

**Association of risk proneness in overtaking maneuvers with impaired  
decision making**

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## **Abstract**

Overtaking maneuvers on two-lane rural roads are difficult maneuvers which involve relatively complicated decisions. The main hypothesis tested in this paper is that the frequency of overtaking maneuvers on a driving simulator is associated with a faulty decision making style in the Iowa Gambling Task (IGT), a popular decision task employed for assessing cognitive impulsivity. In a controlled study, 36 participants drove a scenario involving multiple overtaking decisions in an interactive driving simulator (STISIM) and also completed the IGT.

The results show a significant negative correlation of about 0.3 between the IGT performance and the number of overtaking maneuvers, the average driving speed, and the acceleration noise. We also found a positive correlation of 0.5 between IGT performance and the percent of aborted overtaking maneuvers. A cognitive modeling analysis shows that the associations appear to be modulated by weighting of gains compared to losses obtained during repeated play. These results demonstrate that the IGT has a potential to predict risk prone behavior in overtaking maneuvers and in driving in general.

**Keywords:** Decision Making; Driving Simulator; Cognitive Modeling; Overtaking Maneuvers; Two-Lane Highways

## **1. Introduction**

Overtaking maneuvers in rural two-lane highways significantly affect road capacity, safety, and level of service (Polus et al., 2000). This maneuver, which involves driving in the lane of the opposing traffic direction, is associated with an increase in crash risk (Bar-Gera and Shinar, 2005). Self report ratings indicate that most drivers are indeed aware that overtaking is a risky maneuver (Harris, 1988). In this study we examine the sources of individual differences in overtaking maneuvers.

There are multiple factors that lead drivers to take risk on the road. The most conventional view highlights the role of cognitive limitations, specifically lack of driving experience (e.g., Bragg and Finn, 1982; Brown and Groeger, 1988; Hoyos, 1988) and cognitive overload (e.g., Horswill and McKenna, 1999; Recarte and Nunes, 2003). Other approaches suggest that personality factors are also implicated, especially extraversion, defined as taking interest in other people and external events that are not familiar to the person (Lev et al., 2007; Renner and Anderle, 2000; Smith and Kirkham, 1981). Here we focus on the effect of cognitive style on driving behavior. Cognitive style pertains to a constant and pervasive way a person processes different cognitive stimuli. It encompasses the individual's style of thinking, goal-directed behavior, focus of attention, as well as emotional control (Hjelle and Ziegler, 1981). This study examines the potential of a cognitive decision task to predict risk prone behavior among drivers, by assessing their performance on a driving simulator in a scenario involving multiple overtaking decisions on a rural two-lane highway.

In particular, we explore the impact of a faulty decision making style. For this purpose, we use the Iowa Gambling Task (IGT), a complex decision making task that has shown good stability in assessing various kinds of clinical populations (Bechara et

al., 1994; Yechiam et al., 2005). The IGT reflects decisions based on experience and so, may be suitable to capture decision-making processes involved in driving, which also involves repeated choices that have consequences that can be learned.

To assess risk prone behavior in driving, we employ a driving simulator. Various studies have shown that driving simulators can provide reliable observations of drivers' behaviors (Alicandri, 1994; Blana, 1996; Desmond and Matthews, 1997; Ellingrod et al., 1997; Fraser et al., 1994; Van der Winsum, 1996; Van der Winsum and Brouwer, 1997).

The rest of this paper is organized as follow. Section 2 presents the IGT and the driving simulator used here. Section 3 describes the participants, the experiments (IGT and driving scenario) and data collected. The results and analysis are presented in Section 4. Finally, Section 5 includes a discussion of the results with a focus on potential applications for improving the prediction of risk prone driving.

## **2. Experiment tasks**

### **2.1. Iowa Gambling Task**

The Iowa Gambling Task (IGT; Bechara et al., 1994) is a laboratory decision-making task in which participants make a series of 100 choices from four decks of cards with the goal of maximizing their accumulated payoff. Participants do not know in advance which outcomes are associated with each deck. Each card selection from a particular deck leads to monetary gains, but it may also lead to losses. Two of the decks are *disadvantageous* in that they yield relatively high positive payoffs but at a cost of occasional large losses. These large losses lead to an expected net loss. Good performance is achieved by avoiding these decks, and selecting cards from the other two

decks. These *advantageous* decks lead to an expected net win using lower positive payoffs, but also lower occasional losses (See Table 1).

Performance on the IGT is a reflection of a rich mixture of psychological processes that may vary across individuals. Disadvantageous choices can result from several component processes (Busemeyer and Stout, 2002), such as the tendency to weigh gains more than losses, a tendency to focus on recent outcomes and ignore or rapidly discount past outcomes, including past losses and low choice consistency (i.e. choices made randomly and erratically). These components can be quantified using a cognitive model, the Expectancy Valence (EV) model (Busemeyer and Stout, 2002; Yechiam et al., 2005; Yechiam and Ert, 2007), which is a learning model applied to predict the next choice ahead in each trial. The model has three parameters, each corresponding to one of the psychological components described above: (1) Weight of gains compared to losses, (2) Weight of recent outcomes compared to past outcomes, and (3) The degree of choice consistency. See Appendix for the mathematical details of the model.

Applying the EV model to several datasets of clinical populations who performed worse than controls on the IGT enabled to differentiate various clinical and sub-clinical groups (for a review, see Yechiam et al., 2005; in press). For example, chronic abuse of different substances was associated with different profiles: Cocaine abuse was associated with overweighting of gains compared to losses (Stout et al., 2004) whereas cannabis abuse was associated with overweighting of recent compared to past outcomes (Yechiam et al., 2005).

A single previous study conducted by Lev et al. (2007) focused primarily on risky drivers. Its purpose was to examine differences in decision making and personality

between traffic offenders who were penalized for their high-risk driving behavior and non-offenders. 51 traffic offenders who participated in corrective driving courses were compared to a control group of 36 drivers who were not penalized for traffic offences in the 5 years prior to the study. It was shown that penalized traffic offenders made less advantageous choices compared to the controls in a computerized version of the IGT. Furthermore, this pattern did not diminish with task experience. Analyzing the behavioral performance with the Expectancy Valence (EV) model revealed that, as expected, traffic offenders gave more weight to gains compared to losses, relative to controls. However, while this study sheds light on potential differences between traffic offenders and non-offenders it suffers from the problem of most studies of criminal populations, as it necessarily confounds the likelihood of the offence with the likelihood of the offender being . The current study complements Lev et al.'s (2007) study by focusing on a general population sample and using a driving simulator to directly assess risk proneness in driving behavior.

## 2.2. Driving simulator

There are multiple advantages for using simulators in driving behavior research (Kaptein et al, 1996). Simulators enable the investigation of effects of nonexistent road elements and road situations (including risky situations). Specifically, drivers can be repeatedly confronted with events that infrequently occur in reality, and the presentation of these events can be in a way that allows experimental control, such as having the exact same scenario for each participant. Leung and Starmer (2005) for example, assessed how age, combined with a modest dose of alcohol influenced performance on a driving simulator. The driving tasks included detecting the presence of a vehicle on the

horizon as quickly as possible, estimating the point on the road that an approaching vehicle would pass by (time-to-collision), and overtaking another vehicle against a steady stream of oncoming traffic. Bar-Gera and Shinar (2005) utilized a driving simulator to investigate the speed differential threshold at which drivers decide to pass a lead vehicle. Gray and Regan (2005) investigated the control strategies and decision making of drivers who were executing overtaking maneuvers. These studies found that drivers were frequently inaccurate in deciding whether it was safe to overtake.

The STISIM driving simulator (Rosenthal, 1999) was utilized for this study. STISIM is a personal computer-based interactive driving simulator. The fixed-base driving simulator has a 60° horizontal and 40° vertical display of a simulated driving scene projected onto a wall 3.5 m in front of the driver using a Barco (NEC VT670) projector. The image was continually updated at a rate of 30 frames per second.

### **3. Experiment**

#### **3.1. Participants**

36 (25 males, 11 females) who owned a driving license for at least 5 years and drove on a regular basis participated in the study. The age of the participants ranged between 22 and 62 (mean= 32.6; STDEV= 8.2). All participants were students or employees at the Technion – Israel Institute of Technology who responded to an advertisement of the experiment.

#### **3.2. Experiment and data collection**

The study consisted of two laboratory tasks: IGT and driving simulator. In addition we administered a demographic checklist in which we collected information

regarding gender, age, marital status, socio-economic parameters, and involvement in crashes in the past<sup>(1)</sup>.

In the simulator experiment participants were asked to drive a 9.5 km two-lane rural road with no intersections (see Figure 1). The road was relatively flat with a few curves. Daytime and good weather conditions, which allow good visibility, were adopted in this scenario. The average travel time needed to pass this road section was 8.5 minutes. Following earlier studies using driving simulators (e.g. Bar-Gera and Shinar, 2005; Gray and Regan, 2005; Yan et al. 2007), each participant was given between 5 and 10 minutes to become familiar with the simulator. Drivers were instructed to arrive as they would in the real world.

In the simulation scenario, all vehicles going in the same direction as the participant were traveling at 60 km/hr, whereas the posted speed limit was 90 km/hr. All vehicles going in the opposite direction were traveling at 70 km/hr. Paved lane and shoulder widths of the road section were 3.75 m. and 1.5 m., respectively. Headways between vehicles in the opposing direction were drawn from a truncated negative exponential distribution with a mean of 15 seconds. The headway distributions, as well as other variables selected for the experiments, were based on values obtained for typical two-lane highways in Israel.

The simulator collected data on the longitudinal and lateral position, speed and acceleration of the subject vehicle and all other vehicles in the scenario at a resolution of 0.1 seconds. From this information, other variables of interest, such as the times and

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<sup>1</sup> The average frequency of accidents in the past 5 years in our sample was 1.8. There was no association between this variable and any of the other experimental variables. This is considered to be due to the fact that accident occurrence is rare and therefore is also a function of time on the road (Garber and Wu, 2001; Mayora and Rubio, 2003).

location of overtaking maneuvers, distances between vehicles and relative speeds were calculated. The acceleration noise of the subject vehicle was also calculated. The acceleration noise is defined by the standard deviation of the acceleration the driver applies over time. It is often used as an indicator to the driving smoothness (Leutzbach, 1988).

An overtaking was identified when the vehicle crossed the broken line separating the lanes, and the number of the leading vehicle changed (increased by 1). Overtaking gaps are the time headways between two consecutive vehicles in the opposing lane. An aborted overtaking was also defined. Aborted overtaking maneuvers were identified in the simulation whenever the number of the lead vehicle after the vehicle reverted to its original lane remained as it was before the vehicle began the overtaking. To ensure that the aborted maneuver was not due to other reasons, such as poor vehicle control, only maneuvers that were made while the distance from the lead vehicle was less than 30 meters (~1.8 seconds headway) were included. This value was chosen based on results reported by Hegeman et al. (2004) who found that the distances between overtaking vehicles and the vehicles in front at the start of the overtaking maneuver is distributed with mean 17.8m and standard deviation 9.8m and that in 92% of the overtaking maneuvers this distance was less than 30 m.

After performing the driving experiment, each participant completed the IGT. In the IGT, the participant sees four decks of cards labeled A, B, C, and D displayed horizontally and 'face down' on a monitor controlled by a desktop computer (see Figure 2 for a display example). Using a mouse, the participant can select a card from any of the four decks. Upon selecting a card the participants received gains and losses (see Table 1), which were displayed on the cards. Additionally, two tally bars at the bottom

of the display (see Figure 2), revealed the cumulative net win/loss (top), and the 2000 credit received at the beginning of the task (bottom). The minimum inter-trial interval was set to 0.5 seconds. The total number of trials in the experiment was set to 100. Each deck of cards was programmed to have 60 cards but unlike the original task (in which a deck would be removed on the 60th selection) after 60 selection from a deck, it was restarted (Bechara et al., 1994). Participants were told that some decks are worse than others, and that they should avoid those decks to win money. They were not given any information about the expected payoffs and proportions of gains and losses.

In the IGT experiment, the number of advantageous and disadvantageous choices was recorded. Further analysis of the results was conducted using the revised Expectancy Valence (rEV) model. This model has been described previously (e.g., Busemeyer and Stout, 2002; Yechiam, Busemeyer, et al., 2005; Yechiam and Ert, 2007), and it is summarized briefly in the Appendix<sup>2</sup>. Modeling proceeds as follows. The cognitive model parameters are fit to the card by card selection data from each individual decision maker (see the Appendix). The index of model fit is  $G^2$ , which is a model fit statistic analogous to the chi-square ( $= 2 \times \log$  likelihood difference). In addition to assessing the fit statistics, the model equations are solved to generate values for the model's three parameters (impact of rewards and punishments, weight of recent and past payoffs, and choice consistency) for each participant.

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<sup>2</sup> The only difference between the rEV model (Yechiam & Ert, 2007; Yechiam, 2007) and the original EV model (Busemeyer and Stout, 2002) is that in the original model choice consistency is assumed to change with time, whereas in the rEV it is assumed to be constant. This was shown to increase model accuracy and reliability (Yechiam, 2007). The model can be downloaded from <http://tx.technion.ac.il/~yeldad/papers.html>

The IGT took about 15 minutes to complete, on average; and the driving simulator scenario likewise took about 15 minutes to complete. The duration of the entire laboratory experiment was about 30 minutes.

## **4. Results & analysis**

### *4.1. Driving simulator variables*

We first examined the correlation between the driving simulator variables (see Table 2). Several of the overtaking-related measures were highly associated. First, there were positive associations between the overall number of overtaking passes, the driving speed, and the acceleration noise (consistent with Bar-Gera and Shinar, 2005). A second interesting finding is that the percent of aborted passes was negatively associated with these three variables, denoting the fact that drivers who were more likely to abort an overtaking maneuver also drove more slowly ( $r = -0.54$ ) and completed less overtaking maneuvers ( $r = -0.57$ ).

### *4.2. Decision making and driving behavior*

We proceeded to compare the results obtained from the driving simulator with the results from IGT. A learning curve for the IGT performance is presented in Figure 3, which shows 5 blocks of 20 choices each. The figure shows that participants learned from their experience to prefer the advantageous decks. This replicates patterns previously observed in the Iowa Gambling Task (e.g., Bechara et al., 1994). Pearson correlations between the proportion of disadvantageous deck selections and the simulator variables are also presented in Table 2. The results show that the proportion of disadvantageous deck selections was negatively correlated with the percent of aborted

overtaking maneuvers ( $r = -0.43$ ) and positively correlated with the average driving speed ( $r = 0.34$ ).

To better understand the reasons underlying these correlations we analyzed the results with the rEV model. Table 3 presents summary statistics of the estimated expectancy valence model parameters. The results show that the fit of the model was adequate (a positive  $G^2$  average of 20.66 denoting an advantage of the rEV over the baseline model).

The correlation of these parameters, reported in Table 2 show that the only parameter that had a significant correlation with all simulator variables was the weighing parameter of gains compared to losses, while recency and consistency had no significant relationship with any of the driving simulator variables. Specifically, the weight to gains parameter was negatively associated with the percent of aborted overtaking maneuvers ( $r = -0.47$ ) and positively with the average speed while driving ( $r = 0.30$ ). Surprisingly, this parameter was also associated with the overall number of overtaking maneuvers ( $r = 0.34$ ) and with the acceleration noise ( $r = 0.31$ ). Thus, the model parameter was to some extent more predictive than the mere percent of poor choices in the task.

Examination of the correlation between the participants' age and their driving performance in the simulator reveals that the number of overtaking maneuvers parameter was significantly and negatively correlated with age ( $-0.34$ ), indicating that younger drivers performed more overtaking maneuvers than older drivers. However, no significant correlations were found between age and any of the decision task parameters (see Table 2). The association between the model parameters and driving behavior does not change substantially when controlled for age using partial correlation analysis (for

conciseness the results are not reported). Therefore, age does not seem to be a mediating variable.

In order to correct for the unequal gender distribution we replicated the analysis while controlling for gender. The results were consistent with those in Table 2. In addition, we plotted the relationship between the weight to gains parameter and the number of overtaking maneuvers and average driving speed (Figure 4 and Figure 5). Although a statistical analysis of linearity is not included due to the small sample size, the results are indicative of a linear relationship between the weight to gain parameter and the two simulation parameters. The figures also demonstrate that the effect is not influenced by the participants' gender distribution.

## **5. Discussion, conclusions and further research**

Our findings show that the frequency of overtaking maneuvers on a driving simulator is associated with a faulty decision making style in the IGT. Drivers that made more overtaking maneuvers in a driving simulator were shown to also make less advantageous choices in the IGT. These drivers also drove faster, had higher acceleration noise, and had fewer aborted overtaking maneuvers.

Analyzing the behavioral performance with the rEV model revealed that drivers who made more overtaking maneuvers were characterized by the tendency to weigh gains more than losses. This weighting component, amongst the three components that were quantified using the rEV model, was the only component significantly correlated with drivers' performance on the simulator task. This result supports the prediction that there is a consistent difference in the cognitive style of drivers who are more risk prone,

as indicated by the fact that these drivers had a distinct pattern of decision making in a task that is very different from driving.

Previous studies (Bar-Gera and Shinar, 2005; Polus et al., 2000) found that overtaking maneuvers are associated with an increase in the risk of a crash. Crash risk and severity have also been shown to increase with higher average driving speeds and higher speed variability (Nilsson, 1987; Garber and Gadiraju, 1988; Garber and Ehrhart, 2000; Solomon, 1964). Therefore, it can be concluded that drivers who gave more weight to gains in the IGT are more risk prone.

One limitation of the current study is the small number of participants and the unequal gender distribution. However, the partial correlations between performance on the IGT and the driving variables indicated that the associations cannot be attributed to gender or age differences.

The results of the current paper shed optimistic light on the applicability of the IGT and other cognitive decision tasks to the study of risky behavior in healthy, high functioning drivers. For example, the IGT can be used to identify risk prone drivers, especially those who intend to become professional drivers (taxi, bus, truck drivers, etc.).

Moreover, given that there is a correlation between the results of the IGT and the results of the simulator; the IGT can be used to evaluate whether risk prone driving behavior on the driving simulator is due to cognitive impairments or motor impairments. A challenging avenue for future research is to understand how to combine cognitive decisions tasks such as the IGT and driving simulators, in order to improve the prediction of risky driving behaviors.

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## Appendix: Detailed description of the Expectancy Valence model

The revised Expectancy Valence model has three components:

1) The impact of gains and losses is assessed by the weight gains/losses parameter. The evaluation of the gains and losses experienced after making a choice is called a valence. The valence is denoted  $u(t)$ , and is calculated as a weighted average of gains and losses from the chosen deck in trial  $t$ .

$$(Eq. A.1) \quad u(t) = w \cdot win(t) - (1 - w) \cdot loss(t)$$

Where  $win(t)$  is the amount of money won on trial  $t$ ;  $loss(t)$  is the amount of money lost on trial  $t$ ; and  $w$  is the weight parameter that indicates the subjective importance of gains versus losses ( $0 \leq w \leq 1$ ). In the task used here, giving high weight to gains can lead to more choices from the disadvantageous decks, which produce larger gains.

2) Influence of recent vs. past outcomes is measured by the recency parameter. The valences produced by a deck  $j$  are summarized by an accumulated subjective value for each deck, called an expectancy, and denoted  $E_j(t)$ . A Delta learning rule is used for updating the expectancy after each choice:

$$(Eq. A.2) \quad E_j(t) = E_j(t-1) + \phi \cdot [u(t) - E_j(t-1)]$$

Where  $j$  is the selected deck. The recency parameter,  $\phi$ , describes the degree to which expectations about deck consequences reflect the influence of the most recent outcomes or more distant past experience ( $0 \leq \phi \leq 1$ ). In the task used here, high recency can result in disadvantageous choices due to discounting or forgetting of infrequent negative outcomes.

3) Sensitivity of responses to expectancies is measured by the choice consistency parameter. The probability of choosing a deck is calculated as a strength ratio of that deck relative to the sum of the strengths of all decks (using Luce's rule):

$$(Eq. A.3) \quad \Pr[G_j(t+1)] = \frac{e^{\theta \cdot E_j(t)}}{\sum_j e^{\theta \cdot E_j(t)}}$$

Where  $\Pr [G_j(t)]$  is defined as the probability that deck  $j$  will be selected on trial  $t$  by the model. The term  $\theta(t)$  controls the consistency of the choice probabilities and the expectancies, where:  $\theta(t) = 5^c - 1$  and  $c$  is the choice consistency parameter ( $0 \leq c \leq 10$ ). When the value of the parameter  $c$  is very high, the deck with maximum expectancy will almost certainly be chosen on each trial. When the value of  $c$  is low, choices are inconsistent and more random.

The Bernoulli baseline model:

In addition to the learning models presented above, a baseline statistical model was employed. The baseline model assumes that choices are generated by a statistical Bernoulli process. That is, the choice probabilities for each deck are assumed to be constant and statistically independent across trials.

## List of tables and figures

### Tables

Table 1: The payoffs for the IGT version used in the present experiment.

Table 2: Pearson correlations between simulator and IGT results.

Table 3: Summary statistics for the calibrated expectancy valence model parameters.

### Figures

Fig. 1. Snapshot of the STISIM driving simulator scenario.

Fig. 2. Screen example from the Iowa Gambling Task.

Fig. 3. Learning curve.

Fig. 4. Relationship between number of overtaking maneuvers and weight to gains.

Fig. 5. Relationship between average speed (m/sec) and weight to gains.

Table 1

The payoffs for the IGT version used in the present experiment.

Deck	Wins	Losses	Type
A	100 for sure	0.5 to lose 250	Disadvantageous
B	100 for sure	0.1 to lose 1250	Disadvantageous
C	50 for sure	0.5 to lose 50	Advantageous
D	50 for sure	0.1 to lose 250	Advantageous

Table 2

Pearson correlations between simulator and IGT results.

Variable	1.	2.	3.	4.	5.	6.	7.	8.	
1. Age	-								
Simulator variables	2. Number of Overtaking Maneuvers	-0.31+	-						
	3. Average driving speed (m/sec)	-0.27	0.96**	-					
	4. % Aborted Overtaking Maneuvers	-0.24	-0.57**	-0.54**	-				
	5. Acceleration Noise (m/sec <sup>2</sup> )	-0.21	0.80*	0.74**	-0.43*				
Decision variables	6. Disadvantageous Decks Chosen	0.0	0.34+	0.34*	-0.46**	0.43*	-		
	7. Weight to Gains	0.01	0.34*	0.34*	-0.47**	0.31+	0.45*	-	
	8. Recency	0.13	-0.26	-0.18	0.23	-0.29+	-0.25	-0.57**	-
	9. Choice Consistency	-0.07	0.14	0.13	-0.06	0.04	0.08	0.21	-0.57**

\*\* =  $p < .01$ ; \* =  $p < .05$ ; + =  $p < .1$

Table 3

Summary statistics for the calibrated expectancy valence model parameters.

	Parameter a (Recency)	Parameter b1 (Weight to Gains)	Parameter c (Consistency)	Model Fit ( $G^2$ )
Min	0.000	0.000	0.084	-10.994
Max	1.000	0.844	10.000	145.037
Median	0.029	0.632	1.876	10.757
Average	0.272	0.458	3.891	20.659
STDEV	0.430	0.234	3.720	31.825



Fig. 1. Snapshot of the STISIM driving simulator scenario.

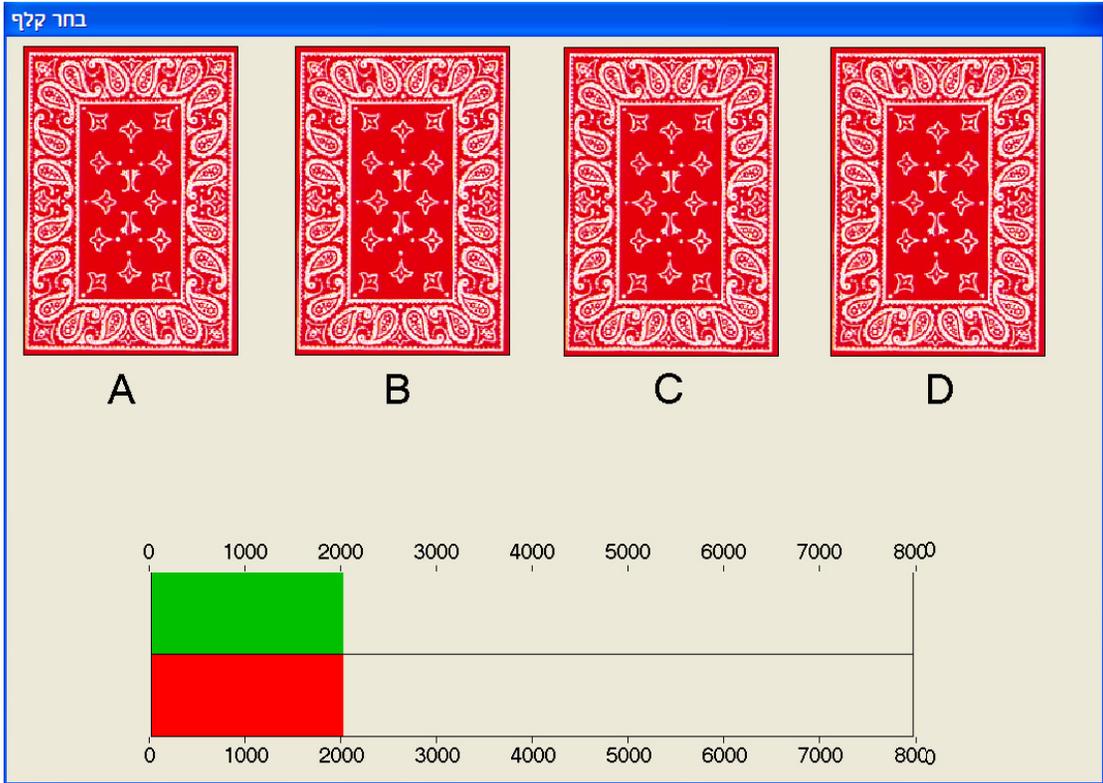


Fig. 2. Screen example from the Iowa Gambling Task.

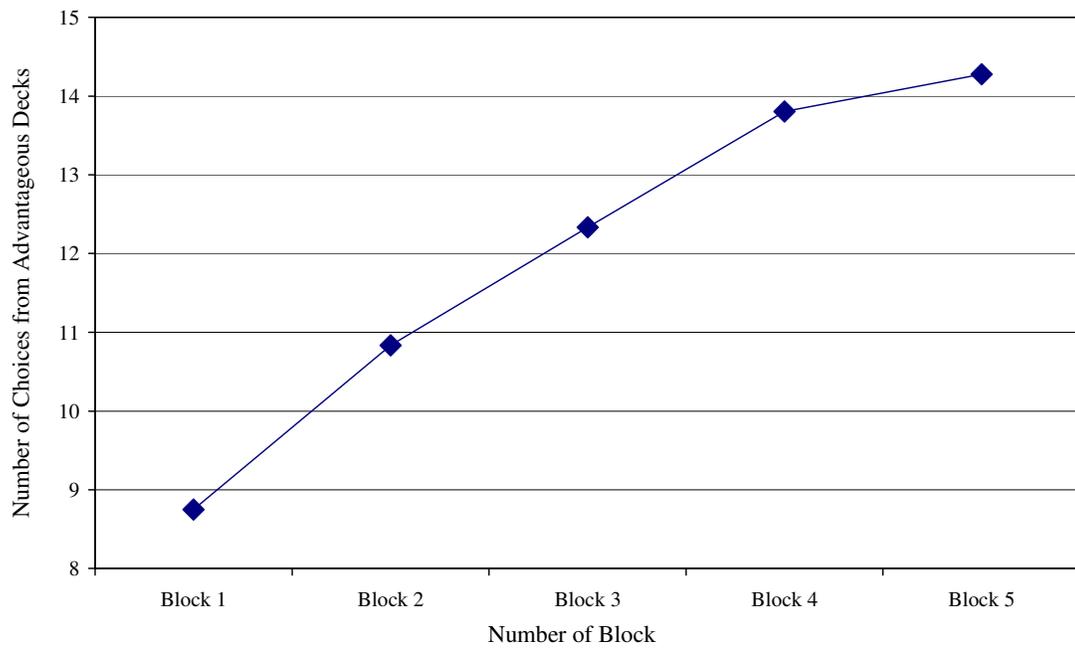


Fig. 3. Learning curve.

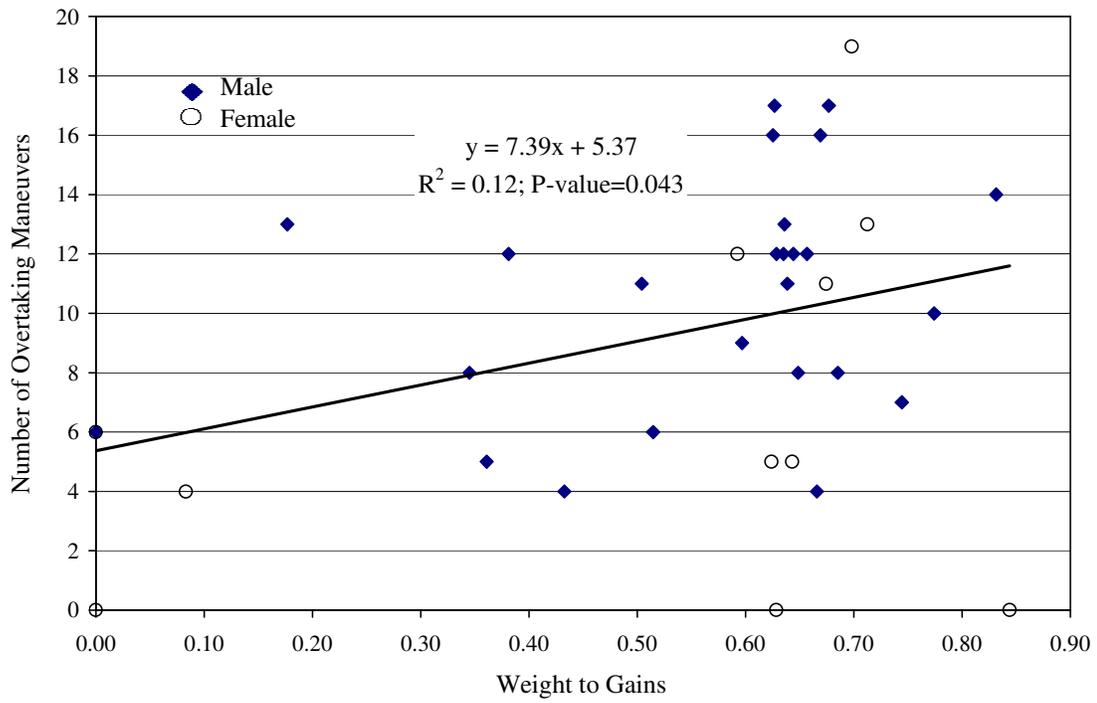


Fig. 4. Relationship between number of overtaking maneuvers and weight to gains.

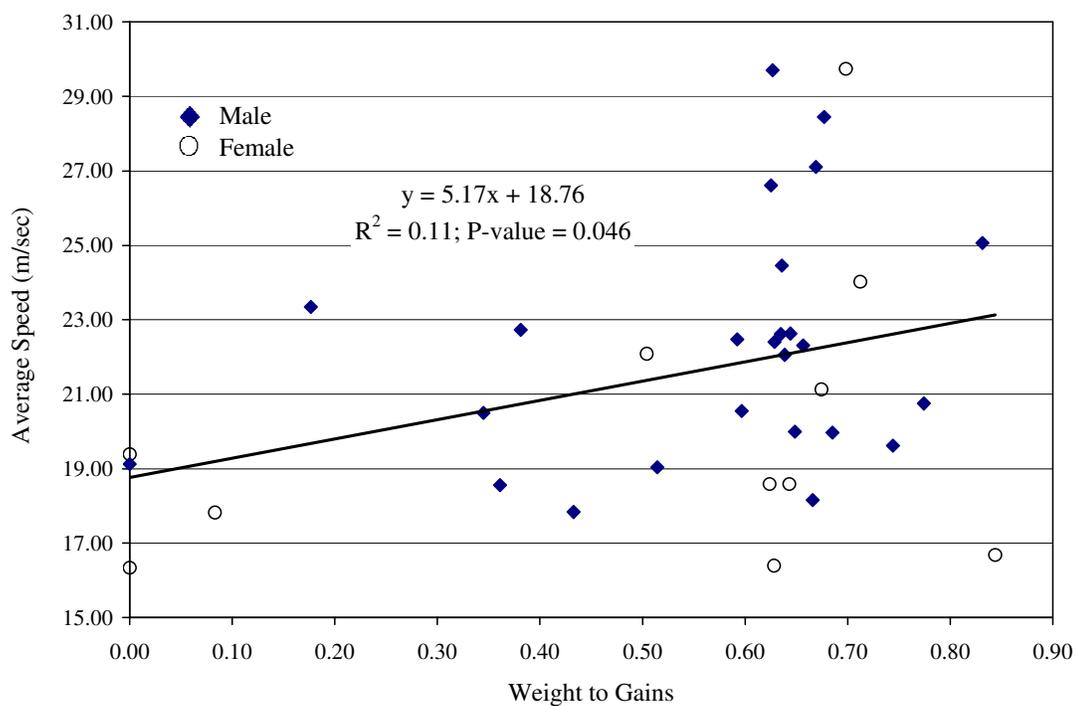


Fig. 5. Relationship between average speed (m/sec) and weight to gains.