Abstract

Slot-machine choice may be influenced by structural features like display labels, independent of the programmed payout probability. Gambling choice may then involve verbal descriptions or rules comparing machines based on structural characteristics such as "this one is better than another. This study developed an experimental analogue examining how display labels influences choices in simulated slot-machine gambling. Eighty-eight participants learned a relational series of arbitrary nonsense words that were either "more-than" (E > D> C > B >A) or "less-than" (A < B < C < D < E). Participants were then exposed to a slot-machine payout probability phase to establish one machine, labelled with the middle-ranking word, C, as having a low likelihood of winning. Another machine, labelled with a novel word, X, had a high likelihood of winning. In the test phase, participants were given choices of slot-machines labelled with all remaining nonsense words. It was predicted that slot-machine choices would be influenced by the underlying relational hierarchy of nonsense words. Findings supported this, with choices showing a gradient-like pattern, despite no prior experience with the payout probabilities. This suggests that slot-machine choices could be influenced by structural properties, and not just payout probability.

Keywords: slot-machine gambling, payout percentage, preferences, symbolic generalization, relational frame theory.

In modern casino and online gambling environments, players are confronted with a myriad of game-playing choices, many of which have similar outcome schedules yet subtly different structural characteristics. Slot-machines, for instance, may be programmed according to random ratio (RR) schedules of reinforcement in which bets or spins are independent of one another and tend to result in high and steady rates of responding (Crossman, 1983). Slot-machine preferences, however, may be only partially controlled by the underlying schedules of reinforcement and punishment (Belisle, Owens, Dixon, Malkin, & Jordan, 2016; Dixon & Delaney, 2006; Dixon, Nastally, Jackson, & Habib, 2009; Dymond & Whelan, 2007). Slot-machine choice is subject to a combination of payout probability, situational factors such as the familiar themed game in which the reel contingencies are embedded, players' current mood, the prior experience of outcomes on the same or similar games, and other conspicuous in-game characteristics like visual and auditory feedback (Barton et al., 2017; Breen & Zimmerman, 2002; Devos, Clark, Maurage, & Billieux, 2018).

The modern gambling environment can be considered a series of concurrent schedules of reinforcement where choosing to play one slot-machine results in not being able to respond to any other available machines (Dixon, Maclin, & Daugherty, 2006). In laboratory-based gambling research, human choice behavior often shows differential sensitivity to programmed reinforcement rates. According to the generalized matching law, "organisms divide their time between alternatives in proportion to the value of the reinforcement consequent on the choice" (Rachlin, 1971, p.249). Dixon et al. (2006) applied the matching law to evaluate preferences for concurrently available slot-machines which paid out on a Variable Ratio- (VR) 10 and a VR-50 schedule, respectively. Participants allocated greatest levels of responding to the VR-10 machine. However, human gamblers do not always allocate responding according to the predictions of the

matching law (Weatherly, Thompson, Hodny, & Meier, 2009). In such cases, differential

sensitivity to payback percentage suggests that slot-machine gambling can come under control of

additional, rule-governed, contingencies. This view is consistent with evidence that humans do

not always behave in ways that maximizes reinforcement on concurrent schedules (Hayes,

Brownstein, Haas, & Greenaway, 1986; Madden & Perone, 1999), suggesting that rules may

interact with, or override, human schedule performance.

Rule-based control over concurrent slot-machine preference and response allocation was

demonstrated through conspicuous manipulation of the non-arbitrary, color-based properties of

slot-machines (Hoon, Dymond, Jackson, & Dixon, 2008; Hoon & Dymond, 2013; Zlomke &

Dixon, 2006). This work demonstrated that when presented with concurrent slot-machines,

identical in payout probability but differing in color, no preference is shown for either machine.

That is, responding is equally distributed between the alternatives. However, following a

training procedure which established one color as a cue for the 'more-than' and the other as a cue

for 'less-than', when re-presented with the slot-machines, participants allocate more responding

to the machine which was the same color as the 'more-than' cue, despite being of equal payout

probability.

This approach to rule-based control mimics, in an artificial manner, the putative

processes inherent when "exposed to a variety of contingencies and verbal stimuli when

engaging in a gamble" (Dixon & Delaney, 2006, p. 173), such as "a fellow casino patron

instructing the slot-machine player that one game is 'hotter' than another" (p. 174). Explanations

for the effectiveness of such internal and external features at controlling response allocation and

persistence under extinction have long emphasized a generalized reinforcement basis, which

assumes that unrelated features of the slot-machine display acquire some of the functions of win

displays through stimulus generalization (Skinner, 1953). For example, in the behavioral

laboratory, near miss outcomes (i.e., two out of three matching symbols on the payline) in

simulated slot-machine gambling have been generated via generalization to total wins (Belisle &

Dixon, 2016) and their neurobiological effects explained, at least in part, on generalized

conditioned reinforcement via physical similarity with actual win displays (Dymond et al., 2014;

Habib & Dixon, 2010). Belisle and Dixon (2016) found that post-reinforcement pauses arranged

along a generalization gradient, with greater pauses following losing outcome displays that were

formally similar to total wins, relative to losing outcomes that were formally dissimilar.

Behavioral control by structural features in slot-machine gambling may also occur when

the stimulus features are symbolically related (Dixon, Bihler, & Nastally, 2011; Dixon et al.,

2009; Dymond, McCann, Griffiths, Cox, & Crocker, 2012). Unlike effects based on formal

similarity, symbolic generalizations are not constrained by sensory overlap between features and

may potentially influence a wider array of behaviors such as slot-machine gambling choices

(Belisle & Dixon, 2016). Research on symbolic generalization has an established tradition in

behavioral psychology (Dymond & Rehfeldt, 2000) and paradigms are being developed in

experimental psychopathology (Dymond, Bennett, Boyle, Roche, & Schlund, 2018) and social

psychology (Hughes, Barnes-Holmes, Van Dessel, de Almeida, Stewart, & De Houwer, 2018).

We contend that symbolic generalization may provide a contemporary empirical model of how

intra-individual (i.e., verbal or relational) processes interact with external sources of conditioned

reinforcement to generate slot-machine preference and response allocation, despite the stimuli

involved not sharing any physical features in common (Dymond & Roche, 2010; Dymond &

Whelan, 2007). Symbolic generalization effects are assumed to occur via relational learning

processes (Dymond et al., 2012; Dymond & Whelan, 2007; Hoon et al., 2008), with research

showing that when language-able humans are taught a series of relations involving physically dissimilar stimuli, the stimuli involved often become related to each other in ways not explicitly trained (Sidman, 1994). To illustrate, if choosing Stimulus X in the presence of Stimulus A is taught (i.e., A-X), and choosing Stimulus Y in the presence of Stimulus A (i.e., A-Y) is also taught, then untrained relations will emerge between X and A, Y and A, X and Y, and Y and X, all in the absence of further feedback (Dymond & Roche, 2013; Hayes & Hayes, 1992). The relevance of symbolic generalization for gambling research stems from the observation that an outcome paired with one member of a relation readily emerges for other, indirectly related members, without further training. That is, using the nomenclature described above, if X is paired with winning, or becomes discriminative for a winning outcome on a slot-machine, then presentations of Y may also actualize win-related behavior and positive appraisals. Because the stimuli are *physically* dissimilar, this symbolic generalization extends the scope of possible mechanism underlying slot-machine preference and gambling persistence.

Dymond et al. (2012) provided empirical evidence for the role of symbolic generalization in slot-machine preference. Participants were trained on a series of relations involving nonsense words in which choosing B and C, respectively, was taught in the presence of A (i.e., A-B and A-C) and choosing X and Y, respectively, was taught in the presence of Z (i.e., Z-X and Z-Y). From these trained relations, participants derived (that is, passed tests without further training) relations between B-C, C-B, X-Y and Y-X. Participants were then exposed to a low payout probability slot-machine containing label B, and a high payout probability slot-machine labelled X. During a preference test, participants provided likelihood of winning ratings and selected between concurrently presented machines labelled C and Y or chose under conditions of non-reinforcement (i.e., the absence of feedback following reel spin) and matched payout

probabilities, respectively. Findings demonstrated that participants showed greater preference for, and gave higher ratings to, the slot-machine related symbolically to the directly experienced high-payout probability machine (i.e., Y) than the slot-machine related symbolically to the low-payout probability machine (i.e., C). Therefore, the high-payout probability experience of playing machine X symbolically generalized to Y, despite never experiencing payouts (or even playing) this machine.

Getting a preliminary empirical handle on the potential impact of such rules as, "these slots are hotter than those slots" and their role in slot-machine preference may help explain the development and influence of maladaptive response allocation and gambling persistence. To do so with symbolic relations of 'more than' and 'less than' entails the following multi-step procedure. First, training is needed to establish two abstract shapes as cues for more-than and less-than, respectively. In the presence of the more-than cue, selecting the larger of two quantities is reinforced, while in the presence of the other less-than cue, selecting the smaller quantity is trained. Second, generalized control by these cues is tested with novel sets of stimuli without feedback. Next, the cues are presented with arbitrary stimuli, such as nonsense words, and arbitrary relations trained that do not involve any formal, physical features. Therefore, an individual learns that A is more than B and B is more than C, then the untrained relations B is less than A, C is less than B, A is more C, and C is less than A, typically emerge without further training. Finally, symbolic generalization is evident when slot machine choices are altered or transformed in line with emergent more-than and less-than relations (i.e., when response allocation increases in the presence of the slot-machine labelled A and is lower in the presence of C). Previous research on symbolic generalization has shown that fear-eliciting behavior

(Dougher, Hamilton, Fink, & Harrington, 2007) and evaluative choices (Dymond, Molet, &

Davies, 2017) may be altered in line with more-than and less-than relations.

The aim of the present study was to examine the role of symbolic generalization of

more-than and less-than relations in slot-machine preference under conditions of non-

reinforcement. Networks of more-than (e.g., E > D > C > B > A) and less-than (e.g., A < B < C <

D < E) relations were trained and tested. Exposure to a simulated slot-machine payout

probability phase established one machine as discriminative for a low likelihood of winning.

Then preference was tested with concurrent presentations of pairs of slot-machines labelled with

stimuli from the more-than and less-than relational network. It was predicted that choices of

concurrently presented simulated slot-machines would be altered in line with the derived

relational network of combined more-than and less-than relations. That is, after training either E

> D > C > B > A (i.e., E is the highest ranked stimulus in the network) or A < B < C < D < E

(i.e., A is lowest ranked), we expected preferences to follow a gradient-like pattern with A

selected least often, followed by B, C, D, and E. Similarly, after training either A > B > C > D >

E (i.e., A is highest ranked) or E < D < C < B < A (i.e., E is lowest ranked), we expected

preferences to follow a gradient-like pattern with E selected least often, followed by D, C, B, and

A. In all cases, a directly learned about, high payout percentage slot-machine, X, was predicted

to be selected most often across all network training types.

Materials and Methods

Participants

Eighty-eight participants (66 women), aged 18 to 30 years ($M = 21.33$, $SD = 2.79$) were

recruited from Swansea University and reimbursed with partial course credit on completion of

the study. Participants were randomly assigned to one of four conditions that varied the direction

and type of trained relations: (Condition 1; n=20) E>D>C>B>A, (Condition 2; n=20)

A>B>C>D>E, (Condition 3; n=24) A<B<C<D<E, and (Condition 4; n=24) E<D<C<B<A.

Ethical approval was granted by Swansea University Psychology department.

Apparatus and Procedure

The experiment took place in a small room containing a desk, a chair, and a desktop

computer with 16-inch display. Stimulus presentation and the recording of responses were

controlled by the computer programmed in *Presentation* (NeuroBehavioral Systems, CA) and

Visual Basic.Net, respectively. The stimuli used throughout the experiment were drawn from

previous work on symbolic generalization (Dymond et al., 2012; Munnelly, Freegard, &

Dymond, 2013). Two images were selected from the Wingdings® font and used as contextual

cues for more-than and less-than, respectively. Twenty-eight stimulus sets consisting of images

of quantities of particular objects (e.g., apples, balls, houses) were employed during non-

arbitrary relational training and testing (Phases 1 and 2). For the arbitrary relational training and

testing phases (Phases 3 and 4), six consonant-vowel-consonant strings were used (BIH, YUT,

JOM, VEK, CUG, PAF). For the slot-machine learning and testing phases, participants were

presented with either one or two concurrently available three-reel slot-machine simulations.

Figure 1 gives a graphic representation of the slot-machine display.

Insert Figure 1 about here

The experiment was divided into two main procedural sequences: *Relational Training*

and Testing (Phases 1 to 4) using a version of the *Relational Completion Procedure* (RCP;

Munnelly et al., 2013) and *Slot-machine Payout Probability Learning and Preference Testing*

(Phases 5 and 6). Each of these sequences was made up of different phases as described below.

Relational Training and Testing

Phase 1: Non-arbitrary relational training and testing. The purpose of this phase was to establish one symbol as a contextual cue for 'more-than' and another symbol as a contextual cue for 'less-than'. At the start participants were presented with the following onscreen instructions:

Thank you for agreeing to participate in this study. You will be presented with a series of images or nonsense words on the top half of the screen from left to right. Then you will be presented with 3 images or nonsense words on the bottom of the screen. Your task is to observe the images or words that appear from left to right and drag one of these images or words from the bottom to the blank, yellow square. Click and hold the mouse over the image or word to drag it to the blank square. To confirm your choice, click 'Finish Trial'. If you wish to make another choice, then click 'Start Again'. Sometimes you will receive feedback on your choices, but at other times you will not. Your aim is to get as many tasks correct as possible. It is always possible to get a task correct, even if you are not given feedback.

During the start of each trial, the bottom third section of the screen appeared grey and the top two thirds appeared blue. A sample stimulus appeared at the left of the blue section of the screen; followed one second later by the contextual cue to the right (therefore appeared central) and after a further one second, a third blank square appeared towards the right of the screen. One second later the three comparison stimuli appeared in the grey section of the screen below (see Figure 2). To make a response, participants selected one of the comparison stimuli, then drag and dropped it in the blank square in the blue section of the screen. For example, a sample stimulus depicting three basketballs presented on the left, followed by the more-than image in the middle, and a blank box on the right-hand side. Two comparison images (one basketball and three

basketballs) then appeared in the grey section at the bottom of the screen. Participants had to select the image showing one basketball and drag and drop it in the blank square, because three basketballs are 'more than' one basketball. The positioning of the comparison stimuli was randomized on all trials. Once a comparison stimulus had been selected and placed in the blank box, two new buttons appeared below the comparison stimuli, labelled 'Finish Trial' or 'Start Again'. Clicking 'Start Again" reset the stimuli. Clicking 'Finish Trial' ended the trial, cleared the screen, then presented feedback. Correct responses produced the word 'Correct' onscreen, whereas incorrect responses produced the word 'Incorrect. Once feedback had been presented, a new trial commenced.

Insert Figure 2 About Here

The sample and comparison stimuli in Phase 1 consisted of shapes or objects that differed along a physical dimension. A total of 12 stimulus sets were used during training. Once a participant responded correctly across 10 consecutive trials, they progressed to testing. The non-arbitrary relational test was identical in format to training except that no feedback was given following trials and six novel stimulus sets were employed. Ten correct responses were required to complete Phase 1 and to progress to Phase 2. If this criterion was not met, participants were re-exposed Phase 1.

Phase 2: Constructed response non-arbitrary training and testing. This phase was identical to Phase 1, except that the sample stimulus was no longer presented, therefore a blank grey box appeared was presented. This then required participants to select the correct sample stimulus and drag and drop it into the grey box (Figure 2), before selecting the correct comparison stimulus. For example, in the presence of the more-than cue, three basketballs, and one basketball, the participant was required to select the image of three basketballs and drop it in

the sample stimulus box on the left, then select the image depicting one basketball and dropping it in the right-hand box. This then, completes the 'sentence like' structure of the RCP that three basketballs are 'more than' one basketball. Participants were presented with on screen feedback to inform them of correct or incorrect answers. Participants were required to make 10 consecutive correct responses to complete training. Upon reaching criterion, participants were exposed to a test phase. The test phase was identical in format except that no feedback was presented. Participants were presented with eight test trials. If they failed to produce eight correct responses, they were re-exposed to Phase 1. On achieving the mastery criterion, participants progressed to Phase 3.

Phase 3: Arbitrary relational training and testing (mutual entailment). The purpose of Phase 3 was to establish a relational network of nonsense words, which for the purposes of the present report will be represented by the letters A, B, C, D, and E. Through this training, participants learned that certain nonsense words were ranked relationally more highly than other nonsense words.

The structure of the network trained differed by condition (Table 1). In Condition 1, participants were trained such that E > D > C > B > A (i.e., E is the highest ranked); in Condition 2, participants were trained that A > B > C > D > E (i.e., A is highest ranked); in Condition 3, participants were trained A < B < C < D < E (i.e., A is lowest ranked); and in Condition 4, participants were trained that E < D < C < B < A (i.e., E is lowest ranked). This training was conducted using the contextual cues from Phases 1 and 2. In Conditions 1 and 2, training was conducted using the more-than (>) contextual cue, whereas in Conditions 3 and 4 training was conducted using the less-than (<) contextual cue.

***Insert Table 1 About Here ***

The onscreen format of Phase 3 was identical to that of Phase 2 except that the sample and comparison stimuli now consisted of arbitrary stimuli (nonsense words). Participants learned through trial and error which nonsense word was more highly ranked (Conditions 1 and 2) or lower ranked (Conditions 3 and 4). In each condition, there were four different trial types in this phase (see Table 1). In Condition 1 for example, these were B > A, C > B, D > C, and D > E, therefore, in the presence of the more-than cue and stimulus A and stimulus B, participants were required to drag and drop stimulus B to the sample stimulus box (on the left-hand side) and drag stimulus A to the comparison stimulus box (right hand side), because 'B is more highly ranked than A'. Participants were given onscreen feedback to notify a correct or incorrect response. Relational training trials were presented in blocks of 12, a correct response across all 12 trials, in order to reach criterion and progress to the test phase. The arbitrary test phase had the same format as training, except participants were presented with the contextual cue for the mutually entailed relations (i.e., the less-than cue after more-than training, and the more-than cue after less-than training).

Feedback was withheld in the test phase. There were four mutually entailed trial types in each condition (see Table 1) which were each presented eight times, generating 32 trials in total. A criterion of 28 correct responses was required to progress to the second arbitrary test. If they failed to meet criterion, the participant was re-exposed to Phase 1.

Phase 4: Arbitrary relational testing (combinatorial entailment). Participants were now presented with a test for combinatorial entailment. Combinatorial entailment occurs when two relations combine to make a third relation. For example, having been trained that B > A, C > B; in the presence of the more-than cue and stimulus A and C, participants can derive that C is more than A. There were ten combinatorially entailed trial types (Table 1). The four trained trials

were also presented in this phase. Fifty-six test trials were presented and a criterion of 54 correct responses was required to progress to Phase 5. If they failed to meet criterion, the participant was re-exposed to the entire task starting with Phase 1.

Phase 5: Slot-machine payout probability learning. The purpose of this phase was to establish two different slot-machines labelled with members of the relational network as discriminative for high or low-payout probability, respectively. Participants were presented with the following onscreen instructions:

You will be given two slot-machines to play. One slot-machine is called [Stimulus C] and the other is called [Stimulus X]. The computer will present the slot-machines one at a time for you to play. To play the machine, click the 'Bet 1' button and then click the 'Spin' button. Your aim is to win as many points as possible. Good luck!

Participants were exposed to two slot-machines of differing probabilities, slot-machine labelled C from the relational network, and slot-machine labelled with novel stimulus X. The slot-machines were grey with three reels. To play a machine, required clicking the 'Bet 1' button, which automatically deducted one credit from the 'Total Credits' box situated above the reels, and made the 'Spin' button available. Clicking 'Spin' caused the three reels to spin for approximately five seconds before stopping. If three matching symbols appeared on the payoff line, then five credits were awarded in the 'Total Credits' box. If fewer than three symbols matched, then no further credits were deducted. Participants started this phase with 100 credits and the machines were programmed such that all participants experienced wins or losses on the same trials and all ended with 155 credits. One slot-machine appeared on screen at a time until each machine had been played 40 times. Slot-machine C had a payout probability of 0.2 (i.e., it 'paid out' on 8 out of 40 trials). Slot-machine X was labelled with a novel, unfamiliar nonsense

word and had a payout probability of 0.8 (i.e., it paid out on 34 out of 40 trials). At the end of

this phase, as a manipulation check that the distinct payout percentages for each slot-machine

had been acquired, participants rated the likelihood of winning on each slot-machine using a 5-

point Likert scale (*1* = very unlikely; *5* = very likely).

Phase 6: Slot-machine preference testing. This phase tested whether participants

would show greater preferences (response allocation) for slot-machines that were labelled with

the higher-ranking stimuli from the derived relational network. At the start of this task,

participants were presented with the following onscreen instructions:

> *You will now be presented with some more slot-machines named after the nonsense*
>
> *words you saw in the previous task. Please select which slot-machine you would like*
>
> *to play by clicking the 'Spin' button on your chosen slot-machine. You will not be able*
>
> *to see how many points you win on each machine, but the computer is still recording*
>
> *your score. Your aim is to try to earn as many points as possible.*

Participants were presented with two slot-machines simultaneously (the sides on which

the machines were presented was counterbalanced) and selected the machine they wanted to play

by clicking on it. However, as this was a test phase under non-reinforcement, the reels did not

actually spin, and credit was neither awarded nor lost. This phase was conducted under non-

reinforcement to be consistent with previous research on Relational Frame Theory. The slot-

machines were identical in appearance except for the nonsense word displayed above the reels,

which were from the relational training procedures, or nonsense word X from Phase 5. All

possible combinations of pairs of slot-machines were each presented twice for a total of 30 trials.

Insert Figure 3 about here

Predicted choices depended on the specific relational network trained across participants (see Figure 3). In condition one (E>D>C>B>A) and three (A<B<C<D<E), in which E was the highest ranked stimulus, the following choices were predicted (preferences marked in italics): A – *B*, A – *C*, A - *D*, A – *E*, A – *X*, B – *C*, B – *D*, B – *E*, B – *X*, C – *D*, C – *E*, C – *X*, D – *E*, D – *X*, and E – *X*. In condition two (A>B>C>D>E) and four (E<D<C<B<A), in which A was the highest ranked stimulus, the following choices were predicted (preferences marked in italics): *A* – B, *A* – C, *A* - D, *A* – E, *A* – *X*, *B* – C, *B* – D, *B* – E, B – *X*, *C* – D, *C* – E, C – *X*, *D* – E, D – *X*, and E – *X*.

Data analysis

Data from the arbitrary relational training exposures and arbitrary relational test accuracy were tested for normality and homogeneity of variance (Shapiro-Wilks) and non-parametric tests conducted (Kruskal-Wallis test statistic reported for arbitrary relational training exposures and the Brown-Forsythe ANOVA F statistic for arbitrary relational test accuracy). Wilcoxon signed ranks test was conducted for the slot machine ratings data, and separate one-way repeated measures ANOVA (with Greenhouse-Geisser correction) were conducted on the slot machines choice data for each condition and followed up with a mixed (group x stimulus) ANOVA and Bonferroni-corrected post-hoc tests.

<div align="center">

Results

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Relational training and testing (Phases 1 to 4)

All participants completed nonarbitrary and arbitrary relational training and testing procedures; however, groups required different numbers of exposures to meet criterion responding. Table 2 shows the trials to criterion and the number of exposures to training and testing phases for all conditions. The number of exposures to arbitrary relational training differed

significantly across conditions (H=14.32, *p*=0.0025) with a mean rank of 4.05 (1.9) for

Condition 1, 3.40 (2.21) for Condition 2, 2.83 (1.46) for Condition 3, and 2.29 (0.95) for

Condition 4, respectively. It is noteworthy that the two "less than" relational conditions were

faster to acquire than the two "more than" conditions (Munnelly et al., 2013).

During the arbitrary relational test, all participants met accuracy on tests for mutual

entailment (ME) ranging between 30.07 (3.34) and 31.52 (1.39) trials correct out of 32, and on

tests for combinatorial entailment (CE) test ranging between 50.24 (10.26) and 54.8 (1.38) trials

correct out of 56. Accuracy on tests for ME did not differ across conditions (F(3.000, 53.60)=

2.070, *p*=0.1151); however, accuracy on tests for CE did differ significantly, F(3.000, 44.14) =

2817557 *p*<0.0001), a finding supported by previous studies (see Munnelly et al., 2013; Reilly,

Whelan, & Barnes-Holmes, 2005).

Insert Table 2 About Here

Slot-machine payout probability learning and preference testing (Phases 5 and 6)

Participants rated the high-probability slot-machine labelled X (*M* = 4.5, *S*D = 0.57) as

more likely to pay out than the low-probability slot-machine labelled C (*M* = 2.07, *SD* = 0.66). A

Wilcoxon Signed Ranks Test indicated that participants' median ratings of the high-probability

slot machine X (*Mdn* = 5.0) were statistically significantly higher than the low-probability slot

machine C (*Mdn* = 2.0), *Z* = 3851, *p* <.0001. This indicates that the slot-machine payout

probability learning phase was effective at making the slot-machines C and X discriminative for

a low and high likelihood of winning, respectively.

Figure 4 shows the mean number of selections made of each slot-machine. As predicted,

in Condition 1 and Condition 3 in which stimulus E was trained as greatest ranked, slot-machine

E was the most preferred slot-machine and slot-machine A was the least preferred. Conversely,

in Conditions 2 and 4 where stimulus A was greatest, slot-machine A was the most preferred

machine and slot-machine E was the least preferred. Slot-machine choices were made in

accordance with the network that had been trained, even though participants never experienced

an actual payout on any of these machines. Slot-machine X was the most preferred when

presented concurrently with any other machine.

Separate, one-way repeated measures ANOVA were conducted for slot-machine

choices made in each condition. Participants' choices of slot-machines to play were significantly

distributed along the direction of predicted training in Condition 1 (E>D>C>B>A),

$F(2.32,44.08) = 45.60$, $R^2 = 0.70$, $\varepsilon = 0.46$, $p < 0.0001$, Condition 2 (A>B>C>D>E), $F(1.50,$

$28.6) = 64.06$, $R^2 = 0.77$, $\varepsilon = 0.30$, $p < 0.0001$, Condition 3 (A<B<C<D<E), $F(2.79, 66.9) =$

2365, $R^2 = 0.99$, $\varepsilon = 0.55$, $p < 0.0001$, and Condition 4 (E<D<C<B<A), F $(2.33, 51.43) = 2336$,

$R^2 = 0.99$, $\varepsilon = 0.46$, $p < 0.0001$. Choice data from Conditions 2 and 4 were reverse scored to

permit a five (stimulus A, B, C, D and E) x four (condition) mixed-factorial ANOVA to be

carried out, which revealed that slot machine choices differed, $F(1.9, 5.8) = 3.68$, p < .001. Since

Mauchley's test of sphericity was violated, the Greenhouse-Geisser correction was used.

Bonferroni post-hoc tests revealed that choices differed between conditions 1 and 2 and 1 and 4,

p < .001. No other comparisons were significant.

Insert Figure 4 about here

Discussion

The present findings demonstrated that participants had preferences for slot-machines

labelled with the highest-ranking stimuli from a derived relational network under conditions of

non-reinforcement even though participants had no prior experience of the payout probabilities

of these machines. Furthermore, the symbolic generalization of slot-machine choices was in

accordance with the specific direction and type of relational network trained, such that a gradient of preference was observed. In Condition 1, where stimulus E was trained as the highest-ranked stimulus in the network and A was the lowest ranked, participants showed preferences for the slot-machine labelled E, and least preference for the machine labelled A. In Condition 2, in which stimulus A was trained as the highest-ranked stimulus, the slot-machine A was the most preferred slot-machine and the machine E was the least preferred. In Condition 3, stimulus A was trained as the lowest ranked stimulus and participants showed minimal preference for slot-machine A, and a higher level of preference for slot-machine E. In Condition 4, stimulus E was trained as the lowest ranked stimulus and subsequently was the least preferred slot-machine, with the slot-machine A being the most preferred. Overall, these findings indicate that response allocation may be influenced by contextual factors like the structural characteristics of a slot-machine, and that gambling preferences may subsequently generalize symbolically across novel machines.

In the test for symbolic generalization, participants chose between concurrently presented pairs of slot-machines in a consistent and predictable manner despite the absence of reinforcement. Participants allocated a greater proportion of responses to machines ranked highest in accordance with the underlying comparative (more-than/less-than) relations and did so across an extended block of trials, in the absence of reinforcement. The consistency in responding observed, regardless of relational network trained, mirrors that of previous studies on symbolic generalization in simulated slot-machine gambling (Dymond et al., 2012) and suggests that persistence of gambling behavior despite the absence of reinforcement. Persistence in slot-machine gambling under non-reinforcement is influenced by several factors such as reinforcement rate and trial timing (James, O'Malley, & Tunney, 2016; Shao, Read, Behrens, &

Rogers, 2013; Templeton, Dixon, Harrigan, & Fugelsang, 2015), and frequency and type of near-misses (Banks, Tata, Bennett, Sekuler, & Gruber, 2017; Barton et al., 2017; Dixon, MacLaren, Jarick, Fugelsang, & Harrigan, 2013; Sharman, Aitken, & Clark, 2015; Wu, van Dijk, Li, Aitken, & Clark, 2017). Here, we supplemented these findings by manipulating payout percentage and exposing participants to a low payout schedule in the presence of one stimulus from the relational network while holding all other characteristics, such as near-miss frequency, constant. Response allocation was remarkably consistent and suggests that the generalized control exerted by labels or names given to slot-machines may be implicated in be partly responsible gambling persistence under non-reinforcement. That is, using a simplified three-reel slot-machine simulation with only win and loss displays, we were able to evoke persistent levels of graded response allocation in accordance with the predicted network. The present findings highlight a role for symbolic generalization in maintaining gambling behavior, and may explain in part, factors affecting slot machine choice.

These preliminary findings may help better understand the multiple sources of control exerted over slot-machine response allocation in the natural gambling environment. The interaction between slot-machine labels or names and response preference has not been studied extensively to date; our findings suggest it would be promising to do so and may help better identify problematic sources of stimulus control influencing gambling choices. As well as enhancing the validity of laboratory-based treatment studies, this approach has the potential to better inform treatment approaches aimed at reducing the frequency of problematic slot-machine gambling rather than eradicating it entirely (Dickerson & Weeks, 1979; Ladouceur, Lachance, & Fournier, 2009). Belisle, Paliliunas, Dixon, and Speelman (2018) demonstrated that the effects of a non-arbitrary relational training task on slot machine choice could subsequently be reduced

through using defusion techniques derived from therapeutic exercises (Assaz, Roche, Kanter, & Oshiro, 2018). Defusion involves altering the way an individual relates to their thoughts and aims to modify undesirable functions of language. The present study could therefore lend support to using defusion to alter the effect of verbal relations over slot machine choice, but further research is needed. Such a harm minimization approach has much to offer the empirical analysis of gambling preference in future translational investigations.

Findings also speak to the philosophical parsimony of approaching the analysis of gambling behavior in contemporary operant conditioning terms. There is a long tradition of operant approaches to the study of gambling (Brown, 1987; Dixon, Whiting, Gunnarsson, Daar, & Rowsey, 2015; Skinner, 1953; Witts & Harri-Dennis, 2015), and the role of reinforcement schedules in gambling is, rightly, considered a case study in the application of learning theory to problems of social importance. This history notwithstanding, the current approach extends previous empirical behavioural research (see Dixon, Bihler & Nastally, 2011; Dymond et al., 2012) of factors affecting slot machine choice by probing the influence that verbal contingencies may have on gambling preferences. . In the present study, when participants chose between slot-machines they were interacting verbally with their environment and acting so on the basis of the aforementioned more-than and less-than training and testing contingencies. Such a perspective does not postulate hypothetical constructs or mediational variables responsible for the observed generalization gradient of response allocation; instead, it considers the current and historical context in which slot-machines and their labels were encountered and arranged, and points to the experimental procedures as partly responsible for evoking the predicted performances we found. There is, therefore, a parsimonious explanation for the observed findings that emphasizes the emergent or symbolic generalization of directly experienced payout contingencies via arbitrary

relations of more-than and less-than to situations (machines) where derived contingencies predominate (Dymond & Roche, 2010). In this way, derived relational responding and symbolic generalization may represent key behavioral processes involved in the initiation and choice of slot-machine gambling behavior. Much remains to be done however to establish the validity of these laboratory-based models of gambling and their relevance to the wider research agenda on functional approaches to complex human behavior informed by derived relations (De Houwer, 2017).

One limitation of the present approach is the artificial context employed which involved forced exposure to concurrent pairs of slot-machines presented under non-reinforcement and in the absence of any game-related feedback. If participants had been exposed to the slot-machine contingencies, the effect of the verbal cues may have been weakened, as participants experienced wins and losses on the machines. Given that real world gambling does not occur under conditions of non-reinforcement, further research should examine response persistence under, for example, different types of reinforcement schedules, frequencies of near-misses or embedded bonus rounds, in multi-line slot-machine play in more realistic settings or via augmented virtual reality technology, and over extended testing sessions to detect effects on gambling perseverance. Additionally, future research is warranted investigating the role of gambling severity in predicting differential levels of symbolic generalization.

In conclusion, the present findings demonstrate a role for symbolic generalization via arbitrary stimulus relations of more-than and less-than in response allocation and player preference on concurrently presented slot-machines.

Declaration of interest statement

Author 1 does not have any conflicts of interest to declare.

Author 2 does not have any conflicts of interest to declare.

Author 3 does not have any conflicts of interest to declare

Author 4 does not have any conflicts of interest to declare.

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of a conditional discrimination paradigm. *Journal of Applied Behavior Analysis, 39*, 351-
361.

Tables

Condition	Network trained	Contextual cue	Phase 3: Arbitrary training trials				Phase 3: Mutually entailed arbitrary test trials			
1	E>D>C>B>A	More than	E>D	D>C	C>B	B>A	D<E	C<D	B<C	B<A
2	A>B>C>D>E	More than	A>B	B>C	C>D	D>E	B<A	C<B	D<C	E<D
3	A<B<C<D<E	Less than	A<B	B<C	C<D	D<E	B>A	C>B	D>C	E>D
4	E<D<C<B<A	Less than	E<D	D<C	C<B	B<A	D<E	C<D	C<B	B<A

			Phase 4: Combinatorial entailment test trials									
1 & 3			C>A	D>B	E>C	A<C	B<D	C<E	D>A	E>B	A<D	B<E
2 & 4			C<A	D<B	E<C	A>C	B>D	C>E	D<A	E<B	A>D	B>E

Table 1: Relations trained during arbitrary relational training and mutually entailed relations and combinatorially entailed relations tested during arbitrary relational testing in each condition. The inequality symbols, < (less than) and > (more than), denote the contextual cue presented and indicate which comparison should be selected over the other, with the reinforced comparison shown on the left and the unreinforced comparison on the right. *Note*: the actual contextual cues used consisted of abstract visual images and not the inequality symbols described here, which are used for the purposes of clarity.

Table 2. Mean trials to criterion and the mean number of exposures (with standard deviations in brackets) during non-arbitrary and arbitrary relational training and testing phases for all conditions.

Condition	Phase 1: Non-arbitrary training	Phase 1: Non-arbitrary test	Phase 2: CR Non-arbitrary training	Phase 2: CR Non-arbitrary test	Phase 3: Arbitrary training	Phase 3: No. exposures to Arbitrary training	Phase 3: Arbitrary test (ME)	Phase 4: Arbitrary test (CE)
1 (E>A)	13.51	7.97	10.64	7.96	9.53	2.41	30.07	50.24
	(7.36)	(0.19)	(2.02)	(0.19)	(2.43)	(0.19)	(3.34)	(10.26)
2 (A>E)	12.70	7.96	10.5	8 (0)	9.94	2.40	31.52	53.21
	(4.20)	(0.19)	(1.90)		(2.31)	(1.52)	(1.39)	(5.97)
3 (A<E)	12.96	7.93	11.4	8.16	10.86	2.60	30.79	53.19
	(6.39)	(0.26)	(4.24)	(0.55)	(7.21)	(1.80)	(1.36)	(5.89)
4 (E<A)	10.65	7.82	10.83	8 (0)	9.92	2.03	30.60	54.80
	(1.84)	(0.39)	(2.36)		(2.52)	(1.03)	(2.14)	(1.38)

Note: CR refers to constructed response training; ME refers to mutual entailment test trials; CE refers to combinatorial entailment test trials.

Table 2. Trials to criterion and the number of exposures to training and testing phases for all conditions.
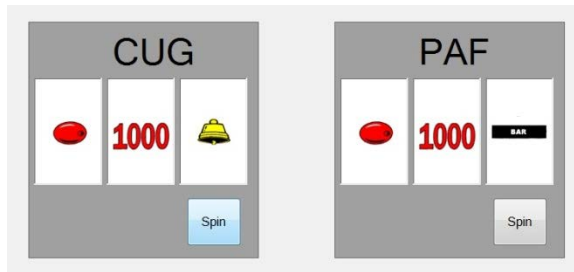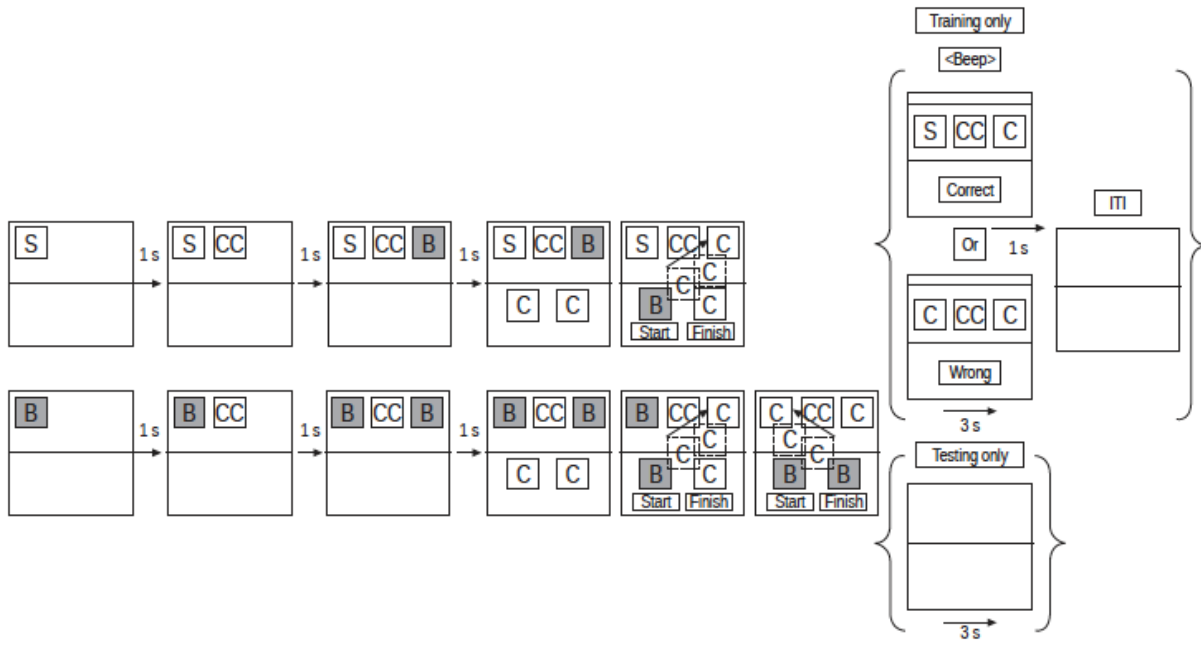
Figure 1

Figure 2

Figure 3

a

E > D > C > B > A   (Condition 1)
A < B < C < D < E   (Condition 3)

A > B > C > D > E   (Condition 2)
E < D < C < B < A   (Condition 4)

b

Slot machine
probability learning

c

Preference testing

d

Predicted choices

A B   A C   A D   A E   A X
B C   B D   B E   B X
C D   C E   C X
D E   D X
E X

Predicted choices

A B   A C   A D   A E   A X
B C   B D   B E   B X
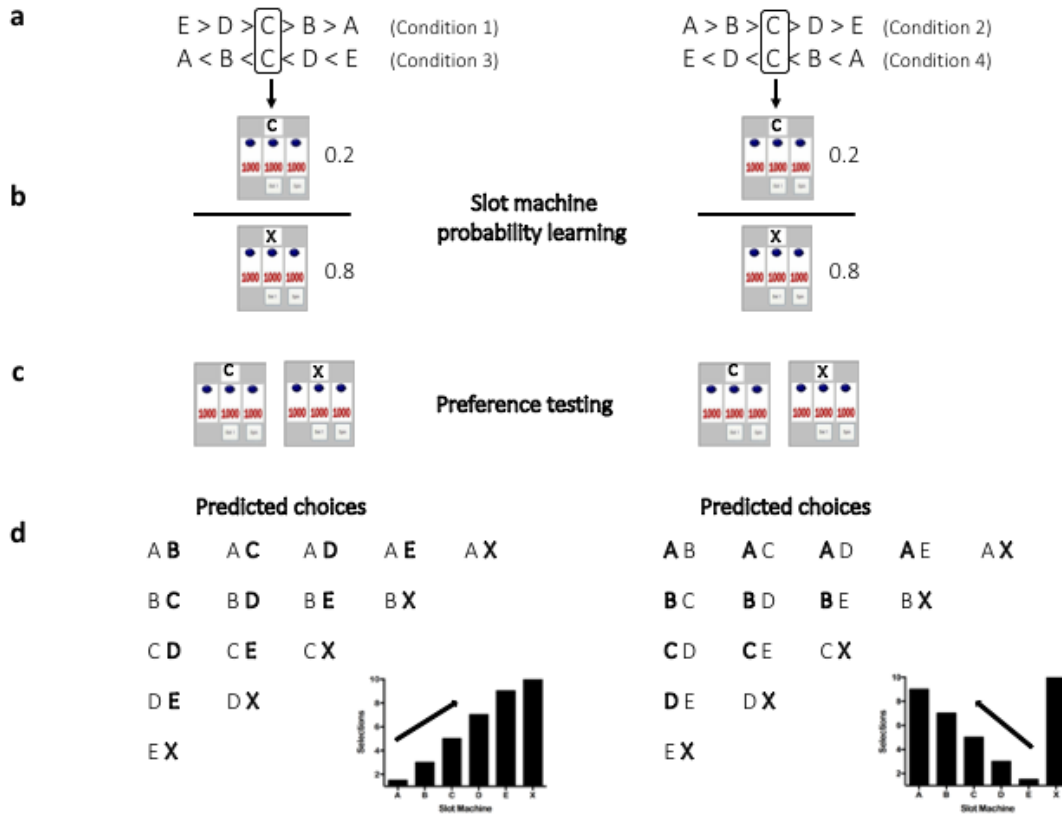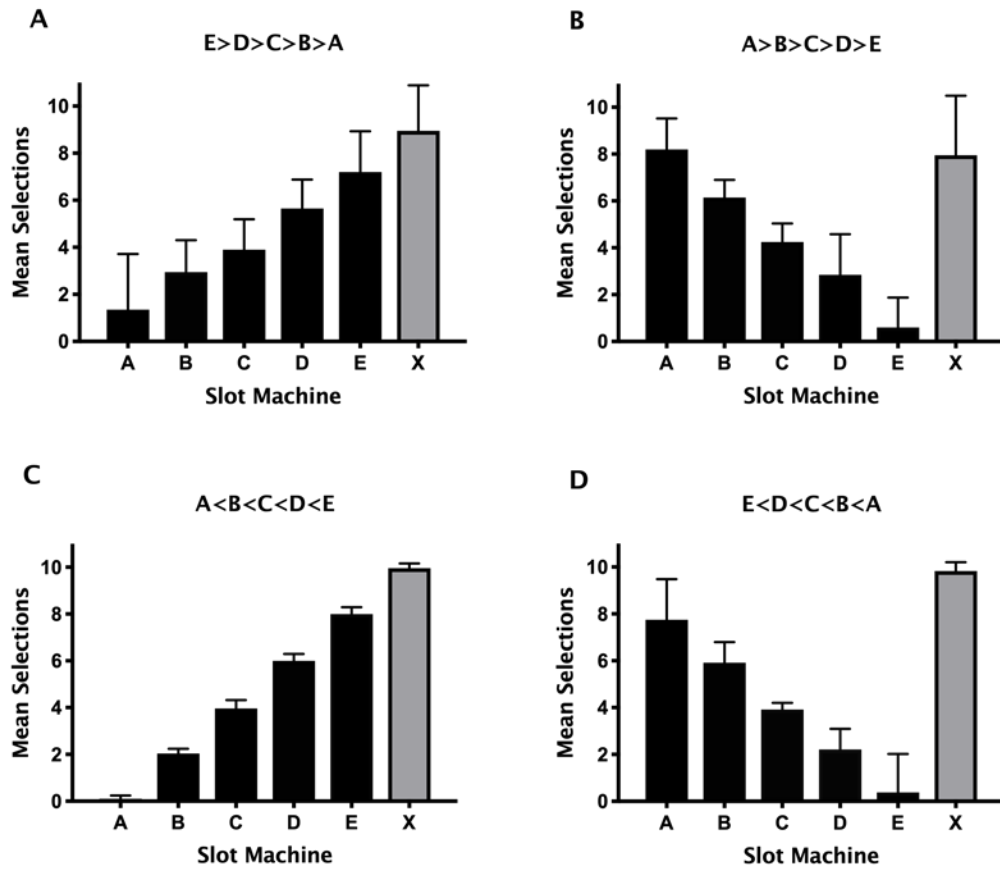C D   C E   C X
D E   D X
E X

Figure 4

Figure Captions

Figure 1. Examples of the onscreen slot-machine displays.

Figure 2. Schematic diagram of the sequence of presentation of stimuli during the nonarbitrary

relational training and testing phases (upper panel) and the constructed-response nonarbitrary

and arbitrary relational training and test phases (lower panel). *Note.* S = sample, cc = contextual

cue, B = blank square, C = comparison, and a dashed line represents "dragging" a comparison

stimulus. The text, "Finish" and "Start", represent the confirmatory response buttons. Arrows

pointing from B to C illustrate that, once selected, the comparison stimulus moved to the upper

portion of the screen, while the screen position in which it was originally, was now replaced by a

blank square.

Figure 3. Overview of the procedure. (a) Relational networks trained between the five term

stimuli, A-E. (b) Graphical representation of the slot-machine displays labelled with the stimulus

corresponding to C from the trained relational network and the novel stimulus X. The slot-

machine labelled stimulus C was associated with a low (0.2) payout percentage, while the slot-

machine labelled stimulus X was associated with a high (0.8) payout percentage. (c) Graphical

representation of the two concurrently available slot-machine displays presented during

preference testing (all combinations of slot-machines labelled with members of the relational

network (A-E), as well as X, were shown in this test phase). (d) Predicted choices of the two

concurrently available slot-machine display combinations presented in the crucial preference

testing phase (with predicted responses in bold). Also shown are graphs of the hypothetical,

predicted graded response allocation (indicated with arrows). See text for details.

Figure 4. Mean selections from the slot-machine preference testing phase for participants trained

in (a) condition one, E>D>C>B>A, (b) condition 2, A>B>C>D>E, (c) condition three,

A<B<C<D<E, and (d) condition four, E<D<C<B<A. Error bars are SD.