How does the phrasing of house edge information affect gamblers' perceptions and level of understanding? A Registered Report

Philip W. S. Newall[1,2*]

Richard J. E. James[3]

Olivia M. Maynard[1]

* Correspondence: Philip.Newall@bristol.ac.uk

1 School of Psychological Science, University of Bristol, 12a Priory Road, Bristol, BS8 1TU, United Kingdom

2 Experimental Gambling Research Laboratory, School of Health, Medical and Applied Sciences, CQUniversity, 400 Kent St, Sydney, NSW 2000, Australia

3 School of Psychology, University of Nottingham, University Park, Nottingham NG7 2RD, United Kingdom

Abstract

The provision of information to consumers is a common input to tackling various public health issues. By comparison to the information given on food and alcohol products, information on gambling products is either not given at all, or shown in low-prominence locations in a suboptimal format, e.g., the "return-to-player" format, "this game has an average percentage payout of 90%". Some previous research suggests that it would be advantageous to communicate this information via the "house edge" format instead: the average loss from a given gambling product, e.g., "~~This~~ this game keeps 10% of all money bet on average". However, previous empirical work on the house edge format only uses this specific phrasing, and there may be better ways of communicating house edge information. The present work will experimentally test this phrasing of the house edge against an alternative phrasing that has also been proposed, "on average this game is programmed to cost you 10% of your stake on each bet", while both phrasings will also be compared against equivalent return-to-player information ($N =$ ~~on a sample of 2~~3,000 UK-based online gamblers). The two dependent measures are gamblers' perceived chances of winning and a measure of participants' factual understanding. ~~As a further aim in order to replicate previous findings, both house edge formats will also be compared against the existing suboptimal format, the "return-to-player" (involving a further subsample of 1,000 gamblers).~~ The optimal communication of risk information can act as an input to a public health approach to reducing gambling-related harm.

Keywords: Public health; gambling; open science; risk information

The provision of information to consumers is a common input to tackling various public health issues. For example, prominent nutrition and calorie labels on food products can beneficially shift consumer behavior (Bleich et al., 2017; Dubois et al., 2021), as can information about the alcohol content of alcohol products (Blackwell et al., 2018; Hobin et al., 2018). ~~Similarly, g~~Gambling is another public health issue where related proposals have been made (Eggert, 2004; Livingstone et al., 2019; Newall, Walasek, Hassanniakalager, et al., 2020). However, by comparison, gambling information can be criticized on the grounds of a lack of prominence, and suboptimalities with which it is communicated (Newall, Walasek, et al., 2022). This Registered Report contributes to this second issue, by experimentally ~~testing~~ comparing two ~~different phrasings of~~equivalent alternatives to some relevant information ~~about~~ that is currently given on many gambling products.

One of the most relevant pieces of information about a gambling product is the amount of money that a gambler might expect to lose over time (Harrigan & Dixon, 2010; Woolley et al., 2013). As gambling products are programmed to only pay-out a percentage of all money bet on average, this amount is typically communicated as a percentage. When this information is communicated to gamblers, it is typically shown via what is called the "return-to-player" format, e.g., "This game has an average percentage payout of 90%" (Collins et al., 2014). This example of 90% means that for every £100 bet, an average of £90 will be paid-out as winnings, for a net loss of £10, and this figure of 90% is roughly representative of the average payouts of electronic gambling machines internationally (~~K.~~ Harrigan & Dixon, 2009; Schwartz, 2013; Woolley et al., 2013). However, previous research suggests that the return-to-player is misunderstood by most gamblers (Beresford & Blaszczynski, 2019; Collins et al., 2014; Harrigan et al., 2017). Contrastingly, there are advantages to flipping the percentages, by instead focusing on the average loss via the "house edge" format, e.g., "This game keeps 10% of all money bet on average". A return-to-player of 90% and a house edge

of 10% are therefore statistically equivalent. However, it has been shown that in comparison

to the return-to-player, that the house edge format is understood better by gamblers (Newall,

Walasek, & Ludvig, 2020a, 2020b), results in lower perceived chances of winning (Newall et

al., 2020; Newall, Walasek, & Ludvig, 2020b, 2020a), and also translates into reductions in

gambling behavior (Newall, Byrne, et al., 2022). Overall, this research demonstrates several

advantages of the house edge format over the equivalent return-to-player format that is

currently used on some products in certain jurisdictions (Beresford & Blaszczynski, 2019;

Collins et al., 2014; Newall, Walasek, et al., 2022). However, seeing as how replication is an

important aspect of gambling psychology research (Heirene, 2021), a secondary aim of the

present research is to attempt to replicate findings on rates of understanding and perceived

chances of winning from the original studies on this topic (Newall, Walasek, & Ludvig,

2020a, 2020b).

One limitation of this literature is that previous experimental research on the house edge

format uses the same way of phrasing this information. This issue is important, as at least one

alternative phrasing has been proposed: "on average this game is programmed to cost you

[10]% of your stake on each bet" (Livingstone et al., 2019; p.3). This phrasing is longer, at 16

words compared to nine words, and contains additional words which might either increase the

perceived severity of the resulting average gambling losses, or improve gamblers'

comprehension of this information. Previous work suggests that added explanation can alter

how gamblers evaluate this information. For example, the addition of a 32-word "volatility

warning" significantly decreased gamblers' perceived chances of winning with both return-

to-player and house edge information (Newall, Walasek, & Ludvig, 2020b). In order to

maximize the present research's usefulness to policymakers, an experimental comparison will

therefore be made between these two exact phrasings of house edge information from the

previous literature. We are aware that they differ across several dimensions, which means

that any significant differences found here should be subject to follow-on work exploring precise mechanisms. While there is some reason to think that the longer alternative phrasing may be more effective, we do not believe that there is sufficient evidence to support a strong directional prediction at this time.

The present research aims primarily to experimentally compare these two phrasings of house edge information, using a hypothetical gambling scenario which closely follows previous research comparing the house edge with the return-to-player (Newall, Walasek, & Ludvig, 2020a, 2020b), using a large sample of UK-based online gamblers. The two outcome measures used are gamblers' perceived chances of winning measured on a 7-point scale, and rates of accurate responding on a multiple-choice question measuring factual understanding of this information. Effective gambling information should result in a low perceived chance of winning (hence encouraging people not to gamble), and be correctly understood by as many gamblers as possible (ensuring that any decisions to gamble are based on an accurate understanding of the statistical outcomes). Furthermore, seeing as how replication is an important aspect of gambling psychology research (Heirene, 2021), a secondary aim of the present research is to attempt to replicate previous findings showing that house edge information results in higher rates of understanding and lower perceived chances of winning than equivalent return-to-player information. As in previous research, this study will do so via a direct replication using the original wording of the house edge (Newall, Walasek, & Ludvig, 2020a, 2020b), and also a conceptual replication using for the first time use the alternative phrasing of the house edge.

The following nondirectional hypotheses are therefore made, that there will be some difference between the two phrasings of house edge information in terms of:

H1. gamblers' mean perceived chances of winning.

H2. gamblers' rates of correct understanding.

Furthermore, in following our research aim to replicate previous findings, we make a secondar~~ily~~ directional hypothesis~~e~~ ~~that~~comparing each of the two house-edge conditions to a third condition where participants will be given equivalent return-to-player information:

H3. ~~Both~~ Each of the two house edge conditions will result in lower perceived chances of winning and higher rates of understanding than equivalent return-to-player information.

Method

Data, materials, an analysis script, and a preregistration of the Stage 1 accepted manuscript will be placed on the Open Science Framework at https://osf.io/6hbyp/. Ethics approval for this study was obtained from the University of Bristol's School of Psychological Science Research Ethics Committee (#12102). The PCI RR study design template is shown in Table 1.

Participants

Participants will be recruited for this study via the crowdsourcing platform Prolific. It has been suggested that Prolific can yield superior data quality compared to other crowdsourcing platforms such as MTurk (Eyal et al., 2021). Participants will be paid £0.50 each [insert average length of time and pro-rata hourly payment here; if the pro-rata payment ends up at under £6/hour then additional bonus payments will be made until they reach this threshold]. We aim for an average sample size of 1,000 participants passing data quality checks per-condition, as this is the closest round number which exceeds the required sample size in each of the below power analyses.

Prolific's balanced sample feature will be used in order to obtain an equal number of females and males. The minimum age will be set at 18 [mean and SD of age distribution to be placed

here after data collection, using Prolific's data export feature]. In order to obtain participants with experience in relevant online gambling games, Prolific's relevant prefilter will be used. Only participants who had previously responded to the following question with one or more of these options will be eligible to take part: "What types of online gambling / casino games have you played? Choose all that apply." Potential answers, "Baccarat / bingo / blackjack / craps / lottery / roulette / slots / video poker / virtual sports betting". At present, there are over 15,000 people based in the UK on the Prolific platform meeting these prescreening requirements, which should be sufficient to collect the desired sample size.

At the end of the experiment, participants will complete the Problem Gambling Severity Index (PGSI; Ferris & Wynne, 2001), and we will report the percentages corresponding to the four groups of: recreational gamblers, low-risk gamblers, moderate-risk gamblers, high-risk gamblers.

Design

Following previous research (Newall, Walasek, & Ludvig, 2020b), participants will be given some short information about a hypothetical gambling scenario:

"Imagine that you are a member of an online casino. You have played many of this online casino's games over the last year.

You know that gambling games are designed so that most gamblers lose money over time. Only a percentage of all the money bet gets paid back out as winnings. Or, in other words, that casino games come with a house edge.

You are about to start playing a new online casino game, when you read the following message about the game:"

Participants will then be given information in one of three formats below this (format manipulated between-participants). In the original house edge format condition, participants will be told, "This game keeps 10% of all money bet on average". While in the alternative house edge format condition, participants will be told, "On average this game is programmed to cost you 10% of your stake on each bet". In the return-to-player condition, participants will be told, "This game has an average percentage payout of 90%". The screen will then show a dependent measure immediately below that. Once participants have completed that dependent measure, they will proceed to the next screen, which will show the same text and then the other dependent measure (with the information given in the same way as on the previous screen). The order of the two measures will be counterbalanced.

Two data quality checks will be performed. First, we will exclude data from participants completing the experiment in under one minute. Based on data from a similar previous study, we expect this to lead to around 3.5% of all data collected being excluded (Newall, Walasek, & Ludvig, 2020b). Second, methodologists have recommended the use of self-reported carelessness checks, such as, "In your honest opinion, should we use your data in our analyses in this study? (Do not worry, this will not affect your payment, you will receive the payment code either way.)" (Brühlmann et al., 2020). This text will be included after the rest of the experiment, and all participants responding with "no, please do not use my data" excluded. Previous data have suggested that up to 11.7% of crowdsourced responses might be careless (Jones et al., 2022), although previous data with that exact item suggest a lower rate of 5.6% self-reported careless responses (Brühlmann et al., 2020). For the present research, we will plan for a rate of 10% self-reported careless responses. Therefore, with these two data quality checks in mind, we will plan to collect data from 1,151 participants per-condition in order to reach our planned sample size.

Measures

The first outcome measure (H1) is a response on a 7-item Likert scale to the following question, "How does the above message affect your perceived chances of winning?" Seven response options allow participant to rate their chances of coming away with more money than they started: "My chances of winning are… Very high / High / Somewhat high / Neither high nor low / Somewhat low / Low / Very low chance of coming out ahead". In a previous study, participants responded on average at the middle item of this scale ($M = 4.1$, $SD = 1.6$) when given the original house edge phrasing only (Newall, Walasek, & Ludwig, 2020b). This suggests that this item should work well for the current research, as the alternative house edge phrasing could result either in higher or lower perceived chances of winning.

The second outcome measure (H2) is a multiple-choice question, measuring participants' factual understanding of house-edge information, "Which of the following best describes what the message means?" Correct response option, "For every £100 bet on this game about £90 is paid out in prizes". Following the first use of this measure by Collins et al. (2014), previous research has used a further three incorrect response options, "90% of people who play this game will win something / This game will give out a prize 9 times in 10 / If you bet £1 on this game you are guaranteed to win 90p". However, when given the original house edge phrasing most participants have tended to answer this question correctly (70.9%; Newall et al., 2020b). It would therefore be beneficial to make this measure harder, so that accurate rates of responding were closer to 50%. Some previous research found that around 20% of participants responded with a "don't know" response when this was added to a list of four

similar responses (Behavioural Insights Team, 2022), suggesting that this would be a good way to reduce accuracy rates via a reduction in successful guessing. Another incorrect response used in this previous research was: "For every £100 bet you will lose no more than £10". Therefore, with the addition of these two additional response options, this will result in a six-alternative choice.

Statistical analysis

The first two hypotheses will be tested using only data from participants in one of the two house edge conditions. H1 will be tested via ordinary least squares regression, with house edge format as the independent variable (original, alternative), and participants' responses on the 7-point scale as the dependent variable. H2 will be tested via logistic regression, with participants' responses as the dependent variable (correct/incorrect), and experimental condition as the independent variable (original, alternative). H3 will be tested via two separate models corresponding to those used for H1 and H2, but where binary variables are used for each house edge condition, which will then be separately compared against responses in the return-to-player condition.

We now consider some power analyses to support our plan to collect 1,000 usable responses per-condition. For H1 and H2, it is impossible to know at this stage what magnitude of change on the dependent measures would lead to meaningful differences in actual gambling environments. Therefore, we were required to proceed heuristically, by powering our study for relatively small effects which were within our budget of resources to run this study. Given this uncertainty, we chose to explore a change on H1's outcome from 4.1 to either 3.8 or 4.4 (SD = 1.6, d = 0.188), with 95% power and an alpha of 0.05. This was calculated using the 'WebPower' package in R (Zhang et al., 2018). This identified a requirement of 1473, or 737 participants per condition. This was calculated via G Power as requiring 741 participants per

condition (Faul et al., 2009). For H2, we chose to explore a change in accuracy of 6% (accuracy moving from 50% to 56% or 44%, OR = 1.27, *d* = 0.133), again with 95% power and an alpha of 0.05. This was calculated via G Power for a logistic regression model as requiring 771 participants per condition (Faul et al., 2009).Using the WebPower package, this identified a required sample ment of 933, or 467 participants per condition. We will not perform a power analysis for H3 here as that is a secondary aim of the present research. However, we do note that previous research found *d*s of 0.48 and 0.69 for the two outcomes when comparing the original house edge phrasing with the return-to-player (Newall et al., 2020b), indicating that H3 should be more than adequately powered.

In the event that the tests for either H1 or H2 are not significant (*p*'s ≥ .05),We will also run equivalence tests will be conducted using the two one sided t-test (TOST) procedure. Whereas standard null hypothesis significance procedures test the hypothesis that the difference between groups, or the association between variables is significantly different from zero, equivalence testing allows effects below a given interval to be rejected as "too small" to be of practical significance, which is referred to as the "smallest effect size of interest" (Lakens, 2017). Power analysis was conducted to test whether the proposed analyses were appropriately powered given the sample sizes proposed using the 'power_t_TOST' function in the TOSTER package (Lakens, 2017) in R (R Core Team, 2020). For this power analyses, the smallest of the two effect sizes from the previous power analysis was used as the smallest effect size of interest (*d* = 0.133), and this suggested a required sample size of 969 participants per-condition to achieve 80% power. This final power analysis supports our intention to collect 1,000 usable responses per-condition.

Finally, we plan some exploratory analyses, investigating H1 and H2, which are the most novel aspects of the present research. These will be marked as exploratory in any future publication. Two exploratory analyses will be run to see if there are any interaction effects

between the phrasing of house edge information and PGSI, in order to detect whether the optimal phrasing of house-edge information might depend on gamblers' level of problem gambling severity. Two extra regression models will be run, adding a main effect of PGSI and an interaction between PGSI and experimental condition. Since p-values on interaction terms in non-linear models are not always interpretable (McCabe et al., 2020), the model for hypothesis 2 will also use ordinary least squares, as this has been recommended as a way of counteracting this issue (Ai & Norton, 2003).

Discussion

[Please note that the discussion is only to be completed in Stage 2 following data collection]

Limitations

This study is subject to various limitations that should be considered while evaluating its results. Participants were collected from a crowdsourcing platform, and so therefore took part in the study in return for payment. Although this data collection methodology introduces limitations (Pickering & Blaszczynski, 2021), it does have some strengths too, such as the ability to cost-effectively oversample from gamblers of high levels of problem gambling severity (Russell et al., 2021). The study yielded self-report measures in response to a hypothetical scenario, which limits the external validity of the findings. However, previous studies have found converging evidence across self-report (Newall, Walasek, & Ludvig, 2020b) and behavioural tasks (Newall, Byrne, et al., 2022) with respect to the related comparison of house edge and return-to-player information, which suggests that the present methodology may be a cost-effective way of investigating novel phrasings of gambling information. Furthermore, there are many other alternative ways of improving information

delivery to gamblers, such as the use of graphical decision aides (Walker et al., 2019), which the study did not test.

Table 1. The PCI RR study design template

Question	Hypothesis	Sampling plan	Analysis Plan	Rationale for deciding the sensitivity of the test	Interpretation given different outcomes
How does the phrasing of house edge information affect gamblers' perceptions and level of understanding	There will be a difference in gamblers' mean perceived chances of winning between the original and alternative format conditions	Collection of 2,000 UK-based online gamblers via Prolific	Ordinary least squares regression. Perceived chances of winning DV (7 = "very high chance of coming out ahead"). Dummy variable (1 for alternative condition) as single IV. Interpretation based on $p < .05$. Sensitivity analysis planned if $p \geq .05$.	In order to detect a change on this outcome from 4.1 in the original condition to 3.8 or 4.4 in the alternative condition (SD = 1.6), with 95% power and an alpha of 0.05, we would require 741 participants in each condition.	A lower mean level in either condition would support usage of that format. Equivalence testing used to reject effect sizes beneath the SESOI.
	There will be a difference in gamblers' level of factual understanding of the information given between the original and alternative format conditions		Logistic regression. DV = 1 if correct response selected ("For every £100 bet on this game about £90 is paid out in prizes"), otherwise 0. Dummy variable (1 for alternative condition) as single IV. Interpretation based on $p < .05$. Sensitivity analysis planned if $p \geq .05$.	Sample size of 1,000 per-condition chosen in order to detect a change in accuracy of 6% (accuracy moving from 50% to 44% or 56%, OR = 1.27), with an alpha of 0.05 and 95% power, which would require 771 participants per-condition	A higher mean rate of understanding in either condition would support usage of that format. Equivalence testing used to reject effect sizes beneath the SESOI.
How does house edge information compare to equivalent return-to-player information	Gamblers will have a lower perceived chances of winning when given house edge information than return-to-player information	Collection of 3,000 (full sample) UK-based online gamblers via Prolific	Ordinary least squares regression. Perceived chances of winning DV (7 = "very high chance of coming out ahead"). Dummy variable (1 for alternative condition) as single IV. Interpretation based on $p < .05$	Power calculation not performed here; should be adequate given that previous literature has used sample sizes as small as 250 per-cell	A lower perceived chance of winning in the house edge conditions would further support the use of the house edge. Equivalence testing used to reject effect sizes beneath the SESOI.

	A higher proportion of gamblers will provide the correct response to the item of factual understanding in the house edge conditions compared to the return-to-player condition		Logistic regression. DV = 1 if correct response selected ("For every £100 bet on this game about £90 is paid out in prizes"), otherwise 0. Dummy variable (1 for alternative condition) as single IV. Interpretation based on p < .05		A higher mean rate of understanding in the house edge conditions would further support the use of the house edge. Equivalence testing used to reject effect sizes beneath the SESOI.

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