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The influence of IQ on pure discovery and guided discovery learning of a complex real-world task

Michael A. DeDonno

College of Education, Florida Atlantic University, 777 Glades Road, Boca Raton, FL 33431, United States

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ABSTRACT

The purpose of the present study was to investigate the predictive ability of IQ on pure discovery and guided discovery learning of a complex real-world task. Hold'em poker is a game of skill with significant complexity. Its attributes resemble real-life activities such as stock market investing, shopping for a home, and the battles of war. To explore pure discovery learning, a group received no guidance while playing a total of 720 hands of poker. To investigate guided discovery learning, a group received poker strategies while playing the game. Results revealed that IQ explained a significant proportion of the variance in pure discovery but not guided discovery learning of hold'em poker. Results suggest that IQ predicts learning of tasks when both cognitive and emotional factors are present. It is possible that for pure discovery learning to be effective, both cognitive and emotional factors need to be present.

1. Introduction

In an interview with Adam Bryant of the New York Times, Laszlo Bock, Senior Vice President of People Operations at Google, the guy responsible for hiring new employees, stated "the number one thing we look for is general cognitive ability, and it's not IQ (Intelligence), it's learning ability…" (Friedman, 2014, para. 1). Certainly a key component to succeed in any environment is the ability to learn. The rapid changes in technology and societal changes due to globalization, make the ability to learn a necessity in maintaining employment and appropriately functioning in society. The success of Google is due in-part to Mr. Bock's hiring practices. However, a question arises as to the value of IQ to learning ability.

The purpose of the present study was to explore the predictive power of IQ on pure, and guided discovery learning. Researchers find individuals with higher intelligence (IQ), tend to do better in academics (Alloway & Alloway, 2010), excel in job training programs, and overall job performance (Schmidt & Hunter, 2004). Studies also find higher IQ to be associated with physiological factors such as increased brain volume (Haier, Jung, Yeo, Head, & Alkire, 2004) and increased cortical glucose utilization (Larson, Haier, LaCasse, & Hazen, 1995). Biologist James Zull (2002) has described an association between neurophysiology and the act of learning. Zull (2002) posits the way our brain processes information is similar to the learning cycle as explained by Kolb and Kolb (2005). Specifically, various functions of the brain are involved in specific processes of the learning cycle. For example, the learning cycle process of reflective observation, involves the integrative cortex while the learning cycle process of active testing, involves the motor cortex. Simply put, "the learning cycle arises naturally from the structure of the brain" (Zull, 2002, p.19). The potential relationship between intelligence and the act of learning has significant value to educators and education researchers.

1.1. IQ

A general mental ability, or *g*, was originally proposed by Charles Spearman in the early 20th century (Spearman, 1927). He observed that children's performance on different school subjects was positively correlated. Spearman reasoned that these correlations were due to an underlying general mental ability, which he labeled *g*. Since Spearman's research in the early 1900's, researchers have developed tests to measure general mental ability. These tests have been termed IQ tests. Popular IQ tests include the Wechsler Adult Intelligence Scale (WAIS), the Stanford-Binet Intelligence Scale, and the Raven's Progressive Matrices test. Researchers have also found tests such as the Scholastic Assessment Test (Frey & Detterman, 2004) and the ACT (Koenig, Frey, & Detterman, 2008) are good indicators of an individual's IQ.

As stated by Gottfredson (1997), my working definition of intelligence is as follows:

> (Intelligence) involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience. It is not merely book learning, a narrow academic skill, or test-taking smarts. Rather, it reflects a broader and deeper capability for comprehending our surroundings – "catching on," "making sense" of things, or "figuring out" what to do. (p. 13)

E-mail address: mdedonno@fau.edu.

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This definition fits nicely with the act of learning which also emphasizes the aspects of "catching on," and "figuring out" what to do next.

1.1.1. IQ in the real-world

Researchers have explored the influence of IQ on various complex real-world activities. For example, Grinblatt, Keloharju, and Linnainmaa (2012), investigated the influence of IQ on trading behaviors of investors. The researchers found that high-IQ investors exhibited superior market timing, stock-picking, and were less subject to the disposition effect. Specifically, high-IQ investors were more likely to buy stocks on days they hit a one-month low and less likely when they hit a one-month high. In addition, high-IQ investors were less likely to ignore losses. High-IQ investors more often appropriately recognized both gains and losses and focused on the overall potential of the investment (Grinblatt et al., 2012). In another study, researchers explored the influence of IQ on delayed discounting (Shamosh & Gray, 2008). The researchers found the willingness to delay a smaller immediate reward for a later larger reward was associated with higher IQ.

1.2. The act of learning

While the act of learning is generally thought to be a structured process, particularly in academic and corporate environments, there's considerable variation in daily life. It's not as common in daily life to learn from lectures or online presentations as it is to learn from active experience. The constructivist revolution has introduced new concepts to the act of learning and teaching (Mayer, 2004). A constructivist view of learning is often thought of as an active process where the student is actively involved in the discovery of valued information (Mayer, 2004). In our daily lives, we may use a guided discovery process where learning is aided by hints, direction, feedback and other helpful information. However, when a priori information is absent, learning may occur through a different path. In a pure discovery learning situation, learning occurs with little or no guidance. Essentially, knowledge is obtained by practice or observation (Shrager & Klahr, 1983).

Over thirty years ago, Moran (1981) stated:

> There may be situations in which we cannot control the user's training, such as the bank customer walking up to an automated teller for the first time. The user(s) in these situations must, if they are to acquire a conceptual model at all, induce it from interacting with the system. This is indeed difficult. (p.43)

Since 1981 when Moran made this statement, our lives have become increasingly more complex. Our ability to function in society is based in-part on our ability to learn without instruction.

Interestingly, there is considerable debate as to the real value of discovery learning approaches (Lee & Thompson, 1997; Mayer, 2004; Steffe & Gale, 1995). Researchers of discovery based learning tend to focus their research on specific domains such as math/numbers, computer skills, science, problem solving, and physical/motor skills (Alfieri, Brooks, Aldrich, & Tenenbaum, 2011). One consistent finding is guided discovery learning is superior to pure discovery learning (Mayer, 2004). Further, upon review of research literature, Mayer (2004) found little evidence that pure discovery learning has any value. However, as Moran suggested in 1981, and with the constant introduction of new technologies, it seems pure discovery learning plays a significant role in our daily lives. In purchasing a new iPhone recently, it was a surprise to find no instruction booklet in the box.

1.3. A complex real-world task

In the real-world we use multiple skills to reason, plan, solve problems, think abstractly, and comprehend complex ideas. To investigate learning of a complex real-world task in a lab environment, several factors need to be considered. Firstly, the complex real-world task needs to incorporate multiple skills and abilities that are evident in daily living. The task should have a consistent set of rules, an objective way of measuring performance, and evidence of reliability. The game of hold'em poker satisfies these requirements.

The game of poker is a complex real-world task (DeDonno & Detterman, 2008; Levitt & Miles, 2014) with a clear set of rules. The complexity of the game can be found in features such as imperfect information where competing players must deal with money management, statistics, emotion management, risk management, unreliable information, and deception. It's a real-world task that philosopher John Lukacs called "the game closest to the Western Conception of life…" (McManus, 2009, p.20). Author and professional poker player James McManus (2003) wrote "Each poker session is a miniature global economy laid out on a baize oval table" (p. 119). Its attributes have been compared to real life scenarios such as striking a bargain in the market, to the clash of war (McDonald, 1996). The game has a clear set of rules and performance can be objectively measured by amount of money earned (i.e., winnings or losses). Participants can play multiple games so as to allow researchers to obtain a reliable measure of poker ability.

Research using poker dates back to the 1920s when John von Neumann used poker as a model in the development of mathematical game theory (Neumann & Morgenstern, 1947). John Nash later extended von Neumanns theories, again using poker as an example (Nash, 1950). More recently, the game of poker has been of interest to researchers in Mathematics (Morris, 2012), Artificial Intelligence (Billings, Davidson, Schaeffer, & Szafron, 2002), and psychology (DeDonno & Detterman, 2008). For example, Billings et al. (2002) describe the design considerations for a computer poker program capable of playing reasonably strong poker. The program uses several action axioms such as hand value, probability of obtaining needed cards, pot odds, and opponent's actions to calculate the maximum expected utility (MEU). When we play poker, we use these same action axioms to calculate MEU. However, our ability to calculate MEU is based on factors including motivation, skill level, knowledge of the game, attentional control, and working memory capacity. For example, working memory capacity is considered an individual differences construct that reflects the amount of information that can be maintained in active memory (Wilhelm, Hildebrandt, & Oberauer, 2013). Certainly poker players who can maintain more information such as the action axioms stated above, but also factors such as the playing behavior of players, would have an advantage at the poker table.

Researchers also find emotions play a role in poker performance (Demaree, 2013; Johansen-Berg & Walsh, 2001). Demaree (2013), highlights the managing one's emotions and understanding those of their opponents as important factors to peak poker performance. Further, Schmeichel, Volokhov, and Demaree (2008) posit that the ability to suppress emotions can be of value when playing poker. Being able to hide excitement when dealt a pair of aces, could help maximize winnings at the poker table. Interestingly, Schmeichel et al. (2008) found individuals higher in working memory capacity, suppressed emotions better than individuals lower in working memory capacity. Indeed, evidence suggests the game of poker requires complex cognitive processing as well as emotional processing.

Researchers also find differences in playing strategies based on skill level. Siler (2010) found tight and aggressive strategies to yield the best financial returns. These strategies are more often found in the expert players than the novice players (Siler, 2010). There is also evidence that expert players tend to practice delayed discounting (Siler, 2010). Specifically, individuals with higher IQ tend to be more willing to wait for a larger reward than accepting an immediate smaller reward. Interestingly, studies find that delayed discounting is associated with higher SAT scores (Benjamin, Brown, & Shapiro, 2013; Shoda, Mischel, & Peake, 1990), and higher IQ (Shamosh & Gray, 2008).

1.4. The present study

The purpose of the present study was to investigate the predictive ability of intelligence on guided discovery, and pure discovery learning of a complex real-world task. The study included two groups of participants who completed a series of hold'em poker games. To investigate guided discovery learning, a group received poker strategies prior to, and throughout playing the game. To explore pure discovery learning, a group received no guidance throughout playing the game. As a measure of intelligence, participants Scholastic Assessment Test (SAT) scores were obtained. Performance in the hold'em poker game (i.e. overall winnings or losses) served as a measure of learning. Two hypotheses were tested: (H_1) intelligence will predict pure discovery learning of a complex task, (H_2) Intelligence will predict guided discovery learning of a complex task.

2. Methods

2.1. Participants

A total of sixty-six (N = 66) students from a highly selective private Midwest university participated in this study. Students were recruited from introductory psychology courses. Twenty (20) participants were removed from the study due to self-reporting of playing the game on a recurring basis or reporting significant knowledge of the game. The remaining forty-six (46) participants had never played poker before or had played only a few times in their life. The sample included 28 males and 18 females (mean [M] age = 19.67, standard deviation [SD] = 1.32, range = 18–24). Two participants identified themselves as American Indian/Alaska Native, nine as Asian/Pacific Islander, five as Black, one as Hispanic, and 29 as White.

2.2. Procedures and materials

Upon completion of a research consent form, participants signed an authorization for the universities registrar's office to release their SAT scores. The SAT scores for the present study were based on the old version of the SAT. Possible scores on each of the two parts of the SAT range from 200 to 800. In any given year, the standard score is set at 500 with a standard deviation of approximately 100. The combined score of the math and reading sections of the SAT yield a range from 400 to 1600.

The poker application used for this study was Turbo Texas Hold'em for Windows, version four copyright 1997–2000 Wilson Software. This is a computerized simulation of a 10-player limit hold'em poker game. Players select one of various options that would maximize earnings while minimizing losses.

In the computer hold'em poker program, the game begins with two cards face down dealt to each simulated player and two cards facing up for the participant. These first two cards are called "pocket cards." After seeing their cards, the participant has the option to fold, call, or raise the bet. If the participant chooses to fold, the hand would end and the winning hand would be identified. If the participant chooses to call or raise, a round of betting occurs and then three cards facing up are dealt and displayed on the center of the screen serving as community cards. These cards are used by all players in creating their best hand. The dealing of these cards is called "the flop." The participant again has the option to fold, call, or raise. By staying in the game, another round of betting occurs and then a fourth card facing up is dealt to the center of the screen, called the "turn" card. The options of fold, call, or raise continue to be available. If the participant chooses to play this hand, a fifth and final card called the "river" is dealt facing up and final betting occurs with a winner being identified. The player with the best five cards selected from the player's own two cards and any three of the five community cards in the center of the table wins the hand. If the participant has the best hand, they win all the money that was bet by all players during the hand. If the participant did not have the best hand, they lose the money they bet during the hand.

Before each game, specific software options were set. The Auto Stop Point was set which caused a stop playing window to open on the screen after a preset number of hands were played. To ensure all participants played the same hands, the Repeatable Deal feature was used. This feature allows for the same set of randomly selected hands to be played by all participants. Games during each of the three sessions were counterbalanced.

At the start of the experiment, the participants were randomly assigned to one of two conditions: pure discovery, or guided discovery group. Each participant then completed a self-assessment questionnaire. The questionnaire was designed to gauge the participant's knowledge and experience with poker. Specific questions such as how long have you been playing poker, and how often do you play were part of the questionnaire.

As in many activities and certainly relevant to poker as any player would attest, there is significant variability in short term performance due in-part to random factors. Utilizing Kuder-Richardson Prophecy formula and data from previous research, it was estimated that participants would need to play a minimum of 552 hands to obtain a reliable measure of poker ability (Chronbach's $\alpha = 0.90$), based on overall winnings or losses. As a result, participants played a total of 720 hands of poker during three separate visits to the experimental lab. Each visit consisted of six games of poker with 40 hands dealt each game.

Upon completion of the questionnaire, the experimenter distributed basic rules of poker to all participants. The document included an ordered listing of the hands in a poker game from best hand to worst. In addition, specifics to the functioning of the computer game were provided.

Once the participant was comfortable with the task, they began the game by selecting the deal button with the computer mouse. This generated two cards face down for each of the nine simulated players and two cards face-up for the participant. At this point, the participant had the option to fold, call, or raise the bet. Throughout each hand, the display showed the decision each of the simulated players made with respect to folding, calling, or raising.

The first session began after all participants reviewed the general rules of the game. After the second game, time 1 (T1), the instruction group received a hand ranking formula created to calculate the value of their pocket cards (Chen & Ankenman, 2006). For example, an Ace is worth ten points, a King is worth 8 points, and a queen is worth 7 points. Points are also given for suited cards, connected cards (e.g., an 8 and a 9), and points are doubled when the pocket cards are paired (e.g., 2 Jacks). As an example, pocket cards of a pair of Jacks, would be worth 12 points. The higher the score, the better the pocket cards. The instruction group was provided this strategy and all subsequent strategies in paper format and could use the documents while playing the game in the lab. At this time and all subsequent times when the instruction group received strategies, the control group received documents discussing the history of poker. During this first session, the instruction group also received an additional poker strategy pertaining to the value of position at the table. Good positioning means you get to see what your opponents do before you have to act. This strategy was distributed after the fourth game, time 2 (T2). The end of game six, time 3 (T3) marked the completion of the first session. Participants were asked not to study or practice the game between sessions.

The second and third sessions began with the distribution of material provided during previous sessions. During session two, after the 8th game, time 4 (T4), the strategy pertaining to the concept of *outs* was distributed. *Outs* refers to the number of cards in the deck that will make your hand. For instance, if your pocket cards include an Ace, and a King, and the community cards include a Queen, Jack, Four, you need a Ten to make a straight. Since there are four Tens in a deck of cards, you have four *outs*. After the 10th game, time 5 (T5), a strategy for calculating *pot odds* was distributed. *Pot odds* are a ratio of the total amount of money being bet and the amount of money required to stay in the game. This strategy included a table that integrated *outs* with *pot odds* to determine appropriate action. The end of the 12th game, time 6 (T6), marked the end of session two. During session three, new strategy documents were distributed after the 14th game, time 7 (T7), and the 16th game, time 8 (T8). The documents distributed during session three included various strategies specific to playing the flop, turn, and river cards. The end of the 18th game, time 9 (T9), marked the end of session three and the participants involvement.

With the purpose of motivating participants to play their best, a contest was included in the study. The contest was for an Apple iPod, now very popular among college students. In hopes of motivating all participants, the contest was designed as a raffle where higher scoring participants received more tickets for the raffle.

3. Results

All participants' SAT scores were obtained from the universities registrar's office. The average SAT Total score was 1313.48 (standard deviation [SD] = 129.65, range = 980–1540). The average SAT Math score was 672.61 (standard deviation [SD] = 70.47, range = 460–800) while the average SAT Verbal score was 640.87 (standard deviation [SD] = 77.39, range = 500–800). For a given year, a SAT total score of 1310 would typically be in the 90th percentile (The College Board, 2006). The high SAT scores of the sample are consistent with the highly selective nature of the university. There were no significant ($p > 0.05$) gender, racial, or ethnic differences in SAT performance. Relating to reliability of poker performance, the Cronbach's α for the 18 games of poker was 0.76.

First, to verify that guided discovery learning was superior to pure discovery learning, A 9 (time: time1, time2, time3…time9) × 2 (treatment: instruction, no-instruction) repeated measures ANOVA was conducted. Results revealed that the within-subjects factor of treatment was significant $F(1,44) = 45.53$, $p < 0.01$, $\eta^2 = 0.509$. Both the pure discovery and guided discovery group improved in performance over time. To visualize change in performance of guided discovery and pure discovery processing, Fig. 1 depicts performance based on time. In addition, between-subjects factor of treatment was significant $F(1,44) = 29.76$, $p < 0.001$, $\eta^2 = 0.403$. The guided discovery group performed significantly better than the pure discovery group.

H_1. Intelligence will predict pure discovery learning of a complex task. To determine the unique contribution of IQ on pure discovery learning, a linear regression was conducted. The dependent variable (DV) was average poker performance (winnings or losses) across all games while the predictor variable was IQ. Results revealed that IQ explained a significant proportion of the variance in poker performance, $R = 0.452$, $R^2 = 0.205$, $F(1,20) = 4.89$, $p = 0.039$. The correlation between IQ and poker performance was significant, $r(21) = 0.452$, $p = 0.039$. For scatterplot of this relationship, please see Fig. 2.

H_2. Intelligence will predict guided discovery learning of a complex task. To determine the unique contribution of IQ on guided discovery learning, a linear regression was conducted. The dependent variable (DV) was average poker performance (winnings or losses) across all games while the predictor variable was IQ. Results revealed that IQ failed to predict poker performance of the guided discovery learning group, $R = 0.040$, $R^2 = 0.002$, $F(1,24) = 0.036$, $p = 0.851$. The correlation between IQ and poker performance was non-significant, $r(25) = 0.40$, $p = 0.851$.

4. Discussion

The present study was designed to explore the predictive ability of intelligence on pure discovery and guided discovery learning of hold'em poker. The finding that intelligence predicted pure discovery learning was expected. Without instructions, the participants had to "figure out" what to do next without the aid of instructions. The present data along with other research may provide additional insight into pure discovery learning. The Iowa Gambling Task (IGT) is known to elicit emotion-based learning in a pure discovery learning environment (Bechara, Tranel, & Damasio, 2000). Further, researchers find that IQ predicts performance on the IGT (Demaree, Burns, & DeDonno, 2010). The IGT is a psychological task designed to simulate real-life decision making. The theoretical framework for the IGT is the somatic marker hypothesis (Bechara & Damasio, 2005). The hypothesis posits that decision making is influenced by emotions and feelings, some of which occur non-consciously (Bechara & Damasio, 2005). Essentially, through emotion based learning, participants learn the task without instruction.

In the IGT, participants select cards from four decks. Upon selection of a card, the participant wins money, but also may lose money. The goal of the game is to win as much money as possible. Unknown to the participant at the start of the game, is that two of the decks are bad decks in that over time, you lose more money than you win. The other two decks are good decks in that over time you win more money than you lose. As participants play the game, they "figure out"

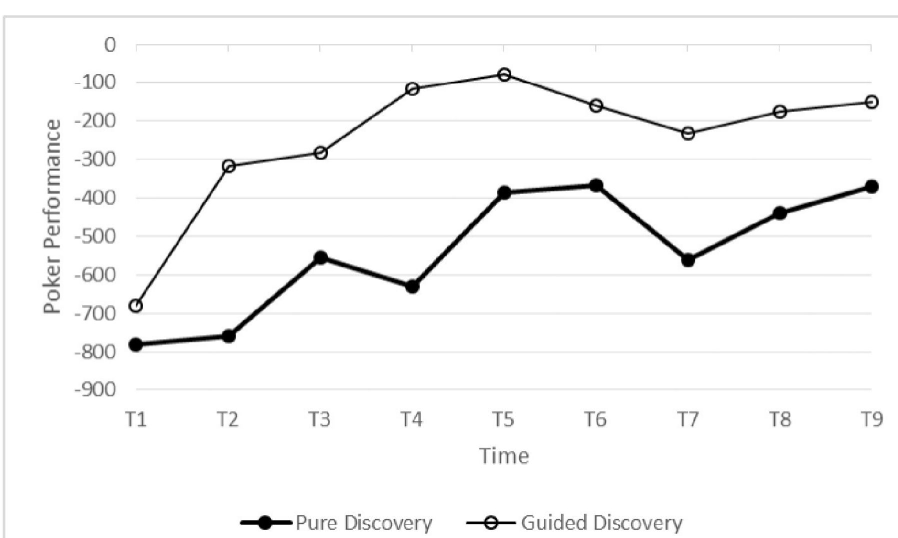

Fig. 1. Poker performance over time. $\eta^2 = SS_{Effect} / SS_{Total}$.

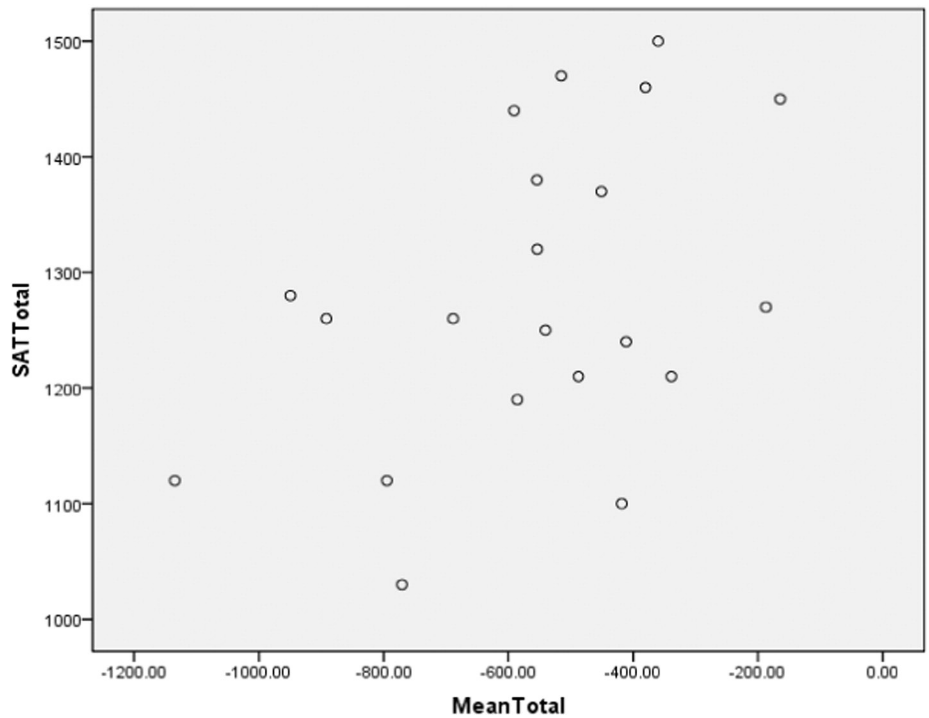

Fig. 2. Scatterplot of IQ vs. Mean Total of poker performance.

the good decks and bad decks. Researchers find learning of the IGT is due to a combination of cognitive and emotions processing (Bechara et al., 2000). As participants play the game, they have emotional responses to the winning and losing of money. Individuals better at cognitively processing these emotional responses tend to have higher scores on the IGT than those who do not adequately process emotions. Individuals with higher IQ have also been found to perform better on the IGT (Demaree et al., 2010).

In the present study, learning hold'em poker in a pure discovery situation may be based in-part on the same processing mechanisms found in learning the IGT. As participants played poker, they had experiences of winning and losing money. These experiences may have triggered emotional responses similar to those felt playing the IGT. Demaree (2013) provides examples of how emotions play a role in hold'em poker. Similar to learning the IGT, the appropriate cognitive processing of these emotional responses may have aided in learning poker. Indeed, much of learning in daily life has a cognitive and emotional processing component.

The finding that intelligence failed to predict guided discovery learning was a surprise. However, the strategies provided may have been too explicit resulting in reduced cognitive processing. The guided instruction participants, may have simply been following directions. For example, the first set of instructions (Time 2) included a hand ranking formula used to calculate the value of the participants pocket cards. As the participant played the game, s/he may have simply computed the hand value and played or folded his/her hand as instructed. Essentially, the participants may have been simply following instructions and not using significant mental activities during the task. If this was the case, a measure of general mental ability (e.g., IQ), may not be a predictor of the outcome. The following of instructions may have also reduced any emotional response to the winning or losing. The participants may have externalized the wins and losses to the perceived value of the instructions. If this was the case, there may have been minimal emotional response due to the participants not taking personal responsibility of the win or loss. There is evidence that individuals who externalize achievement, experience less intense emotions (Phares, 1976). The control-value theory (Pekrun, 2006) posits that achievement emotions are in-part determined by an individual's cognitive appraisal of control. This control appraisal relates to perceived control in various achievement activities (Artino, Holmboe, & Durning, 2012). While the theory's emphasis in perceived control is based on the individual's self-concept, it is possible that the externalizing of the achievement, may also influence achievement emotions.

4.1. Study strengths and limitations

The primary strength in the present study is in the high number of pokers hands the participants played. A goal in assessment is to minimize measurement error to aid in the consistency of the measurement device, in this case hold'em poker. Participants played 720 hands of poker taking approximately a total of 6 h of play. Interestingly, while significant improvement was realized, both groups failed to make money. This may be due in part to the programmed skill levels of the computer players, and the high degree of complexity of hold'em poker. The primary limitation of the present study was in the restricted range of IQ. The average SAT score of the sample was 1318. A score in this range is typically in the 90th percentile.

4.2. Future directions

Future research could explore the predictive abilities of other factors such as emotional intelligence in pure discovery learning of a complex real-world task. Researchers could also explore the predictive ability of IQ on pure discovery learning of other tasks that incorporate cognitive and emotions processing. For example, it would be interesting to see if IQ predicts pure discovery learning of games such as JA Titan, a game that simulates running a business. Finally, researchers could explore the connection and importance of cognitively processing emotional responses during learning situations.

4.3. Conclusion

Pure discovery learning is the act of learning without instruction. The game of hold'em poker is a complex task that resembles real-world actions. The present study provides evidence that IQ predicts pure discovery learning of hold'em poker. In addition when combined with findings from other research (Demaree et al., 2010), the present study suggests that IQ predicts learning of tasks when both cognitive and emotional factors are present. It is possible that for pure discovery learning to be effective, both cognitive and emotional factors need to be present.

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