RUNNING HEAD: Reading the Others' Mind

Meta-perception: How Does Successful Competition Work?

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ABSTRACT

Life is surrounded with situations that involve all sorts of competition. Think about the number of people all over the world that play poker on the Internet and how much money is involved in this. We wonder what determines success in this kind of competition. We propose an influence of (meta)perception: How accurately do you know how the other person thinks about you? This is called meta-perception accuracy and it is known to be a very important ability to navigate oneself in the complex social world. It is known that those who are good at identifying what the other person thinks about him/herself are also good at cheating and exploiting others. We expected to replicate and expand the findings of Burns and Vollmeyer, 1998, who found that those who have high meta-perception accuracy can successfully exploit other people and as a result will be succesful in the one-sum game the participants played in our experiment. However, we found some contradictory results and were not able to replicate these findings, which proves the effect of meta-perception on performance not to be so robust after all.

Keywords: Modeling, adversarial problem solving, competition

Introduction

It was about 1200 years before Christ when the Spartans won their famous war of Troy from the Trojans. A giant hollow wooden horse was given to the Trojans with the inscription:

'The Greeks dedicate this thank-offering to Athena for their return home.'

Believing the war was over; the Trojans dragged the horse inside the city and turned to a night of mad revelry and celebration. In the morning the Spartans entered the city and killed the sleeping population. In this war, a few things were done wrong by the Trojans which were done right by Spartans. The Spartans made an accurate prediction of what the Trojans would think of their behaviour, of how the Trojans would act if they pretended to surrender. They deceived the Trojans successfully and won the war. This exactly is what this paper is all about: competition. In competition one must anticipate, understand and counteract the actions of an opponent. Military strategy, business and game playing all require an agent to construct a model of an opponent that includes het opponent's model of the agent. The cognitive mechanisms required include deduction, analogy, inductive generalization, and the formation and evaluation of explanatory hypotheses (Thagard, 1992). As the story about the Trojan War shows, a strategy often used in competition is deception. Deception implies that an agent acts or speaks so as to induce a false belief in a target or victim (Hymans, 1989). Deception includes imposture, confidence games, practical jokes, forgery, consumer and health fraud, white lies, plays in games and sports, gambling scams, military and strategic deception, psychic hoaxes and many more. These are all examples of everyday events. As you can see our lives are surrounded by different fashions of competition.

Substantial research has been done on this subject. Prisoner's Dilemma game and Game theory are being used in almost all competition-related research. However the focus of this research was: *Why* do people compete or *when* do people compete. Rarely has been investigated: *How* people compete, or what kind of behavior is most successful when trying to maximize your outcome in a game, business deal or war. It has been assumed that success in competition is simply a product of the attributes of the competitors, rather than being a social phenomenon itself (Burns & Vollmeyer, 1998). In this paper competition will be labelled Adversarial Problem Solving (APS). We propose there are components that forecast the level of success in APS, to our understanding the most important one is: Modeling. Modeling is forming a mental model through interpersonal perception. The thing that enables people to model other people is the Theory of mind. Theory of mind separates us from all other species by giving us the ability to attribute mental states, beliefs, intents, desires, pretending, knowledge to ourselves and to others and to understand that others have beliefs, desires and intentions that are different from one's own. This understanding of the other person's mental states can be used to explain and predict others' behaviour. Theory of mind enables us to use the fact that mental states can be the cause of others' behaviour and adapt our own behaviour towards getting closer to our goals. (Premack & Woodruff, 1987). Thagard (1992) believes that it is the ability to model your opponent's behavior and further to model how the opponent models you is what will lead to successful behavior.

> *If you know the enemy and know yourself, you need not fear the result of a hundred battles. If you know yourself but not the enemy, for every victory gained you will suffer a defeat. if you know neither yourself nor your enemy, you will succumb in every battle (Sun tzu, 1983, from Thagard,1992)*

Thagard (1992) proposed to demonstrate the cognitive processes necessary for successful opponent modeling. The work explored three levels of modeling an adversary. At level one, a person has self-insight "What is my strategy" (direct perspective). At the second level, a person thinks about what the other person wants (R2MA, meta-perspective). At level three, a person thinks about how we believe the other person is modeling us (R3MA, meta-

meta-perspective). Thagards' most important contribution from the current perspective would be his discussion of recursion in deception. Thagard (1992) defined recursive modeling (RM) as the ability to place oneself in the mindset of one's opponent. Thagard suggested that depth two (R2MA, meta-perspective) held special importance in success against an adversary, since this is where deception would take place. I would need to understand what an adversary thought of my strategy in order or influence or manipulate that belief. It is in this article that Thagard suggests that second-order modeling is critical for successful competition. Merely in the article of Burns and Vollmeyer (1998) was found that third-order modeling was the determinative factor for being a successful player. In this paper meta-meta-perspective (what does my opponent think about me) is most predictive for success. Another paper written by MacInnes (2004), using a number of intelligent algorithms failed to show a benefit of RM, direct perspective (what's my strategy) was found to be optimal in most conditions.

In this paper we will try to find out if recursive modeling has predictive power, and if so, which component has the strongest predictive power of success. When is second-order modeling useful for successful deception and when is third-order modeling the critical factor? How should people act to compete successfully? Intuitively it makes perfect sense that modeling has an influence on success in competition. For this reason, more research is necessary. One important difficulty in research concerning APS is that tasks are often too complex. Holding (1989) for example pointed out that taking an opponent into account could increase search space of problem states enormously. Also we want to be sure people do compete with each other, because of this we cannot use Game theory or Prisoners dilemma. We use a purely adversarial game: zero-sum-game. In zero-sum games the total benefit to all players in the game, for every combination of strategies, always adds to zero, more informally; a player benefits only at the equal expense of others. Poker exemplifies a zero-sum game, because one wins exactly the amount one's opponents lose. In this zero-sum-game, which is played for many rounds, there are two players: a chooser and an avoider. Both of them have to choose a number one, two or three. In case the two of them have chosen the same number, the chooser wins the game. However if chooser and avoider have chosen a different number, the avoider wins the game. What the players deserve depends on the pay-off matrix.

Insert table one here

For the chooser it is possible to earn three points, while the avoider can only win one point max. To off-set this, the avoider is expected to win more trials than the chooser. As you can see for both of the players it is important to try to forecast the behavior of the other player. On the other hand, their own behavior should be unpredictable, so they can exploit the other player.

Strategy The only real goal in zero-sum games is winning over your opponent. It is not about playing a good game, you just need to play better than you opponent. For achieving this, you need a game-play strategy. Because we want to determine the most rational strategy, game theory is used. Game theory is an essentially descriptive theory as it seeks to analyze a state of affairs that exists or to predict future equilibrium state. Thus game theory can only predict the equilibrium point the players tend toward (Neumann and Morgenstern,1944). For this reason game theory is useful as a tool for analyzing what should happen in our game. Game theory predicts; when no single selection is always best, mixed strategy should be used. Mixed strategy is like randomization; it says that in every following round a different alternative should be chosen. The preceding round should have no effect on your choice; this makes your behavior unpredictable. Game theory analysis suggests a source of success that does not involve modeling the opponent. If this would be true the most successful strategy depends on the behavior of your opponent. However as Rapoport and Orwant, 1962 pointed out, the calculation that must be done to find out what's best is complicated. The concept of mixed strategy is sophisticated; perhaps this is why literature is inconsistent. For example Colman (1982) argues that people do not have a tendency to use mixed-strategy equilibrium. Though Rapoport, Kahan & Stein, (1976) did find some evidence for people using mixed-strategy. We do not believe many people will display mixed-strategy. It is hard for participants to keep up their unpredictable play throughout the whole game. And even if they can calculate that mixed-strategy is most rational, will participant be able to ignore their opponents' play totally? We believe that participants will be most successful when they make an accurate model of themselves and their opponent. The better they do this, the more successful they will be in exploiting their opponent and win the zero-sum game.

Measuring meta-perception (modeling) To assess participants' mental model of each other, we need to think about what important information for the game is. We believe participants should be able to accurately assess some characteristics of the personality of their opponents. To assess this, the participants fill out questionnaires about their own and their opponents' characteristics. The characteristics are being assessed on a 6-point Likert scale and are for the greater part based on the characteristics used in Burns and Vollmeyers' study (1998). Because we need to differentiate between the three levels of modeling the participants fill out this questionnaire three times. First for measuring themselves, self-scale representing direct perspective. Second is for measuring the opponent, the opponent-scale representing meta-perspective (second-order). And the third questionnaire is for measuring how people think their opponent would rate them, the opponent-self scale representing meta-meta-perspective (third-order). Our research focuses on the influence of second and third order models; they are respectively called original second order modeling (R2MA), third order modeling (R3MA) and new second order modeling (R2DMA).

Our research

The first aim of our research is to replicate the findings of Burns and Vollmeyer (1998). In this study the zero-sum game is played, two players are participating; a chooser and an avoider. Second-order (R2MA, meta-perspective) modeling and third-order (R3MA, meta-meta perspective) are measured three-times throughout the game, in the beginning, halfway and at the end of the game. Measures of this modeling will be carried out as described in the method section. In our research a new variable also representing second order modeling is added; new second order modeling; R2DMA; second order modeling calculated in a different way, which will be explained in the method section. We differentiate between these two sorts of second order modeling by calling R2MA: original second order modeling and R2DMA: new second order modeling. still, both variables represent basically the same. In the game the participants played in Burns and Vollmeyers' study, 1998, the whole pay-off matrix was available for the two participants. They had full information about how many points they and their opponent earned in every situation. This is exactly the game we are going to play in the first condition of our study. We hope to find that in this situation that third order modeling (R3MA) will be most predictive of success in the zero-sum game, while second order modeling (R2MA, R2DMA) will not be predictors of successful playing

First hypothesis When both participants have full information, third order modeling (R3MA) will have a positive relation with performance. Second order modeling (R2MA, R2DMA) will have no relation with performance.

In the second part of the study we play again the zero-sum game with two players; a chooser and an avoider. Second order modeling and third order modeling will be measured as often and at the same fashion as in the first condition. We do change some settings of the experiment. As opposed to full information for both players in the first experiment, in the second experiment only choosers have full information of the pay-off for both players. Choosers receive a full pay-off matrix, while avoiders only receive a partial pay-off matrix, they will not know how many points their opponent earns; they have only knowledge about their own points. As a result of this different knowledge-structure participant will probably use another strategy than in the first study. There is still no convincing evidence about which strategy is being used most often or is most successful. We believe that in the situation as described above only avoiders will change their strategy; avoiders know that choosers do not know about their pay-off, so choosers cannot act on that information, this makes third-order modeling (R3MA) useless. As a result, the best strategy for choosers is second-order modeling (R2MA, R2DMA). Choosers will still be able to use third order modeling (R3MA).

Second hypothesis When only avoiders have full information, we expect to find a positive relation between choosers' third order modeling (R3MA) and choosers' performance. For avoiders, we expect a positive relation between avoiders' second-order modeling (R2MA, R2DMA) and avoiders' performance.

In the third part of the study we again play the zero-sum game with two players; a chooser and an avoider. R2MA and R3MA will be measured as often and at the same fashion as in the first and the second condition. We again change some settings of the experiment. In this condition only avoiders will have full information of the pay-off for both players. Avoiders receives a full pay-off matrix, while choosers only receive a partial pay-off matrix, they will not know how many points their opponent earns, they have only knowledge about their own points. We believe that in the situation as described above only choosers will change their strategy; choosers know that avoiders do not know about their pay-off, so avoiders cannot act on that information, this makes R3MA (third-order modeling) useless. As a result, the best strategy for choosers is R2MA (second-order modeling). Avoiders will still be able to use R3MA.

Third hypothesis When only choosers have full information, we expect to find a positive relation between avoiders' third order modeling (R3MA) and avoiders' performance.

For choosers, we expect a positive relation between choosers' second-order modeling (R2MA, R2DMA) and choosers' performance.

Method

Participants Seventy-one pairs or 142 students (28 male and 114 female) from the University of Tilburg, the Netherlands participated in the experiment. Ages of the participants were amongst 17 and 36. We tried to make same-sex-couples in order to exclude gender influences. In exchange for their cooperation students received partial course credit and money dependant on their success during the game in the experiment. Before the experiment started they were asked if they knew each other, if this was the case, they were placed in different pairs. Six pairs were excluded from the analyses because they were not able to finish the experiment due to an error in the computer program.

Procedure Participants entered the lab and were asked if they knew each other, based on this they were placed in couples and were given the general instruction of the experiment. When everything was clear the couple started solving a puzzle for ten minutes. None of the couples finished this puzzle. Aim of this interaction time was to give the couples some familiarity with their opponent. Then the participants were brought to a computer for the second part of the experiment. The participants were separated to make sure they were not able to interact with their opponent during the game. Once they were seated, the instruction of the game was given to them. These included the payoff matrix shown in Table 2.

Insert Table 2 here

All three conditions were explained in the instruction, so participants knew it was possible that they or their opponent might not see the whole matrix during the game. Participants did not know about the assigned roles (chooser or avoider, randomly assigned). To prepare the participant as thoroughly as possible, an explanation of the screen in the game was explained on a separate sheet. This sheet can be found in appendix one. Participants were told that their pay-off at the end of the game was depending on their success in the game they were about to play. The experimenters emphasized this to assure the participants were highly involved in the game. Once each participant understood the task, the computerprogramme was started by the experimenters. The participants were given the self, opponent, opponent-self and opponent-opponent scales to complete. Each scale consisted of the same 14 items, and each item consisted of a pair of words that anchored the ends of a 7-point scale. The first 10 pairs were chosen from the 20 given in Burns (1998) because in that study they were found to have the 10 highest correlations (although not significant) between score in the game and relative third-order modeling accuracy. The first ten evaluation factors were: *Humorous-Serious;, negative-positive; hard-soft; foolish-wise; weak-strong; pessimistic-optimistic; severe-lenient; cruel-kind; rational- intuitive; risk taking-risk avoiding.*

The last 4 pairs were added to make the impression scale more complete, the last four evaluation factors were already used in a study of Ohtsubo et all, in press. They were: *Unfriendly-friendly; sociable-unsociable; responsible- irresponsible; highly motivated-unmotivated.* After completing the four scales, participants played the game for 30 trials and then filled out all four scales again. We did this to see if the participants changed their opinions about themselves or their opponent as a result of the behavior during the first 30 trials. After 30 more trials, they filled out the four scales a third time to see if any opinions changed because of behavior during last 30 trials. Players had as much time as they liked on each trial to select a number. Once each player had made a selection, they were informed of the opponent's selection. Different to the study of Burns & Vollmeyer, (1998) we did not give the participants the opportunity to keep track of their and their opponent's selections. Thus, the participant did not have access to the history of selections, but had to remind all the choices and outcomes by head.

To avoid end-game strategies, we did not tell participants how many trials the game lasted. After the second 30 trials, they were told that the game was over and the participants were asked to fill out an end-questionnaire. This end-questionnaire ought to check up on the empathy quotient (EQ). The EQ-questionnaire we use was formed by Baron-Cohen et al, (2003). This empathy quotient indicates how capable participants are in using theory of mind, the ability to reason about the thoughts and feeling of themselves or others. After the participants finished the end-questionnaire they were asked to come to the desk of the experimenters, they had to sign to get their course-credit and for the money they were about to receive. Participants that had a negative score received four euro, participants that scored between zero and five received five euro and participants that scored above five points, received six euro.

Results

Since the analysing part of this study is very complex, we divided it into two parts. In the first part we will look for a relation between accuracy on impression items and performance in the zero-sum game. We first computed the independent variables: correlation and differentiation scores for the impression items that both choosers and avoiders filled out. These independent variables represent our accuracy measurement. Also dependent variables are formed, which represent successful playing in the game or performance measurement. The exact calculation of this variables will be further explained below. Than, we looked for a relation between accuracy on these impression scores and performance in the game. Also we calculated split pairs by who was most accurate on the impression scale relatively to the other player. We tested these split pair variables against the dependent performance variables using t-tests. In the second part we looked for an explanation for the findings in part one. For this, we used the end-questionnaire all the participant filled out after they played the game. This questionnaire ought to check up on the Empathy Quotient created by Baron et all, 2003. We calculated the EQ for chooser and avoider and looked for a correlation between these variables and our independent (accuracy) and dependent (performance) variables. Also we created a split pair variable for EQ to compute a t-test for this split pair and performance.

Part one

Accuracy measurement We will make correlation scores bases on <u>correlation</u> scores and on <u>absolute differences</u> scores. Burns and Vollmeyer, (1998), made accuracy scores based on absolute differences scores. One problem appears when this method is used; response styles. When absolute difference scores are computed there is no influence of direction of the deviation, so when a participant always chooses around average, it is easy to be accurate. If participants have a risk avoiding response style this will not show when scores are analyzed with absolute differences scores. Accuracy scores based on correlation avoid this problem of response styles, that why we, in addition, choose to conduct accuracy scores based on correlation scores. We started by making new accuracy variables based on <u>correlation</u> scores between the impression scales on all fourteen impression items both the participants filled out about themselves, the other, how the other thinks about them and how the other would think about the other. These new variables were computed in the following way:

Original second order modelling R2MA, this variable consist of the correlation between how the avoider rated the chooser correlated with how the chooser rated him/ herself. The closer this score comes to one the higher the accuracy is of the avoider's impression of the chooser. This correlation score on original second order modeling is computed for both avoider and chooser for the three times the questionnaires were filled out by the participants. In total, we made six new variables.

Third order modelling R3MA, this variable consists of the correlation between how the avoider thinks the chooser rated the avoider correlated with how the chooser rated himself. Also on third order modeling, we made six new variables representing chooser and avoider during three periods.

New third order modelling R2DMA, this variable consists of the correlation between how avoider thinks the chooser rated himself, correlated with how the chooser rated himself. Again, we made six new variables representing chooser and avoider during three periods for new second order modeling.

In total, we formed eighteen new variables based on impression items. These accuracy scores are based on the correlation between the answers of the chooser and the answers of the avoider. This is different to Burns and Vollmeyers' study, (1998). However, one aim of this study was to make a complete replication of Burns and Vollmeyer, (1998) therefore we decided also to use the same method of analyzing: correlation of accuracy with success based on differentiation scores. Again we computed eighteen new variables using impression scores. These variables were formed in the same manner as with correlation scores, only now the absolute differences between the ratings of chooser and avoider are summed up. When this score is close to zero, this means the avoider is very accurate about the chooser. Exact computation of these variables can be found in appendix two.

One other change we made opposed to Burns and Vollmeyer, (1998) we added four impression items. Therefore, again to make a complete replication, we created the same correlation and differentiation scores as above, but based on only the ten impression scores Burns and Vollmeyer, (1998) used in their study. Thirty-six new variables were created based on the first ten ratings on the impression scale.

Performance Measurement Dependent variables representing successful playing in the game are computed. There are two ways in which this can be done; one is by summing up the *points* both chooser and avoider scored in total during the game and the other one is by summing up the *times* avoiders as well as chooser won a round of the game. This means we computed two independent variables that represent performance measurement. First we computed the new variables representing the simple sum of scores, the points players earned during the game. We divided the results in the first half and the second half of the game for the chooser and the avoider which leads to four new variables. This division was made to see if participants would ' learn' about their opponent during the game, what could result in better prediction of the opponent. These variables were named SumOut; numbers of points won. Then we computed the second independent variable, first scores were recoded: scores above zero were changed to one and scores below zero to zero. The four new variables were as following: summed scores for avoider during the first half of the game, for chooser during the first half of the game, for avoider during the second half of the game and for chooser during the second half of the game. These variables were named SumRout; numbers of times won.

Correlation Analyses In this section, we will look for relations between the accuracy variables (independent) and the performance variables (dependent). Correlations between the accuracy of players based on <u>correlation</u> scores and on <u>absolute differences</u> scores of both chooser and avoider on third order modeling, original second order modeling and new second order modeling during the first and the second half of the game are calculated. Each condition will be discussed separately.

Condition one Correlations are computed between seventy-two the independent variables; original second order modelling (R2MA), third order modelling (R3MA) and new second order modelling (R2DMA), based on <u>correlation</u> scores and <u>absolute differences</u> scores for fourteen and ten impression scores and the two dependent variables; number of times won (SumOut) and number of points won (SumRout). In condition one both players had access to full information, we expect to find a positive correlation for third order modeling (R3MA) with performance and no correlation between second order modeling (R2MA, R2DMA) and performance. We could not confirm these hypotheses. We did not find any significant results for the analysis based on correlation scores. We did find eight results in the analyses based on absolute differences scores. Striking is that all these results were found in the first half of the game, no results were found in the second half. To provide a clear overview of the significant results, we put them together in a table.

Insert Table 3 here

No results were found for third order modeling (R3MA), this result reject our hypothesis. For second order modeling (R2MA, R2DMA) we found two different patterns for choosers and avoiders: the more accurate avoiders were on second order modeling, the better avoiders' performance in the game, but the more accurate choosers were on second order modeling, the worse choosers' performance in the game.

Condition two The same correlations as in condition one are computed between the independent variables and the dependent variables, now just for condition two. In condition two only avoider has full information. We expect that avoiders' second order modeling (R2MA, R2DMA) will correlate positive with the performance of avoider and choosers' third order modeling (R3MA) will correlate positive with the performance of the chooser. We did not find this. In condition two again no results were found in the second half of the game. The other results are again displayed in a table.

Insert Table four here

No results were found for new second order modeling (R2DMA) and only one result was found for third order modeling (R3MA). This result indicated a negative correlation between accurate third order modelling and performance in the game. We did find a clear pattern for original second order modeling (R2MA), only for avoider, which correlated negatively with performance in the game multiple times.

Condition three The same correlations as in condition one and two are computed between the independent variables and the dependent variables, now just for condition three. In condition three only chooser has access to full information. We expect that choosers' second order modeling (R2MA, R2DMA) will correlate positive with the performance of chooser and avoiders'. Third order modeling (R3MA) will correlate positive with the performance of the avoider. We could not confirm these hypotheses. In the third condition, there were no significant results for second order modeling (R2MA, R2DMA). Only three significant results were found for third order modeling (R3MA), again only for avoider and only on number of times won. In contrast to the other conditions, all the significant results were found in the second half of the game. The first result was found on correlation, fourteen items (r (18) = −.433, p < .10), the second result was found on absolute differences, fourteen items (r (18) = .446, p < .05), the third result was found on absolute differences, ten items (r (18) = .464, p < .05). These three results point in the same direction; a negative relation between accurate third order modelling and performance in the game.

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T-tests To further investigate the results that were found in the correlation analysis, t-tests of split pairs were done. For every variable we computed until now, the pairs (chooser and avoider) were split by who was more accurate on the impression scale, chooser or avoider. T-tests on performance were done for the three conditions separately. Again, each condition will be discussed separately

Condition one We expect to find a positive correlation for third order modeling (R3MA) with performance and no correlation between second order modeling (R2MA, R2DMA) and performance. Our results did not confirm our hypotheses; we did not find any results for second order modeling. Only one significant result was found for third order modelling (R3MA) on correlation scores, fourteen items on Number of points won (M_{avoider} = 2.72 vs. M_{chooser} = – 6.0, t (16) = 1.75, p < .10). This result indicated positive relation between avoiders' third order modelling and avoiders' performance in the game.

Condition two We expect that avoiders' second order modeling (R2MA, R2DMA) will correlate positive with the performance of avoider and choosers' third order modeling (R3MA) will correlate positive with the performance of the chooser. Our hypotheses were not confirmed. We found no result on third order modelling (R3MA) and new second order modeling (R2MA), but, as in the correlation analysis, a clear pattern of results was found for original second order modeling (R2MA).

Insert Table 5 here

The results of the t-test of condition two are for the greater part in according to the results we found in the correlation analysis. A negative relation between original second order modeling (R2MA) on performance is found in the first half in both analysis. In the t-test we found some extra evidence for the same relation, now in the second half of the game.

Condition three. In this condition only chooser received a full pay-off matrix. We expect that avoiders' third order modeling (R3MA) is positively correlated with the performance of avoider in condition three and choosers' second order modeling (R2MA, R2DMA) is positively correlated with the performance of the chooser. We could not confirm these hypotheses. Three results were found on original second order modeling (R2MA) in the first half of the game. Opposed to the finding in the correlation analyses significant results on third order modeling were found in the second half of the game.

Insert Table 6 here

The results found on second order modeling contradict our hypothesis. The results we found on third order modeling confirm our hypothesis for a positive relation from avoiders' third order modeling on the performance of avoider. In the correlation test however, we found three significant results in the opposite direction.

Part two

In this second part of analyzing we will try to find an explanation for our results in the first part. We will do this by using the end-questionnaire the participants filled out. This end-questionnaire ought to check up on the empathy quotient, EQ, (Baron et al., 2003). This empathy quotient indicates how capable participants are in using theory of mind; the ability to reason about the thoughts and feeling of themselves or others. Two new variables were created to represent the empathy quotient as explained in Baron et al., (2003), one for avoider and one for chooser. Also a split pair variable was computed, representing who has the highest EQ, chooser of avoider.

Correlation analyses and t-tests To test the relation between EQ, modeling and performance, we decided to conduct some analysis. *First,* correlations between EQ from avoider and EQ from chooser with performance were calculated. *Then,* we calculated correlation scores between EQ from chooser and avoider and accuracy scores (on the impression scale). *Finally,* we computed a split pairs t-test on the new split pair variable with performance. We will discuss the results of these analyses separately for each condition. About one thing we can be short; no results were found in the t-tests, in none of the conditions.

Condition one In the correlation analyses between EQ for both roles and performance, one significant result was found for chooser on number of times won in the first half (r (15) –.418 p <.10). This result indicates a negative effect from high EQ of the chooser on the performance of avoider. Then we calculated correlation scores between EQ of chooser and avoider and accuracy scores: we found seven correlations.

Insert Table 7 here

The five results on second order modeling (R2MA, R2DMA) point in the same direction: there is a negative relation between choosers' EQ and avoiders' second order modeling, which implies that when a chooser is high on EQ, avoider is worse in modeling the chooser. The first result on third order modelling points in the same direction as the results we found on second order modelling: when a chooser is high on EQ, avoider scores worse on modeling the chooser. The second result on third order modeling indicates a different relation: when chooser is high on EQ, chooser is worse in modeling the avoider.

Condition two No significant correlations were found between EQ of chooser or avoider and performance. In the correlation analysis between EQ of chooser and avoider and accuracy scores three significant results on new second order modeling were found. The first one was based on correlation scores, ten items; we found a positive correlation between choosers' EQ and avoiders' new second order modeling (R2DMA) (r (17) = –.579, p <.01). The second and third result are based on absolute differences scores, the first one, on fourteen items; a negative correlation between choosers' EQ and avoiders' new second order modeling (R2DMA) . The second one, found on ten items; a negative correlation between choosers' EQ and avoiders' new second order modeling (r (17) = .530, p <.05). These three results imply the same conclusion; when EQ of chooser is high, avoider scores worse on new second order modeling.

Condition three Again, no significant correlations were found between EQ of chooser and avoider and performance. We calculated correlation scores between EQ from chooser and avoider and accuracy scores: We found three results. The first result is found based on correlation scores, fourteen items and concerns a negative correlation between choosers' EQ and choosers' original second order modelling (R2MA) (r (19) = –.401, p <.10). The second result is found based on absolute differences scores, fourteen items and concerns a negative correlation between choosers' EQ and choosers' original second order modeling (R2MA) (r (19) = .432, p <.05). The third result is found based on absolute differences scores, ten items and concerns a negative correlation between choosers' EQ and choosers' original second order modeling (R2MA) (r (19) = .357, p <.05). These three results point out a negative relation between a high score of chooser on EQ and a low score of chooser on R2MA.

Conclusion In the first condition we tried to replicate the findings of Burns and Vollmeyer, 1998. We expected to find that when both participants have full information, third order modeling (R3MA) would be positively correlated with performance. Second order modeling (R2MA, R2DMA) would not be correlated with performance. These hypotheses were nog confirmed. In the correlation analysis (analysis used by Burns and Vollmeyer, 1998) no results for third order modeling were found. In the t-test one significant result for third order modeling in accordance with our hypothesis was detected. Since one result in our elaborate analysis is very weak, we believe Burns and Vollmeyers' findings, (1998) for third order modeling on performance are not robust. For second order modeling (R2MA, R2DMA) we found two different patterns for choosers and avoiders: the more accurate avoiders were on second order modeling, the better avoiders performance in the game, but the more accurate choosers were on second order modeling, the worse choosers performance in the game. This is an unexpected result since there should not be a difference in roles; both players have access to full information. In the second condition only avoiders had full information, we expected to find a positive relation between choosers' third order modeling (R3MA) and choosers' performance. For avoiders, we expected a positive relation between avoiders' second-order modeling (R2MA, R2DMA) and avoiders' performance. Our result did not confirm this hypothesis. In the correlation analysis, again, we found only significant results in the first half of the game. There was one result on third order modeling (R3MA) for avoider: it had a negative relation to performance. A more robust finding was found on original second order modeling (R2MA) for avoider. Eight correlations were found throughout the analysis all pointing in the same direction; when avoider scored high on original second order modeling, his performance in the game got worse. In the t-test we found the same eight results on as found in the correlations analyses and more, two significant results in the same direction were found also in the second half of the game. In the third condition where only choosers have full information, we expect to find a positive relation between avoiders' third order modeling (R3MA) and avoiders' performance. For choosers, we expect a positive relation between choosers' second-order modeling (R2MA, R2DMA) and choosers' performance. Starting with the correlation analysis, here we found, in contrast to the other conditions, only significant results in the second half of the game. These three results were found for R3MA, again only for avoider. The more accurate avoider was in estimating how the other rated him, the less times he won the game. The t-test contradict the findings of the correlation analysis, to start, the results were found in the first half of the game. In the t-test we found three results that indicate that third order modeling (R3MA) is in line with our hypothesis; a positive relation from avoiders' third order modeling on the performance of avoider was found. In the correlation test however, we found three significant results in the other direction. The results found on second order modeling contradict our hypothesis. They imply a negative relation between a high score of avoider on second order modeling (R2MA, R2DMA) and performance.

In the correlation analyses regarding the empathy quotient we did not find any results in the t-test. Between EQ and performance only one effect was detected; in the first condition we found a negative effect from high EQ of the chooser on the performance of avoider, which feels intuitively logic. It means that when chooser scores high on EQ, performance of avoider gets worse. Also in the analyses between EQ and accuracy we detected a 'logic' pattern. Five results proved the same relation: a negative correlation between choosers' EQ and avoiders' accuracy on second order modeling was found, which can be interpreted as following: when a chooser is high on EQ, avoider is worse in modeling the chooser. For third order modeling we found one similar result; when a chooser is high on EQ, avoider is worse in rating how the chooser would model the avoider. And we found one result proving the reverse; when a chooser is high on EQ, chooser is worse in rating how the avoider would model the chooser. In the second condition all three results on original second order modeling were in line with the greater part of the results in condition one; when a chooser is high on EQ, avoider is worse in modelling the chooser. In the third condition three results were found, these three indicated that when a chooser is high on EQ, chooser is worse in modeling the avoider. The most important thing these results teach us is that there is a correlation between EQ and accuracy.

Discussion. The main goal of our study was to gain knowledge about the factors that determine success in competition. To find out *how* people compete, or what kind of behavior is most successful when trying to maximize your outcome in a pokergame, business deal or war. We proposed that a component that forecast the level of success in adversarial problem solving would be modeling. Our main source to build this hypothesis on was the study of Burns and Vollmeyer in 1998; they found third order modeling to be predictive of the success in a one-sum game and for second order modeling, no predictive effect was found. The aim of our first condition was to replicate this finding: we did not find the same results. In our study rather surprising results were found.These unexpected results will be discussed more extensively in this section; For second order modeling (R2MA, R2DMA) we found two different patterns for choosers and avoiders, (the more accurate avoiders were on second order modeling, the better avoiders' performance in the game became. But the more accurate choosers were on second order modeling, the worse choosers' performance in the game was). This is an unexpected result since there should not be a difference in roles; both players have access to full information. Since the only difference is the role the participant were assigned to we cannot think of a reason to account for the contradictory pattern. All these relations were found in the first half of the game. In the second half, no results were found. An explanation for this could be that both chooser and avoider experienced a 'learning effect' from the first half of the game what made both players perform better in the game. Concluding from our results: it is hard to state a definite finding about the effect of second-order modeling as Burns and Vollmeyer, (1998) did; it is succinctly to conclude that seocnd order modeling has no effect at all. As we cannot come up with an explanation for the contradictory findings for choosers and avoiders, we recommend to investigate the effect of second order modeling on performance in a competitive setting with a bigger sample. For third order modeling, no significant results were found in our correlation analyses, neither based on correlation scores, nor on absolute difference scores. It did not matter whether we used fouteen or ten items; there was no result found as expected according to our hypothesis based in the study of Burn & Vollmeyer (1998). Only one effect of third order modeling on performance was found in our t-test of split pairs, this result is in line with the hypothesis. Since only one result in our very elaborate analyses was found, we can sincerely conclude our replication of Burns and Vollmeyers' findings, (1998) of the effect of third order modeling on performance failed. We were not able to replicate the findings of Burns and Vollmeyer on third order modeling. This leads us to believe that there is no 'real' effect of third order modeling on performance in a competitive setting. A cause for the disappearance of this effect might be due to a change we made in our method opposed to the study of Burns & Vollmeyer, (1998); we did not give the participants the opportunity to keep track of their and their opponent's selections. Thus, the participant did not have access to the history of selections, but had to remind all the choices and outcomes by head. Remembering all the choices and outcomes brings the participants under severe cognitive load; effect of cognitive load on the working memory is formulated in the Cognitive Load Theory; (Sweller, 1994). This theory explains the influence of a memory task on the ability of people to reason and to solve problems. The cognitive load on the participants might explain why the participants were not able to use their perception to forecast the opponent's strategy in the game. In Burns and Vollmeyers' study, 1998, there might have been an interaction between knowing which action your opponent has previously taken and estimating what his next action will be. Apparently when the easy access to the history of choices is taken away, the effect of modeling disappears. First of all, this indicates a fundamental confounding between players' modeling and knowledge of their opponents' previous distribution. Second, if the predictive power of third order modeling on performance disappears after just removing access to the history of choices, the effect proves not to be so robust after all.

In condition two, we expected that second order modeling (R2MA, R2DMA) would show a positive correlation with the performance of avoider and third order modeling (R3MA) a positive correlation with performance of the chooser. We can be clear about this; our hypotheses were not confirmed. We did find one clear pattern; all the significant results show that when avoiders or choosers are more accurate on original second order modeling, they perform worse in the game. In the t-test we found ten significant results, eight of them replicated the findings in the correlation analyses, they were found in the first half of the game. In the t-test also two significant results were found in the second half of the game; the results are in line with the other findings in condition two in the first half; more accuracy leads to lower performance. That we did not find this result in the correlation analyses could be due to the use of a different analysing strategy. T-test on split pairs might be a bit more sensitive to results, also, the significance level used in the t-test is rather high ($p < .10$). Anyway, since we found these results in the correlation analyses and the t-tests, multiple times, the negative effect of accuracy on original second order modeling on performance we find in condition two seems quite robust. This result is very odd, not only is it the exact opposite of our hypotheses, also when you think about it in a logical way and transmit it to a situation in the real world it is rather strange; when you are good in estimating your opponent, your performance in a game against this opponent gets worse. As we cannot come up with a logic explanation for this tendency, we tried to look for an explanation in the second part of our analyses. The findings from this analyses will be discussed in the section below. One other result was found in the second condition; on third order modeling for avoider. As we did not make a prediction for avoiders based on third order modeling and this is an isolated result, there will not be conclusion drawn up because of this finding.

In the third condition, we expected third order modeling to be positively correlated with the performance of avoider and second order modeling to be positively correlated with the performance of the chooser. Again, our hypotheses were not fully confirmed; we found contradictory results between the correlation analyses and the t-tests. In the correlation analyses the results implied that when avoider scores high on third order modeling, avoiders' performance in game will be worse. In the t-test however we found results in line with the hypotheses; when avoider is more accurate on third order modeling, he performs significantly better in the game. The results of the t-test confirm the hypothesis of the third condition, while the results of the correlation analyses prove the opposite. We believe these contradictory findings just prove that there is not one definite tendency for us to find in the influence of third order modeling on performance. This is supported by the results of the t-tests in the third condition and the findings in the first and the second condition. In the t-test we did not find any results for third order modelling, only for second order modelling three results were detected; when avoider was more accurate on second order modeling, he performs worse in the game relative to chooser. These three results indicate the same pattern as was found in the second condition: a curious result.

In the second part of our analyses we tried to find a relation between the empathy quotient, EQ (Baron et al., 2003) and performance and accuracy variables. Our goal was to see if there was a pattern in these relations that might explain the findings in the first half of our experiment. We did not find anything in the t-tests we carried out and only one result was found for EQ and performance, but more relations were found between EQ and accuracy scores. In the greater part of the first condition and in the second condition a 'logic'pattern. between EQ and accuracy was detected on original second order modelling and third order modelling; when a chooser is high on EQ, chooser is better in original second order modeling and third order modeling than the chooser. In the third condition three results were found, these indicated that when a chooser is high on EQ, chooser is worse in modelling the avoider. These results can be intrepreted from different angles; for the first two condition we can explain: when a player scores high on the empathy quotient, he or she will be automatically better in making a model of the other player and himself. But also the results in the third condition can be explained: when a player scores high on the empathy quotient, this player might be better in showing how he/she feels himself which makes it more easily for the other player to read his emotions and make an accurate model. Which of this two scenarios' is followed in reality might again be dependent on if there is an overload of information or not

(Sweller, 1994). When there is too much to remember participants are not able to mask their true emotions which makes it more easy for their opponent to make an accurate model. This could be an explanation for our findings in the second condition where avoiders had full information; when avoiders scored high on second order modeling their performance in the game lowered, they were not able to use their accurate second order model due to information overload. But the most important finding in the second part of our analyses is that there is a relation between EQ and accuracy. This shows that our accuracy measured exactly what they were supposed to measure (high internal validity) and that our participants were motivated to fill out the impression questionnaires accurate. Moreover this implies that the fact that we could not replicate Burns and Vollmeyers' findings, (1998) is not due to inaccurate measurement of the accuracy variables. This again proves that the findings of Burns and Vollmeyer, (1998) just were not robust enough and we should consider that at least, there might not be an effect of modeling on performance in the one-sum game, in this game it is better for participants to just use the randomization strategy. One conclusion we can draw for sure: the effect of an accurate model of the opponent on performance in a competitive setting is not as robust as we had expected.

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Table 1. Example of a pay-off table used in zero-sum games.

	Avoider's selection		
Chooser's selection	1	2	3
1	+1/-1	-1/+1	-1/+1
2	-1/+1	+2/-2	-1/+1
3	-1/+1	-1/+1	+3/-3

Table 2. Explanation of the pay-off matrix in the instruction of the game

		The Other's Action	
		X	Y
Your Action	A	–2 +2	+2 –1
	B	+1 –3	–1 +3

Table 3. Correlations between accuracy and performance in condition one.

	R2MA	14items_C	10items_C	14items_A	10items_A
SumOut _1stHalf	Avoider				−.432*
	Chooser				.390*
SumRout _1stHalf	Avoider			−.398*	
	Chooser				.541**

	R2DMA	14items_C	10items_C	14items_A	10items_A
SumOut _2ndHalf	Avoider				−.541*
	Chooser			.403**	
SumRout _2ndHalf	Avoider				−.426**
	Chooser			.502*	

Note. Only significant results are shown; * = $p < .05$ ** = $p < .10$ SumOut stands for number of points won, SumRout stands for number of times won. 1stHalf marks in which half of the game results were found. R2DMA stands for New second order modeling, R2MA stands for Original second order modeling. _C marks the results found based on correlation scores. _A marks the results found on absolute differences scores. N = 19.

Table 4. Correlations between accuracy and performance in condition two.

	R2MA	14items_C	10items_C	14items_A	10items_A
SumOut _1stHalf	Avoider	−.431*	−.405**	.402**	.377**
	Chooser				
SumRout _1stHalf	Avoider	−.513*	−.387**	.498*	.439*
	Chooser				
	R3MA	14items_C	10items_C	14items_A	10items_A
SumOut _2ndHalf	Avoider		−.405**		
	Chooser	.			
SumRout _2ndHalf	Avoider		−.387**		
	Chooser				

Note. Only significant results are shown; * = p < .05 ** = p < .10 SumOut stands for number of points won, SumRout stands for number of times won. 1stHalf marks in which half of the game results were found. R2MA stands for Original second order modeling, R3MA stands for third order modelling. _C marks the results found based on correlation scores. _A marks the results found on absolute differences scores. N = 21.

Table 5. T-tests in condition two.

		14 items		10 items	
	R2MA	Mean	Mean_Abs	Mean	Mean_Abs
SumOut_A_1stHalf	Avoider	–4.25*	–4.15*	–3.33**	–2.94*
	Chooser	4.22*	5.12*	3.00**	6.00*
SumRout_A_1stHalf	Avoider	5.83*	5.69*	6.33**	6.00*
	Chooser	10.44*	11.25*	9.78**	10.22*
		14 items		10 items	
	R2MA	Mean	Mean_Abs	Mean	Mean_Abs
SumOut_A_2ndHalf	Avoider		3.67**		2.50 *
	Chooser		8.00**		8.22*

<u>Note.</u> Only significant results are shown; * = $p < .05$ ** = $p < .10$ SumOut stands for number of points won and SumRout stands for number of times Won. 1stHalf and 2ndHalf mark in which half of the game results were found. R2MA stands for Original second order modeling. Mean shows the results based on correlation scores. Mean_Abs shows the result bases on absolute differences scores. N = 21.

Table 6. T-tests in condition three.

		14 items		10 items	
	R2MA	Mean	Mean_Abs	Mean	Mean_Abs
SumOut_A_1stHalf	Avoider			–1.13*	
	Chooser			6.13*	
SumRout_A_1stHalf	Avoider		6.11*	7.53**	
	Chooser		11.14*	12.25**	

		14 items		10 items	
	R3MA	Mean	Mean_Abs	Mean	Mean_Abs
SumOut_A_2ndHalf	Avoider	3.25**			
	Chooser	–2.63**			
SunRout_A_2ndHalf	Avoider	10.50**			
	Chooser	5.26**			

Note. Only significant results are shown; * = p < .05 ** = p < .10 SumOut stands for number of points won and SumRout stands for number of times Won. 1stHalf and 2ndHalf mark in which half of the game results were found. R2MA stands for Original second order modeling. Mean shows the results based on correlation scores. Mean_Abs shows the result bases on absolute differences scores. N = 21.

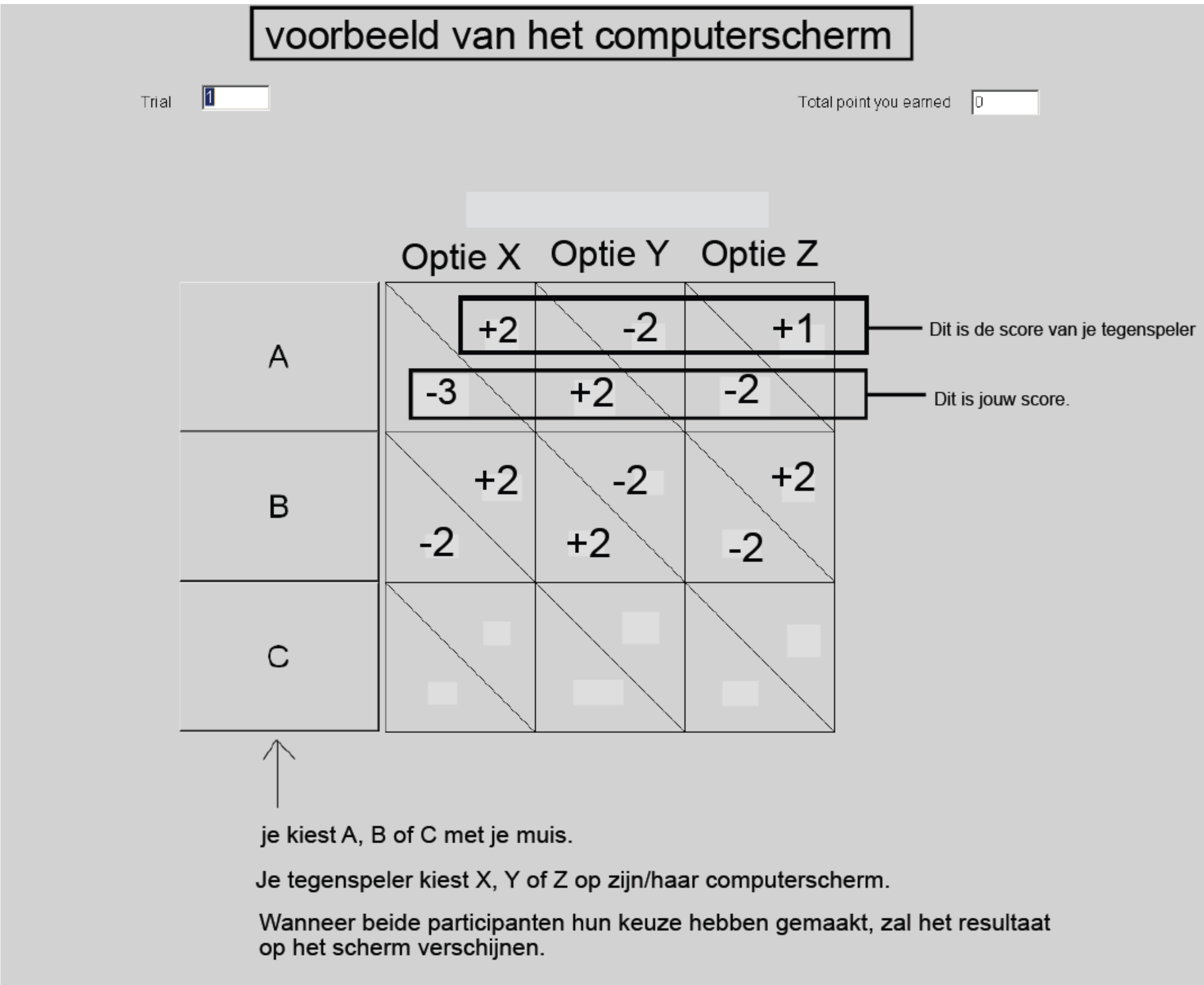
Table 7. Correlations between EQ and accuracy scores in condition one.

	R2MA	14items_C	10items_C	14items_A	10items_A
EQ_Avoider	Avoider				
	Chooser				
EQ_chooser	Avoider	–.560		.447*	.631***
	Chooser				
	R3MA	14items_C	10items_C	14items_A	10items_A
EQ_Avoider	Avoider				
	Chooser				
EQ_chooser	Avoider	–.560			
	Chooser			.435*	
	R2DMA	14items_C	10items_C	14items_A	10items_A
EQ_Avoider	Avoider				
	Chooser				
EQ_Chooser	Avoider			.486*	.594*
	Chooser				

Note. Only significant results are shown; * = $p < .05$ ** = $p < .10$ *** = $p < .01$.

R2MA stands for Original second order modeling, R3MA stands for third order modeling, R2DMA for New second order modeling. EQ stands for empathy quotient. _C marks the results found based on correlation scores. _A marks the results found on absolute differences scores. N = 19.

Appendix one



Appendix one shows an example of what the one-sum-game looks like in the instruction of the game given to the participants before the beginning of the game. The screen is in Dutch, since all our participant were Dutch students.

Appendix two

Appendix two explains in detail how the accuracy variables of impression items on absolute differences scores are formed.

Original second order modeling: R2MA, second-order modeling for avoiders based on absolute differences scores we compared the avoider's ratings on the impression scale of the chooser with the chooser's rating of him or herself by summing the absolute differences between the ratings of the same item on these two scales. When this score is close to zero, this means the avoider is very accurate about the chooser. We computed six new variables representing original second order modeling, for avoider as well as for choosers, during the three time periods.

Third order modeling: R3MA, consists of a sum of the absolute differences between items on the avoider's rating on the impression scale of what the chooser thinks about the avoider and what chooser actually thinks about the avoider. This led to six new variables representing third order modeling based on differentiation scores.

New second order modeling: R2DMA; absolute differences were summed up between the ratings how avoider thinks the chooser thinks about himself and how chooser rated himself. Six new variables of new second order modeling were computed.