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Modeling Gambling: An Application of the Mathematical Principles of Reinforcement

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The *Mathematical Principles of Reinforcement* (*MPR*) has proved a useful model for predicting and describing the behaviour of non-human animals on different schedules of reinforcement. This research tests the ability of MPR to accurately predict performance of adult humans on a simulated gambling task. A simulated electronic gaming machine was used in three experiments and gambling responses were reinforced according to series of Random Ratio schedules. In Experiment 1, when participants experienced either an ascending or descending order of ratios, rates of responding were well described by a bitonic response gradient. In Experiments 2 and 3 participants experienced either an early large win or an early large loss before experiencing a series of ratio schedule values that were presented in ascending order. Again rates of responding, expressed as a function of ratio schedule value, were well described by a bitonic response gradient. The early large loss condition produced higher response rates than the early large win condition. The bitonic response gradients of all conditions were well described by MPR via changes in the parameter *a*, *specific activation*.

Keywords: Random Ratio, Mathematical Principles of Reinforcement, gambling simulation, wins, losses, human

An understanding of reinforcement schedules is central to behaviour analytic accounts of behaviour. Early research has clearly demonstrated that different schedules are characterized by different patterns of responding (e.g., Ferster & Skinner, 1957). Over the years there have been calls for more systematic study of schedule performance in general (e.g., Zeiler, 1984), and for the systematic study of human schedule performance (e.g., Mace, 1994), specifically. Recently, there have been calls for a more scientific analysis of gambling behaviour and those factors that promote the development of problem gambling (Lyons, 2006).

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It has long been known that intermittent schedules of reinforcement maintain high rates of behaviour (e.g., Ferster & Skinner, 1957). As a human activity, gambling lends itself to an analysis in terms of schedules of reinforcement because it shares two obvious characteristics with behaviour maintained by schedules of reinforcement in non-human animals. First, gambling is a function of its consequences. In relevant settings, individual acts of gambling may be followed by potent reinforcers such as money and social approval. Second, the acts of gambling that are followed by reinforcer delivery are essentially unpredictable and intermittently reinforced (e.g., Haw, 2008a). For all forms of gambling the act of placing a bet or wager is intermittently followed by monetary reward. Whilst not every gambling response is reinforced, it is true that in order to "win", one has to "bet".

The extent to which human behaviour can be said to be sensitive to a contingency of reinforcement can be judged from the extent to which behaviour changes following a change in the contingency (e.g., Kollins, Newland & Critchfield, 1997). While it is tempting to generalize from research on schedules of reinforcement with non-human animals to humans it is best to do so with caution. For example, it has been shown that human schedule performance can be both similar (e.g., Lowe, Beasty & Bentall, 1983) and dissimilar to that of non-human animals (e.g., Lowe, Harzem & Bagshaw, 1978).

Mathematical Principles

Killeen's *Mathematical Principles of Reinforcement* (*MPR*; Killeen 1994) is a quantitative model of schedule performance that has proved its utility for describing and predicting non-human animal behaviour on both fixed ratio (FR) (Avila, et al., 2009; Bizo & Killeen, 1997; Leslie, Boyle & Shaw, 2000; Reilly, 2003; Sanabria, Acosta, Killeen, Neisewander & Bizo, 2008), variable ratio (VR) (Bizo & Killeen, 1997; Bizo, Kettle & Killeen, 2001), and progressive ratio (PR) schedules of reinforcement (Covarrubias & Aparicio, 2008; Killeen, Posadas-Sanchez, Johansen, & Thrailkill, 2009; Rickard, Body, Zhang, Bradshaw & Szabadi, 2009). It has also proved its ability to describe human responding reinforced by VR schedules (Bizo, Remington, D'Souza, Heighway, & Baston, 2002). The goal of this paper is to explore the application of MPR to describe a human activity, gambling, and more specifically, its ability to describe patterns of gambling on a simulated poker machine.

MPR is based upon three key principles; motivation, constraints on responding, and learned associations. The first principle, *motivation*, captures the activity engendered by reinforcers. Formally, the model defines this as *specific activation* (a), the number of seconds of responding a single reinforcer will support. It is a function of the amount of behaviour a reinforcer incites (A) and the rate (r) at which the reinforcer is provided (Killeen & Sitomer, 2003).

$$a = A/r \qquad \text{(Equation 1)}$$

The second principle, *constraint,* captures the extent to which the rate of responding is constrained by the time and difficulty required to make the appropriate response. Formally, the model defines this as *temporal constraint (δ),* the minimum inter-response time that an organism can produce for a specific target response. If it takes δ seconds to make a response then the maximum response rate would be 1/δ (Killeen, 1998).

The final principle, *association,* is determined by the type of response, the schedule and the organism's memory for the target response (Killeen, 1994). This principle captures the strength of association between the response and reinforcement. Formally, the model defines this as the coupling coefficient, which is unique for different schedules of reinforcement (see Killeen, 1994; Killeen & Sitomer, 2003). The coupling coefficient for VR schedules is:

$$C = \frac{n}{n + (1-\beta)/\beta}, \quad \text{where } 0 < \beta \le 1. \qquad \text{(Equation 2)}$$

The parameter β captures the proportion of the association attributed to the target response that precedes a reinforcer, formally $\beta = 1 - e^{-\lambda\delta}$ (Killeen & Sitomer, 2003). Where, λ is the rate of decay of memory for the target response.

MPR describes and predicts performance on different schedules of reinforcement based on interactions of the principles of *arousal, temporal constraint* and *coupling*. Parameters are combined in Equation 3 which describes and predicts response rates (B) on VR schedules:

$$B = \frac{n/\left(n + \left(e^{\lambda\delta} - 1\right)^{-1}\right)}{\delta} - \frac{n}{\delta a} \qquad \text{(Equation 3)}$$

The curve generated by Equation 3 describes a bitonic response gradient such that it predicts that response rates will increase to a maximum before deceasing over successively larger ratios. This is counterintuitive since rate of response is not predicted to be at its highest when the response requirement is at its smallest. The shape of the response gradient predicted by MPR is determined by the values of the parameters, *a,* δ and λ.

Haw (2008b) has pointed to differences in the distribution of responses reinforced on VR and random ratio (RR) schedules and suggested that RR schedules are a better model of what gamblers usually experience when gambling on slot machines. Note that the constant probability nature of VR schedules makes them a special example of an RR schedule. Thus, Equation 3 applies to RR as to VR schedules.

To date human operant behaviour has received limited analysis using MPR. Bizo et al. (2002) demonstrated with humans that response rates across ratio sizes were bitonic in nature; response rates first increased and then decreased with successive increases in ratio requirement. Their task involved participants searching a map or blank screen for hidden treasure. The treasure search task was designed to mask the VR reinforcement schedules being used. Elsewhere masking (e.g., Lieberman, Sunnucks, & Kirk, 1998) has been shown to attenuate the influence of rule governed behaviour on human schedule performance (e.g., Svartdal, 1989). MPR described human schedule performance on the task used by Bizo et al. adequately in terms of changes in the parameters *a, δ* and λ. Bizo et al. (2002) only tested a limited range of ratio values, however, and did not succeed in varying rates of responding across a wide range.

Although considerable experimental evidence suggests that adult human and non-human animal behaviour differs markedly on the same schedules (e.g., Matthews, Shimoff, Catania & Sagvolden, 1977), it has been suggested that these differences may be less acute when the reinforcement schedule is not apparent to the human participant (Svartdal, 1991). One way to mask schedules is to imbed them in an engaging computer simulation. Computer simulations have the added advantage that they provide an ethical and valid way to investigate operant principles in relation to applied problems generally, such as the teaching of discrete trial training (Randell, Hall, Bizo & Remington, 2007), and to understanding factors that may control adherence to physiotherapy (Tijou, Yardley, Sedikiedes & Bizo, 2010), and provide an ethical procedure for studying variables that affect gambling behaviour (e.g., Dixon, Hayes & Ebbs, 1998; Weatherly, Sauter & King, 2004), specifically.

The use of computer simulated forms of gambling has allowed researchers to investigate a variety of variables that may control gambling behaviour (e.g., MacLin, Dixon & Hayes, 1999), such as; the “near-miss” effect (MacLin, Dixon, Daugherty & Small, 2007), “big wins” (Weatherly et al., 2004), pay back percentages (Weatherly & Brandt, 2004), gambling across repeated conditions of play, (Brandt & Pietras, 2008), and between concurrently available slot machines (e.g., Dixon, MacLin & Daugherty, 2006). The validity of simulations as a research tool for studying gambling is supported when performance obtained using simulations mirrors patterns of behaviour and results obtained from real world settings (e.g., Dixon & Schreiber, 2002; 2004; Livingstone & Woolley, 2008; Lyons, 2006).

EXPERIMENT 1

The aim of this study was to use a simple computer simulated electronic gaming machine to test human schedule performance on RR schedules and determine if the response gradient, as a function of response rate and ratio value, is bitonic as would be predicted by MPR, and if performance would differ if the ratios were presented in a descending versus an ascending series. Research with rats tested on ascending and descending FR schedules has shown that performance is well described by a bitonic response gradient with rates of responding significantly higher on the descending ratio values (Reilly, 2003). It was hypothesized that performance on descending ratio values will also be described by a bitonic response gradient.

This research makes use of a simulated electronic gaming machine to mask the schedules being tested by creating ambiguity about the nature of the research. The use of a simulated gambling environment will ensure that this research has both face validity for participants and direct relevance to the understanding of the learning processes by which addictive gambling is established and maintained.

METHOD

Participants

The participants were undergraduate students who did not receive any payment or course credit for their participation in this experiment. Three female (M_{age} = 22.7 years, *SD* = 1.6) and 2 male (M_{age} = 33.5 years, *SD* = 16.3) participants experienced the ascending RR condition, and 12 female (M_{age} = 24.6 years, *SD* = 9.5) and 3 male (M_{age} = 26.3 years, *SD* = 12.7) participants experienced the descending RR condition. A requirement of participation in this study was that all participants were at least eighteen years of age and scored less than eight out of twenty seven on the *Problem Gambling Severity Index* (PGSI), which is a nine item questionnaire designed to assess prior gambling behaviour, and is a component of the *Canadian Problem Gambling Index* (Wynne, 2003). Items on the PGSI are scored on a four point Likert scale (0 – 3) with possible totals ranging from 0 to 27. Scores obtained from the scale are used to classify participants as either non-gamblers or non-problem gamblers (0), low risk gamblers (1-2), moderate risk gamblers (3-7) or problem gamblers (8 and over) (Wynne, 2003). One of twenty one participants screened using the PGSI was excluded because they scored in the problem gambler range.

Apparatus

The computer program “Fruit Machine 9.0” was programmed in Visual Basic.net 2005 controlled and recorded experimental events. It was installed on five Intel ® Core ™ 2 Duo computers, running Microsoft Windows XP ™ Professional Version 2002. The program ran a simulated electronic gaming machine that participants interacted with which allowed them to play with virtual money (see Figure 1). The simulation allowed the manipulation of the bet, win and loss sizes and ratio requirement.

Participants pressed the space bar to initiate each “spin”. Bets subtracted from, and wins added to, the “pot” amount. The wav “Win” (2198 ms) and “Lock-in” (435 ms) sound files were used to provide auditory information about the outcome of each “spin”. Three identical symbols in a line represented a win which paid out at a fixed rate of “$5”.

Procedure

The RR values used in the ascending condition were; 2, 4, 6, 8, 10, 20 and 50. The RR values used in the descending condition were; 54, 18, 6 and 2. It should be noted that the ascending and descending RR conditions were not originally arranged to act as counterpoints to each other but as independent conditions to assess the participants’ performance on a series of ratio values. They are reported together because they are germane to the question of the shape of the function relating response rates to ratio schedule requirement. Each ratio remained in effect for ten wins or 15 minutes, whichever occurred first. Participants in the ascending condition started with a ‘pot’ amount of $50. Participants in the descending condition started with a larger ‘pot’ amount of $500 to ensure sufficient funds to complete the early large ratios. In

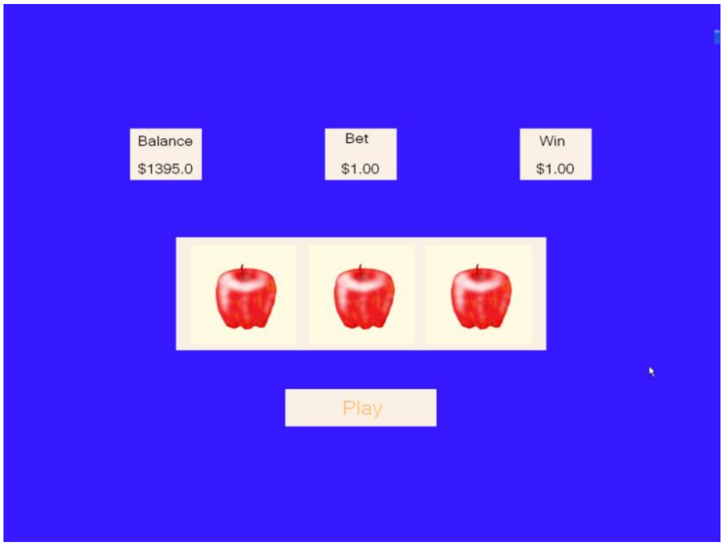


Figure 1. Screen shot of 'Fruit Machine 9.0' showing the pot value 'balance', bet size 'bet' and size of wins and losses 'win'. An apple symbol is displayed on each of the three reels and in this configuration constitutes a win.

both conditions each spin cost $1 with all wins equal to $5. Experimental sessions for both conditions ran for 30 minutes. Prior to commencing play each participant received the following instructions:

> *"Welcome and thank you for your participation. This research utilizes a simulated fruit machine with three wheels. You will not win or lose any real money on this task. The simulation will start with an amount of money in your jackpot that you are able to draw from to make bets. You commence each spin by pressing the space bar after the wheels have stopped spinning and the sound has stopped playing. Each time you press the space bar the displayed bet amount will be deducted from your jackpot before the wheels start spinning. A spin will be considered a win when three identical symbols, other than lemons, are presented together. Three lemons constitute a losing spin. Wins and losses will be reflected in your pot total. You may make as many bets as you like within the 30 minute duration of the simulation. Please press the space bar to begin. Good luck."*

RESULTS AND DISCUSSION

Individual response rates on each RR value were calculated by dividing the total number of responses by the total time a RR was in effect and available to the participant to respond on. The response rates were averaged across individual participants for each RR value in the ascending and descending conditions are displayed Figure 2. The error bars are the standard error of the mean and the smooth curves represent the best fit of Equation 3 through the data points. MPR provided a good description of the averaged data in both the ascending ($R^2 = 0.88$) and descending ($R^2 = 0.91$) conditions. Both response gradients were bitonic with planned comparison t-tests demonstrating significant increases and decreases in the rate of responding in both the ascending (RR 2 to RR 8; $t(4) = -1.7$, $p = 0.08$: RR 8 to RR 50; $t(4) = 2.2$, $p < 0.05$) and

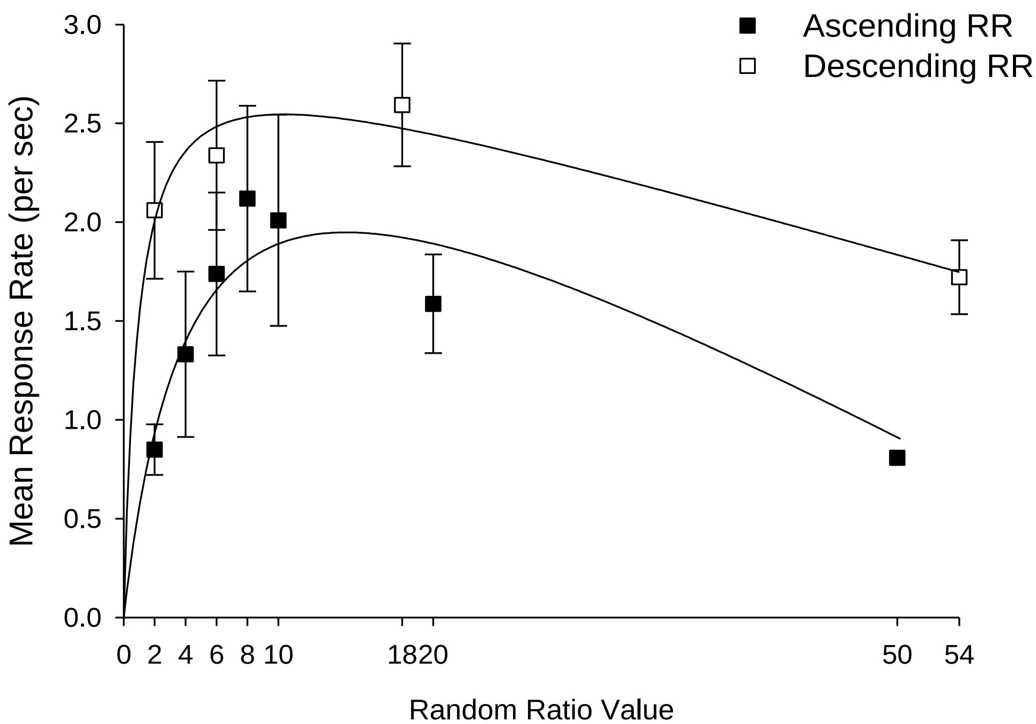


Figure 2. Mean response rates as a function of Random Ratio (RR) value size for ascending (filled squares) and descending (empty squares) RR value conditions in Experiment 1. The smooth curves are drawn by Equation 3. The error bars are the standard error of the mean.

descending ratio conditions (RR 2 to RR 18; $t(14) = -1.8$, $p < 0.05$: RR 18 to RR 54; $t(14) = 3.1$, $p < 0.01$). The results confirm the bitonic shape of the function relating rate of responding to RR schedules for humans on a gambling simulation.

The patterns of responding on the ascending and descending conditions are comparable with data reported by Reilly (2003) from rats tested on ascending and descending FR values. We also observed higher rates of responding in the descending condition at the larger ratio values.

EXPERIMENT 2

Self-reported desire to gamble has been reported to be higher after a large win than after a series of small wins (Young, Wohl, Matheson, Baumann & Anisman, 2008). Gambling research has demonstrated that response rates increase after a large loss (Wohl & Enzle, 2003) and decrease after a large win (Dixon & Schreiber, 2004; Weatherly et al., 2004). Consequently it was hypothesized that response rates would be higher and more persistent after an early large loss than an early large win. It was anticipated that differences between the win and loss conditions would be reflected through variations in MPR estimates of *specific activation, a*. Certainly, there have been numerous reports that gambling alters physiological arousal (e.g., Anderson & Brown, 1984; Coventry & Constable, 1999; Diskin & Hodgins, 2003), and that to some extent this is mediated by participants expectancies about gambling outcomes (e.g., Ladouceur, Sévigny, Blaszczynski, O'Connor, K., & Lavoie, 2003), which might suggest some associative coupling of arousal to the gambling environment.

The aim of Experiment 2 was to assess what effect, if any, large wins and large losses at the start of a gambling session would have on subsequent performance on the gambling simulation as participants were exposed to a progression of RR values.

METHOD

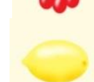
Participants

The participants were 20 undergraduate students at Southern Cross University who did not receive any payment or course credit for their participation in this experiment. There were 17 females (M_{age} = 25.0 years, SD = 10.4) and 3 males (M_{age} = 27.7 years, SD = 15.0) who were screened with the PGSI, which indicated our sample included 11 non-gamblers or non-risk gamblers, 4 low risk gamblers and 5 moderate gamblers.

Apparatus

The apparatus was the same as used in Experiment 1 except for the following. The values attributed to three identical symbols presented in a line was changed such that participants could experience “wins” ranging from $1 to $200 as well as a “loss” equal to minus $200. The complete set of symbols and their associated monetary amount are shown in Table 1.

Table 1. Each reel on the simulation “Fruit Machine 9.0” has ten different symbols with the presentation of three identical symbols resulting in a win or loss to the value indicated.

Symbol	Win/Loss	Display
Apple	$1	
Apricot	$2	
Banana	$5	
Grapes	$10	
Watermelon	$12	
Pear	$15	
Orange	$17	
Strawberry	$20	
Cherries	$200	
Lemon	-$200	

Procedure

Participants were randomly assigned to either an early-large "win" condition or an early-large "loss" condition. Participants in the "win" condition started with a 'pot' amount of \$100. The first win, valued at \$1 was delivered on a RR 3, and was followed by two consecutive wins of \$200 each delivered on an FR 1. Participants in the "loss" condition started with a 'pot' amount of \$900. The first win, that was also valued at \$1 and delivered on a RR 3, was followed by two consecutive losses of \$200 each delivered on an FR 1. Except for these differences at the beginning of an experimental session participants in both conditions experienced the same five ascending RR values; 3, 6, 12, 24, and 48. Each ratio remained in effect for ten wins to a total value of \$120. The experimental session ended after a participant had earned 50 wins or 60 minutes had elapsed, which ever occurred first.

RESULTS AND DISCUSSION

The average response rates for the win and loss condition are displayed in Figure 3. The error bars represent the standard error of the mean and the smooth curves represent the best fit of Equation 3 to the mean response rates. The response gradients for both conditions are bitonic with both conditions experiencing an increase in response rate from RR 3 to RR 12 then decreasing at RR 48. The increase in response rates from RR 3 to RR 12 was significant in both the win ($t(9) = -4.1$, $p < 0.1$) and loss conditions ($t(9) = -4.2$, $p < 0.01$), however, the decrease in response rates from RR 12 to RR 48 was only significant in the win condition ($t(9) = 2.1$, $p < 0.5$).

Planned comparison t-tests showed non-significant differences in response rates between the win and loss conditions at each of the five different ratio sizes of RR 3, $t = 0.55$; RR 6, $t = 0.47$; RR 12, $t = 0.73$; RR 24, $t = 0.82$; and RR 48, $t = 0.89$. The smooth curves generated by Equation 3 provide a good description of individual performance, and the average variance accounted was $R^2 = 0.80$ and $R^2 = 0.97$ for the win and loss conditions, respectively. The averaged parameter estimates generated by the model for the win and loss condition were $a = 101$ s, $\delta = 0.28$, $\lambda = 0.84$ and $a = 112$ s, $\delta = 0.17$, $\lambda = 0.55$, respectively.

Increased estimates of a in the loss condition is represented by a response gradient that had a greater x intercept. The strength of memory association for the last reinforced response was stronger for the win condition, with larger estimates of λ generating a response gradient with a steeper ascending limb with the maximum response rate evident at a lower ratio value. The estimates for δ were also larger for the win condition, which is consistent with the uniform reduction in response rates for the win condition.

This experiment offers qualified support for the ability of MPR to describe human operant behaviour on a series of RR values. The data obtained from both the win and loss condition on this simulated gambling task are well-described by MPR. The response gradient generated by MPR for both conditions shows a marked increase in response rates across ascending ratios. The results have demonstrated that within a thirty minute session on a simulation of an electronic gaming machine, humans were sensitive to changes in ratio size with rates of responding varying substantially across the range of ratio values. It also appears that gambling on this simulation may have been sensitive to early large wins or losses. Although not statistically significant, the difference in response rates for the win and loss conditions was greatest at the largest ratio value, which suggested to us that exposing participants to larger ratio values than experienced in Experiment 2 may allow differences in response rates between the two conditions to develop further.

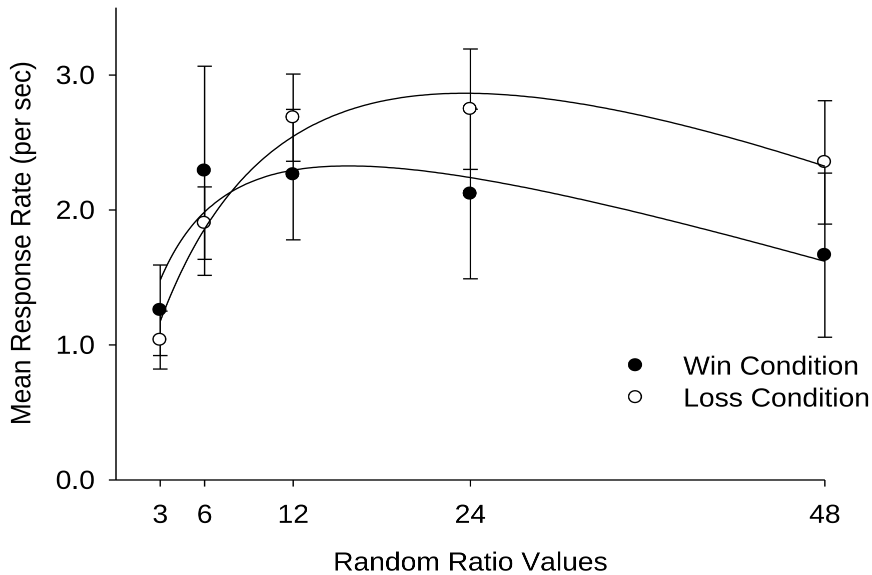


Figure 3. Mean response rates as a function of Random Ratio (RR) value size for the early large win (filled disks) or early large loss (empty disks) conditions in Experiment 2. The smooth curves were derived from Equation 3 and are based on the mean response rates. The error bars are the standard error of the mean.

EXPERIMENT 3

This experiment tested performance at larger ratio values to see if the divergence between the win and loss conditions at the large ratios used in Experiment 2 would become obvious at even larger ratios. If the range of ratio values is not large enough then response rates will not show a downturn at the larger values of the restricted range (e.g., Bizo et al., 2001; Leslie, et al., 2000), however, when the range of ratios is sufficiently large response rates will show a downturn and the pattern of responding will be well described by a bitonic function (e.g., Bizo et al., 2001; Sanabria et al., 2008). Consequently, in Experiment 3 we increased the range of ratio values from RR 3 through RR 48 used in Experiment 2, to RR 3 through RR 192 with the expectation that response rates would show a more pronounced decrease at the larger ratio values between the win and loss conditions. If the trend evident in the Experiment 2 replicated it was hypothesized that response rates for the loss condition will be significantly greater than for the win condition at the larger ratio value of RR 192.

METHOD

Participants

The participants were 22 undergraduate students from Southern Cross University, who did not receive any payment or course credit for their participation in this experiment. There were 19 female (M_{age} = 24.0 years, *SD* = 9.4) and 3 male (M_{age} = 27.0 years, *SD* = 8.3) participants. Twenty three participants were screened for gambling problems resulting in 13 participants classified as non-gamblers or non-risk gamblers, 6 as low risk gamblers and 3 as moderate gamblers and 1 as a problem gambler. The participant classified as being a problem gambler was excluded from this research.

Apparatus

The apparatus used in this experiment was the same as used in Experiment 2.

Procedure

The procedure remained the same as Experiment 1 with the exception of the ratio values and starting pot size. The ratio values were; RR 3, RR 12, RR 48 and RR 192. The higher ratio of bets to wins required a larger initial pot size to enable participants to respond throughout an entire session. Accordingly the pot sizes were increased to $600 in the win condition and $1400 in the loss condition.

RESULTS AND DISCUSSION

Individual response rates were calculated for each ratio value then averaged across participants in the win and loss conditions. Figure 4 shows the mean response rates at each ratio value for the win and loss condition with the error bars representing the standard error of the mean. The smooth curves generated by Equation 3 were fitted to the average data for each condition. This experiment confirmed the findings of Experiments 1 and 2: the rate of responding across ratio values produced average data that could be fitted to a bitonic curve with significant increases in response rates at small ratio values (RR 3 & RR 12) for the win ($t(10) = -6.4$, $p < 0.01$) and loss conditions ($t(20) = -5.8$, $p < 0.01$).

A one-way between groups MANOVA revealed no significant main effect for the win/loss condition on response rate [$F(4, 12) = 2.04$, $p > 0.05$; Wilks' Lambda = .57]. A one-way between groups ANOVA with

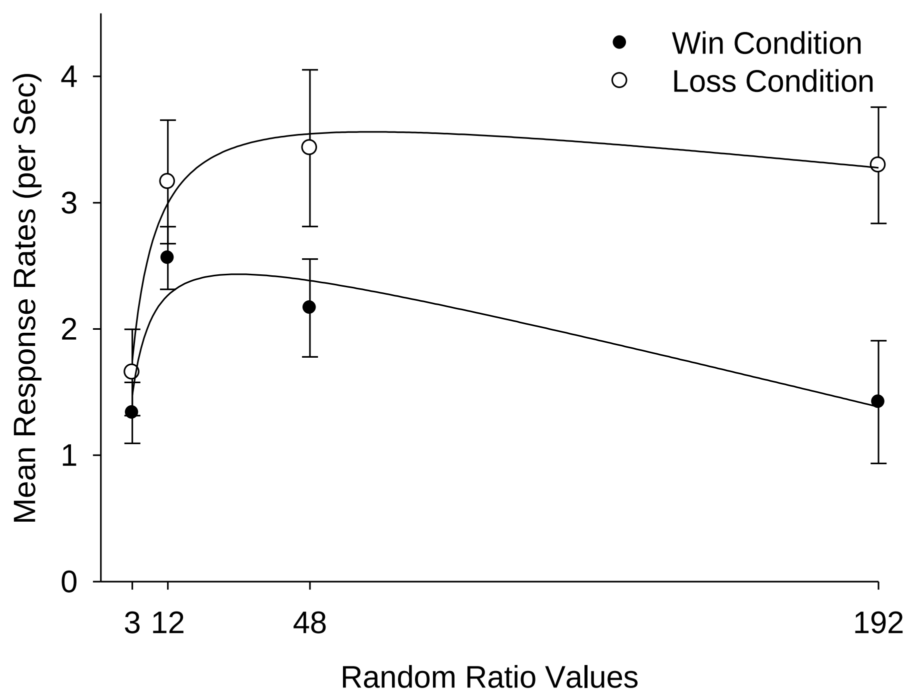


Figure 4. Mean response rates as a function of Random Ratio (RR) value size for the early large win (filled disks) or early large loss (empty disks) conditions in Experiment 3. The smooth curves were derived from Equation 3 and are based on the mean response rates. The error bars are the standard error of the mean.

planned comparisons revealed significant higher response rates for the loss condition than the win condition at RR 48 [$F(1, 20) = 3.0$, $p = .05$] and RR 192 [$F(1, 15) = 6.1$, $p = .01$] but non-significant results for RR 3 [$F < 1.0$] and RR 12 [$F(1, 20) = 1.2$].

Non-linear least squares regression was used to fit Equation 3 to the response rate data for individual participants, it provided a good description of the data. The average R^2 value for the win condition was 0.87 and was 0.93 for the loss condition.

<<Insert Figure 4 about here>>

The parameter estimates of a, δ and λ were screened for extreme and unrealistic values, with estimates of a greater than 2500 and estimates of λ greater than 20 not used in any subsequent parametric statistics. Results from a one-way ANOVA revealed estimates of specific activation on the loss condition was significantly higher than the win condition [$F(1, 13) = 5.9$, $p < .05$] with eta squared ($\eta^2 = .31$) indicating a moderate effect size. Estimates of δ and λ did not differ significantly between the win and loss conditions: δ [$F(1, 13) = 1.4$] and λ [$F<1$].

The higher response rate in the loss over the win condition shown in Experiment 2 was replicated in Experiment 3. These findings are consistent with previous research that has shown that rates of gambling are lower after a large win (Weatherly et al., 2004) and elevated after a large loss (Wohl & Enzle, 2003). Participants were sensitive to changes in RR value and early machine events. MPR was able to account for variations in performance between the win and loss conditions via the parameter *specific activation*.

GENERAL DISCUSSION

The bitonic shape of human schedule performance was confirmed in all three experiments. The results of Experiment 1 are consistent with the findings with rats, showing faster response rates at larger ratio values when experienced descending order rather than ascending order (Reilly, 2003). The results of Experiment 2 also showed that response rates were low at small ratio, higher at intermediate ratios and then low at the largest ratios. The data from this experiment were reliably fit by MPR (Equation 3) supporting the ability of MPR to predict human RR schedule performance. The *loss* condition showed the greatest increase in responding over the win condition at the largest ratio value. In Experiment 3 the variable ratio values were increased, and as such, was able to demonstrate that the early large loss condition elicits significant higher response rates than the large win condition. MPR was able to account for the difference in performance through increases in parameter estimates of specific activation, a. The ability of the win and loss conditions to incite behaviour is supported by current gambling research which reports both changes in patterns of play (e.g., Livingstone & Woolley, 2007) and physiological arousal (e.g., Coventry & Constable, 1999). Experiment 3 was also able to demonstrate that the significant increase on the ascending arm of the response gradient was counterpoised by a significant downturn at larger ratio values.

The symbolic values used in this research were $1 for each bet with normal wins ranging from $1 to $20 and a ‘large’ win or loss condition worth $400. The determination of what constitutes a “large” win or loss is relative and would vary across individuals based on factors such as income and past gambling experience. In determining the size of the ‘large’ win or loss condition an examination was made of the methodology of a previous study using hypothetical reinforcers to investigating the effect of a large win on performance. In their investigation of persistence in gambling performance Weatherly et al. (2004) used a bet size of $0.10 with a large win condition worth $10. Performance variations were evident after experiencing either, an initial large win ($10), a later large win ($10), two small wins ($0.80), or no wins. The ratio of 1:100 was sufficient to obtain obvious group differences in total responses after a win, however, Weatherly et al. did not observe a difference in performance between the large win and no win condition, and they suggested that the 'large' win size may not have been large enough to produce significant differences between these conditions. In the present study we chose a win/loss ratio of 1:400 with the expectation that would be sufficiently large enough to produce obvious differences in response rates across conditions which was what was subsequently observed.

The computer simulation used in this research was able to demonstrate significant schedule performance differences on RR schedules. The present experiment used a simulated electronic gaming machine to present different ratio requirements to participants. The electronic gambling machine simulation was chosen because of the ability to mask the schedules as well as the opportunity to draw from existing gambling research on human performance on electronic gambling machines. However, the use of a simulation raises the issue of the external validity of results. Quite simply would participants behave similarly if they were given real money? The answer is "yes" - probably. Bizo et al. (2002) gave real money to participants in their research of human schedule performance and obtained similar results to the present study, with response rates across different ratio sizes also producing a bitonic response gradient.

In conclusion, this research was two-fold in its purpose: First, to identify patterns of human schedule performance and assess the ability of mathematical principles of reinforcement to describe performance and account for variations. Second, to draw explicit links between quantitative models of schedule performance and issues that are important to researchers focused the effects of gambling experience on gambling behaviour. The results of these three experiments provide support for the ability of MPR to describe and predict human schedule performance on RR schedules. The bitonic nature of RR schedule performance was reliably fitted by MPR with response rate variations on the win/loss condition accounted for through the parametric estimate of specific activation. The first principle of MPR shows that *specific activation* is a function of the amount of behaviour a reinforcer incites. The ability of MPR to account for variations in response rate on the parametric measure of *specific activation* means predictions about future response rates can be made when the knowledge of reinforcer rate and levels of incitement are known (Killeen & Bizo, 1997).

This research has shown the utility of MPR to reliably describe performance and the potential to make predictions about future performance in the field of behavioural pharmacology (e.g., Avila et al., 2009; Reilly, 2003; Sanabria et al., 2008). The potential ability of MPR to extend our current knowledge of human schedule performance has numerous implications for our understanding of gambling (Livingstone & Woolley, 2008), where the influence of complex schedules of reinforcement on an individual's behaviour appears significant but is in need of further sustained and systematic experimental investigation.

Addictive behaviours, such as drinking alcohol or gambling, are often considered abnormal only when engaged in at unusually high rates. The frequency with which individuals engage in certain actions may determine whether their behaviour falls within social norms. Knowledge of the mechanisms that regulate the frequency of behaviour can enhance our understanding of behaviour that falls outside social norms and negatively affect an individual. This knowledge may also aid the development of methods of treatment and prevention.

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