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The role of individual differences in risk learning: Who learns to place optimal wagers?

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ABSTRACT

Managing risk is an integral part of life. Whereas risk-taking is sometimes construed as only "bad" (e.g., drug use) or "good" (e.g., investing), the present research focuses on "optimal risk-taking." In economic settings, optimal risk on an exceedingly large number of repeated wagers can be computed using Kelly's Formula (Kelly, 1956). We tested whether individual differences in cognitive abilities (fluid intelligence and working memory) and emotion-related traits (behavioral inhibition and behavioral activation system sensitivity) predict learning to take optimal risks in an investment paradigm. Participants first completed a Learning Phase in which they received explicit feedback on what the optimal wager was for each of a series of gambling opportunities. Next, they completed a Test Phase where they were asked to transfer the information from the Learning Phase to predict the optimal wager on a new set of gambling opportunities (not taught during the Learning Phase). Last, with this second set of gambling opportunities, they were asked to manage a bankroll and place wagers in a Gambling Phase. During the Learning Phase, we found that participants with greater cognitive resources (fluid intelligence and working memory) and behavioral activation system (BAS) strength learned faster. During the Test Phase, participants generally struggled to transfer this learning to novel (unlearned) opportunities and often assumed too little risk. Those with higher working memory capacities showed the best transfer of learning. During the Gambling Phase, we found that those high in BAS were less prone to the error of assuming too little risk when managing a bankroll. Thus, cognitive resources and BAS appear to be important predictors for who is best able to both learn and utilize optimal risk taking.

1. Introduction

Risk-taking propensity has immense real-world effects (McDonald, 1950). When should one place a bet? How many shares of stock should one buy? The present research uses an investment paradigm to examine how cognitive and emotion-related traits influence the ability to learn and utilize optimal risk taking.

Despite a long literature on when and why individuals take risks, typically focusing on risk taking in clinical (e.g., Wallsten, Pleskac, & Lejuez, 2005) or adolescent (e.g., Sternberg, 2008) populations and as a public health problem (e.g., Wallsten et al., 2005), there is minimal research on *optimal* risk taking among healthy, young adults. Optimal risk taking involves not only a decision regarding *whether* to take a risk, but *how much* of one's assets should be wagered. Specifically, we define optimal risk-taking using a

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model well-known in economics called "proportional betting," aka Kelly's Formula (Kelly, 1956). Kelly's Formula indicates how to achieve maximum net profits assuming an infinite number of trials (Kelly's Formula is loosely related to Expected Utility Theory, but Kelly's Formula additionally incorporates the notion of optimal repeated wagering over an unlimited number of trials). When expected values are negative or 0 (e.g., lotteries), one should never wager anything (i.e., one should never accept risk without a long-term payoff). However, for repeated gambling opportunities with positive expected values, Kelly's Formula indicates that one should consistently wager a fraction of one's bankroll—one's expendable assets. The optimal wager (Kelly's Value) is based on the expected value (E) of the wager and the probability (P) of winning:

$$\frac{E * P}{E + 1 - P} = \text{Kelly's Value}$$

For example, if a repeated expected value (E) of the payout $= +10$ % and the probability (P) is a $50-50$ chance of winning, the optimal percentage of one's bankroll wagered is:

$$\frac{0.1 * 0.5}{0.1 + 1.0 - 0.5} = 8.33\,\%$$

Thus, if one's bankroll = \$100, the wager should be \$100 * .0833 = \$8.33. Wagering less than this amount would not take full advantage of the "edge" held over the entity offering the wager. Wagering more than that makes one too susceptible to a string of bad luck (a few big losses risk rapidly depleting the bankroll). For more on the derivation of Kelly's Formula, please see Wu, Rsai, Chung, and Chen (2020).

In this research, we ask two questions. First, can individuals learn optimal risk-taking from a small set of examples? Second, do individual differences in cognitive abilities and/or emotion-related traits predict the ability to learn optimal risk-taking? Note that in investment paradigms, the optimal decisions involve not just whether to take a risk or which risk to take, but *how much* of one's assets to risk. This is a substantial departure from much of the previous literature on risk-taking (as in the Iowa Gambling Task; Bechara, Damasio, Damasio, & Anderson, 1994, but see Ferguson, 1989; Frey, Rieskamp, & Hertwig, 2015), which focuses on one's propensity to take risks rather than *how much* risk to take.

We were interested in whether individuals could learn to extract the general relationship between the potential payout, chance of winning, and the percentage of their bankroll they should wager from a small set of examples. This is similar to research on rule learning (also known as function-learning) by McDaniel et al. (e.g., DeLosh, Busemeyer, & McDaniel, 1997; McDaniel, Cahill, Robbins, & Wiener, 2014). McDaniel et al. had participants guess how much of a substance an alien lifeform would excrete based on how much it consumed. The relationship between the two variables was v-shaped. They found that some participants could extract general rules from a small set of examples with feedback and then extrapolate and apply them to novel problems. Importantly, McDaniel et al. (2014) found that participants with higher working memory capacity—the ability to retain and process large amounts of information in the focus of attention (Engle & Kane, 2004)—were more likely to extract the rules.

Our investment paradigm differs from McDaniel et al.'s paradigm in its complexity: McDaniel et al.'s (2014) rule was a simple "V-shaped" function between the numeric value provided to the participant and the value of the participant's correct response, whereas the "rule" for optimal wagers is based on a much more complex and non-linear function with multiple input values (potential payout and chance of winning). Despite these differences, we predict that people with greater fluid intelligence to be more likely to extract the underlying function and use it to make more optimal wagers. Likewise, we expect to find that working memory capacity positively predicts the ability to extract an intuitive sense of Kelly's Formula. People capable of holding more information in immediate memory at once should be able to simultaneously consider more examples when trying to extract the underlying function.

Also differing from McDaniel and colleagues' function-learning research, our study explores learning in the risk- management domain as opposed to their novel task of estimating an alien's mineral output based on its input. When learning occurs in an environment with potential risks and rewards, we anticipate that emotion-related traits will additionally influence learning and motivate behavior. Specifically, we predict that Behavioral Inhibition System (BIS) and Behavioral Activation System (BAS) strength will affect risk-taking (e.g., Gray, 1994). BIS is associated with feelings of anxiety and withdrawal behavior to perceived threats whereas BAS is associated with greater positive affective experience and motivate goal-directed behavior to appetitive stimuli (e.g., Gray, 1990). In risk-taking situations where the outcome could be either an aversive loss or an appetitive win, we expect that individuals with higher BIS will decrease risk-taking while individuals with higher BAS will increase risk-taking. This is consistent with past work in the area, which has found that BIS and BAS predict decreased and increased risk- taking, respectively, on games of chance (Demaree, DeDonno, Burns, & Everhart, 2008; Kim & Lee, 2011). Even if someone has the requisite working memory capacity and fluid intelligence abilities to learn to place optimal wagers, they may be reluctant to do so if they are strongly driven by either of the behavioral tendencies to avoid risks or seek rewards.

We examine participants' ability to place optimal wagers in three scenarios. First, in a learning phase, participants place wagers and are given feedback on a series of gambling opportunities. As is the case with most learning tasks (e.g., Engle & Kane, 2004), we expect working memory capacity and fluid intelligence will predict the ability to learn via feedback, regardless of whether one is using an instance learning or extrapolation strategy. Second, we test individuals' ability to rule-extract by asking participants to estimate the optimal wager for a new series of gambling opportunities without any feedback. We predict that individuals with higher executive functioning (e.g., working memory capacity and fluid intelligence) will be better at extracting the rule and applying it to a new set of circumstances (as in McDaniel et al., 2014) in this test phase. This is because fluid intelligence should be necessary to identify the pattern. However, rule-extraction learning should still be further limited by the ability to hold all of the relevant variables and past instances in memory at once (i.e., working memory is required because the participant cannot see the data from previous trials). Finally, in a gambling phase, we ask participants to attempt to place optimal wagers and be in charge of a bankroll. We include this condition because, although participants might be able to extract a rule in a hypothetical, no-stakes scenario, individual differences in risk avoidance and reward seeking might differentially motivate behavior when gains and losses are at stake. We predict that the same variables (fluid intelligence and working memory) will remain important, but that high BIS or high BAS will further hinder optimal betting if participants are too eager to approach or avoid risk. To help ensure that participants were motivated to perform well, they were paid money and provided with candy based on their performances.

This is the first study, to our knowledge, to investigate how individual differences contribute to people's ability to extract general rules about risk learning (learning and test phases) and use those rules for optimal risk management (gambling phase).

2. Material and methods

2.1. Participants

One hundred and twenty-nine Case Western Reserve University students and one hundred and twenty-nine Texas A&M University-Commerce students participated in the full experiment in exchange for partial course credit or extra credit. An additional 28 Case Western Reserve University students served as a gambling-phase only control group (see Gambling Phase below). Because a priori hypotheses did not involve these constructs, data regarding sex and age were not collected. Due to computer errors, four participants were missing Reading Span data, and were excluded only from analyses involving that variable. An additional four participants were missing multiple measures and were excluded from all analyses.

2.1.1. BIS/BAS

Participants first completed a computerized version of Carver and White's (1994) behavioral inhibition/behavioral activation system (BIS/BAS) questionnaire. BIS (seven items) measures behavioral sensitivity to expected punishment. BAS (13 items) measures sensitivity to and willingness to seek reward. BIS and BAS responses (1–4, reverse scored where appropriate) are summed for each measure.

2.1.2. Raven's

Next, participants completed a computerized version of the Raven's Advanced Progressive Matrices (ten-minute time limit, odd numbered items; Raven, Raven, & Court, 1998). Raven's measures fluid intelligence. For each item, participants saw a 3×3 matrix with the bottom right area missing. Participants chose which of eight options best completed the pattern. Raven's was scored as the number correct out of 18.[1]

2.1.3. Reading Span

Participants next completed the short form of the Reading Span task (Oswald, McAbee, Redick, & Hambrick, 2015). Reading Span measures working memory capacity. In this task, participants read a series of sentences and indicated whether or not the sentence was nonsensical. Immediately after verifying each sentence participants were presented with a letter. After verifying 2–6 sentences, participants recalled, in order, each of the letters that appeared after the sentences. Reading Span was scored as the proportion of items recalled in correct serial order (unit load scoring).

2.1.4. Risk Learning task

Next, participants were asked to describe in words what Kelly's Formula was, or type "I don't know."[2] Participants then read the instructions for the Risk Learning task. Participants were told there was a mathematical formula that determined the optimal percentage of one's bankroll one should wager given the likelihood of winning and the potential payout. Participants were asked to imagine that they were applying for a job and that their potential employer, who can make repeated investments for the lifetime of the company, wanted to see how close they could get to the optimal wagers. At no point were participants given the formula. Participants did not have access to calculators, paper, or pencils during the experiment. Instead they had to learn the appropriate wagers based on feedback provided during an initial Learning Phase and a later Gambling Phase.

2.1.4.1. Learning Phase. In the first phase of the Risk Learning task, participants were told that they would train with "Alex," an employee who knew and always placed the optimal percentages for each gambling opportunity. Their job was to guess how much Alex would wager.

Participants made their guesses in terms of the percentage of Alex's bankroll. As the participants entered their guesses, the computer displayed the dollar amount for the wager and how the bankroll would change if Alex made this wager and lost or won. This was done to avoid computational errors by the participant, decrease the cognitive effort required to make wagers, and ensure that each participant fully understood how each wager would impact the bankroll.

Following each guess, participants were shown Alex's wager (Kelly's Value) and given feedback on whether Alex won and how Alex's bankroll changed as a result (Figure 1). They were also given feedback on their own guess. If they entered the exact value of

[1] As nearly all participants were young adults these data were not normalized for age.

[2] No participant indicated knowledge of Kelly's Formula.

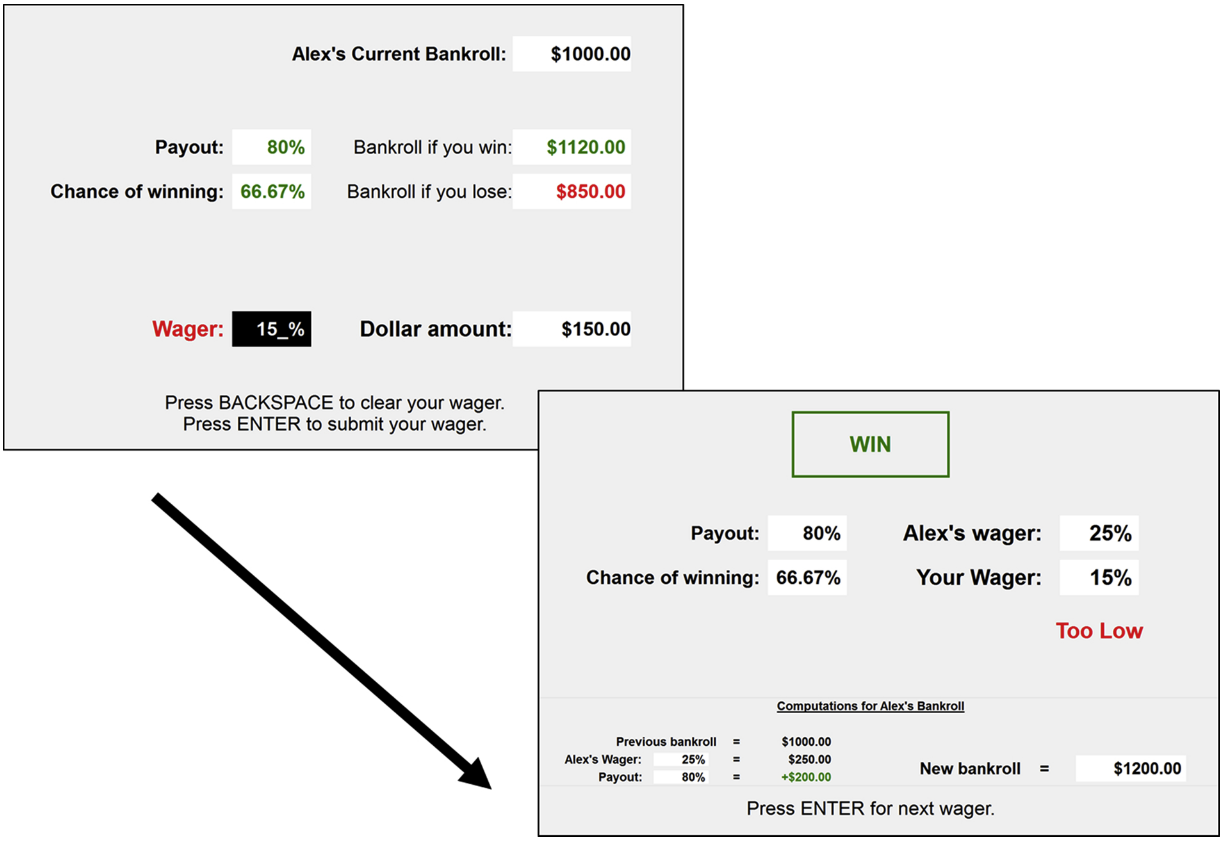

Fig. 1. Screenshots of the wager and feedback interfaces for the Learning Phase. Note that in this phase the new bankroll is computed based on Alex's wager (Kelly's Value) and not the participant's wager.

Alex's wager, the word "Perfect!" appeared in green below their wager. If their wager was off by one percent, the words "Very Close!" appeared in green below their wager. Otherwise, the words "Too High" or "Too Low" appeared in red below their wager.

Participants guessed Alex's wager on six blocks of eighteen trials each. The chance of winning, potential payouts, and correct responses (Kelly's Values) used in the Learning Phase can be found in Table 1. Each combination appeared three times per block. Trials with a 66.67% chance of winning each appeared twice as wins and once as a loss. Likewise, trials with a 33.33% chance of winning appeared once as a win and twice as losses. Trial order was randomized within each block. Participants were not made aware of when a block ended.

2.1.4.2. Test Phase. After the Training Phase, participants were asked to guess what Alex would wager on each of nine *new* combinations (Table 2). No feedback was given during this phase. Participants were not told the optimal (Kelly's Value) wager. The purpose of this phase was to test how well participants were able to transfer the information from the Learning Phase to new gambling opportunities, when their own bankroll was not at stake, i.e., how well participants could extract the rule (see Fig. 2).

2.1.4.3. Gambling Phase. In the Gambling Phase, participants were given their own bankrolls to manage. Participants placed wagers on the same nine combinations used in the Test Phase, except now they received feedback on whether they won or lost and saw how their bankrolls were affected. This was the only feedback they received during this phase (see Fig. 3). Participants were not told the

Table 1
Learning Phase Stimuli.

Chance of winning	33.33%			66.67%		
Payout	170%	230%	260%	35%	65%	80%
Kelly's Value	0%	4%	8%	0%	15%	25%

Note. Chance of winning = the likelihood of winning money on a gambling opportunity. Payout = the percentage of the wager gained in addition to getting the wager back if the trial is a winning trial. Kelly's Value = the optimal wager (percentage bankroll) according to the Kelly Formula for a given gambling opportunity. According to the Kelly Formula, wagers should only be placed if there is a long-term expected net profit; otherwise 0% (no wager) is optimal.

Table 2
Test and Gambling Phase Stimuli.

Chance of winning	25%			50%			75%		
Payout	300%	340%	380%	100%	120%	140%	33.3%	46.6%	60.0%
Kelly's Value	0%	3%	5%	0%	8%	14%	0%	21%	33%

Note. Chance of winning = the likelihood of winning money on a gambling opportunity. Payout = the percentage of the wager gained in addition to getting the wager back if the trial is a winning trial. Kelly's Value = the optimal wager (rounded) according to the Kelly Formula for a given gambling opportunity. According to the Kelly Formula, wagers should only be placed if there is a long-term expected net profit; otherwise 0% (no wager) is optimal.

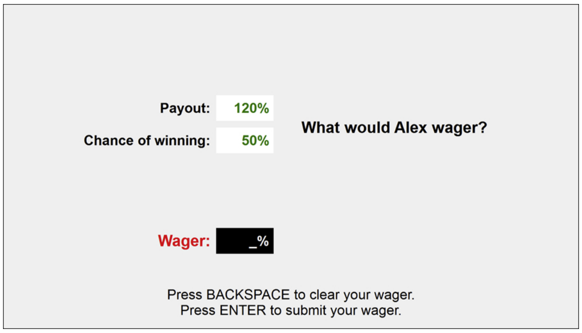

Fig. 2. Screenshot of Test Phase interface.

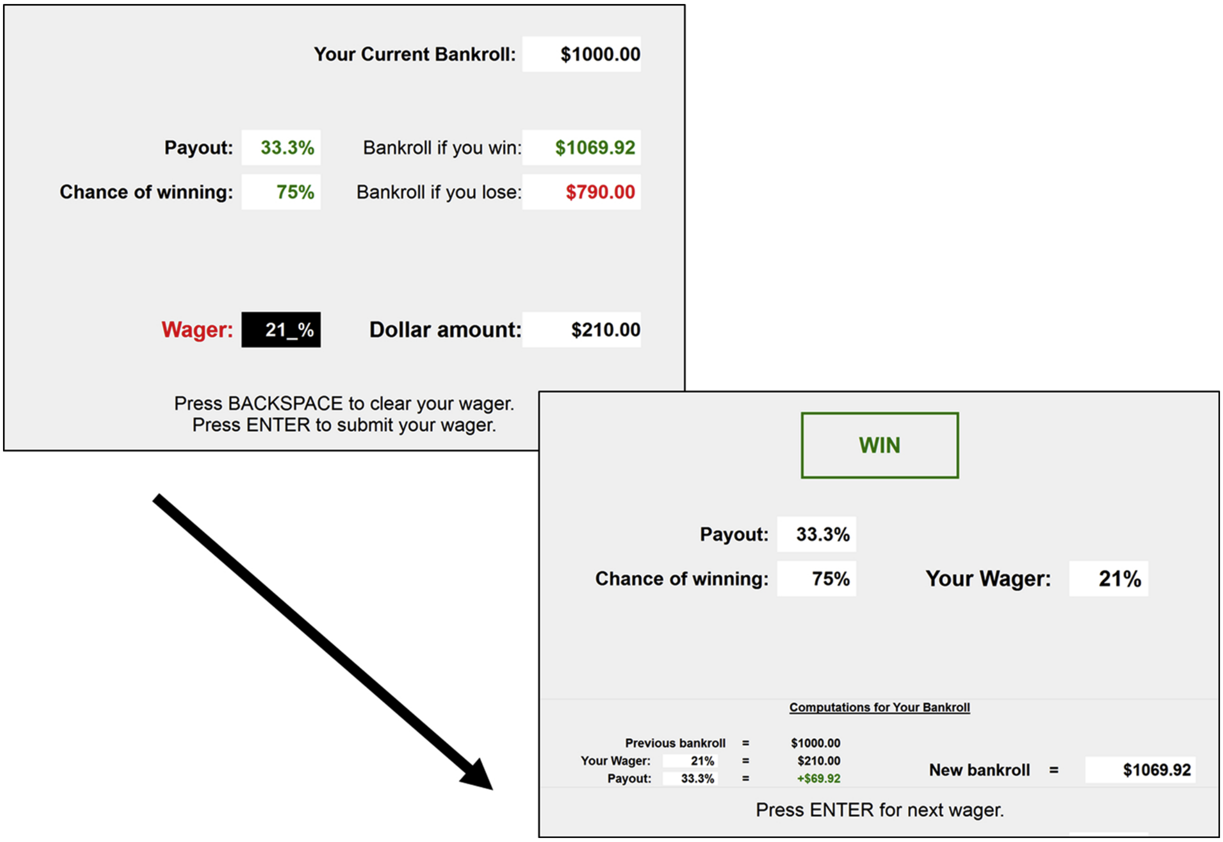

Fig. 3. Screenshots of the wager and feedback interfaces for the Gambling Phase. Note that unlike the Learning Phase, the new bankroll is computed based on the participant's wager.

optimal (Kelly's Value) wager. The task limited participants from wagering > 50% of the bankroll (to avoid bankruptcy). As in the Learning Phase, the wager screen displayed the computed the dollar amount and potential effects to the bankroll prior to submitting the wager. Trials were randomized within three blocks of 36 trials. Each possible combination appeared four times per block and wins and losses were balanced within a block to achieve the correct average chance of winning. Participants were not made aware of when a block ended. Participants were told that they had the opportunity to earn up to ten US dollars and five pieces of candy depending on how close they came to the optimal wagers on the Test Phase and Gambling Phase.

Lastly, we included a Gambling Phase only control group that did not complete the Learning or Test Phases. This group allowed us to compare performance between those who received feedback during a Learning Phase and those who attempted to learn by only observing changes to their bankroll.

2.1.5. Gambling questionnaire

After completing the Risk Learning task, participants completed a computerized risk experience questionnaire (see Supplemental Materials).

2.1.6. SES and parental education

Lastly, participants completed a computerized version of the parental occupation status (ISE scores; adapted from Caro & Cortés, 2012) as a measure of socioeconomic status (SES), as well as a parental education questionnaire (see Supplemental materials).[3] Following these questionnaires, participants were rewarded based on their performance.

3. Results

Table 3 shows means, variances, and ranges of each variable. To ease interpretation, performance on the Risk Learning task was reverse coded in terms of absolute distance from Kelly's Value. Specifically, performance = 100 – |Kelly's Value – participant's wager|. Thus a score of 100 indicates perfect performance (wagering Kelly's Value) and lower scores indicate wagers that are above or below Kelly's Value—the lower the score the greater the departure from Kelly's Value.

To evaluate the importance of cognitive (intelligence and working memory capacity) and emotion-related (BIS/BAS) traits during each phase of the experiment, we regressed Raven's scores, Reading Span, BIS, and BAS onto mean performance collapsed across each block of a given phase. For these analyses, average performance on each phase and performance on each predictor variable was standardized.

3.1. Learning Phase

A repeated measures ANOVA confirmed that performance improved over trials, $F(5, 1280) = 195.69$, $p < .001$, $\eta^2 = .43$, see Fig. 4. Half of all participants (129 of 258) wagered within 2% of Kelly's Value (on average) by the final block of the Learning Phase. However, participants varied in how quickly they learned the information. A regression analysis indicated that higher Raven's scores, Reading Span, and BAS were all related to better overall performance on the Learning Phase (see Table 4). Thus, fluid intelligence, working memory capacity, and approach motivation predicted better learning with feedback.

3.2. Test Phase

A regression analysis indicated that higher Reading Span predicted better performance on the Test Phase (see Table 4). Thus, working memory capacity predicted better transfer of learning from the Learning to the Test Phase.

However, it is possible that participants used the exemplars from the Learning Phase not to extract a general rule for optimal wagers, but as starting points for their estimates during the Test Phase (Hoffmann, von Helversen, & Rieskamp, 2014). For example, participants may have used the correct answers from the Learning Phase for trials with payouts of 260%, 35%, and 65% as starting points for estimating payouts in the Test Phase of 300%, 33.3%, and 60% respectively. Only 14 of 258 participants placed wagers within two percentage points of the Learning Phase correct responses for each of the three similar Test Phase items, suggesting that most participants were not exclusively using an exemplar–based approach.

3.3. Gambling Phase

A repeated measures ANOVA confirmed there were small improvements in performance throughout the Gambling Phase, $F(3, 768) = 8.66$, $p < .001$, $\eta^2 = .03$ (Greenhouse-Geisser corrected). See Fig. 4.

A regression analysis indicated that higher Raven's scores, Reading Span, and BAS led to better overall performance on the Gambling Phase (see Table 4).

Performance on the Gambling Phase was significantly higher for those who experienced the Learning Phase ($M = 92.17$, $SD = 2.63$) than for the control group ($M = 89.64$, $SD = 5.41$)[4] following equivalent practice with the Gambling Phase values (first three

[3] Education, SES, and gambling experience did not strongly predict performance on the Risk Learning task (see Supplemental materials).

[4] Case Western Reserve University participants who completed the entire experiment were compared with the control group (who only experienced the Gambling Phase) because the control group consisted of only Case Western Reserve University students.

Table 3
Descriptive Statistics.

Measure	Mean	SD	Min	Max
Raven's	11.64	3.33	1.00	17.00
Reading Span	0.71	0.21	0.00	1.00
BIS	13.58	3.94	7.19	24
BAS	26.59	5.36	14	39
Learning Phase	94.9	4.43	60.9	99.7
Test Phase	90.4	4.47	69.2	97.6
Gambling Phase	91.3	3.68	65.8	96.9

Note: Raven's = Raven's Advanced Progressive Matrices. BIS = Behavioral Inhibition System sensitivity. BAS = Behavioral Activation System sensitivity.

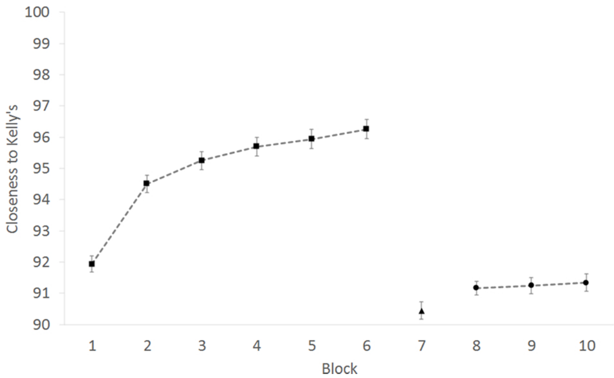

Fig. 4. Performance over the Learning Phase (Blocks 1–6), Test Phase (Block 7), and Gambling Phase (Blocks 8-10). Closeness to Kelly's = 100 minus the absolute value of the distance above or below Kelly's Value. One hundred indicates perfect performance.

Table 4
Regression Results Predicting Performance.

Learning Phase			R-Squared	.22
Predictor	Estimate	SE	t-value	p-value
Intercept	0.00	0.06	0.00	1.000
Raven's	0.32	0.06	5.18	<.001
Reading Span	0.18	0.06	2.89	.004
BIS	0.05	0.06	0.91	.364
BAS	0.17	0.06	2.94	.004
Test Phase			**R-Squared**	**.06**
Predictor	Estimate	SE	t-value	p-value
Intercept	0.00	0.06	0.00	1.000
Raven's	0.04	0.07	0.57	.572
Reading Span	0.25	0.07	3.66	<.001
BIS	0.04	0.06	0.65	.518
BAS	0.06	0.06	0.92	.361
Gambling Phase			**R-Squared**	**.12**
Predictor	Estimate	SE	t-value	p-value
Intercept	0.00	0.06	0.00	1.000
Raven's	0.21	0.07	3.16	.002
Reading Span	0.16	0.07	2.51	.013
BIS	0.03	0.06	0.55	.581
BAS	0.15	0.06	2.54	.012

Note: Raven's = Raven's Advanced Progressive Matrices. BIS = Behavioral Inhibition System sensitivity. BAS = Behavioral Activation System sensitivity.

blocks for the control group), $t(149) = 3.55$, $p = .005$, $d = 0.82$. Results were similar when comparing performance following equivalent experience with the Risk Learning paradigm in general (Blocks 8–10 for both groups) ($M_{Control\ Group} = 89.76$, $SD = 5.60$), $t(149) = 3.34$, $p = .001$, $d = 0.78$.

3.3.1. Distance above or below Kelly's Value

To test for systematic over- or under-betting during the Gambling Phase, we scored performance direction in terms of how far above or below Kelly's Value a participant was on average. A score of zero indicates no bias—the participant was as likely to over-bet as to under-bet. Positive values indicate a tendency to over-bet, whereas negative values indicate a tendency to under-bet. We predicted that BIS and BAS would be related to systematic under- and over-betting respectively during the Gambling Phase.

Overall, participants systematically under-bet, $\beta = -5.49$, $SE = 2.09$, $F(1, 252) = 6.86$, $p = .009$. BIS did not predict bias, $\beta = 0.29$, $SE = .063$, $p = .652$. However, BAS did, $\beta = 2.51$, $SE = 0.89$, $F(1, 252) = 7.97$, $p = .005$. Specifically, higher BAS tempered the under-betting bias. For each standard deviation above the mean on BAS, participants wagered, on average, 2.51% more of their bankroll. An individual slightly over two standard deviations above the mean in BAS offsets the general under-betting participants demonstrated.

4. Discussion

This is the first study to our knowledge to examine the ability to learn optimal risk-taking in an investment paradigm. Using a large and diverse sample we found that participants were able to learn proportional betting from a set of examples with feedback.

Participants with relatively higher working memory capacity, controlling for the effects of other predictors, performed better than participants with relatively lower working memory capacity throughout all phases of the experiment. We found that people with higher fluid intelligence were better able to learn proportional betting from a set of guided examples with (Learning Phase) and without (Gambling Phase) explicit feedback (compared to people with relatively lower fluid intelligence and after controlling for other predictors).

We suspect that working memory is necessary for weighing multiple pieces of information at once (i.e., they can consider both the odds of winning and the potential payout), whereas fluid intelligence assists more with learning from experience. If a person cannot maintain and manipulate multiple pieces of information within the focus of attention, then s/he is unlikely to be able to extract the rules of the task or use that information to make optimal decisions. Thus, working memory was beneficial in all phases, whereas fluid intelligence was specifically useful for learning from feedback in the Learning and Gambling Phases of our paradigm.

Our results contrast somewhat to McDaniel and colleague's (e.g., Little & McDaniel, 2014; McDaniel et al., 2014) findings. First, McDaniel et al. found that some individuals learn the rules. We found little transfer of learning. However, the function in the McDaniel et al.'s paradigms is simpler than the more complex proportional betting function in our study. There is also evidence that people are reluctant to trust rules in probabilistic tasks (e.g., Arkes, Dawes, & Christensen, 1986; Dietvorst, Simmons, & Massey, 2015). This is particularly the case when the rules do not provide a "perfect" solution (Arkes et al., 1986; Dietvorst et al., 2015). For example, Arkes et al. (1986) found that participants were reluctant to use a categorization rule that was only correct 70% of the time, despite that rule being the best strategy for the task. This was exacerbated when participants received feedback on their, and thus the rule's, performance. Although our Learning Phase provided rewards and feedback based on the optimality of wagers, participants could still see Alex occasionally losing money despite optimal wagers. Thus, even when rewarded for optimality, people may struggle to ignore the influence of individual rule "failures" in probabilistic tasks.

Little and McDaniel (2014) reported significant correlations between stimulus response learning and both fluid intelligence and working memory capacity. We found that working memory capacity predicted learning, transfer, and application, but fluid intelligence only predicted learning from feedback, whether that feedback was explicit (Learning Phase) or derived from experience managing one's bankroll (Gambling Phase). However, Little and McDaniel (2014) only report bivariate correlations; therefore, it is unclear whether working memory capacity would have predicted learning in their paradigm if they had controlled for fluid intelligence or vice versa.

On average, people wagered within 8.7% (absolute value) of Kelly's Value. However, variance from Kelly's Value was not random. People exhibited a strong bias toward risk aversion when given control of their own bankroll in the Gambling Phase. Interestingly, people with high BAS were less prone to this error than people lower in BAS. We note that, although feedback improved overall performance, individual differences remained on the Gambling Phase such that individuals with lower BAS under-bet to a greater extent than individuals with higher BAS. This finding is consistent with past findings (e.g., Demaree et al., 2008) and speaks to the notion that differences in emotional/personality traits may have an enduring effect on risk-taking behavior even after training. Continued investigation of how emotional/personality traits may impact risk taking over time relative to Kelly's Formula is warranted.

There are a number of limitations to the current study. First, participants were rewarded based on how close their wagers were to the optimal value on the Test and Gambling Phases. Hence, they were rewarded for optimality and not net gains (which are influenced by chance) even during the Gambling Phase. We suspect that BIS and BAS would influence performance more when final compensation is linked directly to gains and losses (as opposed to optimality).

We were surprised that fluid intelligence did not predict performance on the Test Phase. Theoretically, the ability to identify patterns (as measured by Raven's Advanced Progressive Matrices) should be critical for extracting the rule in the task. We consider two possibilities. First, working memory and fluid intelligence are typically highly correlated (though this correlation was only $r = .42$ in our sample). The inclusion of both predictors may have diluted the effect of either. Alternatively, working memory capacity may have been more important in this task given that one had to consider not only the odds of winning, the potential payout, and the associated Kelly's value for the current trial, but also for all other trials in order to gleam a sense of the underlying rule. Thus, logic and reasoning alone may have been insufficient for extracting this relationship absent superior working memory abilities.

Participants in our study only had the opportunity to *earn* candy and money. They could not *lose* money during the experiment. We suspect that BIS influences performance when net losses are possible.

Although many risk management decisions—such as investing decisions—can be effectively managed by directly calculating Kelly's Formula, others must rely on an intuitive sense. In military and medical situations, people must decide whether to take a risk under serious time pressure. In these situations, one cannot be expected to calculate the potential rewards, chances of success, and engage in a lengthy series of computations. The same is true for stockbrokers who must make rapid investment decisions in a dynamic and ever-changing market. Thus, it is particularly noteworthy that some people were able to gain an intuitive sense of Kelly's Formula and apply it without extensive calculations.

Lastly, future research should seek to generalize these findings beyond a college sample. The sample in this study was quite variable, sampling from both an elite private midwestern urban university with a large contingent of international students and a smaller rural southern university with a large contingent of first generation students and a range of SES. However, these results may differ when examining people of different ages or those who are not college educated.

5. Conclusion

Whether playing poker, running a business, or deploying soldiers, risk management is an important skill. Assuming too much or too little risk can lead to failed businesses or even loss of life. Our findings suggest that individual differences may be important for the learning and performance of proportional betting (e.g., repeated day trading). Specifically, people with relatively high working memory capacity were able to approximate Kelly's value across multiple scenarios better than people with relatively low working memory capacity. People with relatively high fluid intelligence were better able to learn to approximate Kelly's value when given feedback than people with relatively low fluid intelligence. People with relatively high BAS were less likely to under-bet than people with relatively low BAS. Our findings suggest that when selecting people for risk management tasks, one should consider cognitive abilities but also avoid persons who are overly reward seeking. These findings have wide spread implications, such as for Wall Street investing, hiring and promoting in business, and electing politicians who make high-stakes decisions.

Disclosure statement

None of the authors have any financial interest or benefit that has arisen from the direct applications of this research.

Declaration of Competing Interest

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