Index (PGSI; Ferris & Wynne, 2001). In-line with the WSLS heuristic, it was hypothesized (H3) that participants would be more likely to quit playing after a loss rather than a win (across both conditions), and be more likely to switch themes after a loss than after a win (in the multiple theme condition). Finally, we planned to test enjoyment as a potential driver of behavior in this task, by testing the null hypothesis that there would be no difference between the two conditions in the measured likelihood of playing on the slot game again (H4).

Method

Data, materials, analysis code, and supplementary materials can be accessed from: https://osf.io/2smj3, and the preregistration is available from https://osf.io/37ge2. Ethical approval was obtained from the University of Bristol School of Psychological Science Research Ethics Committee (#17804).

Participants

Participants ($N = 990$; 395 females; Age, $M = 39.6$ years) were recruited from the Prolific crowdsourcing platform, which provides better data quality than alternative online platforms such as MTurk (Peer et al., 2022). Participants were aged 18 and over and resident in the UK. We further required prior experience of gambling on online slots reported via Prolific's prescreen, as this study was principally interested in understanding the effects of providing multiple themes in those who already participate in online gambling. Moreover, the PGSI poses questions related to past 12-month gambling, and as such is not applicable to those who have not gambled in that period.

Potential participants were first recruited via an additional prescreen questionnaire. This prescreen consisted of the PGSI, demographic questions about age and gender, and a final question explicitly asking participants if they were happy to be invited to a further study involving an online slot machine with which a financial bonus could be wagered on. The prescreen questionnaire was conducted between 2 and 12 February 2024. A total of 3,612 participants completed this prescreen questionnaire. Only participants that scored 7 or less on the PGSI, and asked to be considered for this further study, were invited to the experiment in order to protect those most at risk of harm. Therefore, 2,494 eligible potential participants were invited to the experiment until the preregistered sample size of 1,000 participants was attained. Three participants were approved without completing the experiment due to technical issues.[1] Examination of the data further revealed a small number ($N = 7$) of participants who exploited a workaround in the code that allowed them to return to an earlier point in the sequence of spins, thereby earning a higher bonus. These participants have been excluded from analysis here, yielding a final sample size of 990 participants. A CONSORT diagram summarizing this participant flow is shown in Figure 1.

The median completion time was 7.75 minutes, and the average final bonus payout was £4.40 (range: [£0, £5]), which was added to the £4.50 participation fee. Overall, 259 participants (26.1%) made no spins on the slot game, thereby keeping the entire £5 bonus. Ten participants made 100 spins and received no bonus. On average, participants played for 18 spins (median: 12). Participants had a mean PGSI score of 1.6 (SD = 1.91) and 39% were no-risk gamblers (PGSI = 0), 38% were low-risk gamblers (PGSI = 1 or 2), and 23% were moderate-risk gamblers (PGSI between 3 and 7).

Task

Eligible participants were then presented with an opportunity to sign up to the experiment, for which they were paid £4.50 each. Participants could earn a further £5 bonus, which could then be risked on the slot game. Since gambling experiments cannot require participants to gamble with their own money, a procedure from behavioral economics was used to make participants feel more like this money was their own, as has been used in previous simulated gambling experiments (Behavioural Insights Team, 2022; Newall, Byrne, et al., 2022). In these ‘real-effort’ tasks, participants have to perform some effortful action to earn their bonus money, which is thought to then lead to more realistic risk-taking behavior later on (Erkal et al., 2011). We used the same task as has been used in previous gambling experiments (Newall et al., 2023; Newall, Byrne, et al., 2022; Newall, Weiss-Cohen, Singmann, Walasek, et al., 2022), which involved retyping 10 ‘captcha’ codes that are typically used on the internet to prove that a given user is a human and not a computer. In order to proceed to the task itself, participants had to successfully retype at least nine captcha codes. So as not to bias the final sample away from participants who might struggle with this sort of task, participants were given feedback on which codes were retyped incorrectly, and provided with as many opportunities as they required to retype at least nine codes correctly.

Once successful, participants were immediately informed that they could ‘use your £5 bonus to play a slot game’, and could, ‘choose to play the slot game as much or as little as you like, or not at all.’ Participants were then presented with instructions relevant to either the single or multiple theme condition, which were kept as similar as possible to minimize confounds. Figure 2 shows screenshots from the multiple theme condition,

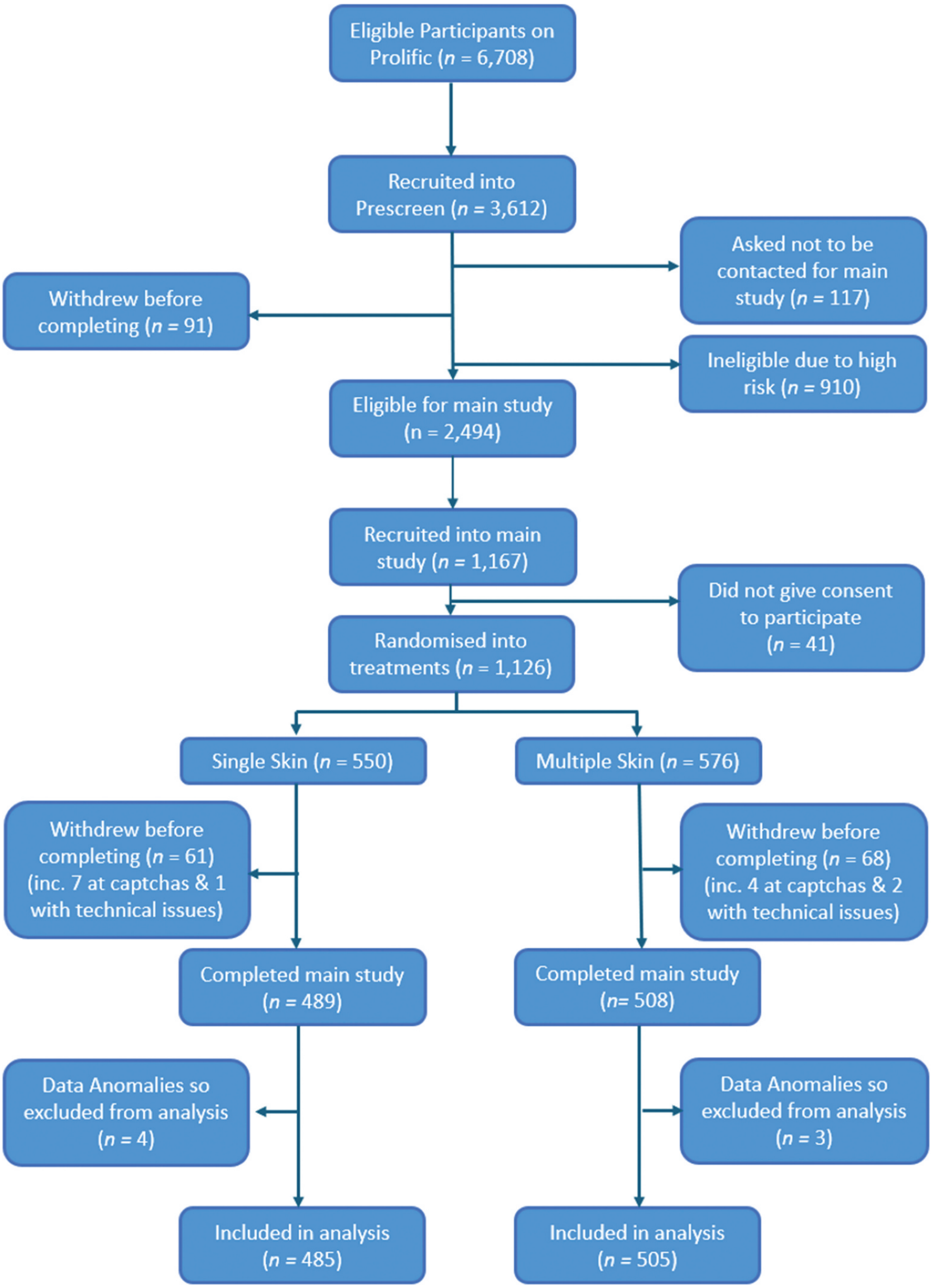

Figure 1. Consort diagram for participant recruitment.

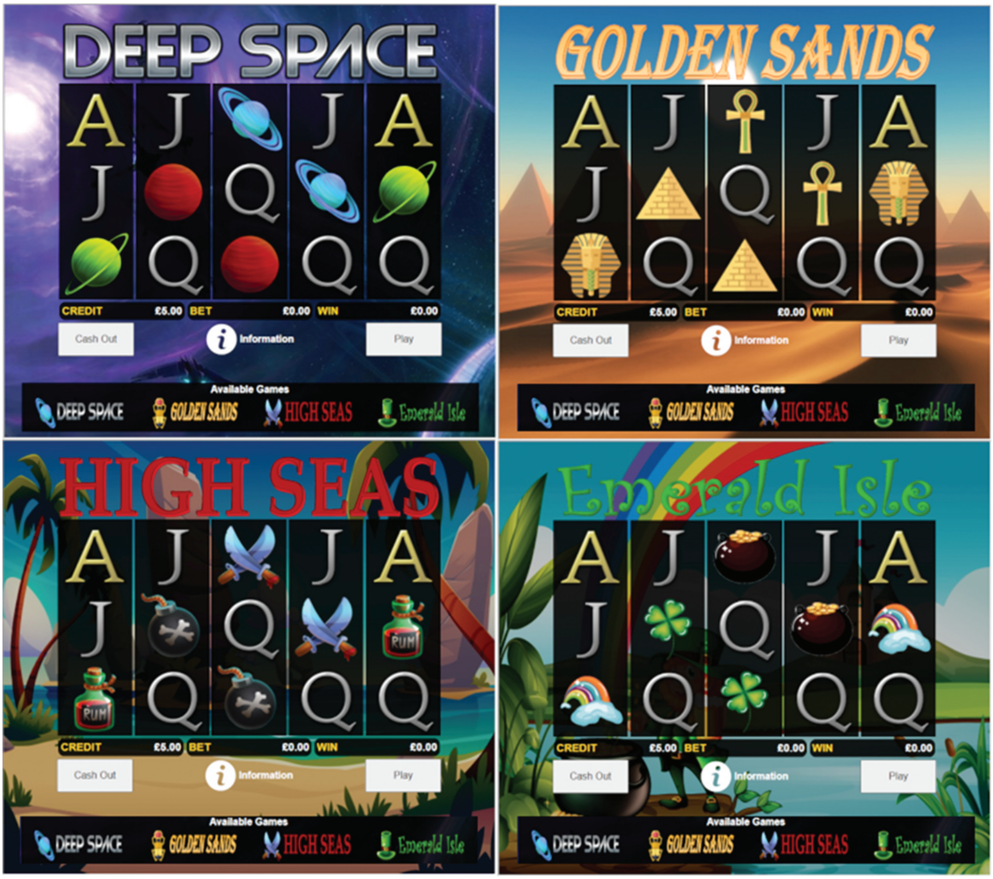

Figure 2. Screenshots from the multiple theme condition. Participants could freely change between themes. For the single theme condition, one of these themes was randomly selected for each participant, without the "available games" option underneath. The "available games" were always shown in the same fixed order.

displaying the four themes that were designed for the experiment to mimic some of the themes that commonly appear in slot games. We simplified the slot task compared to commercially available slots activities to improve experimental control and reduce noise in the dependent variable.

Each game came with a distinct theme, expressed across different background graphics, images on the spinning reels, and celebratory sounds. Clicking 'information' furthermore yielded a theme-specific description on how payouts were calculated. A further page of instructions explained how to use the information, 'cash out', and 'play' buttons, with the multiple theme condition containing an additional sentence explaining how to switch between the four themes via the 'available games' menu. The 'available games' menu was always shown in the same fixed order. The single theme condition did not include this menu nor the sentence of instructions on using it.

Each press of the play button led to the next spin in the predetermined sequence of outcomes, which did not vary across themes or conditions. The bet size was £0.30 on each spin, which could not be changed by participants. The initial spin led to a loss, and the sequence was programmed to exhaust the £5 bonus over 100 spins without ever returning to the initial value. The sequence involved three types of outcomes: 44 losses (an outcome of zero), 30 losses-disguised-as-a-win (LDW: a spin 'winning' less than £0.30), and 26 wins (greater than the £0.30 bet). The task's payoff sequence excluded non-monetary outcomes, such as 'free spins', and breakeven outcomes of £0.30, as these are difficult to interpret within the framework of a Win-Stay-Lose-Leave/Shift model. The game was designed to follow Gambling Commission regulations, with a spin-time of at least 2.5 seconds, and distinct sounds used for losses-disguised-as-wins and wins (Gambling Commission, 2021).

Participants exited the slot game either by pressing 'cash out' or were forced to proceed after playing all 100 spins. After which, all participants who played at least one spin were presented with the following screen:

> "You started with £5 and you ended the game with £{X}, resulting in an overall loss of £{5-X}.
>
> How likely would you be to play on this again?
>
> (1) Extremely likely to (7) Extremely unlikely"

Participants were then provided with some helpline information.

Analysis

H1 and H2 used the number of spins played as the dependent variable, for which we expected spikes at zero (participants who did not play in the slot game at all) and 100 (the maximum number of spins). We therefore preregistered a zero-one inflated beta regression (ZOIB) for these analyses. The ZOIB model was estimated using the 'zoib' package (Liu & Kong, 2015) in R (R Core Team, 2023). The implementation of the ZOIB model in the *zoib* package consists of four separate components. The first two components are sets of coefficients that model the zero and one inflation, operationalized as the probability of the response being zero, and the probability that the response is one, conditional that it is greater than zero. Both of these are modeled with a logit link function. The second two components are the coefficients of the beta regression for responses between 1 and 99 spins, specifically the mean of the beta parameter, and the precision parameter, which captures the variance around the mean. It is only the mean parameter and not the shape parameter which corresponds to task persistence in terms of statistical inference.

For H1 experimental condition was used as a predictor of each of these four parameters, and in H2 PGSI scores and a condition x PGSI interaction term were added, with the interaction term serving as the key variable of interest. To interpret both the main effects and the interaction, PGSI score was mean centered for the interaction analysis. The *zoib* package creates a Bayesian model estimated in JAGS (Kruschke, 2014). A diffuse normal prior (mean = 0, s.d. = 31.62, or precision = 0.001) was specified for each parameter. For each model, Monte Carlo Markov Chains were used to estimate the model parameters, with 5 chains used per model, utilizing 5000 iterations and a burn-in period of 1000 iterations. No thinning was applied to the posterior samples. Additional analyses (reported on the OSF) replicated the analysis using *brms* (Bürkner, 2017). The model is effectively the same, except the inflation parameters are operationalized differently.

MCMC convergence was assessed using the potential scale reduction factor metric (1 = chains converged).

For H3, we investigated how well a series of cognitive models, based on the WSLS model, could predict the behavior of participants cashing out and leaving the study, which we called the Win-Stay-Lose-Leave (WSLL) variant of the model. We compared the individual best fitting parameters across experimental conditions to evaluate if the leave behavior was influenced by the availability of multiple themes in comparison to a single theme. For the multiple theme condition, we also evaluated how well the different models predicted the shifting behavior between themes after wins and losses.

To shed additional light on the leave behavior of participants during the game, we fitted a series of variations of the WSLS cognitive models to the behavioral data. Each model was based on a different prediction of behavior during the game, based on reaction to different types of outcomes. The most common implementations of the WSLS model has two free parameters, a probability of staying after a win, Pr(Stay|Win) and a probability of switching after a loss, Pr(Switch|Loss). To this we also considered the behavior of leaving the game altogether, in what we called Win-Stay-Lose-Leave (WSLL). While traditional WSLS models evaluate the probability of staying after a win, we opted to call this free parameter the probability of leaving after a win, which is its complement: Pr(Leave|Win) = 1 - Pr(Stay|Win). This approach facilitates the comparison of behaviors after different outcomes. We assumed losses be outcomes below £0.30, and wins to be outcomes above £0.30.

We compared this two-parameter traditional model with three variations. We started with a base model with a single parameter, the probability of leaving being the same regardless of which outcome was received. This model assumes participants would have a fixed probability of leaving after any spin: Pr(Leave). If the other models fit the behavioral data better than the base model, it indicates that the leave behavior depended on the type of outcome for each spin.

To allow for the difference between losses (outcomes = £0) and LDWs (£0 < outcomes < £0.30), we also fitted a three parameter model, with a separate probability of leaving after an LDW, Pr(Leave|LDW), in addition to the behavior after losses (in this case outcomes = £0) and wins (outcomes > £0.30). This model assumed that the leave behavior would be different across the three different types of outcomes.

Our final and most complex model had seven parameters. Previous models react to every single individual loss, win, and LDW, before triggering a leave behavior, which might be too restrictive. But participants might instead persevere and wait for a certain number of individual outcomes (greater than 1) to accumulate before deciding to leave based on that outcome. We fitted a count model that started with a base probability of leaving regardless of outcome, similar to the base model. After a certain number of outcomes for each type (N_{Losses}, N_{Wins}, N_{LDWs}, which were three additional free parameters), the probabilities of leaving after a win, loss, or LDW, changed to their own individual free parameters. In other words, the model changed from the base model to the three-parameter model as outcomes accumulated. We predicted that the new free count parameters N would be larger in the multiple-theme conditions than in the single-theme condition, to allow for larger persistence over multiple outcomes before triggering a leave behavior. All four models are summarized in Table 1.

Table 1. Descriptions of the win-stay-lose-leave (WSLL) model to fit the behavior of leaving the game.

Model	Parameters	Description
Base model	Pr(Leave)	Same probability of leaving after each spin, regardless of outcome
Two-parameters	Pr(Leave | Win) Pr(Leave | Loss)	Different probabilities of leaving after a loss (outcome < £0.30) or after a win (outcome > £0.30)*
Three-parameters	Pr(Leave | Win) Pr(Leave | Loss) Pr(Leave | LDW)	Different probabilities of leaving after a loss (outcome = £0), after a win (outcome > £0.30), or after an LDW (£0 < outcome < £0.30).
Count model	Pr(Leave) Pr(Leave | Win) Pr(Leave | Loss) Pr(Leave | LDW) N_{Losses}, N_{Wins}, N_{LDWs}	Participants start with the same probability of leaving after each spin, Pr(Leave), regardless of outcome. After N_{Losses}, the probability changes to Pr(Leave | Loss), and analogously to Wins and LDWs.**

(*) We also fitted a two-parameter model in which losses were only outcomes = £0, and wins were any positive outcome, however this model resulted in a worse fit.
(**) The count model counted the number of outcomes since the beginning of the game for each participant. We also fitted a reset model that counted the number of outcomes since the most recent switch between themes, but this resulted in a worse fit. Results from these additional models are on OSF.

Details of the model fitting approach and results are in the supplementary cognitive modeling material in OSF, including parameter boundaries, different starting values, and optimization function used. In order to penalize models for unnecessary complexity, we used Akaike's Information Criteria (AIC) to choose the best fitting models (Wagenmakers & Farrell, 2004). Models with lower AIC values fit the data better.

For H4, which investigated whether participants' self-reported likelihood to play the slot game again varied across conditions, we used a cumulative Bayesian ordinal regression, using the data from all participants who played at least 1 spin. Evidence in favor of the null hypothesis was estimated using Bayes Factors, via the 'bfpack' package (Mulder et al., 2021) in R (R Core Team, 2023).

Results

Overall, participants persisted for an average of 22.08 (S.D = 26.28) spins in the single theme condition, compared to an average of 21.85 (S.D. = 27.26) spins in the multiple theme condition. Participants switched themes an average of 2.27 (S.D. = 3.09) times in the multiple theme condition. Within the multiple theme conditions, participants played an average of 4.45 (S.D. = 10.51) spins with the 'Deep Space' theme, 4.91 (S.D. = 10.99) with the 'Golden Sands' theme, 5.00 (S.D. = 10.49) spins with the 'Emerald Isle' theme, and 7.36 (S.D. = 14.32) spins with the 'High Seas' theme. An exploratory frequentist analysis suggested that the number of plays on the 'High Seas' theme was significantly greater than the other themes ($F = 14.28$, $p < .001$). Similarly, the number of theme switches was significantly correlated with the level of persistence ($r = .508$, $p < .001$), and PGSI score ($r = .123$, $p = .006$).

Effect of condition (H1)

The ZOIB regression was estimated with an effect of condition to test H1. All of the condition parameters' credibility intervals overlapped with zero, indicating that there was no evidence of an effect of condition on persistence in the task (Table 2), which means that H1 was not supported.

Table 2. Coefficients and credibility intervals of ZOIB regression testing H1.

Effect	Estimate	95% Credibility Intervals
Zero-inflation		
Intercept	−1.166	[−1.375, −0.957]
Condition	0.040	[−0.253, 0.329]
Beta (Mean)		
Intercept	−1.092	[−1.197, −0.988]
Condition	−0.091	[−0.238, 0.059]
Beta (Shape)		
Intercept	1.499	[1.355, 1.642]
Condition	−0.086	[−0.292, 0.115]
One-inflation		
Intercept	−2.639	[−3.069, −2.251]
Condition	0.200	[−0.341, 0.751]

Effect of PGSI and interaction with condition (H2)

In contrast, there were several effects of higher levels of PGSI severity on behavior in the task, as shown in Table 3. Higher PGSI scores were associated with a lower propensity of cashing out without playing the slots game, as measured by the zero-inflation component (B = −0.195, 95% CI [−0.286, −0.108]; greater persistence in the game as measured by the beta mean component (B = 0.041, 95% CI [0.004, 0.079]); and a greater likelihood of persisting until 100 spins had been reached, as measured by the one-inflation component (B = 0.299, 95% CI [0.176, 0.419]). However, we did not observe any credible interactions which could have suggested that high PGSI participants were likely to persist longer in the multiple theme condition, with the beta mean component coming closest to the preregistered threshold (B = 0.037, 95% CI [−0.002, 0.075]). The beta shape component did show a credible interaction (B = −0.059, 95% CI [−0.110, −0.007], however, as stated earlier in the analysis section, this model component does not reflect task

Table 3. Coefficients and credibility intervals of ZOIB regression testing H2.

Effect	Estimate	95% Credibility Intervals
Zero-inflation		
Intercept	−1.196	[−1.352, −1.045]
Condition	0.057	[−0.096, 0.210]
PGSI Score	−0.195	[−0.286, −0.108]
Condition : PGSI	0.071	[−0.017, 0.160]
Beta (Mean)		
Intercept	−1.145	[−1.218, −1.069]
Condition	−0.053	[−0.127, 0.021]
PGSI Score	0.041	[0.004, 0.079]
Condition : PGSI	0.037	[−0.002, 0.075]
Beta (Shape)		
Intercept	1.473	[1.371, 1.573]
Condition	−0.024	[−0.126, 0.078]
PGSI Score	−0.028	[−0.079, 0.022]
Condition : PGSI	−0.059	[−0.110, −0.007]
One-inflation		
Intercept	−2.789	[−3.141, −2.471]
Condition	0.217	[−0.115, 0.557]
PGSI Score	0.299	[0.176, 0.419]
Condition : PGSI	−0.081	[−0.202, 0.036]

persistence itself, only variability in the level of persistence. An exploratory analysis estimating the same model in the alternative R package 'brms' (Bürkner, 2017) did suggest the potential for some credible interaction effects linked to task persistence. However, this analysis should be treated with caution due to its non-preregistered nature and small estimated effect sizes. Interested readers can, however, consult the relevant results output reported on OSF.

Cognitive modelling (H3)

The best WSLL fitting model overall was the Count model (Table 4). Despite its higher complexity with seven parameters, it had the lowest AIC overall, therefore outperforming all other models. The best-fitting parameters of the Count model predict that the probability of leaving starts at 4.26% after any trial, and goes up to 6.93% for wins after 5 wins, and goes down to 1.66% and 1.24% for losses and LDWs respectively, after 7 losses and 2 LDWs. Participants showed some persistence, and after a few outcomes from each type, were more likely to leave after wins, and least likely to leave after LDWs (Figure 3). However, as the sequence of outcomes was predetermined, it is impossible to isolate if the effect was due to the number of spins (i.e. more time playing the game) or to the specific outcomes obtained: wins, losses, or LDWs. Results from the WSLS switching models that predict switching behavior can be found in the supplementary cognitive modeling material in OSF.

When comparing between the multiple-theme and single-theme conditions, we observe very similar parameters across the different models. The only notable differences were a lower probability of leaving after an LDW in the single theme than in the multiple theme condition. We also observe that the number of outcomes needed to trigger a leave were higher in the multiple theme condition, showing higher persistence after losses (N_{Loss}: single = 7, multi = 9) and after LDWs (N_{LDWs}: single = 2, multi = 3), but no difference in N_{Wins} which was 5 for both conditions (Figure 3).

Overall, and across all models, the cognitive modeling analysis showed that participants were more likely to leave the game after a win, and least likely to leave after an LDW. This is the opposite of the predicted behavior, where the typical WSLS model predicts that participants will persist with winning strategies and abandon losing ones. Here, participants were more likely to persist after LDWs, and more likely to cash out after wins.

Table 4. Best fitting parameters for the four win-stay-lose-leave (WSLL) models across both experimental conditions.

Parameter	Base model	Two-parameters	Three-parameters	Count model
Pr(Leave)	0.0319	–	–	0.0426
Pr(Leave | Win)	–	0.0555	0.0555	0.0693
Pr(Leave | Loss)	–	0.0220	0.0282	0.0166
Pr(Leave | LDW)	–	–	0.0159	0.0124
N_{Wins}	–	–	–	5
N_{Losses}	–	–	–	7
N_{LDWs}	–	–	–	2
AIC	6056	5908	5881	5754

AIC stands for Akaike's Information Criteria which measures how well a model fits the data, with a penalty for higher complexity (more parameters). Lower AIC values indicate better model fits.

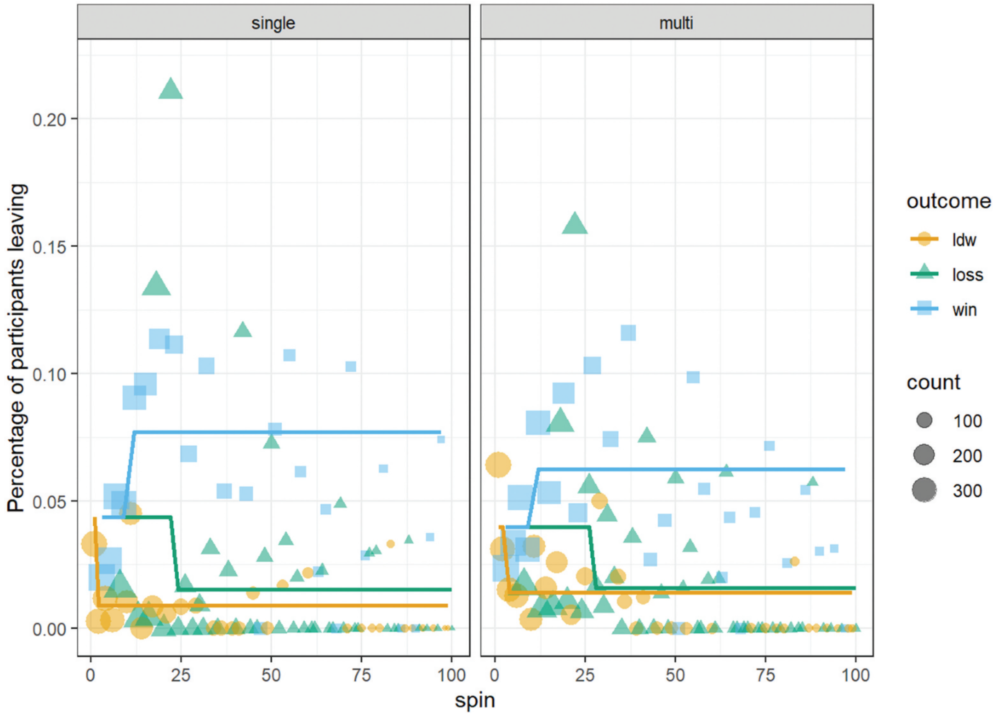

Figure 3. Percentage of participants leaving after every trial, for each experimental condition, for participants who reached that spin. The color and shape of the dots represent the three different types of outcomes: wins, losses, and LDWs. The size of the dots represents how many participants reached that specific spin. The lines represent the best fitting parameters of the Count model, predicting when participants would leave the game after each spin and type of outcome.

Table 5. Ordinal regression of willingness to play.

Effect	Estimate	Credibility Intervals
Model 1		
Condition	0.176	[−0.079, 0.432]
Model 2		
Condition	0.176	[−0.077, 0.429]
PGSI Score	0.035	[−0.055, 0.124]
Condition : PGSI	−0.005	[−0.130, 0.122]

Self-reported likelihood to return (H4)

There was no effect of condition, PGSI, nor an interaction between PGSI and condition on self-reported willingness-to-play-again (Table 5) ($M = 4.11$, S.D. = 1.65; single-theme $M = 4.03$, S.D. = 1.68; multiple-theme $M = 4.19$, S.D. = 1.62). Willingness-to-play-again again was not significantly correlated with PGSI score ($r(747) = 0.037$, $p = .316$), but was mildly correlated with persistence ($r(747) = 0.083$, $p = .023$).

Discussion

Slot games are commonly seen as one of the most harmful gambling products, largely due to their fast and immersive continuous nature (Livingstone et al., 2008; Schüll, 2012). The present work explored within a preregistered simulated online task whether the provision of multiple game themes might be another harmful 'structural characteristic' of slot games, which are readily observable on any EGM or online casino, but which have been subject to little previous research (Chen et al., 2013; Paliwal et al., 2014). H1 was not supported, as participants persisted on average for an identical number of spins in each condition. H2 was also not supported, although there was a tendency for participants with higher PGSI scores to persist on the task longer in either condition. This higher persistence of participants with higher PGSI scores is perhaps unsurprising, as PGSI correlates with gambling engagement (Delfabbro et al., 2024), so this increase can likely be explained by this group's higher levels of engagement in gambling in general. H3 was not supported, as in contrast to previous findings in the cognitive psychology literature (Worthy et al., 2013), participants were more likely to persist after a loss than after a win. Finally, H4 was supported, as there were no statistically-credible differences in participants' self-reported likelihood to play on this slot game again. Overall, while these findings do not provide emphatic evidence that the provision of multiple game themes is a neglected structural characteristic, they do provide some suggestions for future research on this topic.

First, previous research has highlighted the lack of external validity of simulated gambling tasks (Anderson & Brown, 1984; Ladouceur et al., 1991). The present experiment attempted to maximize the task's external validity in several ways, by for example recruiting a sample of gamblers with experience in online slots, instead of recruiting university undergraduates (Gainsbury & Blaszczynski, 2011); and by using a real effort endowment task to make the bonus feel more like participants' own money (Erkal et al., 2011). However, the effects may well have been different if gamblers had been using their own money on an online gambling site (Auer & Griffiths, 2020; Delfabbro et al., 2023; Heirene & Gainsbury, 2021), but our team lacked the necessary collaboration from an industry partner to make this sort of study feasible. While our research team put significant effort into designing aesthetically distinct and pleasing themes, the task was likely less immersive than the slot games found on online gambling sites. Real slot games also frequently have distinct bonus rounds (Belisle et al., 2017), which the present task did not have. Some previous experimental research has been conducted by purchasing and editing the code of commercial online gambling games (Newall, Weiss-Cohen, Singmann, Boyce, et al., 2022), and so this could be one way of creating a more externally-valid experiment without needing access to an industry partner. Furthermore, only participants with PGSI scores of seven or below were recruited for the experiment, which therefore cannot be considered representative of gamblers experiencing higher levels of harm. As participants with higher PGSI scores tended both to persist for longer and to switch themes more often, different patterns may well be observable among that group.

Following previous research (Ladouceur et al., 2003), the present experiment used a preset sequence of pay-offs, in order to minimize external noise. However, the artificiality of the pay-off sequence used may have affected participants' behavior in ways that could have reduced the experimental manipulation's effect. This could be indicated for example by the unanticipated pattern of results for H3, where participants were more likely to leave after wins than losses. This type of behavior was a good response to the pay-off sequence used, which involved a relatively uniform spacing of local maxima, as

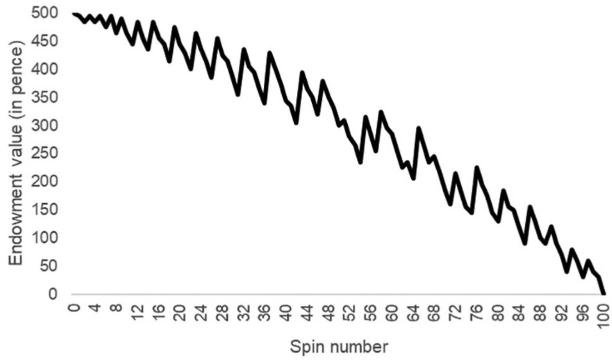

Figure 4. Preset sequence of spin outcomes used in the experiment.

can be seen in Figure 4, which participants might have learned to anticipate. However, other simulated tasks have seen reliable between-condition differences despite using preset pay-off sequences (Byrne & Russell, 2020; Ladouceur et al., 2003), so this may not have been the only factor leading to this overall pattern of findings. The tendency to persist after losses and leave after wins could also be explained by the gambler's fallacy, where a gambler believes that losses will be followed by wins and vice-versa (Ayton & Fischer, 2004). This pattern of behavior is particularly deleterious in slot machines where most of the spins lead to losses, which will keep the gambler engaged while consistently losing money. Overall, future research may want to consider using random spin outcomes, as this could result in greater external validity, and would also lead to a range of different outcome sequences, which would be useful for further examination via cognitive models.

Other limitations regarding the task's ecological validity also need to be acknowledged. The task was additionally limited by a maximum number of 100 spins, and a median total completion time of 7.75 minutes. Therefore, even if more of the experimental hypotheses had been supported, any inferences regarding persistent and harmful gambling in real world gambling scenarios would have been limited by the much more constrained nature of the experiment. It would have been infeasible from a resource standpoint, and also ethically questionable, to force participants to persist in the task for longer, or to return on multiple occasions. The potential £5 loss from maximally engaging in the task was also unlikely as in real gambling to lead to harmful consequences, as this amount was small and also was not the participants' own money. Again, resource and ethical limitations constrained the ecological validity of the task. Additionally, the low volatility of outcomes – particularly during the early spins – may have influenced participant behavior, as prior research shows that low volatility is associated with shorter session lengths (Percy et al., 2021). Finally, although the 'high seas' theme was found to be more popular than the other themes, this may have been because the four theme icons were always shown in the same order, with some previous psychology research suggesting that placement can influence choice (Nisbett & Wilson, 1977). Future more controlled studies are therefore needed to compare various slot game themes.

In conclusion, the preregistered findings were either null, in terms of persistence (H1), persistence among people experiencing gambling harm (H2), desire to play again (H4), or contradictory, with participants being more likely to leave after a win (H3). Future research should build on these findings, by researching this topic in a more ecologically-valid manner, especially since the provision of multiple themes is used in other gambling products, such as scratchcards (Nibert, 2000) and other online casino games (Newall, Walasek, et al., 2022).

Note

1. These three participants are included in the 'withdrew before completing' numbers in the CONSORT chart.

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Data availability statement

The data are available from: https://osf.io/2smj3/

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