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Abstract

An experiment aiming to assess the use of stopping rules in information acquisition was performed. Participants were requested to make a decision in 24 financial scenarios with the possibility of buying information pieces. Behavioral and EEG data were recorded for analysis. Results showed that participants followed Bayesian calculations in order to determine a stop on information acquisition and decide. Moreover, the information acquisition strategies were consistent with prospect theory, in which participants will weigh information pieces differently and seek more or less information given different manipulations in scenario probability and consequences. EEG data suggest Slow Cortical Potentials at fronto-central electrodes.

Keywords: decision making; information acquisition; EEG; slow cortical potential.

Introduction

As Taghavifard, Damghani and Moghaddam (2009) discuss, it is only possible to know the risks inherent in a decision if the individual has a relatively small degree of uncertainty. One way to diminish levels of uncertainty is by reducing residual uncertainty (Courtney, Kirkland & Viguerie, 1997) through information acquisition. To acquire information is to search both internally and externally for elements that can affect the decision process. In their daily lives individuals receive a considerable amount of information through various modalities. Auditory, visual, tactile, emotional stimuli can be sources of new information. Each piece of information has some importance toward deciding either by improving the quality and quantity of information or by impairing an individual´s ability to decide given that the amount of information is so great that the performance will be deteriorated (Di Caprio, Santos-Arteaga, & Tavana, 2014). When information reveals itself and is processed by the decision maker, we find a transition from a situation of uncertainty to a situation of risk. In other words, the decision maker now knows enough information about the problem so that he is able subjectively infer a probability for each outcome (Di Caprio et al., 2014).

Pretz, Naples, and Sternberg (2003) discuss the role of experts and the fact that too much information can actually impair the decision process. They propose that when an expert (a person that possesses a great deal of knowledge, acquired by experience and information gathering) in chess plays with slightly different rules, his performance might actually be worse than that of a player that is new to chess and plays the same modified game as the expert. This suggests that when an otherwise static environment becomes dynamic, a difficulty in deciding might appear. Too much information may be suboptimal for a decision maker (Di Caprio et al., 2014), whereas not enough information will prevent him from calculating risks properly and brings the decision process to one of most uncertainty (Taghavifard, Damghani & Moghaddam, 2009). On the other hand, Frey, Hertwig and Rieskamp (2014) propose that there is no way to determine when the right amount of information is reached and no further acquisition needs to be done, at least in decisions from experience, although they also say that there may be benefits in small samples and frugal search. The question that remains is: how does a decision maker knows that he/she acquired enough information to go through with the process?

Many researchers are investigating the subject of information acquisition and how and when individuals stop searching for new information and proceed to decide. Gigerenzer (2000) proposes a fast and frugal way to decide in environments where both time and knowledge are restricted. By searching past information and knowledge in order to recognize elements regarding the decision and cues about those elements, the Take the Best (TTB) heuristic searches for the best cue in order to make a choice. In the experiments by Gigerenzer (2000), when people where asked which of two German cities was the most populated, individuals would most likely use TTB in order to decide. Even so, the individual might seek other cues about each city from memory (i.e., perhaps if he saw the city on the news). According to the subjective validity of the cues, the one with the highest ranking is considered the best and thus appropriate for a decision. Little information search and acquisition are performed. Stern, Gonzalez, Welsh, and Taylor (2010) conducted and experiment in which individuals were presented with two decks with varying proportions of red and blue cards. Four draws of cards were made and at each draw the individual would have to state from which deck the card had been drawn from. Each draw represented acquiring a new piece information about the decision. After all four draws the individual would have to make a final decision between the decks or they could decline to choose. It is clear that each new information presented changed or reaffirmed the decision made by the individual. When conflicting information was presented (two draws were red cards and two were blue) individuals mostly declined to choose, inferring a 50% chance to each deck. When all draws were the same color, by the third draw individuals were already 100% confident from which deck the draws were made. This experiment poses that information acquisition can update individual beliefs about the outcome and that searching for information might improve the decision making process by incrementing it with a better view about the problem at hand.

Fifić and Buckmann (2013) probed the use of stopping rules by individuals. Stopping rules might determine the moment where the decision maker stops, or should stop, searching for information and actually decide. The authors reviewed some options of stopping rules that might require higher or lower cognitive demands. The first one is the so-called optimal stopping rule for evidence accumulation. It is based on Bayesian inference and implies that there should be an optimal number of pieces of information that need to be acquired. In their example the optimal stopping rule is 3. This number represents that the individual will search for positive (+1) and negative (-1) pieces of information and will only stop searching when the sum of the search reaches either +3 or -3, in which case the individual will choose the option represented by the positive or negative sum, in their example to proceed or not with a risky cancer treatment. There is criticism regarding this rule, in order to calculate the optimal number there is a need to have a perfect knowledge of the situation and enough calculating skills to solve it through Bayesian probability (Fifić & Buckmann, 2013). This option requires great amounts of time, knowledge and cognitive effort. In most cases in the real world there are limited amounts of each available to the decision maker. They then propose a stopping rule selection theory based on bounded rationality.

Two rules are suggested that do not depend on high amounts of knowledge about the environment and the situation. The first one is the fixed sample size. This rule entails that the decision maker will determine a sample size before the beginning of the information search process, for example five. The individual will then search for information and will make the choice based on the valence that appears the most (positive or negative). The other rule is called runs stopping rule. In this case the decision maker will begin the search for information without determining a fixed sample. She will stop searching when a streak of either positive or negative pieces of information is found, three consecutive positive opinions for example.

The stopping rule selection theory proposes that each individual might use different stopping rules given time and cognitive efforts available (Fifić & Buckmann, 2013). That is because there is no evidence that one single stopping rule can account for all responses from individuals. According to Fifić and Buckmann (2013) each individual will search a decision operative space in which the rules and values are stored. Given a decision situation the individual will then retrieve a stopping rule – a process that the authors call cast-net retrieval. Much like fishing, each individual will select a space and a net size to cast and retrieve a stopping rule that will be applied. What is considered in order to cast a net in the decision operative space is the level of uncertainty with the environment, time frame, cognitive demand, and accuracy expectancy (Fifić & Buckmann, 2013). After the stopping rule is selected, the individual will then proceed to collect information and finally decide.

Cognitive demand and the search for a stopping rule might reflect high levels of task engagement. That is, the individual is fully focused on solving the problem and anticipates the outcomes of the decision given each new information. This situation represents higher use of brain resources, especially in frontal areas. Few studies focus their analysis on pre-stimulus ERPs, especially when decision making is concerned. Böckner, Bass, Kenemans and Verbaten (2001) studied one form of Slow Cortical Potential (SCP). They found a Stimulus-Preceding Negativity at fronto-central electrodes in fear-induced trials. Oswald and Sailer (2013) found fronto-central SCPs before and after response in a temporal discounting task.

Other elements also influence the information acquisition process. Frey, Hertwig and Rieskamp (2014) found that both a facial expression of fear or the subjective feeling of fear may cause an individual to search more information. Söllner, Bröder, Glöckner and Betsch (2014) discovered that when intruding incompatible information appears, individuals trained in the TTB heuristic would not stop searching for information when they were supposed to if following TTB. Individuals rather adapted their information search, choice and confidence judgment processes to the content of such intruding information. It is widely recognized that the amount of information available and acquired by each individual will augment complexity levels in the decision situation, much like what happened with the intruding information.

Methods

The objective of this study was to probe, based on the models of Fifić and Buckmann (2013), Stern et al. (2010) and Söllner et al. (2014), the use of stopping rules in the information acquisition and evidence accumulation processes and its electrophysiological correlates. A financial decision task was devised so that the use of stopping rules could be measured by the amount of information acquired by the individuals in each of the scenarios. As with real world decisions, scenarios were presented with varying levels of risk, uncertainty and consequences. During the task, EEG was continuously recorded to investigate correlates of information acquisition and decision behavior processes. A total of 47 (mean age: 18.89, SD: 1.68, 33 females) undergraduates from the University of Michigan Pysch Pool participated. Data was collected from 50 participants, however 3 were discarded because of poor electrode readings interfering with the EEG data. This study was approved by the University of Michigan's Institutional Review Board.

Financial decision task

Each participant was presented with all 24 financial decision scenarios. The scenarios were presented written in a single paragraph. In all scenarios participants would have to choose whether to accept or reject the proposed situation, but they could also choose not to decide at all (a procrastination behavior). For every scenario there were 20 information pieces (or advices) that a participant may or may not buy in order to help them decide. Participants were instructed to press the "I" key on the keyboard whenever they wanted to buy information in a scenario. All information was presented in a crescent and pseudorandom order. The order of information appearance was made to resemble the stopping rules tested by Fifić and Buckmann (2013). Each new information was presented using simply the words "positive" or "negative", thus diminishing the probability of bias. The words mean a positive or negative opinion about accepting or rejecting the proposition in the scenario. Each information had a price ($1 for the first 10 pieces and $2 for the other 10). There was a fixed fictional amount of $480 available to any participant to complete the experiment – this amount was created specifically to refrain participants from always buying all 20 pieces of information. They were instructed not to use all the money available.

Each scenario showed a situation involving aspects of financial decisions such as investments, purchases, asset management, losses, etc. After reading the description of the situation, participants could obtain (buy) information regarding that scenario. Even if not buying any information, participants would be required to make a decision for each scenario. They could decide to buy/invest/pay (Positive), not to buy/invest/pay (Negative) or to not decide at the moment (Procrastination). After a decision, there was no feedback on the success of it, and the next scenario was presented. Participants did not receive any instructions regarding a maximum period of time to decide at each scenario. They were free to use as much time as they wanted to read the scenario description, seek information and make a decision.

The 24 scenarios were divided as such: 1) 12 scenarios with stated probabilities (risk scenario) in the description, composed of 3 scenarios with low negative consequences, 3 with high negative consequences, 3 with low positive consequences and 3 with high positive consequences; 2) 12 scenarios with unstated probabilities (uncertainty scenario) in the description, composed of 3 scenarios with low negative consequences, 3 with high negative consequences, 3 with low positive consequences and 3 with high positive consequences.

One example of a stated probability, low positive consequence scenario is: "You are thinking about buying a bicycle. There is a model that is 35% better than the alternative. You don't know what the average maintenance costs might be. You must decide if you: buy the bicycle, don't buy the bicycle or rather not decide now.", as shown in Figure 1. The stated probability is the 35% chance depicted, low consequence is due to the amount (35% is considered a low chance), positive consequence is the referred chance of being better than the alternative. Scenarios differ in the presence or not of the stated probability, consequences and valences of consequences. That means that the example above might be presented in another form, representing an unstated probability, high negative consequence scenario, like: "... There is a model that is much worse than the alternative ". Phrasings of probabilities and consequences were randomized. That means that the object of the scenario would be the same (bicycle, student loan, car fixing, etc.), but the probabilities (stated or not), and consequences (high or low and positive or negative) were randomized across participants for any given object.

EEG data was recorded through Acknowledge 4.4 software using an ABM B-Alert X10, with a 9 channel setup (Fz, F3, F4, Cz, C3, C4, Pz, P3 and P4) using linked mastoid as reference. Data was collected at a sampling rate of 256 Hz. Electrode scalp impedances were kept below 5 kΩ. Behavioral data and stimulus presentation was made via PST E-Prime Professional 2.0. The data was analyzed using ERPLab (Lopez-Calderon & Luck, 2014). Data went through moving window artifact detection and filtered for both low and high pass (0.1 Hz and 30 Hz, respectively). ERP epoch was from -2000 ms before the decision was made and 200 ms after the decision was made, giving the possibility of observing variations that occurred in a window of time before the actual decision. The use of this epoch is justified given that the information acquisition process is over before the decision is actually made, so in order to analyze event related potentials of stopping rules it is necessary to observe what happens before the decision. Target electrodes were located at fronto-central sites in order to search for SCPs (Oswald & Sailer, 2013). Mean voltage over a specific time epoch was used to analyze the data.

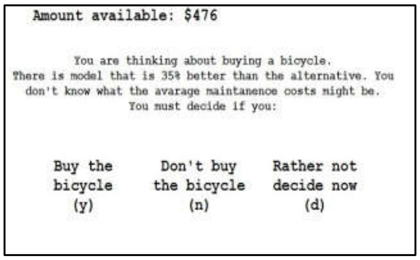

Figure 1: Example of a scenario.

Results

In order to determine the use of stopping rules and strategies for information acquisition we focus our analyses on two measures: information quantity (QTY) and balance (BAL). Information quantity is the mean amount of information pieces that each individual bought during each scenario. The balance is, just as Fifić and Buckmann (2013) proposed, one of the stopping rules, the Bayesian calculation of the valences for each information bought. That is, if an information is positive, then the value considered is +1, if an information is negative, then the value considered is -1. At the end of a given scenario, for example, if the pieces of information acquired were 3 positives and 2 negatives (independent of order of appearance), the balance will be +1. The conditions compared to the two measures were: decision (positive, negative and procrastination), probability (risk and uncertainty), and the combination of consequences (high or low) and valence of consequences (positive or negative) in risky and uncertainty.

Information acquisition

Of the total of possible scenarios, 40.63% were decided without any kind of information acquisition, thus without the use of stopping rules. This behavior might emerge given the objects of the scenarios at hand. In order to better control the conditions, the objects of decision (car, bicycle, motorcycle purchase, student financial aid, home and car repair, investments) were less complicated. That might have made the decisions easier based on each individual set of preferences. However, there is no data to back this hypothesis. Next, there were 44.88% of the scenarios that were decided using 1 through 5 information pieces. The 14.50% of cases left used 6 through 20 information pieces.

Decision

Regarding the decisions available for the participants, the mean information quantity gathered when a decision was positive is 4.11, when a decision was negative also 4.11 and when participants decided to procrastinate the mean quantity was 5.04. That shows that, despite the fact that participants had up to 20 information pieces available they sought only a small amount. Also it shows that the procrastination behavior was observed with more acquisition of information. On the other hand, when the balance is considered, a positive decision was made with a mean balance of +1.13, negative decisions -0.73 and procrastination decisions -0.05. That means that the information acquisition stopping point behavior is more influenced by the so called balance of the valences, regardless of the quantity of information acquired. A one-way ANOVA was conducted to test for differences between each decision. The test revealed that there is a difference between the decisions both for QTY and BAL, $F(2,1146)=189.9$, $p<0.001$ and $F(2,1149)=6.35$, $p<0.01$, respectively. Post-hoc analysis using Tukey HSD test revealed significant differences between all interactions: positive-negative ($p=0.001$), negative-procrastination ($p<0.001$) and positive-procrastination ($p<0.001$) for the BAL measure and only negative-procrastination ($p<0.05$) and positive-negative ($p<0.05$) for the QTY measure.

Probability

Analyzing only if the scenario presented risk or uncertainty, the only significant difference was observed in the BAL measure, $F(1,1150)=4.75$, $p<0.05$. The mean BAL for risk scenario was 0.031. For uncertainty scenario the mean BAL was 0.262. As for the QTY measure the mean value for the risk scenario was 4.263 and 4.100 for the uncertainty scenario.

Combining the conditions

The conditions were not presented isolated to the participants. Combining the conditions yielded 8 possible scenarios, as it was previously explained, that were randomly presented three times each for the participants. If all conditions are analyzed there is a significant difference for the BAL measure ($F(7,1128)=8.090$, $p<0.001$). A post hoc Tukey HSD test revealed significant differences between several of the possible combinations. However, two differences between conditions are of particular interest. The first one is between scenarios with uncertainty, low positive consequence ($M=0.118$) and scenarios with uncertainty, low negative consequence ($M=0.326$), with $p<0.001$. The second one is between scenarios with risk, high positive consequences ($M=0.007$) and scenarios with risk, high negative consequences ($M=0.181$) with $p<0.001$.

EEG

EEG analysis focused on risky and uncertain scenarios and both of the combined conditions highlighted previously. As was discussed earlier SCP might emerge in a situation where there might be prolonged use of cognitive control and resources in fronto-medial electrodes (Oswald & Sailer, 2013). As it was seen, BAL has significant differences in risky and uncertain scenarios and also in scenarios with different valences and consequences. That might point to the fact that prior to a decision individuals may exert more thought and allocate more cognitive resources to decide given the conditions presented.

The comparison between risky and uncertain conditions showed SCP negativity for the uncertain condition and a positivity for the risky condition in F4 between -950 ms and

-500 ms, with statistically significant difference (F(1,98)=5.847, $p<0.05$) as shown in figure 2.

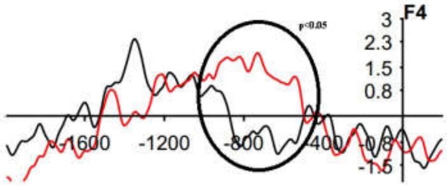

Figure 2: SCPs in risk x uncertain condition in F4. Black line represents uncertain condition, red line risk condition. The ellipsis shows the point of the significant difference. Y axis represents micro voltages, X axis represents the epoch in milliseconds.

As for the comparison between risky and uncertain scenarios in a low consequence condition, we found a SCP negativity for the uncertain condition and a positivity for the risky condition in Fz and F4 between -1290 ms and -490 ms, with statistically significant differences for both electrodes (F(1,98)=3.631, $p=0.05$ and F(1,98)=4.720, $p<0.05$, respectively) as shown in figure 3.

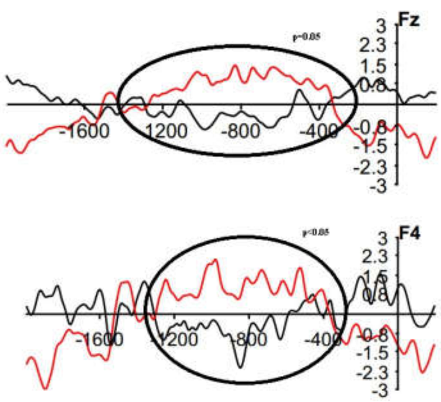

Figure 3: SCPs in risk x uncertain, low consequence condition. Top part represents Fz electrode. The bottom panel depicts voltages in the F4 electrode. Black line is uncertain condition, red line is risk condition. The ellipsis shows the point of the significant difference. Y axis represents micro voltages, X axis represents the epoch in milliseconds.

When high consequences are observed, there is a marginal statistical significance between a SCP positivity in risky conditions and a negativity in uncertain conditions in F4 between -920 ms and -500 ms (F(1,98)=3.517, $p=0.06$) as shown in figure 4.

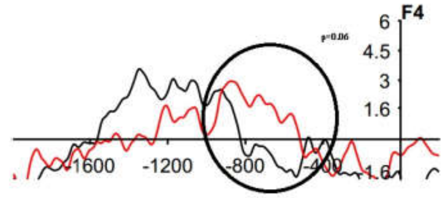

Figure 4: SCPs in risk x uncertain, high consequence condition in F4. Black line represents uncertain condition, red line risk condition. The ellipsis shows the point of the significant difference. Y axis represents micro voltages, X axis represents the epoch in milliseconds.

Discussion

Behavioral data suggests that the balance of acquired information (BAL), according to Bayesian calculations (Fifić & Buckmann, 2013), is a preferred stopping rule. EEG data supports this conclusion given the fact that where BAL represented significant differences, there was the emergence of SCPs. According to Oswald and Sailer (2013), the SCPs are task-related and the negativity might mean conflict processing and the usage of cognitive resources to resolve such conflicts. Even though there was also a significant difference for the quantity of information bought and the decisions, consciously or not participants behave according to Bayesian calculation in order to determine the end of the information acquisition process.

This holds up even if the conditions are considered (combined or isolated). This means that the participants will take into account the valences of the information pieces acquired and when they reach a particular threshold (depending on the scenario characteristics), the decision is made. That becomes clearer when the threshold is approximately +1 for a positive decision, approximately -1 for a negative decision and approximately zero for a procrastination decision. The procrastination decisions show that even though there are more pieces of information acquired, participants often would feel more uncertain and would rather skip the decision. This means that that particular scenario and the set of information acquired would not diminish the residual uncertainty acknowledged by the participant, thus making it harder to assess which decision is better given the probabilities and consequences.

Uncertain scenarios needed less QTY and a higher BAL in order to reach a decision than risk scenarios. The appearance of the SCP negativity for uncertain scenarios can reflect a higher conflict in this condition given that, even though participants seek less information, they need higher valences to resolve the conflict. This conflict may arise due to the difficulty to assign a value to the unstated probability described in the scenarios. As in Stern et al. (2010) each new information can change the subjective probability that the participant assigns to the outcome. These changes can require more BAL and result in more use of cognitive resources in order to decide.

When conditions were combined, especially the two highlighted previously, the same effect is also present. In uncertain low negative consequence conditions there is the need for more BAL and there is also a SCP negativity although with higher amplitude than the one described on the last paragraph. This, according to Oswald and Sailer (2013), mean that there is an expanded cognitive effort in resolving the conflict that the valences and the condition might imply.

Lastly, in high negative consequence conditions, risky scenarios need more BAL, however, in high consequence conditions the SCP negativity is seen for uncertain scenarios. We hypothesize that the lack of stated probability in a high consequence scenario might mean that the information has a higher weight for the participants and therefore there is no need to allocate as much cognitive effort as with risky conditions. In this case, a stated probability might introduce some level of ambiguity given that the risk is apparent and the consequences can be large.

Conclusion

We developed an experiment aiming to observe different strategies, or stopping rules, that individuals might use in order to cease information acquisition and make a decision in a given scenario. Departing from the stopping rules proposed by Fifić and Buckmann (2013), we manipulated scenarios in order to show or not show probabilities, high or low consequences and positive or negative consequences. The data suggests that individuals do not actually follow a particular stopping rule, rather they tend to use, consciously or not, Bayesian calculations in order to consider all the information that was bought in a scenario, when considering the decisions participants made. Moreover we found SCP waves for different conditions in the experiment. That can mean that for those conditions there was an expanded allocation of cognitive resources in order to solve conflicts that emerged from the information acquisition and the scenario description. Those manipulations showed that the information acquisition behavior resembled prospect theory (Tversky & Kahneman, 1992) in that different levels of risk or uncertainty combined with high/low and positive/negative consequences will directly affect the quantity of information bought and the weight that the information will have in order for a participant to feel satisfied and proceed to a decision.

This was an exploratory experiment in order to study the moments leading to a decision in an information acquisition task. Further studies should focus on confirming the behavior and electrophysiological correlates of each condition separately. Also, there is an opportunity for the use of integrated psychophysiological measures in order to confirm task engagement and cognitive effort in those conditions (ECG and eyetracking, for example)

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References

Böcker, K.B.E, Baas, J.M.P, Kenemans, J.L., & Verbaten, M.N. (2001). Stimulus-preceding negativity induced be fear: a manifestation of affective anticipation. *International Journal of Psychophysiology*, 43, 77-90.

Courtney, H., Kirkland, J., & Viguerie, P. (1997). *Strategy under uncertainty*. Harvard Business Review, (December), 81–90.

Di Caprio, D., Santos-Arteaga, F. J., & Tavana, M. (2014). Information acquisition processes and their continuity: Transforming uncertainty into risk. *Information Sciences*, 274, 108–124. doi:10.1016/j.ins.2014.02.144

Fifić, M., & Buckmann, M. (2013). Stopping Rule Selection (SRS) Theory Applied to Deferred Decision Making. In *Proceedings of the 35th Annual Meeting of the Cognitive Science Society* (pp. 2273–2278). Retrieved from http://mindmodeling.org/cogsci2013/papers/0415/paper0415.pdf

Frey, R., Hertwig, R., & Rieskamp, J. (2014). Fear shapes information acquisition in decisions from experience. *Cognition*, 132(1), 90–99. doi:10.1016/j.cognition.2014.03.009

Gigerenzer, G. (2000). *Adaptive thinking: Rationality in the real world*. New York: Oxford University Press.

Lopez-Calderon, J., & Luck, S. J. (2014). ERPLAB: An open-source toolbox for the analysis of event-related potentials. *Frontiers in Human Neuroscience, 8:213*. doi: 10.3389/fnhum.2014.00213

Oswald, F., & Sailer, U. (2013). Slow cortical potentials capture decisions processes during temporal discounting. *European Journal of Neuroscience*, 37, 1159-1169. doi:10.1111/ejn.12108

Pretz, J. E., Naples, A. J., & Sternberg, R. J. (2003). Recognizing , defining and representing problems. In *The Psychology of Problem Solving*. Cambridge University Press.

Söllner, A., Bröder, A., Glöckner, A., & Betsch, T. (2014). Single-process versus multiple-strategy models of decision making: Evidence from an information intrusion paradigm. *Acta Psychologica*, 146, 84–96. doi:10.1016/j.actpsy.2013.12.007

Stern, E. R., Gonzalez, R., Welsh, R. C., & Taylor, S. F. (2010). Updating beliefs for a decision: neural correlates of uncertainty and underconfidence. *The Journal of Neuroscience*, 30(23), 8032–41. doi:10.1523/JNEUROSCI.4729-09.20104

Taghavifard, M. T., Damghani, K. K., & Moghaddam, R. T. (2009). Decision Making Under Uncertain and Risky Situations. In *Enterprise Risk Management Symposium Monograph Society of Actuaries*. Chicago, IL.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty*, 5(4), 297–323.