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Original Article

Illusionary pattern detection in habitual gamblers☆

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ABSTRACT

Does problem gambling arise from an illusion that patterns exist where there are none? Our prior research suggested that "hot hand," a tendency to perceive illusory streaks in sequences, may be a human universal, tied to an evolutionary history of foraging for clumpy resources. Like other evolved propensities, this tendency might be expressed more stongly in some people than others, leading them to see luck where others see only chance. If the desire to gamble is enhanced by illusory pattern detection, such individual differences could be predictive of gambling risk. While previous research has suggested a potential link between cognitive strategies and propensity to gamble, no prior study has directly measured gamblers' cognitive strategies using behavioral choice tasks, and linked them to risk taking or gambling propensities. Using a computerized sequential decision-making paradigm that directly measured subjects' predictions of sequences, we found evidence that subjects who have a greater tendency to gamble also have a higher tendency to perceive illusionary patterns, as measured by their preferences for a random slot machine over a negatively autocorrelated one. Casino gamblers played the random slot machine significantly more often even though a training phase and a history of outcomes were provided. Additionally, we found a marginally significant group difference between gamblers and matched community members in their slot-machine choice proportions. Performance on our behavioral choice task correlated with subjects' risk attitudes toward gambling and their frequency of play, as well as the selection of choice strategies in gambling activities.

1. Introduction

Why do we gamble? The simple answer, of course, is to win. But when games of chance are truly random and entirely unaffected by human skill, as many are, the rationale for engaging in them is far from obvious. If the statistics of the game mean that the best one can expect in the long run is to break even—and usually not even that—why play? Why do so many people around the world spend substantial portions of their income on games of chance, such as lotteries, that will only make them poorer on average?

One possibility is that gamblers do not fully grasp the random nature of the games they are playing. There is a large psychological literature documenting what is sometimes called "apophenia:" a human tendency to perceive patterns in random data that simply do not exist (e.g., Falk & Konold, 1997). In particular, people seem to have difficulties when perceiving independent events, or series of events whose outcome has no influence on the outcome of future events (Nickerson, 2002). One of the best known of these biases is the "hot-hand" phenomenon, first identified in a study of observers' predictions about basketball shots (Gilovich, Vallone, & Tversky, 1985). Both players and fans tended to judge a player's chance of hitting a shot to be greater following a successful shot than a miss, despite the fact that hit rate was statistically the same in both cases. Perhaps not surprisingly, illusory pattern perception of this kind has also been found among gamblers. For example, roulette players often bet on more numbers after winning than after losing (Wagenaar, 1988). Lottery players tend to redeem winning tickets for more tickets rather than for cash, reflecting a belief that they are more likely to win again (Clotfelter & Cook, 1989). Many lottery players believe in "hot" and "cold" numbers, returning to previously "hot" numbers once they've been given time to cool off (Rogers, 1998). And lottery tickets are sold more often at stores that have just issued a winning ticket, reflecting a hot hand or "lightning strikes twice" mentality (Guryan & Kearney, 2008). Another fallacy, known as the "gambler's fallacy," is in some ways the flip side of hot hand, reflecting a belief that a streak is coming to an end—leading roulette gamblers, for example, to bet on black after several reds in a row (e.g., Ayton & Fischer, 2004; Croson & Sundali, 2005). Both hot hand and the gambler's fallacy, then, seem to reflect illusory perception of clumps or streaks in data that do not contain them.

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Where do these beliefs come from? Why might people systematically perceive streaks where there are none? In previous work, we have proposed that hot hand may have its roots not in basketball or in financial markets, but in a much more ancient mode of human cognition: foraging (see Scheibehenne, Wilke, & Todd, 2011; Wilke & Barrett, 2009; Wilke & Mata, 2012; Wilke & Todd, 2012; see also Reifman, 2011). On this view, a tendency to look for clumps is not just a quirk of modernity, but a deep-seated part of our psychology that evolved because there are many contexts in which the world is *not* random, and looking for clumps is therefore adaptive. In particular, clumped distributions of resources such as plants, animals, water sources, and human settlements are common in natural environments, and animal and human foragers appear to adapt their search strategies to these observable statistical regularities in their foraging landscape (Bell, 1991; Hills, 2006; Krause & Ruxton, 2002; Taylor, 1961; Taylor, Woiwod, & Perry, 1978).

Consistent with this, we found that hot hand occurs in both Western cultures and a traditional foraging culture, and seems to be a kind of psychological default which is only partly erased by experience with true randomizing mechanisms like coin tosses (Wilke & Barrett, 2009). Importantly, hot hand is not necessarily irrational when clumps actually do exist, and in cases where they do not—for example, when trying to predict random sequences of independent and equiprobable events (such as when playing roulette)—hot hand does not decrease accuracy, because all strategies produce chance-level performance (c.f. Scheibehenne et al., 2011). Therefore, the tendency to assume or look for patterns or regularities in a given sequence may be a reasonable default strategy: If there is in fact a pattern, expecting that particular pattern can be advantageous by providing an edge in predicting future events, and if there is no pattern, expecting one will do no worse than any other strategy.

Could hot hand play a role in human gambling behavior? The tendency to search for patterns in random data could explain part of the pleasure humans experience in gambling—for example, the experience of winning several times in a row could be highly compelling, leading one to believe that one is on a hot streak. But in addition to this universal propensity, there could be differences between individuals in just how "hot-handed" they are—just how prone they are to perceive streaks, even when they do not exist—that could lead to differences in how much gambling on random outcomes is enjoyed. As for many evolved traits, individual differences in pattern perception could arise from a variety of factors, including genetic differences, environmental differences, or differences in individual experience. If such individual differences are predictive of propensity to gamble, this could have implications both for developing assessment tools to detect risk of developing a gambling problem and for interventions that might be effective, such as targeting gamblers' perceptions of randomness (c.f. Petry & Armentano, 1999). Moreover, if the hypothesis that hot hand is a universal human cognitive adaptation is right, then the risk of developing a gambling problem might also be a human universal, not restricted to those with a cultural history of gaming, or individual experience with it.

Several prior studies have suggested that beliefs about illusory patterns, such as hot hand and its opposite effect the gambler's fallacy, may play a role in preferences for gambling (Ayton & Fischer, 2004; Croson & Sundali, 2005; Gaboury & Ladouceur, 1989; Joukhador, Blaszczynski, & Macallum, 2004; Oskarsson, van Boven, McClelland, & Hastie, 2009; Toneatto, 1999). However, these studies were based on questionnaires about subjects' gambling beliefs, not on direct measurements of subjects' predictions of streaks. While questionnaires can be useful, asking subjects to report their beliefs about their own behavior is not the same as measuring what subjects actually do (c.f. Nisbett & Wilson, 1977). For example, many college students report understanding that coin tosses are perfectly random. However, their judgments of actual sequences of coin tosses reveal that they expect them to contain fewer streaks than they actually do, revealing a bias that they might not realize they have (Falk & Konold, 1997). To truly measure hot-handedness then, observation of actual behavior is necessary. In the case of gambling, one might expect subjects to prefer to bet on sources that they perceive as containing clumps, compared to sources they perceive as less clumpy—even when the clumps are illusory. Here we gave subjects a choice between paired sequence generators that varied in how hot-handed they actually were, and measured which the subjects preferred to bet on (c.f. Shaffer, Peller, LaPlante, Nelson, & LaBrie, 2010).

In order to assess the possible role of the hot-hand phenomenon in the propensity to gamble, we adopted a mixed-method approach that looked for within-subject correlations between hot-handedness, as measured with a behavioral task, and separate measures of proneness to gamble. Our behavioral task, adapted from Scheibehenne et al. (2011), presented subjects with a choice between two simulated slot machines (see Fig. 1). One was slightly *anti*-clumpy, or negatively autocorrelated, while the other was entirely random, with no clumps. In a prior study, Scheibehenne et al. (2011) found that subjects preferred to play the truly random machine, consistent with the perception that it generated more streaks. Thus, degree of preference for the random over the negatively autocorrelated machine is a direct behavioral measure of preference for an illusorily hot-handed machine.

Our research design looked for correlations between performance on the gambling task, and separate, independent measures of gambling propensity. The latter involved both a natural between-group component and a variety of individual difference measures. For the between-group component, we tested two groups of people: habitual gamblers and a control population. For the individual differences component, we examined several factors potentially related to gambling: measures of cognitive capacity as well as standardized screens of gambling history and psychometric measures of risk-taking propensity (a version of the DOSPERT scale, described below). In addition, because our task involved a long sequence of individual gambling decisions, we used quartile analysis to look for changes in strategy, including possible learning effects, within the task.

Our study examined two main hypotheses. First, we predicted that as a group, habitual gamblers would be more prone to see illusionary patterns in random data sets than a matched sample of non-gamblers (Hypothesis 1). Second, we predicted that individual differences in hot-handedness across groups would correlate with gambling-related risk attitudes and individual differences in gambling experience (Hypothesis 2).

2. Methods

2.1. Participants

We collected data from two target populations. In close proximity to Clarkson University is the territory of the St. Regis Mohawk Tribe, or Akwesasne, who are presently situated on more than 30,000 acres of tribal land extending from New York into Quebec and Ontario. With the permission of the Akwesasne Mohawk Casino, a gaming enterprise under the supervision of the St. Regis Mohawk Tribe, we recruited 92 experienced adult gamblers [58 females (63%), 34 males (37%)]. The Akwesasne Mohawk Casino offers visitors gaming and entertainment experience from more than 1600 slots and 22 live action table games. North Country residents were contacted via newspaper and radio advertisments for recruiting participants for our sample of 72 adults that have only little gambling experience [45 females (62%), 27 males (38%)]. All 164 participants were reimbursed for traveling to Clarkson University and participating in our study. Participants

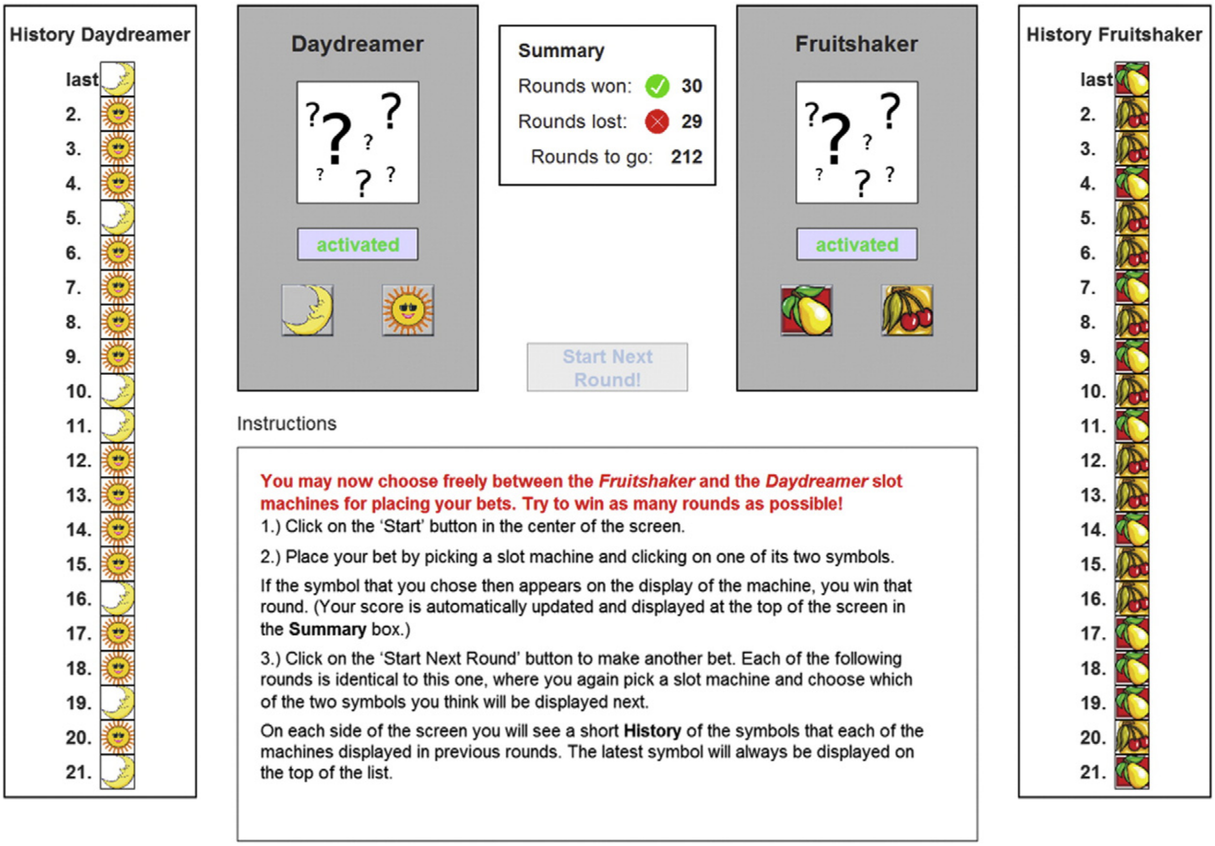

Fig. 1. Screenshot of the experimental setup for selecting and predicting one of two slot-machine sequences (adapted from Scheibehenne et al., 2011).

across both two groups were closely matched on sex, age, and educational background (see Table 1 for details).

2.2. Measures and procedure

All participants were tested at the first author's psychological research facilities at Clarkson University. In individual 2-h sessions, each research participant completed the following tasks: 1) A pre-experimental *gambling questionnaire* to assess participants' basic demographic information and their gambling involvment (e.g., games of play, frequency of engagement, amount of money they gamble with; see Winters, Specker, & Stinchfield, 1996), 2) a computerized *sequential slot-machine choice task* (Scheibehenne et al., 2011), 3) three short measures of *cognitive capacity* (Mata, Schooler, & Rieskamp, 2007) to assess participants' ability to deliberately control attention and manipulate information in working memory, 4) a shortened two-domain version of the *Domain-Specific Risk-Attitude Scale* (Weber, Blais, & Betz, 2002) to assess participants' likelihood of engagement in risk, their perceptions of risk and the expected benefits they attribute to risks in the gambling and investment domain, 5) a paper-and-pencil version of the DSM-based *South Oaks Gambling Screen* (Stinchfield, 2002) to screen for indications of problem gambling and pathological gambling, and 6) a paper-and-pencil version of the DSM-based two-item *Lie/Bet Questionnaire* (Johnson & Hamer, 1997) to screen for pathological gambling.

In the behavioral choice task, we asked gamblers and non-gambling community members to predict 271 outcomes on two simulated slot machines that each generated a binary sequence of symbols (see Fig. 1). While both slot machines had the same base rate for their binary outcomes (i.e., 50%), one machine generated a completely random sequence, whereas the other machine generated a sequence that was moderately negatively autocorrelated (i.e., $r = -.4$, equivalent to an alternation probability of $p(A) = .7$). After an initial training phase of 21 trials on each machine, participants were free to choose which slot-machine sequence to bet on. To facilitate subjects' learning about the patterns, the previous 21 symbols displayed on each machine were shown to the left and to the right of each slot machine. Which side of the screen contained the negatively autocorrelated machine was counter-balanced. Based on our previous research findings, we hypothesized that gamblers would be more prone to bet on the random slot machine (as they will perceive more illusory patterns in these sequences) and forgo the possibility of betting the opposite outcome on the negatively autocorrelated slot machine to earn money in the long run (see Falk & Konold, 1997; Scheibehenne et al., 2011; Wilke & Barrett, 2009).

After each bet, participants received feedback as to whether their prediction was correct or not. Each correct prediction earned them

Table 1
Means and standard deviations across participant characteristics and psychometric measures by sample.

Measure	Casino ($N = 92$)		Community ($N = 72$)		*t*-Test	
	M	SD	*M*	SD	*t*	*p*
Age	51.80	14.32	51.10	13.17	0.33	.746
Years of education	13.86	3.26	14.68	3.37	1.58	.117
Frequency of gambling	17.04	3.49	13.85	2.77	6.35	<.001
SOGS	3.29	3.14	0.53	1.49	6.60	<.001
Lie-bet	0.52	0.69	0.06	0.29	5.42	<.001
DOSPERT gambling	1.41	0.72	1.05	0.33	3.93	<.001
DOSPERT investment	2.21	1.25	2.41	1.10	−1.07	.286

Note: SOGS = South Oaks Gambling Screen, DOSPERT = Domain-specific Risk-attitude Scale.

$0.10. In addition to a baseline show-up fee, a few randomly selected participants also received their actual cash payout via an additional post-experimental lottery.

3. Results

3.1. Clinical sample recruitment and subjects gambling history

The two left-hand subplots of Fig. 2 show histograms of subjects' clinical score on the South Oaks Gambling Screen (SOGS). In line with published prevalence rates of gambling disorders, only very few subjects in our non-gambling community sample had SOGS scores high enough to indicate a serious gambling disorder (about 3%; see Kessler et al., 2008; Shaffer, Hall, & Bilt, 1997). The SOGS score distribution in our gambling group, however, showed that our recruiting strategy was successful in recruiting problem and pathological gamblers: 49 subjects (53%) had SOGS scores indicating at least a problem gambling orientation, whereas 26 subjects (28%) scored high enough to indicate a serious gambling pathology. Additional data from our other clinical questionnaires, including subjects' reported frequency of engagement in various gambling activities, their score on the Lie–Bet screen, as well as their domain-specific risk-taking attitude toward gambling activities (but not investment activities), further support the utility of our chosen recruitment procedures by directly advertising to regular local casino attendees (see Table 1).

3.2. Risk attitudes in gamblers

We further analyzed our clinical population's risk-taking behavior by looking at their scores on the Domain-Specific Risk-Attitude scale (DOSPERT). We found substantial differences among non-gamblers, problem gamblers and pathological gamblers in their risk attitudes and predictors of engagement in gambling activities. Risk attitudes can be thought of as a person's baseline likelihood of engaging in a certain activity (i.e., a subject's risk *behavior*) depending upon that person's underlying perceptions toward this activity, with regard to how safe or dangerous it is (i.e., a subject's risk *perception*) and what potential benefits might come out of engaging in this activity (i.e., a subject's expected *benefits*). Therefore, conceptualizing risk-taking behavior as a risk-return framework (see Weber et al., 2002) allows us to better understand how and why people differ with regard to their risky choices across various contexts (e.g., Johnson, Wilke, & Weber, 2004; Hanoch, Johnson, & Wilke, 2006).

We grouped respondents based on clinical gambling assessment (i.e., their SOGS score) and then regressed risk behavior on expected benefit and risk perception for each group. A person's behavioral

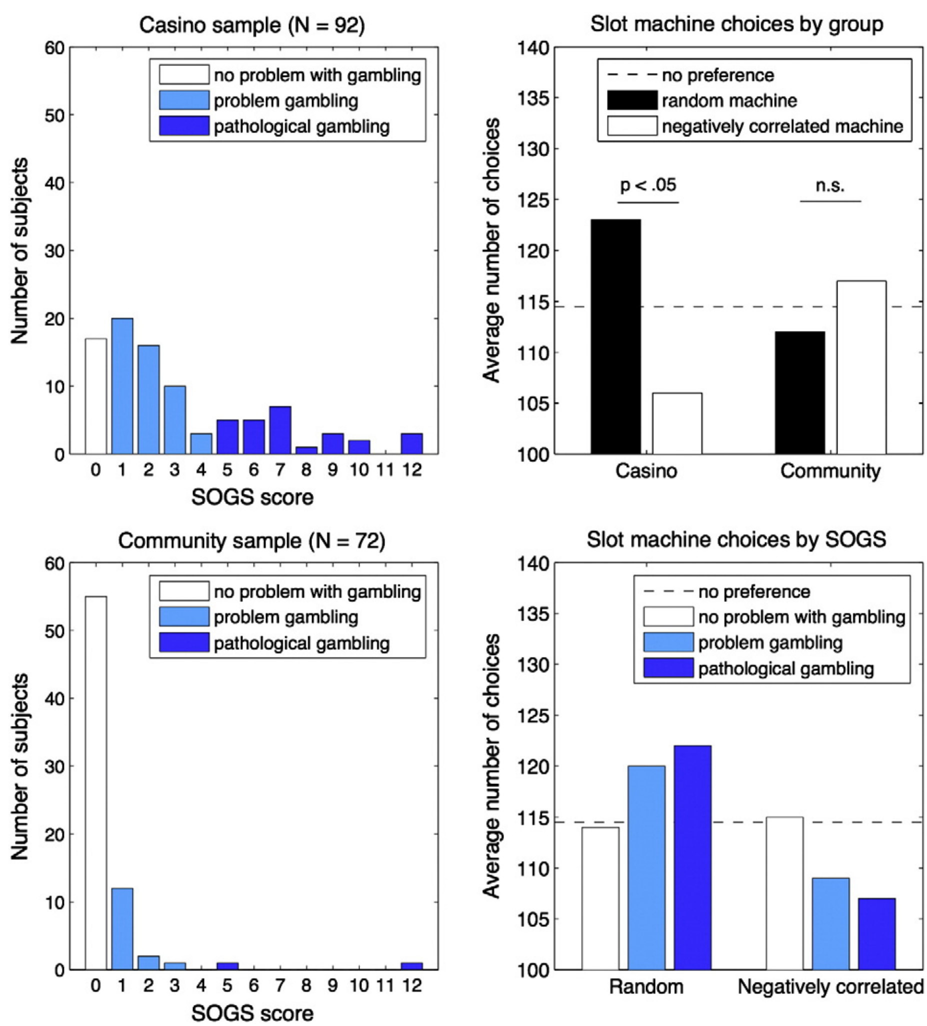

Fig. 2. Clinical sample characteristics of a group of regular casino attendees (upper left subplot) and North Country community members (lower left). Average number of choices out of 229 trials in the main experiment made on the random and negatively autocorrelated machine by sampled group (upper right) and by clinical assessment based on scores on the South Oaks Gambling Screen (lower right).

intention (here, the intercept) can be interpreted as showing how much baseline risk is attributed to behaviors in the domain when perceived risks and benefits are zero. The perceived risk coefficients show the degree to which risk perception *decreases* the likelihood of the associated behaviors in that domain (indicated by the negative sign), and the perceived benefit coefficients show the degree to which the expected benefit *increases* the likelihood of engaging in that behavior (shown by the positive sign). Thus, the coefficients show the impact of perceived risk and perceived benefit on a person's risk behavior. As can be seen in Table 2, problem gamblers and pathological gamblers show a much stronger influence of the perceived benefits of their gambling behaviors, compared to non-gamblers (i.e., .44 and .62 compared to .17, respectively). Furthermore, pathological gamblers, compared to problem gamblers and non-gamblers, have perceived risk coefficients with a positive sign indicating that gambling-related activities may not be perceived as having any inherent risk at all (c.f. Mishra, Lalumiere, & Williams, 2010; Powell, Hardoon, Derevensky, & Gupta, 1999).

3.3. Sequential decision-making task

On first inspection, the proportion of choices that either gamblers or community members made on the more random slot-machine was not different from the 0.5 indifference point that subjects were to have if they do not have a clear preference for either slot machine [M casino = 0.47, SD = 0.25, $t(91) = -1.17$. $p = .245$; M community = 0.52, SD = 0.21, $t(71) = 0.75$, $p = .455$]. Our predicted difference that gamblers would show *more* choices on the random machine compared to their age, sex and educational level matched community counterparts was also non-significant [$t(162) = -1.33$, $p = .185$]. Upon closer inspection of the raw data, however, we found that a number of subjects in both groups did not play both slot machines, and therefore did not explore the properties of both. 16 subjects in the gambling group (17.4%) and 5 subjects in the community group (6.9%) made not a single choice on the second slot machine after the initial training phase. As there was no difference in either group which of the two (counterbalanced) slot machines subjects ignored (sign test: $ps = 1$), we excluded these participants from further analysis of our behavioral choice task.

The top right subplot of Fig. 2 shows the distribution of choices that subjects in the casino gambling and community group made on the negatively autocorrelated machine. Among habitual gamblers who sampled both machines, gamblers indeed preferred playing the random slot machine over the negatively autocorrelated machine [123 vs. 106 trials, $t(75) = -2.21$, $p = .030$]. This effect was non-significant in the matched community group [112 vs. 117 trials, $t(66) = -0.60$, $p = .55$] with the trend going in the opposite direction. Overall, comparing habitual gamblers to community members, gamblers also had a marginally significantly lower proportion of choices on the negatively autocorrelated machine [$t(141) = -1.87$, $p = .064$].

The lower right subplot of Fig. 2 visualizes the distribution of choices in our slot-machine task when respondents were grouped again based on their clinical assessment. Whereas non-gamblers, on average, had an even split of how many times they played the random vs. the negatively autocorrelated machine (115 vs. 114 trials), problem gamblers (120 vs. 109 trials) and pathological gamblers (122 vs. 107 trials) shifted their playing time more and more toward the random slot machine. However, given the lower power of these smaller subsamples, there was no statistical difference between clinical group membership and the amount of choices that were made on the random slot machine [$F(2,142) = 0.69$, $p = .504$].

Our previous research using this paradigm on student populations had shown that the combination of a random and *moderately* negatively autocorrelated sequence is particularly difficult for most participants, and that subjects find the correct slot machine to play more easily when a random machine is paired with a slot machine of either varying positive autocorrelation or a strong negatively autocorrelated sequence (see Scheibehenne et al., 2011). We used quartile analysis, comparing the choices from the first quartile of trials with the last quartile of trials, to ask whether there were any changes in subjects' choices from the beginning to the end of play that would indicate learning effects. This analysis showed that community members, on average, slightly increased their preferences for the negatively autocorrelated machine over time (q1: 0.50 vs. q4: 0.53) whereas gamblers show the reverse pattern (q1: 0.50 vs. q4: 0.46). However, these quartile differences within gamblers and community members were not significant [casino: $t(75) = 1.13$, $p = .263$; community $t(66) = -0.62$, $p = .538$] and there was no overall interaction effect between-group membership and quartile of choice data [$F(3,560) = 0.73$, $p = .535$].

Thus, it seems as if gamblers indeed perceive more clumps in random sequences than people with only little gambling experience, and that gamblers—everything else being the same—may be more prone to have their decisions affected by their erroneous perceptions of sequential events. We find no evidence for any significant changes of these erroneous perceptions over time (e.g., due to learning).

3.4. Choice strategies and individual differences

A more detailed analysis of the data indicates that the performance gap between gamblers and community members is also caused by differences in choice strategies in our task as well as individual differences in subject's personality.

To increase the overall payoff, a subject playing a negatively correlated slot machine should play a win-shift lose-stay strategy. In our sample, however, we found that the majority of subjects across both groups actually played the opposite win-stay lose-switch strategy more often [$t(140) = 2.90$, $p = .004$]—a strategy subjects should play instead on a positively autocorrelated machine. While community members had a tendency to misapply this strategy only when playing the random machine [$t(62) = 3.41$, $p = .001$], subjects in the gambling group used this strategy as their overall most frequently played strategy across both slot machines [$t(75)$, = 2.79, $p = .007$]. Thus, one additional reason why gamblers may lose money in a casino setting might be due to their inappropriate choice of cognitive strategies.

The percentage with which subjects chose the alternating sequence in our behavioral choice task both negatively correlated with a subject's frequency of gambling [$r(143) = -.170$, $p = .042$] and their risk-taking propensity on the DOSPERT gambling domain [$r(143) = -.168$, $p = .045$]. This indicates that, everything else being equal, a higher propensity for hot-handedness is more common

Table 2
Coefficients and R^2 of regression of risk behavior scale mean on risk-perception scale mean and expected benefit scale mean, by domain.

DOSPERT domain	Intercept	Perceived risk	Perceived benefit	R^2
Non-gamblers ($n = 72$)				
Gambling	1.04	−0.10	0.17	0.04
Investing	1.13	−0.16	0.54***	0.38
Problem gamblers ($n = 64$)				
Gambling	1.06	−0.15	0.44***	0.23
Investing	1.35	−0.24*	0.50***	0.34
Pathological gamblers ($n = 28$)				
Gambling	0.07	0.12	0.62***	0.36
Investing	−0.26	0.02	0.52**	0.27

Note: Subsamples are based on their score on the South Oaks Gambling Screen; 0 = non-gamblers; 1–4 = problem gamblers; 5+ = pathological gamblers.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

in people who regularly play games of chance and who show a higher willingness to take gambling risks.

None of the other individual difference metrics that we collected yield significant results between groups. There were no differences between gamblers and community members in their overall cognitive capacity as measured by the *digit span* test (a numerical memory span test), the *symbol task* (a neuropsychological test sensitive to brain damage and dementia), and the *trail-making task* (a test of visual attention and task switching). We found no sex differences in our behavioral choice task.

4. Discussion

Pathological gambling is a psychological and medical disorder identified in both the DSM-V and ICD-10 (American Psychiatric Association, 2013; World Health Organisation, 1992; see also National Center for Responsible Gaming, 2013). The lifetime prevalence varies worldwide, but has been estimated at 0.6% to 1.1% of adults in the United States, with an additional 2.3% defined as problem gamblers (Kessler et al., 2008; Shaffer et al., 1997). Problem gambling is on the rise in older populations (e.g., Tse, Hong, Wang, & Cunningham-Williams, 2012) and is often comorbid with other problems, such as substance abuse or mood disorders (Hodgins, Stea, & Grant, 2011; Stea & Hodgins, 2011). Thus, unique approaches for studying gambling disorders could be helpful for the understanding and treatment of this disorder.

In summary, we found evidence that habitual gamblers were more prone to commit the hot-hand fallacy. When given the choice between playing a random and a (more alternating) negatively autocorrelated slot machine, gamblers significantly more often played the random slot. We also found a marginally significant group difference between gamblers and matched community members in their overall proportion of slot-machine choices with gamblers less often playing the non-random slot machine. Gamblers were more likely to select non-optimal choice strategies, and subjects' degree of wrong slot-machine choices correlated with both the frequency of gambling and risk-taking attitudes in the gambling domain. These results provide evidence for a systematic link between the tendency to perceive illusory patterns and the tendency to gamble. This study is, to our knowledge, the first study to use a direct behavioral measure of illusory pattern detection in the context of gambling propensity. However, it should be noted that while our task directly measured subjects' decision making, in the form of choices between two slot machines with different degrees of autocorrelation, our task measured a binary choice between distributions differing in clumpiness rather than individual hot-hand judgments on each of the sequences. We feel that this is justified in the context of studying gambling propensity for ecological validity reasons, because our task resembles a real-world gambling task in which perception of clumps would play a role. It is thus important to note that our results could, in theory, result from something other than hot hand per se, such as some other preference related to the difference between distributions. However, we believe that hot hand is the most likely theoretical explanation for the patterns of preference between machines that we observed.

If illusory pattern detection does indeed reflect an evolved cognitive strategy, and if differences in the strengths of these illusions predict gambling pathology, then this suggests a possible evolutionary explanation for this particular psychiatric condition. Previous research in other areas of psychiatry has suggested a possible role for an evolutionary framework in understanding mental illness (e.g., Andrews & Thomson, 2009; Hagen et al., 2009; Nesse, 1998). Our results point to the possibility of new screening instruments for gambling risk, based on an understanding of the possible functional origins of illusory pattern perception. So far, a number of reliable paper-and-pencil gambling screening tools have been developed (e.g., Stinchfield, 2002) and some even exist in additional computerized versions (e.g., Cunningham-Williams, Cottler, Compton, & Books, 2003), but a modified version of our behavioral choice task could potentially measure subjects' propensity toward illusionary pattern detection directly. Such approach might be particularly useful when subjects may not be willing to report on their gambling history or when studying younger adult subjects who do not yet have such a gambling history (Derevensky, 2012). Recently, sequential decision-making paradigms have been used to study such cognitive aspects in other mental disorders (e.g., Pleskac, Wallsten, Wang, & Lejuez, 2008; von Helversen, Wilke, Johnson, Schmid, & Klapp, 2011).

Our research also points to new ideas for treatment. Our prior work, for example, suggested that hot-handedness might be reduced in populations that are familiarized with the properties of random devices such as coins (Wilke & Barrett, 2009). Thus, it is possible that interventions to teach subjects the properties of random devices might reduce the propensity to cognitive illusions that lead to gambling.

Future studies should focus on replicating our results in different hot-hand choice tasks and target larger samples of subjects. Here, the emerging influence of online gaming might allow for the testing of a larger sample of gambling participants. Potentially, one could analyze their past playing behavior for a propensity to show hot hand in various gambling contexts without directly testing them.

5. Conclusion

The present study provides the first evidence of a direct link between illusory pattern perception and gambling risk. Because of the magnitude of gambling and gambling addiction as a global socioeconomic phenomenon, replication and further investigation are required before our findings can be translated into actual policy recommendations or interventions. However, the results are both consistent with the commonsense intuition that people who are more prone to perceive “luck” where there is none are also more prone to fall prey to gambling, and point to a potential evolutionary explanation for why this illusion exists. We hope that further work will help to clarify the ultimate sources of the human propensity to gamble, and potentially to alleviate suffering caused by pathological gambling.

Supplementary Materials

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.evolhumbehav.2014.02.010.

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