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The possible influence of emotional intelligence and cognitive ability on ambiguity attitudes

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Abstract

In this thesis the relationship between emotional intelligence (EI), cognitive ability and ambiguity attitudes is investigated. Measuring ambiguity attitudes is done using the method of Dimmock, Kouwenberg & Wakker (2016). EI could not completely be measured due to the long duration of EI tests and budget constraints. EI consists of four branches according to Mayer, Caruso and Salovey (2016). Only one of the branches, namely emotional management is measured. The Cognitive reflection test of Frederick (2005) is used as a proxy for cognitive ability. The results do not show significant results for a relationship between emotional management, cognitive reflection test and ambiguity attitudes. A significant effect is found between age and a-insensitivity. Next to this, multiple employment statuses appear to have an effect on ambiguity attitudes. In the discussion, several limitations are used to explain that the results from this paper do not necessarily mean that there is no relationship between EI, cognitive ability and ambiguity attitudes.

Keywords: A-insensitivity, ambiguity aversion, emotional intelligence, emotional management, cognitive ability, cognitive reflection test

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1. Introduction

Some people are confronted with ambiguity almost every day, even though not everyone realises that many choices involve an ambiguous situation. A situation where the probability of the outcome is unknown is called an ambiguous situation. This is a situation under uncertainty. Money-related issues such as the choice of whether or not to invest in a stock are often thought of in terms of ambiguity. The probability of the price of a share falling or rising is not known and it is therefore an ambiguous situation. There are several factors that cause people to react differently to particular choices under uncertainty. Attitudes that people have toward ambiguity, play a role in a large number of decisions that people make. Some factors such as intelligence are found to be predictive of the attitude people have toward ambiguity. An example of an ambiguous situation is the decision of a skater who hesitates between a new training schedule and a known training schedule in order to qualify for the Olympic Games. The exact impact of the new training schedules on his or her race times is unknown, while he or she already knows some of the impact of the old training schedule. It is not clear what the consequences are of choosing either schedules. Choosing (in hindsight) an inferior training scheme can have huge consequences for the skater's career and qualifying for the Olympics. The skater's choice depends partly on his or her attitudes towards ambiguity. People can have different attitudes towards an ambiguous choice.

It has been shown that the most important components of ambiguity attitudes are ambiguity aversion and ambiguity likelihood insensitivity (a-insensitivity) (Abdellaoui, Baillon, Placido & Wakker, 2011; Dimmock, Kouwenberg & Wakker, 2016). People who are ambiguity averse prefer known risks over unknown risks, when a choice has to be made between a known and unknown risk. In a study by Muthukrishnan, Wathieu and Xu (2009) it was found that ambiguity aversion can even cause people to choose for products from a brand with a more established name, even when the features of the product are dominated by a product with a less established brand name. The other component is a-insensitivity. The more a-insensitive people are, the less people understand of an ambiguous situation and the less ability people have to cope or deal with ambiguity. People who are a-insensitive do not sufficiently discriminate between different levels of ambiguity, thereby moving subjective likelihoods towards 50-50 (Dimmock, Kouwenberg & Wakker, 2016). Meaning that a-insensitive people are ambiguity seeking for low likelihoods and ambiguity averse for high likelihoods. The ambiguity attitudes and components of these attitudes will be explained further in the literature review.

Ambiguity aversion or a-insensitivity can cause people to deviate from their optimal choice that would have been chosen in absence of ambiguity or when people would better understand ambiguity. Therefore, it is important to understand what factors contribute to ambiguity aversion and a-insensitivity. Because attitudes toward ambiguity can have a major impact on choices people make, it is important to look at factors that can predict people's ambiguity attitudes. Two of these factors that may be related to ambiguity attitudes are emotional intelligence (EI) and cognitive ability in the form of intelligence. EI is someone's capacity to reason about emotions and use these emotions to enhance thinking (Mayer, Salovey & Caruso, 2004). Hess & Bacigalupo (2011) found that practical application of EI skills can enhance decision making and outcomes. Cognitive ability in the form of intelligence is someone's mental capacity to facilitates reasoning, problem solving, decision making, and other higher order thinking skills, such as learning from experience (Gottfredson, 1997). To understand more about people's ambiguity attitudes, it is interesting to study whether EI or cognitive ability are determinants of ambiguity attitudes with regard to decision making in an ambiguous situation. The main focus of this study is to investigate whether an individual's EI or cognitive ability is related to ambiguity attitudes. If there is a relationship between the former two and ambiguity attitudes, it is interesting to see which of the two has a stronger relationship with ambiguity attitudes, or which of the two is a better indicator for ambiguity attitudes. To sum up, I will examine whether EI or cognitive ability in the form of intelligence has a relationship with ambiguity attitudes. This study will therefore explore the following research question:

What is the relationship between EI, cognitive ability and ambiguity attitudes?

Some research has been done into the relationship between cognitive ability and ambiguity attitudes in the gain domain. This paper will try to contribute to the knowledge about the relationship between cognitive ability and ambiguity attitudes. In addition, there is not much know about the link between EI and ambiguity attitudes. The method of Dimmock, Kouwenberg & Wakker (2016) that is used to measure ambiguity attitudes makes it possible to look at a-insensitivity. The link between a-insensitivity and EI has not been investigated before. Therefore, a novel link could be found to (partly) explain why people have particular ambiguity attitudes. An choice between a risky choice and ambiguous option or ambiguity in general could arouse emotions. Then, I expect that higher emotional intelligence will lead people to higher emotional balance, which will make people less ambiguity averse or a-insensitive. The link between EI and intelligence has been studied many times. Nonetheless, not yet in the context of ambiguity attitudes. This all contributes to the scientific relevance of this paper. The social relevance of this paper is the examination of characteristics that may contribute or are linked to ambiguity aversion or a-insensitivity. Both ambiguity aversion and a-insensitivity can be seen as a bias. If a link can be found between EI, intelligence or both and ambiguity attitudes. In the case that a significant link is found there could be examined which persons are more likely to suffer from these biases. These people could be helped to overcome these biases. This may be necessary because ambiguous situations often arise and can affect people a lot (negatively). For example, EI and cognitive abilities can both be trained.

The structure of this thesis is as follows: First the current literature on ambiguity attitudes, EI, cognitive ability and the link between these will be reviewed. Here, I will also review which tests are available to measure EI and cognitive abilities and I will present the tests used in this research for both EI, cognitive ability and measuring ambiguity attitudes. Afterwards, I will present the hypothesis that will be used to answer the research question. The hypotheses in this study are based on the current literature. Next, the methodology will be discussed. Here, I will elaborate on both the survey used to collect the data and the method that will be used to elicit ambiguity attitudes. Afterwards, the results will be discussed followed by a discussion and conclusion.

2. Literature Review

2.1 The components of ambiguity attitudes

As indicated in the introduction, ambiguity attitudes consist of two components. Ambiguity attitudes depend on the likelihood of uncertain events, the source of uncertainty and on the outcome domain (Trautmann & van de Kuilen, 2015). Factors that presumably influence ambiguity attitudes are cognitive ability and EI, these two factors will be discussed in sections 2.2 and 2.3, respectively. Next to this, attitudes toward ambiguity are the key indicators for explaining decision making under ambiguity. It is therefore important to look at what is known so far about ambiguity attitudes and how ideas about ambiguity attitudes are constructed. Both ambiguity attitudes, ambiguity aversion and a-insensitivity, will be discussed below.

2.1.1 Ambiguity attitudes: Ambiguity aversion

Researchers have been trying to understand and explore decision making under ambiguity and have built quite a framework on ambiguity. Knight (1921) and Keynes (1921) were the first to distinguish between measurable uncertainty and unmeasurable uncertainty. Which they also referred to as risk and uncertainty, respectively. Ellsberg (1961) continued to study the differences between risk and ambiguity and people's preferences between risk and ambiguity. Ellsberg (1961) showed in his thought experiment, extensively confirmed later, that people are ambiguity averse if they get a choice between a choice under risk and a choice under uncertainty. From the results, the Ellsberg paradox originated. The Ellsberg paradox will be discussed in more detail in §2.1.3. Partly because of the Ellsberg paradox, ambiguity aversion is well known. Tversky and Fox (1995) showed that people are not ambiguity averse in all cases. They showed that ambiguity aversion only arises or is intensified when a risky task and an ambiguous task are presented simultaneously. Ambiguity aversion is decreased or even disappears when people are presented solely with an ambiguous task. Tversky and Fox (1995) related this to the comparative ignorance hypothesis. However, there are often situations where a choice has to be made between a risky task and an ambiguous task. A study by Dimmock, Kouwenberg, Mitchell & Peijnenburg (2013) found that in a sample, representative for the American population, 52% of the participants were ambiguity averse. It is therefore important to illustrate that ambiguity averse behaviour sometimes has significant effects on people's decisions. Berger, Bleichrodt & Eeckhoudt (2013) found that ambiguity aversion resulted in a lower propensity to opt for certain medical treatments when the risks are less known. This is an example of how ambiguity aversion caused people to deviate from their optimal choice of treatment that would have been chosen in absence of ambiguity.

2.1.2 Ambiguity attitudes: Ambiguity likelihood insensitivity

For a while it was thought that only ambiguity aversion played a role in the assessment between an ambiguous and a risky option. However, there appears to be a second component involved in the ambiguity attitudes that are at play for the assessment between an ambiguous and a risky choice. The second component next to ambiguity aversion is, as already mentioned, a-insensitivity (Abdellaoui, Baillon, Placido & Wakker, 2011; Dimmock, Kouwenberg & Wakker, 2016). Both a-insensitivity and ambiguity aversion are important to explain ambiguity attitudes that are found in empirical research. How a-insensitive a person is can indicate how well this person can distinguish between different levels of likelihood in an ambiguous situation, i.e., a situation with unknown probabilities (Dimmock, Kouwenberg & Wakker, 2016). A-insensitivity reflects a lack of understanding of uncertainty and is the extension to ambiguity of the well-known inverted S-shaped probability weighting (Baillon, Cabantous, & Wakker, 2012). The inverse S-shaped probability weighting function has only been actively researched for a number of years. However in 1979, Kahneman and Tversky (1979) already came up with the idea that people underweight high probabilities and overweigh small probabilities, resulting in an inverted S-shaped value function. An a-insensitive person will see ambiguous situations as if they have a 50-50 percent chance to happen. For example, an a-insensitive person will perceive the chances of a stock going up or down as 50-50. This means that if the likelihood of a stock is going down is small, this likelihood will be overweighted (ambiguity seeking behaviour). On the other hand, if the likelihood of a stock going down is high, then this likelihood will be underweighted (ambiguity averse behaviour). It is important to note that overweighting and underweighting as described only happens for the domain of gains. For the domain of losses an a-insensitive person will have the opposite patterns. Meaning that an a-insensitive person will overweight events with high likelihoods (ambiguity seeking behaviour) and underweight events with low likelihoods (ambiguity averse behaviour) (Baillon & Bleichrodt, 2015).

2.2 How to measure ambiguity attitudes

As indicated, the ambiguity attitudes will be measured with an elicitation method proposed by Dimmock et al. (2016). Here, the source method of Abdellaoui et al. (2011) is used. This method is based on a distinction between sources of uncertainty. In the method of Dimmock et al. (2016), the classical Ellsberg paradox of Ellsberg (1961) is used to measure ambiguity attitudes.
However, it has long been assumed that the Ellsberg paradox violated classical decision models (i.e. expected utility) using subjective probabilities.

In the Ellsberg experiment, people could choose between betting on a colour in an urn with two colours (black and red) with unknown probabilities and betting on a urn with two colours (black and red) with 50% red balls and 50% black balls. The Ellsberg experimented showed that most people prefer betting on the known urn with a 50% chance winning over choosing one of the two colours of the urn with unknown probabilities. However, if the unknown urn has black and red balls and you prefer the 50% chance of winning over chance of picking the red ball in the unknown urn because you expect the chance of winning to be higher in the urn with a 50% chance of winning. Then you expect that less than 50% of the balls in the unknown urn are red. However, then it should be that the amount of black balls in the unknown urn are more than 50% of the balls. Thus, people should prefer gambling on the black balls in the unknown urn over choosing the known urn if they prefer the chance of winning with 50% over choosing the red balls in the unknown urn. However, most people always prefer the known urn with a 50% of winning over choosing one of the two balls in the unknown urn. This contradiction was thought to violate expected utility. Mathematically, this can be explained by setting the chance of winning by pulling a black ball from the unknown urn as p(b) and setting the chance of winning by pulling a red ball from the unknown urn as p(r). If most people prefer betting on the known urn over betting on pulling a red ball from the unknown urn, then p(r)<50%. But, we also know that most people prefer betting on the known urn over betting on pulling a black ball from the unknown urn. This gives p(b)<50%. However, in the end this would mean that p(r) + p(b)<100%. This was assumed to be impossible. There was expected that Ellsberg paradox could not be accommodated by subjective probabilities.

However, a new insight was provided by Chew and Sagi (2008). They came up with source-dependent weighting functions. This implied that the unknown and known urn in the Ellsberg experiment are two different sources of uncertainty. The probability of winning by choosing black in the known urn is still 50%. However, people have subject probabilities that can be different for both urns. Subjective probabilities can create source dependent weighting functions that can be different the known and unknown urn. Meaning that there is no violation of expected utility. One implication of this finding is that if someone prefers an unambiguous choice over an ambiguous choice, this person is not necessarily ambiguity averse. It can be that a lower subjective probability is assigned to the ambiguous choice and that this person is ambiguity neutral for example. Therefore, if ambiguity attitudes are measured there should be controlled for subjective probabilities.

Dimmock et al. (2016) describe their method as tractable and empirically well working. Kothiyal et al. (2013) showed that the source method that is used by Dimmock et al. (2016) predicts choices under ambiguity better than other models that where popular around that time. Next to this, the advantage of the method of Dimmock et al. (2016) is that the method is easy to implement and does not take long and that both ambiguity aversion and a-insensitivity are captured with matching probabilities. The method of Dimmock et al. (2016) takes on average five minutes to complete. Dimmock et al. (2013) found that the reliability of measuring ambiguity is increased if ambiguity attitudes are measured through sequential elicitation compared to direct matching techniques for measuring ambiguity attitudes. Directly asking participants for what probability they would be indifferent between an ambiguous and unambiguous choice (direct matching technique) is also more practical. Another advantage is that the method of Dimmock et al. (2016) can capture both ambiguity aversion and a-insensitivity and that the interpretation of the indexes that can be derived to look at both attitudes are straight forward. However, the main advantage of the method of Dimmock et al. (2016) is that the method measures ambiguity attitudes relative to risk attitudes. All other components important in decision making are differenced out by this, such as probability weighting and risk attitudes (Dimmock et al. 2013). This makes matching probabilities measures within-subject comparison between the ambiguous and unambiguous boxes, what is done in this thesis and in the method of Dimmock et al. (2016) so convenient. In theorem 3.1 in the paper of Dimmock et al. (2016) theoretical proof for the fact that matching probabilities of ambiguous events capture individual ambiguity attitudes is given.

2.3 Factors that are related to ambiguity attitudes

Apart from EI and cognitive ability, there are other factors that affect ambiguity attitudes. A small positive relationship was found between being college educated, old and male and ambiguity aversion (Dimmock, Kouwenberg, Mitchell & Peijnenburg, 2015). However, Han, Reeve, Moser & Klein (2009) found that low education was associated with higher ambiguity aversion.
Tymula et al. (2012) found that age had an effect on ambiguity tolerance. They found that adolescents tolerate ambiguous monetary lotteries more than adults. Han et al. (2009) found a

correlation between older age and ambiguity aversion. However, they found that the youngest respondents also demonstrated more ambiguity aversion. Dimmock et al. (2016) found a positive relationship between education and ambiguity aversion. Borghans, Golsteyn, Heckman & Meijers (2009) found that women respond more favourable to ambiguity initially than men. However, when ambiguity increased no difference in response to ambiguity was found between men and women. Likewise, Dimmock et al. (2015) found no relationship between gender and ambiguity attitudes.

Li (2017) found a relationship between income and ambiguity attitudes. In a Chinese context, when comparing urban rich people with rural poor people, the rich people where less ambiguity averse and a-insensitive compared to their poor counterparts. There was also found that among the rural poor people, ambiguity aversion and a-insensitivity was negatively correlated with income. However, among the richer urban adolescents, income had a positive relationship with a-insensitivity. Butler, Guiso and Jappelli (2013) found a positive correlation between ambiguity aversion and wealth. They also stated that empirically, people who dislike risks are also more likely to be ambiguity averse. Han et al. (2009) also found a positive correlation between income and ambiguity aversion. Multiple characteristics affect ambiguity attitudes. However, the results sometimes contradict each other. This thesis could add new insights into the relationship between multiple characteristics and ambiguity attitudes. The characteristics that will be looked at regarding their relationship to ambiguity attitudes are, besides cognitive and emotional intelligence: Age, sex (gender), school level, employment, marital status, household number, ethnicity and income.

2.4 Emotional intelligence

In this study, I will look at the relationship between emotional intelligence, cognitive abilities and ambiguity attitudes. This section will examine the literature on emotional intelligence.

Salovey and Mayer (1990) were the first to analyse EI and give a definition to EI in a journal article. This was the first time that EI was constructed in a formal model. EI can be conceptualised and measured in two complementary constructs, trait EI and ability EI (Petrides, 2001; Petrides & Furnham, 2000a; Petrides & Furnham, 2000b; Petrides & Furnham, 2001). Trait EI can be measured trough self-reported questionaries about your emotions. Petrides, Pita & Kokkinaki (2017) define trait EI as a construct of emotional self-perceptions at the lower levels of personality hierarchies that is measured with the trait emotional intelligence questionnaire. Not much later, a more concrete interpretation is given, which shows that emotional intelligence is still research a lot theoretically. Petrides, Sanchez-Ruiz, Siegling, Saklofske and Mavroveli (2018) refer to trait EI as our perception of our emotional world about our own emotional dispositions and how good we believe we are in perceiving, understanding, utilizing and managing our own and other’s people’s emotions .

The other EI construct is Ability EI. Ability EI is measured through tests of maximal performance. In the ability model of Mayer, Salovey & Caruso (2004), Ability EI can be seen as the indicator for someone's ability to process and use emotional information to navigate through the physical and social setting that people encounter or in which people live. Mayer, Roberts & Barsade (2008) made this more concrete by explaining that Emotional intelligence (EI) involves the ability to carry out accurate reasoning about emotions and the ability to use emotions and emotional knowledge to enhance thought. Data from a study that subsequently looked further into EI highlight the differences in what trait and ability EI both measures and that study also highlights the importance to distinguish between the two EI constructs (O'Connor & Little, 2003). It is important to mention that for this research I will only look into Ability EI. This is because Ability EI is expected to be linked to cognitive ability and intelligence and that this is not likely to be the case for trait EI (Barchard & Hakstian, 2004; Pérez, Petrides, & Furnham, 2005). According to a meta-analysis of Mattingly and Kraiger (2019) ability EI or scores on EI measures can be increased via training. Higher EI scores are related with more education and receiving psychotherapy (Goldenberg, Matheson & Mantler, 2006).

2.4.1 The ability model of emotional intelligence

Ability EI can be divided into four areas/dimensions or branches. Mayer and Salovey (1997) referred to this as the four-branch model. Later on, Mayer, Caruso and Salovey (2016) made some adjustments to the model. Since 2016, the four branches of the ability model are:

1) Perceiving emotions, which captures the capacity to recognize emotions in others.

2) Facilitating thought using emotions, which involves the capacity of emotions to assist thinking. Mostly this is about using your emotional state or considering emotions of other people to make the right decision in problem-solving and thinking.

3) Understanding emotions, this builds upon perceiving emotions. However, understanding emotions is more about analysing emotions and understanding what events will arouse what types of emotions.

4) Managing emotions. Managing emotions can be used to avoid feelings or to reframe your emotions in order to achieve something. This is the branch that will be used as indicator for emotional intelligence in this paper by the means of the STEM-B.

The branches go from less complex to more complex for the problem solving area of emotional intelligence (Mayer, Caruso & Salovey, 2016). Furthermore, the four branches model is hierarchical. Meaning that a person must be able to use lower-level branch abilities in order to develop higher-level branch abilities. For example, in theory a person must be able to perceive emotions and facilitate emotions in order to understand emotions (Joseph & Newman, 2010). Gilar-Corbi, Pozo-Rico, Sánchez and Castejón (2019) found that the ability-based branches can be improved after training for the business environment. Important for this paper is to see what branch(es) could be mostly involved in decision making with the presence of an ambiguous situation. By looking at the types of reasoning for the four branches which were provided by Mayer, Caruso and Solevey (2016), there can be discussed what branches are the most important for this research. Perceiving emotions does not directly have types of reasoning or abilities involved in the decision process with an ambiguous choice. The same applies to facilitating thought using emotions. However, understanding emotions could be important in the process of decision making with an ambiguous option. Amongst other, appraise the situations that are likely to elicit emotions, and determine the antecedents, meanings, and consequences of emotions, are types of reasoning that fall under understanding emotions. Managing emotions also seems to be important in the decision making process with a choice option with ambiguity. Effectively manage one's own emotions to achieve a desired outcome, monitor emotional reactions to determine their reasonableness and evaluate strategies to maintain, reduce or intensify an emotional response and engage with emotions if they are helpful; disengage if not are likely, all seem to be types of reasoning that can be important in a decision process with an ambiguous choice. However, the 3rd and 4th branches or abilities are more likely to be strongly developed when the 1st and 2nd branches are as well. Thus, both perceiving emotions and facilitating thought using emotions could also be indirectly important in decision making with an ambiguous choice.

2.4.2 Choosing an Ability EI test

To measure Ability EI multiple tests can be used. McEnrue and Groves (2006) analysed multiple EI tests (MSCEIT, ECI-2, EQ-I and EIQ) and advocated to use the MSCEIT(V2.0) to test EI because of its psychometric properties and human research development application potential. The MSCEIT(V2.0) is researched a lot and is a supported measure of ability EI. The MSCEIT(V2.0) was developed by Mayer, Salovey, Caruso and Sitarenios (2003) and the test uses the four branch approach to measure ability EI. The test takes between 30 to 45 minutes. Due to the fact that this test is time consuming and that there are high costs associated with its use, the use of MSCEIT(V2.0) is not appropriate or feasible for this study. The same arguments apply for the use of the ECI-2, EQ-I and EIQ.
Luckily, some other ways to measure ability EI are designed. MacCann and Roberts (2008) designed two tests to test parts (or branches) of EI based on the ability EI model described above. Both tests are maximum-performance emotional management situational judgements tests. MacCann and Roberts (2008) designed the Situational Test of Emotion Management (STEM) and the Situational Test of Emotional Understanding (STEU). The STEM can be seen as a measure of emotional

management in oneself and the STEU as a measure of emotional understanding. Making it possible to measure two of the four branches from the ability EI model. Joseph and Newman (2010) found a correlation of 0.55 between emotional management and emotional understanding in a meta-analysis.

MacCann and Roberts (2008) tested their designed ability tests and found that the results of their test did not provide an unequivocal verdict on whether the STEM and STEU measure the same constructs as MSCEIT Managing and Understanding. They found that both the MSCEIT(V2.0) and the STEU are positively correlated to intelligence. Both the STEM and STUE are not correlated to trait EI and personality. The STEM shows reliable and consistent internal validity, while this is not the case for the STEU (MacCann & Roberts, 2008). The Cronbach's alpha for the STEU was 0.71 and 0.68 for the STEM (MacCann & Roberts, 2008). Libbrecht and Lievens (2012) found a two-week test-retest reliability of 0.72 for the STEU and 0.85 for the STEM. Both the STEM and STEU are freely available for use, however these tests are still time consuming with respectively having 44 and 42 items. To make these test less time consuming, brief version of both the STEM (STEM-B) and STEU (STEU-B) were developed (Allen et al., 2015; Allen, Weissman, Hellwig, MacCann, & Roberts, 2014). Allen et al. (2015) indicated that the STEM-B in comparison with the STEM might even be a better test for emotional management since the STEM-B does not lose much validity compared to the STEM and is much shorter. In a Chinese context, both the STEM-B and STEU-B were found to be psychometrically adequate measurements of emotion regulation and emotion understanding (Yan, Feng, Xu & Li, 2019). Da Motta, Carvalho, Pato & Castilho (2020) found in a Portuguese setting that the STEM-B is a psychometrically adequate measure for emotional management skills. They emphasise in their study that the STEM-B is especially well-suited when measuring emotional management in vulnerable populations or when participation fatigue is a concern.

Since participation fatigue may be a problem in this study, there is chosen for this research to use the STEM-B. As explained before the reduction in time, for both the STEM-B and STEU-B, comes with a small reduction in validity and Da Motta et al. (2020) therefore also mention that without the above mentioned constrains the use of the STEM would be better. Both the STEM-B and STEU-B are a good fit for measuring (parts of) ability EI within a short amount of time and thus feasible for this study. However, I expect emotion management to have a more direct relationship with ambiguity attitudes and I therefore chose to focus on the STEM-B. This believe is based on the abilities involved in emotion management compared to emotion understanding and the fact that emotion management is the highest branch. The use of both the STEM(-B) and STEU(-B) or the use of the MSCEIT(v2.0) would be even better, but this is not feasible due to the fact that this would drastically increase the duration of the survey that will be used in this study which could lead to participation fatigue. This will be addressed in more detail in the discussion.

2.4.3 STEM-B

The STEM-B has 18 items or questions and there are multiple choice answers. In the test there is emphasized that people are expected to answer what they should do in the situation explained in each item or question. The Cronbach's alpha of this test is 0.84 (Allen et al., 2015). For the scoring system, emotion experts looked at the answers of the STEM-B and indicated what they thought were the best answers. From these results, points were divided among the answers per question in ratio with respect to what the emotion experts indicated as the best answer. From here, the total number of points of an individual can be calculated. The STEM-B takes approximately 10 minutes to complete for people with English as native language. The questions/items were constructed with the use of the critical incident method and scoring syntax for both the STEM(-B) and STEU(-B) can be found on: https://osf.io/mqp2x/.

2.4.4 Ability EI as cognitive ability

There is a presumption that ability EI (or EI in general) is a cognitive ability that is not measured by standard intelligence tests, and that Ability EI (or EI in general) is important in tasks of reasoning and problem solving in the emotional domain (Austin, 2010). This presumption is supported by the fact that the MSCEIT, one of the most well-known tests for measurement of ability EI, is correlated to measurements of general ability (correlation between 0.25 and 0.32) (O'Connor & Little, 2003). However, the fact that a test is correlated to an intelligence or ability test does not mean that this test measures a new form of cognitive ability. Brody (2004) is of the opinion that there is no convincing evidence that EI or the MSCEIT has incremental predictive validity equal to or above standard measures of intelligence. On the other hand, Alba-Juez & Pérez-González (2019) explained in their study that ability EI might be interpretated as the cognitive or conscious component of emotional competence. Gutiérrez-Cobo, Cabello and Fernández-Berrocal (2016) found in a meta-analysis that in 64.28% of the studies that was looked at, ability EI was more related to positive results in hot (emotionally laden) cognitive tasks. For cold or not emotionally laden cognitive tasks, EI appeared not to be related.

Despite the fact that research on emotional intelligence has been done for more than 20 years by now, there are still certain questions that need to be answered. According to Mestre, MacCann, Guil and Roberts (2016), EI research has benefitted from the integration with intelligence research. They explain that EI is a distinct group factor within intelligence research, especially the branches understanding and management which are aligned with knowledge and conceptualizations of intelligence. Also because people's ability for emotional management and emotional understanding are likely to increase with the years. MacCann, Newman and Roberts (2014) argue that the inclusion of EI in the intelligence framework could be an important step in charting the sphere of human cognitive abilities. They found that tasks involved in processing emotional information can constitute to a separate and distinct group factor of intelligence. Gray, Braver & Raichle (2002) looked at the integration of emotion and cognition in the brain and especially the in the lateral prefrontal cortex. They found that at some point of processing, emotion and higher cognition can be integrated. Then functional specialization is lost and both emotion and cognition contribute to the control of thought and behaviour. Next to the discussion about whether ability EI is a cognitive ability, the way ability EI measured is still debated. Pérez, Petrides & Furnham (2005) were critical about the ability EI tests. This came from the fact that at that moment, even after a decade of research and development, there were still ongoing questions about internal validity and factor structure of ability EI tests. However, measuring trait EI is probably not always a good option. People are not good at estimating their own emotional intelligence or general intelligence (Brackett et al., 2006). Self-estimated abilities differ between persons and for some people these abilities might not be good enough to create a good picture of someone's EI if measured with trait EI tests.

2.5 Cognitive abilities

In this study, I will look at the relationship between emotional intelligence, cognitive abilities and ambiguity attitudes. This section gives a short overview of literature on cognitive ability.

Cognitive ability can be measured in different ways. The most well-known way of measuring intelligence is with IQ (intelligence quote) scores. IQ scores measure the performance of individuals on tests designed to assess intelligence (Duckworth, Quinn, Lynam, Loeber & Stouthamer-Loeber, 2011). Duckworth et al. (2011) refer to IQ as an manifest variable since IQ can be measured. They define intelligence as a latent variable since intelligence cannot be observed. However, cognitive ability is also the ability to perform well on intelligence tests. IQ are mostly time consuming but there are also (shorter) tests designed to test (parts) of cognitive ability next to IQ tests, such as the numeracy test or the CRT (cognitive reflection test). High numeracy test scores indicate that people do understand probabilities and proportions accurately most of the times. Both understanding of probabilities and proportion affect decision making in ambiguous and/or risky situations. However, numeracy is a cognitive ability that is separated from other cognitive abilities/skills. Whereas a CRT test touches on more areas of cognitive abilities. Although I expect numeracy to be more predictive of / have a higher (negative) correlation with a-insensitivity, I measure cognitive ability using CRT in this thesis. This is mostly because the short amount of time that is necessary to complete an CRT.

This could help overcome participation fatigue as much as possible while measuring cognitive ability skills. The disadvantage of the CRT is that a lot of people already had some of the questions asked in their live or are familiar with the questions.

2.5.1 Cognitive Reflection Test

In this thesis, I chose to use the CRT as a proxy for cognitive ability. The reasons for this choice have already been explained above. The CRT was developed by Frederick (2005) and consists of three open questions that be found in figure 1. Kahneman (2011) explained that the ability to find the correct answer can be seen as the ability to override system 1 and activate system 2. The CRT was designed to measure someone's tendency to override an incorrect automatic process response (system 1) by using further reflection and thinking harder (system 2) to find the correct answer. Frederick (2005) found a correlation of 0.44 between CRT performance and the SAT (Scholastic Assessment Test) which is used as an admission test for universities and colleges in the United States. Toplak, West & Stanovich (2011) indicate that the CRT has a moderate overlap with measures of cognitive ability and is moderately associated with rational thinking skills.

Cognitive Reflection Test

(1) A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?
(2) If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
(3) In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

Figure 1 Cognitive reflection test questions
Notes: Test taken from Frederick (2005)

2.6 Emotional intelligence, cognitive abilities and decision making

Both EI and cognitive ability are important (influencing) factors in decision making. Here, I will summarize effects of EI and cognitive ability on decision making that have been found.

Lilleholt (2019) found a negative relationship between cognitive ability and risk aversion in the domain of gains in a meta-analysis. In Dohmen, Falk, Huffman & Sunde (2010) the participants who had lower cognitive abilities were more impatient and risk averse in the gain domain. Higher cognitive ability led to higher willingness to take risks. Burks, Carpenter, Goette & Rustichini (2009) also found that cognitive ability is negatively correlated to risk aversion. However, Andersson, Holm, Tyran and Wengström (2016) found that cognitive ability is correlated to mistakes (choice error) rather than to risk preferences. Mahmoud, Kamel and hamza (2020) found that creative thinking abilities, which fall under cognitive ability, are positively correlated to tolerance for ambiguity. This leads to the first hypothesis:

H1: CRT score is negatively correlated to ambiguity aversion.

Little is known about the relationship between cognitive ability and a-insensitivity. Enke & Graeber (2019) found suggesting evidence that a-insensitivity is reflected by cognitive uncertainty. There is also found that people with lower cognitive skills view stock returns as more fuzzy and ambiguous (Binswanger & Salm, 2017). As explained before, a-insensitivity reflects a lack of understanding of uncertainty and is seen as irrational. I expect that higher cognitive ability is related with a higher CRT score and, thus, a higher CRT score will positively affect someone's understanding of uncertainty and ability to cope with uncertainty. This leads to the second hypothesis:

H2: CRT score is negatively correlated to a-insensitivity.

While not much is known about cognitive abilities and ambiguity attitudes, even less is known about the association between EI and ambiguity attitudes. However, emotions can affect someone's risk preferences or ambiguity attitudes. Happiness and anxiety in a person make people more risk averse, while being in an emotional state of sadness makes people risk tolerant or risk seeking (Blanchette & Richards, 2010). Nguyen and Noussair (2014) found that the emotions fear, anger, happiness and surprise increase risk aversion. Furthermore, they found that people who were relatively emotions-free and had less emotional reaction during the experiment where less risk averse. Panno, Donati, Chiesi, & Primi (2015) showed that trait EI is indirectly related to risk-taking. Negative mood and anticipated fear, which are two emotions that naturally occur during the decision making process, were two mediators of the relationship between trait EI and risk-taking. Negative mood and anticipated fear are negatively correlated to risk-taking (Pann et al., 2015).

Asgarnezhad, Motamedi and Soltani (2017) found a positive relationship between emotional intelligence and ambiguity aversion in financial behaviour in investor on the stock market in Tehran. Sadness induces choices that come closer to ambiguity neutral attitudes, compared to joy, fear and a control group (Baillon, Koellinger & Treffers, 2016). Yesuf and Feinberg (2016) suggested that lack of trust and happiness are predictors of ambiguity aversion. Burrus et al. (2012) found that emotional management, which was measured with the use of the STEM, is related to both hedonic and eudaimonic well-being. Furthermore, higher emotion management on average also meant higher psychological well-being and more frequently experiencing positive affect and less frequently experiencing negative affect. Cardenas and Carpenter (2013) found that higher well-being is negatively correlated to ambiguity aversion and loss aversion in Latin America. Combining both could mean that higher emotional management could indirectly lead to less ambiguity aversion.

Potamites and Zhang (2012) found that in an experiment with subjects from a Chinese brokerage house, subjects who reported an increased level of anxiety during the trading day also displayed higher ambiguity aversion. Lashgari (2015) found that in the capital market, EI can help investment managers and other traders to form opinion regarding likely actions, which can reduce the degree of ambiguity in the market. It is imperative for investors to identify, understand and use their emotions to achieve and maintain an acceptable level of performance in the noisy capital markets. Probability weighting functions of people with high emotional balance tend to be more neutral and exhibit lower curvature. Therefore, it seems that emotional balance pushes people in the direction of normative expected utility theory (Charupat, Deaves, Derouin, Klotzle, & Miu, 2013). It is clear that emotions have an effect on choices involving risk or ambiguity. Higher emotional management will probably lead people to higher emotional balance, which will make people less ambiguity averse or a-insensitive I expect. However, for this to hold there must be expected that ambiguity, or choosing between a risky choice and ambiguity, will arouse emotions. Then people's ability to manage emotions could help them to react more rational and with less bias. I expect that being able to manage one's emotion should help people to use their cognitive abilities more which could also help people to make more rational or better decisions. This leads to the third and fourth hypothesis.

H3: STEM-B score is negatively correlated to ambiguity aversion.

H4: STEM-B score is negatively correlated to a-insensitivity.

If no emotions will be aroused by choosing between an ambiguous and a risky choice, then emotion management will probably not play a role in the task and then I expect no association between STEM-B score and ambiguity attitudes. However, I expect that an ambiguity situation will arouse emotions among the participants.

3. Methodology

The purpose of this thesis is to investigate whether there is a relationship between emotion management (one of the four branches of EI), cognitive ability and ambiguity attitudes. The data was collected by using an online survey in Qualtrics in English. In this section, the experimental design will be explained. Afterwards, the method used for measuring ambiguity attitudes and obtaining the global ambiguity attitude indexes will be discussed.

3.1 Experimental design

As stated above, the survey was done in Qualtrics. In the survey, people were first asked for their consent to participate in the experiment. The survey was accessible from 24 April 2022 till 19 May 2022. The consent form can be found in figure A1 in Appendix A. If people consented, the survey was started. If people did not give consent, the experiment was terminated. In figure A1, the introduction of the survey can be found as well.

In the first part of the survey, people were asked some personal characteristics which will later be used as independent variables in the analysis. These were:

Continuous variables:

- Age
- Household number

Categorical variables:

- Sex
- School level
- Employment
- Marital Status
- Ethnicity
- Income

Table 1 presents the different possible categories that participants could choose for each characteristic/variable. After the participants filled in their general characterises, they had to answer the three questions of the Cognitive Reflection Test. Participants had one CRT questions displayed per page and they had to go to the next page to see the next question. These questions and the explanation of the test can be found in §2.5.1 and are used as independent variables. In the third part of the survey, the participants had to take the multiple choice form of the STEM-B. In this part, the participants saw 6 multiple choice questions per page. The score that people achieved in the STEM-B is used as an independent variable. The explanation of the STEM-B can be found in §2.4.3 and the questions of the STEM-B can be found here: https://osf.io/mqp2x/. In last part of the survey, questions were asked to elicit participants' attitudes towards ambiguity which are used as dependent variables. This was done according to the method of Dimmock et al. (2016) which will be discussed in §3.2. Next to this, two check questions which were also used by Dimmock et al. (2016) where asked to the participants in order to check consistency. After this, participants could fill in their email if they wished to have a chance of winning 5 euro. This monetary incentive will be discussed in §3.2.

3.2 Measuring ambiguity attitudes

This section will explain how the ambiguity attitudes are measured. An important note here is that the method of Dimmock et al. (2016) is followed. Any deviation from this method will be mentioned. To elicit participants' attitudes towards ambiguity, the participants played three games with multiple rounds. For part one there is a maximum of 5 rounds. For part two and three there is a maximum of six rounds. Each round started with a choice between a gamble with unknown probabilities (ambiguity) and known probabilities (risk). Participants could choose which of the two options they preferred. However, there was also a third option that was labelled as indifferent. If the participants chose to be indifferent between the unknown and known probability, the game ended. The game also ended when the maximum amount of rounds per game was reached.

Dimmock et al. (2016) stress the importance of real incentives for their method to elicit ambiguity attitudes. They found in their study that hypothetical choices do not work well with their methods for non-academic participants. Since I did not only invite academic subjects or people who have an academic background, I wanted to have a real incentive as well in my study. I was allowed and able to divide up to €50 among the participants. I introduced real monetary incentives in the eliciting ambiguity attitude part. This was done by means of a random lottery incentive. It was made clear to the participants that randomly participants would be chosen to play for real incentives. The computer would then randomly select one of the rounds played by that participant. The computer then would choose a random ball from the box that was chosen in that round by the participant. If the drawn ball was purple, the participant won 5 euro. If not another participant was chosen. This process continued until 10 participants had won and the maximum amount of 50 euro was distributed among the participants.

The differences with Dimmock et al. (2016) is that in their experiment, participants all had a chance of winning 15 euros. Here, the exact chance of winning is not known since it depends on whether the chosen participant did win or not. If participants wanted to have a chance of winning 5 euro, they had to give their email. However, It may be that participants did not want to provide an email for privacy reasons or because they found the incentive too little or a combination of both reasons. Only 45 (32.3%) out of 139 participants did fill in their email. Therefore, it seems that only this part of the participants did the games on ambiguity with the perception of a chance of real monetary incentives. However, it could be that the participants felt they had a real monetary incentive despite the fact that they did not want to fill in their email. This can be the case because the participant had to fill in

their email at the end of the survey. As can be seen in table 1, a great proportion of the sample has an academic background. For this group, hypothetical choice is expected to work well.
In the first game, the participants needed to choose between an ambiguous box (Choice U) and an unambiguous box (choice K) or they could choose to be indifferent between the two options for every round. Both boxes contained 100 balls in two different colours. In line with Dimmock et al. (2016) the colours purple and yellow were chosen for the boxes. There was chosen to deviate from the colours black and red that are standard used in the Ellsberg urn/experiment. This was also done by Dimmock et al. (2016) since colour-blind people (could) have problems with distinguishing between these colours.

I deviated from the method used by Dimmock et al. (2016) by not giving participants a choice to choose their own “winning colour”. This was done by Dimmock et al. (2016) to increase trust in the experiment. Pulford (2009) suggested that distrust in the experiment could increase ambiguity aversion. Also the amount of people who changed the winning colour can be derived from letting people choose their own winning colour and this amount could show whether there is a lot of suspicion towards the experiment. However, I could not find an way to include this in Qualtrics. This is unfortunately a lost opportunity to increase trust in the experiment and a lost opportunity to see if there is a lot of suspicion towards the experiment.

For the ambiguous box (Choice U), the proportion of different colours was not known. For the unambiguous option (Choice K), the distribution was 50 purple balls and 50 yellow balls in the first round. The first round of the game can be seen in figure 2. If the participant chose Choice K, then Choice K was made less attractive. If Choice K was chosen again, then Choice K was also made less attractive again. However, if Choice U was chosen, then Choice K was made more attractive. This continued until the participant chose the option Indifferent or when the maximum amount of iterations was reached. If the participant chose Indifferent, then the amount of purple balls in box K was taken as the matching probability. For all games, if the participant reached the maximum number of iterations without choosing indifferent, the average of the remaining upper and lower bound was taken to calculate the matching probability. Game two and three are basically the same as game one. However, the difference between the games lies in the initial chance of winning for the unambiguous box (Choice K). These chances for each game are 0.5, 0.1 and 0.9, respectively. In game two and three there are ten different colours in the boxes. Every colour has a chance of 10% to be drawn in the first round. Again the proportion of colours is unknown to the participants in the ambiguous box. Game two and three are necessary to measure a-insensitivity. The first round of game 2 can be seen in appendix A, figure A2. In game three you win if a colour other than purple is drawn. This game can be seen in appendix A figure A3.

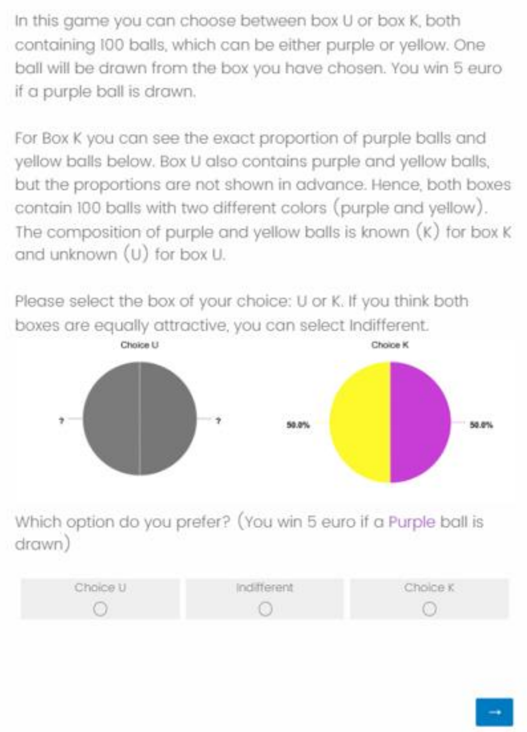

Figure 2 Screenshot of choice presented to subjects in game one round one

For the first game and second game, the exact new percentage of purple balls to make Choice K more and less attractive in each round was done by calculating the chance of winning in the unambiguous box with the following formula's from Dimmock et al. (2016):

- If choice at previous question = Box K, then new chance of winning = (previous chance of winning (e.g. 50%) + ceiling (100%)) / 2 (= e.g. 75%)

  new floor:= previous chance of winning (e.g. 50%)
- If choice at previous question = Box U, then new chance of winning = (previous chance of winning (e.g. 50%) + floor (0%)) / 2 (= e.g. 25%)

  new ceiling:=previous chance of winning (e.g. 50%)}

For the third game the calculation of the new percentage of purple balls to make Choice K more and less attractive in each round, obtained from Dimmock et al. (2016), is as follows:

- If choice at previous question = Box K, then new chance of losing = previous chance of losing (e.g. 10%) + floor (100%) / 2 (= e.g. 55%)

  new ceiling:= previous chance of losing (e.g. 10%)

- If choice at previous question = Box U, then new chance of losing = previous chance of losing (e.g. 10%) + floor (0%) / 2 (= e.g. 5%)
  new floor:=previous chance of losing (e.g. 10%)}

However, eliciting matching probabilities with the method of Dimmock et al. (2016) can only be done if two important assumptions hold, or if these assumptions are reasonable to hold when they cannot be tested. The first assumption is that both symmetry and the exchangeability condition (Chew and Sage, 2008) holds for all three the games. For this assumption to hold, it must be the case that the weight of the probability of the winning colour to be drawn from the ambiguous box is the same as the weight of the probability of the winning colour to be drawn from the unambiguous box for ambiguity neutral decision makers. Meaning that the matching probability should be 0.1 in game two for each colour in the 10-colour urn for an ambiguity neutral person. The seconds assumption cannot be tested. However, to use the method of Dimmock et al. (2015) there must be assumed that the source function of the ambiguous box (Choice U) should be the same when the ambiguous box (Choice U) contains two different colours and when the ambiguous box (Choice U) contains ten different colours. Meaning that it should be the case that betting on one colour in the two colour ambiguous box is the same as betting on five colours in the ten colour ambiguous box. Dimmock et al. (2016) find this assumption to be reasonable since both ambiguous urns underlie similar mechanisms. Meaning that both assumptions hold and eliciting matching probabilities with the method of Dimmock et al. (2016) should not give a problem here.

3.2.1 Matching probabilities

The results from the three games discussed above are used to elicit matching probabilities m(p). Three matching probabilities were calculated: m(0.5), m(0.1) and m(0.9). This was done with the following formula:

$$m(p)= X/100 \tag{1}$$

In this formula X is the chance of winning in the round that the participant is indifferent between the unambiguous box (Choice K) and the ambiguous box (Choice U), thus drawing a purple ball in game one and two or drawing a ball other than purple in game three. However, if the participants reached the maximum amount of iterations without choosing indifferent, then the average of the remaining upper and lower bound was taken as X. For example, if in game one the participant is indifferent between the unambiguous box (Choice K) with 25 purple balls and the ambiguous box (Choice U), then X is 25. M(p) is then the percentage of 0.25. With the matching probability of game one m(0.5) it can be seen whether people are ambiguity averse or not. When m(0.5)<0.5, the participant is ambiguity averse. When m(0.5)>0.5, then the participant is ambiguity seeking. The participant is ambiguity neutral when m(0.5)=0.5. the matching probabilities m(0.1) and m(0.9) are necessary to deduce a-insensitivity. However, before something can be said about a-insensitivity, the ambiguity indices need to be calculated.

3.2.2 Event-specific ambiguity Indexes

With the matching probabilities, the event-specific ambiguity indexes can be calculated (AA50, AA10 and AA90). These event-specific ambiguity indexes can show the level of event-specific ambiguity aversion with ambiguity neutral probability p (Dimmock et al., 2016). p denotes the chance of winning for the unambiguous box in round 1. The formulas for the event-specific ambiguity indexes are:

$$AA50 = 0.5 - m(0.5) \tag{2}$$

$$AA10 = 0.1 - m(0.1) \tag{3}$$

$$AA90 = 0.9 - m(0.9) \tag{4}$$

An index with a positive value implies ambiguity aversion and an index with a negative value implies ambiguity seeking. Event-specific ambiguity indexes with value zero indicate ambiguity neutrality. A-insensitivity is indicated with a positive value for AA90 and negative value for AA10. For example, the participant from the former example that was indifferent between Choice K and Choice U with 25 purple balls in game one has a matching probability of 0.25 which can be calculated with equation (1). The event-specific ambiguity index is then 0.25 which can be calculated with equation (2). The value 0.25 is positive and indicates ambiguity aversion for that participant for that specific event.

3.2.3 Global ambiguity indexes

One advantage of eliciting matching probabilities using the method of Dimmock et al. (2016) is that both ambiguity aversion and a-insensitivity can be studied. This is done by looking at the global ambiguity indexes. The method of deriving global ambiguity indexes for both ambiguity aversion and a-insensitivity was developed by Abdellaoui et al. (2011). Below there will be shown how Dimmock et al. (2016) found a way to use their matching probabilities to measure the global ambiguity attitude indexes of Abdellaoui et al. (2011). To derive the global ambiguity indexes Ordinary Least Squares (OLS) is used to find the best fitting line between m(p) and p. The best fitting line between m(p) and P is the neo-additive weighting function. The neo-additive weighting function is created by letting OLS estimate:

$$m(p) = c + s*p \tag{5}$$

Here, c is the constant and s is the slope of the neo-additive weighting function and the coefficient of p. The neo-additive weighting function is constructed for each participant with p: 0.1, 0.5 and 0.9 and corresponding matching probability: m(0.1), m(0.5) and m(0.9). With both the slope and constant, the global ambiguity index for ambiguity aversion can be calculated as follow:

$$b = 1 - s - 2*c \tag{6}$$

The index of a-insensitivity can be calculated with the following formula:

$$a = 1 - s \tag{7}$$

The distance of the regression line from 1 at p=1 is called d. then d can be calculated as: $d = 1 - c - s$. The above source function is more convincing than other potential source functions due to the clear interpretation of these indexes even though the data is not necessarily fit best by the neo-additive source function (Wakker, 2010). However, to find the best fitting neo-additive source function some conditions or characteristics have to be met (wakker, 2010). These are:

$$m(0) = 0;\ m(1) = 1;\ 0 < p < 1 : m(p) = c + s*p;\ s \geq 0,\ c \geq 0,\ s + c \leq 1 \tag{8}$$

Meaning that best-fitting neo-additive source function is obtained with regression m(p) on p on the open interval (0,1) (abdellaoui et al., 2011). This implies that the linear regression should be truncated at the endpoints 0 and 1. This could be done by regressing m(p) on p and restricting the coefficients. However, Stata does not provide the option to impose interval restrictions for the regression coefficients as proposed by abdellaoui et al. (2011). Therefore the matching probabilities were regressed on p without coefficient restrictions. In this thesis manual adjustments are done to make sure that the conditions of equation (8) holds at for the neo-additive source functions. These adjustments are necessary because without the restrictions on the OLS regression, some parameters violate the conditions of equation (8). Martinsons (2015, December 18) manually adjusted neo-additive source functions in his thesis in order to make sure that the conditions of equation (8) holds. I used the same manual adjustments and one extra manual adjustment to make sure that the conditions of equation (8) hold for this thesis. A description of the manual adjustments that were made to restrict some neo-additive source functions can be found in Appendix C.

3.2.4 Check questions

In order to check for inconsistency, two check questions were asked to participants. For the first question the matching probability for the first game, which started with a distribution of 50 purple balls and 50 yellow balls, is used. In this check question the probability of winning with the unambiguous box is the matching probability in the first game plus 20%. For the second check questions the probability of winning is the matching probability in the first game minus 20%. The subject is considered inconsistent when in the first check question the ambiguous box (Choice U) is preferred and/or if for the second check question the unambiguous box is preferred, this is in line with Dimmock et al. (2016). An example of the first check question can be seen in figure 3.

Figure 3 Check question one
Notes: This probability of winning was presented to people who in the first round of game one were indifferent between an unknown chance of winning and a chance of winning of 50%.

3.3 Sample

The online survey was distributed via WhatsApp, Instagram and SurveySwap to (mostly Dutch) family, friends and students. The subject were provided with a monetary incentive, namely a chance of winning 5 euro. The monetary incentive is discussed in detail in §3.2. The minimum age to fill in the survey was eighteen. An attempt was made to collect as many respondents as possible. In the end, 139 participant completed the survey.

The duration of the whole survey is estimated to be around 15-20 minutes on average. The minimum time necessary to complete the survey is estimated to be approximately seven minutes. Four participants took less than 7 minutes to complete the survey and these participants were dropped from the sample because I think that less than 7 minutes is not enough to fill in the whole survey seriously. Qualtrics took the time between the start of the survey and the end of the survey as the time people took to complete the survey. However, it was possible for participants to continue the survey at a later moment. According to Qualtrics some people needed more than two days to complete the survey. Although these participants probably used less time to complete the survey. To look at the average time participants took to finish the survey the average time that participants used to finish the survey is calculated for all participants that finished the survey within one hour. Assuming that people who took longer than one hour took a break to finish the survey. The average time that 122 participants took to complete the survey assuming they completed the survey in one attempt without a break was 24 minutes and seven seconds. The fact that the average time to complete the survey was longer than expected may be due to several factors. One of these factors could be that the survey was in English while the native language of most participants is probably Dutch. Whereas students are used to the English language, this is not always the case for older people or former students. What could be seen as problematic is that 10.37% of the participants chose indifferent in all three games used to elicit matching probabilities which could show that people did not try their best in the survey. However, these results are not deleted since being indifferent in all three games can be seen as realistic. In the end the full sample consists of 135 observations.

4. Summary statistics

4.1 Control variables

Table 1 and 2 show the independent variables that will be used as control variables in the regression analysis.

Table 1 Summary statistics categorical independent control variables

Variable	Categories	Freq.	Percent	Cum.
Sex				
	Female	78	57.78	57.78
	Male	57	42.22	100
School level				
	Bachelor's Degree (WO)	21	15.56	15.56
	Higher Professional Education (HBO)	40	29.63	45.19
	Master's Degree (WO+)	51	37.78	82.96
	Pre-University Education (VWO)	4	2.96	85.93
	Primary School	1	0.74	86.67
	Secondary Vocational Education and Training (MBO)	10	7.41	94.07
	Senior General Secondary Education (HAVO)	8	5.93	100.00
Employment				

	A homemaker or stay-at-home parent	1	0.74	0.74
	Other	4	2.96	3.70
	Retired	8	5.93	9.63
	Student	26	19.26	28.89
	Working full-time	46	34.07	62.96
	Working part-time	50	37.04	100.00
Marital status				
	Divorced/Separated	6	4.44	4.44
	Living with a partner	24	17.78	22.22
	Married	59	43.70	65.93
	Never been married	45	33.33	99.26
	Widowed	1	0.74	100.00
Ethnicity				
	Asian	2	1.48	1.48
	Black or African American	1	0.74	2.22
	North African	1	0.74	2.96
	White / Caucasian	131	97.04	100.00
Income				
	Less than 10000	23	17.04	17.04
	10000 - 24999	18	13.33	30.37
	25000 - 49999	42	31.11	61.48
	50000 - 74999	17	12.59	74.07
	75000 - 99999	7	5.19	79.26
	100000 - 149999	3	2.22	81.48
	150000 or more	2	1.48	82.96
	I prefer not to say	23	17.04	100.00

Table 2 Summary statistics continuous independent control variables

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
Age	135	40.57	41	16.192	18	80
Household number	135	3.052	3	1.323	1	6

4.1.1 Representativeness of the sample

To look at the representativeness of the sample in this thesis, the statistics of the Dutch population are compared with the summary statistics above. The Dutch population is taken as comparison because most survey respondents are likely to be Dutch since the survey was mostly distributed to Dutch people. In this thesis, the sample consist of 78 females (57.78%) and 57 males (42.22%). The percentage of males in the Dutch population was 49.7% in 2020 (Centraal Bureau voor de Statistiek, 2020). Thus, males are a bit under presented in this sample. The average age in this sample is 40.57 years old. The average age in the Dutch population is 42.3 years old (Centraal Bureau voor de Statistiek, 2022). The average age of the Dutch population is a bit less than 2 years older than the average age of the sample.

Onderwijs in cijfers (2021) shows the highest achieved diploma of the Dutch population between the ages 15 and 75 in 2021. However, Onderwijs in cijfers (2021) grouped some achieved level of education different compared to the sample in this thesis. Nevertheless, an attempt will be made to compare the sample with the Dutch population as closely as possible. 7.7% of the Dutch population completed primary school as highest degree. This is only 0.74% in the sample. Next to this 18.1% of the Dutch population started Secondary Education (HAVO), Pre-University Education (VWO) but did not finish or finished Education and Training (MBO-1) and these people should fall in the category primary school in this sample or in the category Education and Training (MBO). This is not taken into account for the comparison. 37.9% of the Dutch population has Secondary Education (HAVO), Pre-University Education (VWO) or Education and Training (MBO) as highest degree. If we combine these categories in the sample, then 16.9% of the sample achieved Secondary Education (HAVO), Pre-University Education (VWO) or Education and Training (MBO) as highest degree. Bachelor's Degree (WO) or Higher Professional Education (HBO) are the highest degree for 22.1% of the Dutch population. The percentage that completed Bachelor's Degree (WO) or Higher Professional Education (HBO) as highest degree is 45.2% in the sample. 13.4% of the Dutch population finished A Master's Degree (WO+). For the sample this 37.78% finished A Master's Degree (WO+). At last, for 0.8% of the Dutch population, the highest achieved education is not known. There is no corresponding category to this in the sample. For the comparison of the highest achieved school level of the Dutch population and the sample there can be seen that the sample is skewed towards higher educated people.

From (Centraal Bureau voor de Statistiek, 2022) we know that from everyone in the Dutch population of 15 years and older in 2021, 45.2% was married. In the sample this is 43.70%. In 2021, 39.6% of the Dutch population had never been married. In the sample that are people who have never been married or are living with a partners. Together this accounts for 51.11% of the sample. 9.3% of the Dutch population is divorced which is 4.44% in the sample. At last, 5.8% of the Dutch population is widowed. In the sample, only 0.74% is widowed. There is no data available on either income or employment status that can be compared to the data available from the sample. Ethnicity will not be discussed further either. However, the data clearly shows that most people who completed the survey have a Western background. The expected amount of students (MBO, HBO, WO and Wo+) in the Dutch population in 2022 is 1.352.100 (De Algemene Onderwijsbond, 2021).This corresponds to approximately 7.75% of the Dutch population. In this sample, 19.26% is students. This shows that the sample has an overrepresentation of students.

4.2 STEM-B and CRT

Table 3 shows the summary statistics of the score of the STEM-B, which will be one of the main independent variables in the regression analysis. The highest score that could be achieved for the STEM-B was 15.08. Table 3 shows that no one selected the best answer to all the STEM-B questions.

Table 3 Summary statistics STEM-B score

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
EISCORE	135	10.104	10.333	2.045	1.417	14.25

Table 4 shows the percentage and frequency of people who had respectively 0,1,2 or 3 correct answers for the CRT questions. The mean CRT score is 1.98 (standard deviation: 0.98). Frederick (2005) found in the first experiment using CRT questions that on average 33% had 0 correct answers with the CRT questions, 28% had 1 correct answer, 23% had 2 correct answers and 17% had 3 correct answers. In Frederick (2005) no one was already exposed to one of these questions. Later, Haigh (2016) found a mean score of 1.93 (standard deviation: 1.17) for CRT correct answers in his experiment. However, 51.4% of the participants had already been exposed to at least one of the CRT questions. The difference in the number of correct answers was also significantly different for people who already had been exposed to at least one of the CRT questions compare to people who did never see the CRT questions before. In that study, 19% had 0 correct answers. 14.8% had 1 correct answer. 20% had two correct answers and 45.8% had three correct answers. Since the results in this sample, which can be seen in table 4, look more like the results of Haigh (2016) it is likely that multiple participants had already been exposed to one or multiple CRT questions. Table 5 shows that in this sample on average, people found question 1 the most difficult while question 3 seemed to be the easiest question.

Table 4 Summary statistic CRT correct answers

amount of correct CRT questions answers	Freq.	Percent	Cum.
0	13	9.63	9.63
1	27	20.00	29.63
2	45	33.33	62.96
3	50	37.04	100.00
Total	135	100.00	

Table 5 CRT percentage correct or wrong answers per question

	Correct (%)	Wrong (%)
CRT Q1	67 (49.63%)	68 (50.37%)
CRT Q2	91 (67.41%)	44 (32.59%)
CRTQ3	109 (80.74%)	26 (19.26%)

4.3 Ambiguity attitudes

In table 6, the percentage of participants that is ambiguity-averse, ambiguity neutral or ambiguity averse for every game or ambiguity neutral probabilities can be found. This is revealed by the first round choices of the participants for every game. 37.04% of the participants preferred the unambiguous box (known probability of 50%) over the ambiguous box with unknown probabilities in the first round of the first game (figure 2). For these participants, m(0.5) is smaller than 0.5, which indicates ambiguity aversion. 37.04% of the participants is ambiguity averse in game one. However, a chi-square goodness of fit test shows that ambiguity aversion is not the dominant ambiguity attitude for the ambiguity neutral probability of 50% ($\chi 2$ = 1.11, p = 0.57) . For the ambiguity neutral probability of 10%, ambiguity seeking is the dominating attitude ($\chi 2$ = 16.94, p <0.01). Ambiguity aversion is the dominating attitude for the ambiguity neutral probability of 90% ($\chi 2$ = 53.74, p=0.00). The results of the chi-square tests are in line with Dimmock et al. (2016) for the ambiguity neutral probabilities of 10% and 90%. However, the results of the chi square test indicate that for the ambiguity neutral probability of 50%, ambiguity aversion is not the dominant attitude. However, Dimmock et al. (2016) found in their study that ambiguity aversion was the dominant attitude for the ambiguity neutral probability of 50%.

Table 6 Ambiguity attitudes in percentages

A-neutral probability p	**0.10**	**0.50**	**0.90**
Ambiguity averse	18.52%	37.04%	62.96%
Ambiguity neutral	34.07%	33.33%	20.74%
Ambiguity seeking	47.41%	29.63%	16.30%

Table 7 gives the summary statistics of the local and global ambiguity attitude indexes. The global and local ambiguity indexes will be used as dependent variables. The average matching probabilities m(0.5) = 0.48 and m(0.9) = 0.70 show ambiguity aversion. However, a two sided t-test shows that m(0.5) is not significantly different from 0.5 (p= 0. 0.33). Therefore, it cannot be said that the participants are on average ambiguity averse for moderate likelihoods (game 1). For high likelihoods (game three), ambiguity neutrality and ambiguity seeking can be rejected (m(p)<p) in favour of ambiguity aversion (p=0.00). The average matching probability m(0.1) = 0.21 implies ambiguity seeking behaviour on average for low likelihoods (game two). A two sides t-test confirms that m(0.1) is greater than 0.1 (p=0.00).

Table 7 Descriptive statistics ambiguity attitude indexes

Variable	Mean	Median	Std. Dev.	Min	Max
Matching probability m(0.1)	0.21	0.10	0.20	0.01	0.99
Matching probability m(0.5)	0.48	0.05	0.18	0.02	0.98
Matching probability m(0.9)	0.70	0.77	0.25	0.01	0.99
AA 10	-0.11	0.00	0.20	-0.89	0.09
AA 50	0.02	0.00	0.18	-0.48	0.48
AA 90	0.20	0.13	0.25	-0.09	0.89
index b (ambiguity aversion)	0.06	0.00	0.30	-0.97	0.97
index a (a-insensitivity)	0.38	0.30	0.36	0	1

Index b ranges from -1 to 1. Positive values for index b imply pessimism regarding ambiguity compared to risks (ambiguity aversion). Negative values for index b imply optimism regarding ambiguity compared to risks (ambiguity seeking). The more positive/negative index b the more ambiguity aversion/seeking people are. Index a can have values from 0 to 1. The higher index a the more people underweight high likelihood events and overweigh low likelihood events.
Index b has an average of 0.06 what indicates ambiguity aversion on average and a two sided t-test shows that index b is greater than zero (p<0.00). Index a has an average of 0.38 which indicates a-insensitivity on average. Here, a two sided t-test shows that index a is greater than zero (p=0.00). This is in line with Dimmock et al. (2016). In table 8, the correlations between the global and local ambiguity indexes can be found. Index a and index b are positively correlated with a correlation of 0.22 (p-value = 0.0108), which is consistent with the fact that both indexes are related to irrationality. This correlation shows that both indexes capture different components of ambiguity attitudes. This results are in line with the results of Dimmock et al. (2016).

Table 8 Correlations between ambiguity attitude indexes

Variables	(1) a	(2) b	(3) AA10	(4) AA50	(5) AA90
(1) index b (ambiguity aversion)	1.00				
(2) index a (a-insensitivity)	0.22*	1.00			
(3) AA10	0.65*	-0.57*	1.00		
(4) AA50	0.77*	0.04	0.50*	1.00	
(5) AA90	0.74*	0.78*	0.05	0.40*	1.00

Notes: Correlations that are significant at 0.10 level are indicates with *.

5. Results

The purpose of this thesis was to research the relationship between emotional intelligence, cognitive ability and ambiguity attitudes. Emotional intelligence is partly measured by the STEM-B which measures the branch of emotional management. Cognitive ability is tested by the means of the CRT and ambiguity attitudes are elicited by the use of the method of Dimmock et al. (2016). Now that these data are known for 135 participants, there can be looked at the relationship between these variables. To investigate the effect of Emotion management and cognitive ability on ambiguity attitudes, multiple regression is used.

5.1 Regression results

Table 9 OLS regression on ambiguity indexes

VARIABLES	Index b	Index a	AA10	AA50	AA90

STEM-B score	0.005	-0.009	0.004	0.004	-0.006
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
amount of correct CRT questions	-0.023	-0.014	-0.006	-0.027	-0.017
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Age	-0.003	-0.041*	0.015	0.003	-0.026*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Age^2	0.000	0.000*	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex	-0.041	0.092	-0.075*	0.003	-0.001
	(0.07)	(0.08)	(0.04)	(0.05)	(0.06)

Notes: This table is an abridged version of the full regression with only the independent variables amount of correct CRT questions, EI score, Age, and Gender. The full regression can be found in Appendix B, table B1. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table 9 shows some variables of the full regression on the ambiguity indexes. The full regression can be seen in table B1 in appendix B. The local ambiguity indexes go from -1 to 1 and as explained before. A local ambiguity index of zero means ambiguity neutrality while a negative local ambiguity index means ambiguity seeking and the more negative the more ambiguity seeking that participant is. A positive local ambiguity index means ambiguity aversion.

The full regression on the ambiguity indexes can be found in Appendix B, table B1. Firstly, I will discuss AA10 which describes the local ambiguity aversion at the 10% probability event. Here, males have a local ambiguity index at the 10% probability event which is on average 0.075 lower compared to females, ceteris paribus. Meaning that males are less ambiguity averse (or more ambiguity seeking depending on the sign of AA10) than females at the 10% probability event. This is significant at the 10% significance level. People who have primary school as highest achieved education have on average a local ambiguity index at the 10% probability event which is 0.140 lower compared to people who achieved a bachelor's degree (WO), ceteris paribus. This means that people who have primary school as highest achieved education are less ambiguity averse (or more ambiguity seeking depending on the sign of AA10) for the 10% probability event than people who achieved a bachelor's degree (WO), This is significant on a 5% significance level. The local ambiguity index at the 10% probability event is 0.175 lower on average for people who achieved Secondary Vocational Education and Training (MBO) compared with people who have a bachelor's degree (WO) as highest achieved education, ceteris paribus. This is significant at a 10% significance level. For the OLS regression on the local ambiguity index at the 10% probability event no other variables have significant coefficients.

AA50 represents the local ambiguity index at the 50% probability event. On average, people who are retired have a local ambiguity index at the 50% probability event that is 0.447 lower compared to people who are a homemaker or stay at home parent, ceteris paribus. This effect is significant at a 1% significance level. Both people who work full-time and part-time have on average a local ambiguity index at the 50% probability event that is 0.181 lower compared to people who are a homemaker or stay at home parent, ceteris paribus. For both working full-time and part-time this is significant at a 5% significance level. People who earn €150000 or more have on average a local ambiguity index at the 50% probability event that is 0.270 higher compared to people who earn less than €10000, ceteris paribus. Meaning that people who earn €150000 or more are more ambiguity averse (or less ambiguity seeking) compared to people who earn less than €10000.

The local ambiguity index at the 90% probability event is represented by AA90. On average, if Age increases with one year, then the local ambiguity index at the 90% probability event decreases with 0.026, ceteris paribus. This is significant on a 10% significance level. On average, people with employment other have a AA90 that is 0.657 higher compared to people who are homemaker or stay at home parent, ceteris paribus. This is significant on a 10% significance level. Students have a AA90 that is 0.439 higher compared to people who are homemaker or stay at home parent, ceteris paribus. This is significant on a 5% significance level. The local ambiguity index for the 90% probability event (AA90) is 0.432 higher for people who work full-time compared to people who are homemaker or stay at home parent, ceteris paribus. This is significant on a 1% significance level. People who work part-time have a local ambiguity index for the 90% probability event that is 0.412 higher compared to people who are homemaker or stay at home parent, ceteris paribus. This is significant on a 5% significance level. People who are married have on average a local ambiguity index at the 90% probability event that is 0.196 higher compared to people who are divorced, ceteris paribus.

In table 9 the main dependent variables index a and index b are regressed on the independent variables. For the regression in table 9 with index b as dependent variable no significant variables can be found. However, for index a some explanatory variables can be found. Index a decreases with 0.041 if Age increases one year, ceteris paribus. This is significant on a 10% significance level. Meaning that older people are less a-insensitive. However age^2 has a positive coefficient that is significant on a 10% significance level. This shows that although older people are less a-insensitive, this effect is smaller for older people. Index a is 0.319 higher for people who achieved Secondary Vocational Education and Training (MBO) compared to people who have a bachelor’s degree (WO) as highest degree, ceteris paribus. This is significant on a 10% significance level. Meaning that people who have MBO as highest degree are more a-insensitive than people who have WO as highest degree.

People who indicated other as employment status have an index a that is on average 0.940 higher compared to people who are a homemaker or stay at home parent, ceteris paribus. This is significant on a 1% significance level. The index a is 0.493 higher for students compared to people who are homemakers or stay at home parent, ceteris paribus. This is significant on a 5% significance level. Meaning that students are more a-insensitive than homemakers or stay at home parents. Index a is 0.569 higher for people who work full-time compared to people who are homemakers or stay at home parent, ceteris paribus. This is significant on a 5% significance level. Meaning that people wo work full-time are more a-insensitive than homemakers or stay at home parents. Index a is 0.476 higher for people who work part-time compared to people who are homemakers or stay at home parent, ceteris paribus. This is significant on a 5% significance level. Meaning that people wo work part-time are more a-insensitive than homemakers or stay at home parents.

5.2 Inconsistencies check

For the first check question, 10.37% of the participants chose Choice U, implying inconsistency. 9.63% of the participants chose indifferent in the first check question. For the second check question 15.56% of the participants chose box K, implying inconsistency. 16.30% of the participants chose indifferent for the second check question. In appendix B table B2, a robustness test is done to see whether the results are robust when excluding participants who made inconsistent choices in the check questions. The regressions have substantially higher R-squared values. However the amount of observations is also lower. The most interesting finding is that the STEM-B score is significant on a 10% significance level for dependent variable AA90. One point extra on the STEM-B decreases AA90 with 0.020, ceteris paribus. This means that people with a higher STEM-B score are less ambiguity averse (or more ambiguity seeking depending on the sign of AA90) at the 90% probability event. The coefficient for STEM-B is not significant on a 10% significance level for any of the other dependent variables in table B2.

5.3 Regression results real incentive and (ex) academic subject

As discussed in 3.2, only 45 participants did fill in their email to have a chance to receive a real incentive. Dimmock et al. (2016) stress the importance of real incentives for eliciting ambiguity attitudes for non-academic subjects. The regression results for all participants that filled in their email for the real incentive at the end of the survey can be seen in table B3 in Appendix B. I assume that those participants that filled in their email had a feeling of a real incentive. The results show small positive significant effects of a higher STEM-B score on the 10% and 50% probability events, ceteris paribus. Meaning that people with an higher STEM-B score are more ambiguity averse (or less ambiguity seeking depending on the sign of AA10 and AA50). The amount of correct CRT questions has a small significant negative effect on the 50% probability event, ceteris paribus. Meaning that people with an higher CRT score are less ambiguity averse (or more ambiguity seeking depending on the sign of AA10). However, no significant results can be found for the variables STEM-B score and Amount of correct CRT questions for the dependent variables index b and index a. Real incentives are probably not necessary for academic subjects. I expect that this also applies to people who have finished academic education in the past. Therefore, the regression results of all 112 participants who finished HBO, WO or WO+ can be seen in table B4 in appendix B. Here, the main independent variables STEM-B score and amount of correct CRT questions also do not have an effect on the dependent variables index b and index a. However, STEM-B score has a small positive significant effect on AA50, ceteris paribus. Meaning that participants with an higher STEM-B score are more ambiguity averse (or less ambiguity seeking depending on the sign of AA50).

6. Discussion

The purpose of this thesis was to look at the relationship between EI, cognitive ability and ambiguity attitudes. However, most test that can measure EI take around one hour to complete. Therefore, there was chosen to test only one branch of EI. The branch emotional management was measured with the STEM-B, which takes approximately 10 minutes to complete. Because several reasons made it preferable not to make the survey too long, the CRT was chosen as a proxy for cognitive ability. This test takes less than two minutes on average to complete. Next to this, two ambiguity attitudes, ambiguity aversion and a-insensitivity where measured with the method proposed by Dimmock et al. (2016). To find an answer to the main question, multiple hypotheses where created. The method proposed by Dimmock et al. (2016) is used. In general, the results of this thesis are consistent with the results of Dimmock et al. (2016) regarding the summary statistics and percentage of ambiguity averse, neutral and seeking participants per probability event. To look at the relationship between cognitive ability and ambiguity attitudes, the following hypotheses were set up:

H1: CRT score is negatively correlated to ambiguity aversion.
H2: CRT score is negatively correlated to a-insensitivity.

I found no significant effect of the amount of correct CRT questions on index b and index a and thus on respectively ambiguity aversion and a-insensitivity. Therefore, *H1* and *H2* need not hold. This is not in line with Mahmoud et al. (2020) who found that cognitive ability is positively related with tolerance of ambiguity. Enke & Graeber (2019) found that a-insensitivity is reflected by cognitive uncertainty. I expect that being able to score better on the CRT would mean higher cognitive ability and thus less cognitive uncertainty towards ambiguity. Meaning that the results are not in line with

Enke & Graeber. However, there are some limitations concerning the CRT which could explain why the CRT would not be a proper proxy for cognitive ability.

To look at the relationship between emotional management and ambiguity attitudes, the following hypothesis were set up:

H3: STEM-B score is negatively correlated to ambiguity aversion.

H4: STEM-B score is negatively correlated to a-insensitivity.

No significant effect was found for the STEM-B score on the dependent variables index b and index a. This means that the STEM-B score did not significantly influence the ambiguity attitudes, ambiguity aversion and a-insensitivity. Therefore, *H3* and *H4* need not hold. From the hypotheses, a relationship between ambiguity attitudes and EI or cognitive ability was expected. However, no significant relationship was found. Charupat et al. (2013) found that higher emotional balance will push people in the direction of expected utility theory. Especially in an environment where emotions are strongly aroused, emotional management could help people to react more rationally or be less affected by their emotions I expect. In this thesis, I assumed that the presence of ambiguity could arouse emotions that could make people deviate more from ambiguity neutral attitudes. People who are better at emotion management would then deviate less from the optimal outcome and have more ambiguity neutral attitudes since I expected that those people would better control their emotions. Assuming that emotions cause you to deviate from ambiguity neutral attitudes.

The results from this thesis could mean that choosing between a risky choice and an ambiguous choice does not arouse emotions in such a way that emotional management could play a role. However, it could also be the case that there is no relationship between ambiguity attitudes and EI even if emotions are aroused by ambiguity. I expect the first. Baillon et al. (2016) found that sadness had effect on ambiguity attitudes. Nguyen and Noussair (2014) found that emotions do affect risk aversion. I expect that higher emotional management can help people to be less influenced by these emotions. The question here is whether higher emotion management will make people less ambiguity averse or a-insensitive or that for example in the case of Baillon et al. (2016) emotional management will make people less sad, which then cause people to have ambiguity attitudes that will make people less close to ambiguity neutral attitudes that would have been caused by their sadness. In the study of Baillon et al. (2016) there was namely found that sadness caused people to be more ambiguity neutral compared to the control group. It could therefore be that higher emotional management reduced the sadness and brings people closer to the control group. One recommendation for future research would therefore be to do a randomized experiment and put participants in different emotional states. Then by measuring EI and ambiguity attitudes, there could be analysed if people's ambiguity attitudes are affected by their EI if higher EI could help reduce the influence of different emotional states compared to no influence of an emotional state and in what direction.

7. Limitations

This thesis has several limitations. The first is that the survey was in English. This could make the STEM-B and the CRT questions harder to understand since most participants are Dutch. It may also be the case that participants took longer to complete the survey as a result. This could lead to participation fatigue. However, the responses of participants could be affected due to the translation of the STEM-B and therefore and it would be best if an emotion expert or psychologist would check the translation to reduce the chance that the translated version will yield different answers compared to the original version. This was for example done by Libbrecht & Lievens (2012). However, I did not have the opportunity or resources to have the translation checked by an emotion expert. By keeping the STEM-B in English, there was no chance that the responses of the participants would be influenced by any translation. However, the downside of this is that the survey was not in the native language of most participants. A possible solution for this problem would be asking the help of an emotion expert when the STEM-B is translated or asking people how fluent their English is to see whether the self-reported fluency of English affects people's choices or duration time.

Next, Qualtrics only measured the total amount of time between beginning and finishing the survey. However, if the time between questions was measured then there could be seen more easily if people spent too little time on one question and these participants could be removed from the sample. Furthermore, as explained in 4.1.1 the distribution of the sample is skewed. Which means that the sample is not representative for the Dutch population. Furthermore, only the branch emotional management was measured for EI. As explained before this was done due to the duration of tests that measure EI. Although I expect that the branch emotional management would have the highest effect on ambiguity attitudes from all the branches, there cannot be concluded that other parts of EI do not have an effect on ambiguity attitudes.

Dimmock et al. (2016) found that real incentives are desirable for ambiguity and non-academic subjects. In this thesis real incentives were also used. However, only 50 euro could be divided over the participants. The way the real incentive was distributed is explained in §3.2. Dimmock et al. (2016) gave every participant a chance of winning 15 euro. It is not certain whether the incentive in this thesis was received the same as the incentive from Dimmock et al. (2016). However, this does not seem to be the case as only 45 people filled in their email for having a chance of winning the real incentive. It could be that people found the amount to low or that they found the chance of winning to be to low or they did not understand the way the real incentive was distributed. This could mean that validity of the results of the main regression are lower than expected if the participants reacted the same as the participants without a real incentive (hypothetical choice) in the study of Dimmock et al. (2016. However, both the main regression and the regression with participants that probably had a feeling of a real incentive and the regression with only (ex) academic subject do not seem to differ in terms of effect of emotional management score and CRT score on index b and index a. to overcome this possible problem, it would be best to provide the same real incentive of 15 euro to the participants as was done in Dimmock et al. (2016).

Something else that was different in eliciting ambiguity attitudes compared to Dimmock et al. (2016) was that in the survey people could not choose their own winning colour. No way could been found to include this in the proper way to the survey in Qualtrics. As a result, it was not possible to see if there was trust or distrust in this experiment. Giving people the option to choose their own winning colour is always preferable, when possible, because this could increases the reliability when this shows that people trust the research. This is because distrust toward the survey would probably increase ambiguity aversion according to Pulford (2009) and this could bias the results. In this study, neo-additive source functions are created to derived ambiguity attitudes. Abdellaoui et al. (2011) explained that these neo-additive source functions should be on the open interval (0,1). However, in Stata it is not possible to restrict the estimated regression coefficients directly. Therefore, the neo-additive source functions were adjusted manually as was done before by Martinsons (2015, December 18). However, in some programs such as R it is possible to create interval restrictions for the estimated coefficients.

Next to this, CRT was used as a proxy for cognitive ability. However, CRT only has moderate overlap with measures of cognitive ability (Toplat et al., 2011). Therefore, it would have been better to use multiple tests, such as for example the numeracy test, to measure more and different parts of cognitive ability. However, adding more tests would extend the duration of the survey to such an extent that the disadvantages would outweigh the advantages in my opinion. Offering compensation to fill in the survey, could make it possible to increase the survey duration and add more tests as proxy for cognitive ability. However, due to the constrain of money restriction for this thesis this was not possible. Another possible problem with the CRT is that there is a chance that multiple participants already had seen one or multiple CRT questions or answers to these questions before they filled in the survey. As a result, people who answered these questions wrong or would have answered these questions wrong the first time may now know the correct answer. This could be taken into account if participants were asked how many of the CRT test question they already had seen before or for how many CRT questions they already knew the answer. One recommendation regarding further research regarding the relationship between ambiguity attitudes and cognitive ability is to measure cognitive ability using multiple tests.

8. Conclusion

The aim of this thesis was to explore whether there is a relationship between EI, cognitive ability and ambiguity attitudes. EI was partly measured with the STEM-B which measures the branch emotional management. Therefore, in the remainder of the thesis the relationship between emotional management and ambiguity attitudes was investigated. As last, cognitive ability was tested with the CRT. The main question of this thesis was:

What is the relationship between EI, cognitive ability and ambiguity attitudes?

The main results showed that the variables STEM-B score and Amount of correct CRT questions did not have a significant effect on the ambiguity attitudes in the main regression analysis. Thus, no significant results were found in favour of the hypothesis. Also, for the 10%, 50% and 90% probability events, no significant effects where found for STEM-B score and Amount of correct CRT questions. However, some general characteristics had significant effect on ambiguity attitudes and thus on index b and index a. For the consistencies check and regression with (ex) academic subjects STEM-B score and Amount of correct CRT questions did have some small significant effects on some of the probability events (10%, 50%, 90%). However, STEM-B score and Amount of correct CRT questions did not have a significant effect on the ambiguity attitudes index b and index a in these regressions. Therefore, no evidence for a significant relationship between emotional management, cognitive ability and the ambiguity attitudes, ambiguity aversion and a-insensitivity could be found in this thesis.

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Appendix A

Welcome to this research study!

For my thesis at the Erasmus University Rotterdam, I am interested in the relationship between emotional intelligence, ambiguity attitudes and cognitive intelligence.

This survey should take you on average between 10 to 20 minutes to complete. Your participation in this research is voluntary. You have the right to withdraw at any point during the study, for any reason, and without any prejudice. If you would like to contact me to discuss this research, please send an e-mail to me: (Rogier van Oosterhout) 513070ro@student.eur.nl. By clicking on the consent button below, you acknowledge that your participation in the study is voluntary, you are 18 years of age, and that you are aware that you may choose to terminate your participation in the study at any time and for any reason. The results will only be presented at a group level and cannot be linked back to individuals. The data will be stored anonymously using password protection.

Please note that this survey will be best displayed on a laptop or desktop computer. Some features may be less compatible for use on a mobile device.

◯ I consent, begin the study

◯ I do not consent, I do not wish to participate

→

Figure A1: Consent form survey

Notes: In the message that people to invite them to participate in this study, it was made clear that the survey was used to measure of elicit people's ambiguity attitudes, cognitive abilities and emotional intelligence.

Figure A2 Screenshot of choice presented to subjects in game two round one

Figure A3 Screenshot of choice presented to subjects in game three round one

Appendix B

Table B1 Regression results

VARIABLES	Index b	Index a	AA_10	AA_50	AA_90
STEM-B score	0.005	-0.009	0.004	0.004	-0.006
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
amount of correct CRT questions	-0.023	-0.014	-0.006	-0.027	-0.017
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
Age	-0.003	-0.041*	0.015	0.003	-0.026*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
Age^2	0.000	0.000*	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex	-0.041	0.092	-0.075*	0.003	-0.001
	(0.07)	(0.08)	(0.04)	(0.05)	(0.06)
Household number	-0.023	0.002	-0.017	-0.009	-0.011
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
School level = 2, Higher Professional Education (HBO)	-0.080	0.094	-0.092	-0.082	0.011
	(0.08)	(0.12)	(0.06)	(0.05)	(0.08)
School level = 3, Master's Degree (WO+)	-0.041	0.032	-0.053	-0.039	-0.013
	(0.08)	(0.11)	(0.05)	(0.05)	(0.07)
School level = 4, Pre-University Education (VWO)	-0.038	0.078	-0.062	-0.057	-0.009
	(0.10)	(0.20)	(0.07)	(0.06)	(0.14)
School level = 5, Primary School	-0.084	0.161	-0.140**	0.029	-0.041
	(0.11)	(0.13)	(0.07)	(0.07)	(0.09)
School level = 6, Secondary Vocational Education and Training (MBO)	-0.054	0.319*	-0.175*	-0.104	0.172
	(0.14)	(0.19)	(0.10)	(0.08)	(0.14)
School level = 7, Senior General Secondary Education (HAVO)	-0.061	-0.056	-0.027	0.025	-0.060
	(0.16)	(0.19)	(0.09)	(0.09)	(0.15)
Employment = 2, Other	0.349	0.940***	-0.207	-0.073	0.657***
	(0.27)	(0.26)	(0.13)	(0.12)	(0.24)
Employment = 3, Retired	-0.202	0.480	-0.256	-0.447***	0.185
	(0.28)	(0.31)	(0.20)	(0.15)	(0.22)
Employment = 4, Student	0.227	0.493**	-0.058	-0.151	0.439**
	(0.16)	(0.23)	(0.10)	(0.10)	(0.17)
Employment = 5, Working full-time	0.162	0.569**	-0.132	-0.181**	0.432***
	(0.16)	(0.22)	(0.11)	(0.09)	(0.16)
Employment = 6, Working part-time	0.179	0.476**	-0.076	-0.181**	0.412**
	(0.17)	(0.21)	(0.10)	(0.09)	(0.16)
Marital status = 2, Living with a partner	0.242	0.103	0.073	0.160	0.153
	(0.18)	(0.19)	(0.13)	(0.11)	(0.11)
Marital status = 3, Married	0.219	0.257	-0.017	0.185	0.196**
	(0.18)	(0.19)	(0.14)	(0.12)	(0.09)
Marital status = 4, Never been married	0.194	0.091	0.059	0.136	0.135
	(0.18)	(0.19)	(0.13)	(0.13)	(0.11)
Marital status = 5, Widowed	0.041	-0.094	0.018	0.070	-0.030
	(0.21)	(0.23)	(0.14)	(0.13)	(0.15)
Income = 2, 10000 - 24999	-0.024	-0.052	-0.015	0.028	-0.055
	(0.10)	(0.15)	(0.07)	(0.06)	(0.10)
Income = 3, 25000 - 49999	-0.096	0.090	-0.099	0.008	-0.001
	(0.11)	(0.16)	(0.09)	(0.06)	(0.10)
Income = 4, 50000 - 74999	0.066	0.038	0.026	0.030	0.084
	(0.14)	(0.18)	(0.10)	(0.07)	(0.12)
Income = 5, 75000 - 99999	-0.022	0.018	-0.014	-0.030	0.051
	(0.18)	(0.23)	(0.14)	(0.09)	(0.16)
Income = 6, 100000 - 149999	-0.185	-0.022	-0.099	-0.077	-0.095
	(0.17)	(0.24)	(0.17)	(0.07)	(0.14)
Income = 7, 150000 or more	0.459	0.406	0.055	0.270*	0.431
	(0.33)	(0.31)	(0.14)	(0.16)	(0.27)
Income = 8, I prefer not to say	-0.042	-0.029	-0.010	-0.026	-0.001
	(0.12)	(0.16)	(0.10)	(0.07)	(0.10)
Constant	-0.124	0.562	-0.239	0.033	0.251
	(0.49)	(0.58)	(0.32)	(0.31)	(0.42)
Observations	135	135	135	135	135
R-squared	0.201	0.215	0.269	0.259	0.171

Notes: These are the main OLS regression result. Robust standard errors In parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B2 Regression results for non-inconsistent participants

VARIABLES	Index b	Index a	AA_10	AA_50	AA_90
STEM-B score	-0.008	-0.029	0.006	-0.001	-0.020*
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
amount of correct CRT questions	-0.037	-0.038	-0.005	-0.022	-0.038
	(0.04)	(0.06)	(0.03)	(0.02)	(0.04)
Age	-0.004	-0.067**	0.022	0.014	-0.041*
	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)
Age^2	0.000	0.001*	-0.000	-0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Sex	0.119	0.132	-0.009	0.069*	0.104
	(0.09)	(0.10)	(0.06)	(0.04)	(0.08)
Household number	-0.070**	-0.069	-0.012	-0.027	-0.067**
	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)
School level = 2, Higher Professional Education (HBO)	-0.126	0.032	-0.098	-0.021	-0.044
	(0.09)	(0.16)	(0.09)	(0.05)	(0.09)
School level = 3, Master's Degree (WO+)	0.006	-0.035	0.015	0.006	-0.016
	(0.09)	(0.14)	(0.07)	(0.05)	(0.09)
School level = 4, Pre-University Education (VWO)	-0.053	-0.034	-0.022	0.006	-0.081
	(0.08)	(0.19)	(0.08)	(0.06)	(0.12)
School level = 5, Primary School	-0.015	0.143	-0.107	0.126**	-0.027
	(0.09)	(0.16)	(0.06)	(0.05)	(0.10)
School level = 6, Secondary Vocational Education and Training (MBO)	0.091	0.522*	-0.141	-0.064	0.346*
	(0.21)	(0.26)	(0.15)	(0.10)	(0.18)
School level = 7, Senior General Secondary Education (HAVO)	-0.289	-0.020	-0.169	-0.073	-0.167
	(0.19)	(0.38)	(0.20)	(0.10)	(0.21)
Employment = 2, Other	0.639**	1.164***	-0.101	0.030	0.917***
	(0.27)	(0.31)	(0.18)	(0.12)	(0.22)
Employment = 4, Student	0.219	0.618	-0.066	-0.224*	0.524*
	(0.22)	(0.42)	(0.16)	(0.12)	(0.26)
Employment = 5, Working full-time	0.172	0.632**	-0.128	-0.214*	0.506**
	(0.21)	(0.29)	(0.15)	(0.11)	(0.19)
Employment = 6, Working part-time	0.249	0.575**	-0.036	-0.206**	0.521***
	(0.20)	(0.27)	(0.12)	(0.10)	(0.19)
Marital status = 2, Living with a partner	0.053	0.182	-0.033	-0.009	0.126
	(0.13)	(0.23)	(0.11)	(0.07)	(0.17)
Marital status = 3, Married	0.099	0.594***	-0.212*	0.046	0.333*
	(0.15)	(0.22)	(0.11)	(0.08)	(0.17)
Marital status = 4, Never been married	0.057	0.238	-0.070	-0.004	0.160
	(0.15)	(0.21)	(0.11)	(0.08)	(0.17)
Marital status = 5, Widowed	-0.317	0.025	-0.200	-0.136	-0.145
	(0.20)	(0.28)	(0.15)	(0.10)	(0.22)
Income = 2, 10000 - 24999	0.005	-0.038	-0.014	0.057	-0.034
	(0.08)	(0.18)	(0.09)	(0.04)	(0.10)
Income = 3, 25000 - 49999	-0.042	0.264	-0.145	-0.013	0.098
	(0.13)	(0.17)	(0.11)	(0.07)	(0.11)
Income = 4, 50000 - 74999	0.133	0.168	0.016	0.027	0.153
	(0.17)	(0.21)	(0.13)	(0.09)	(0.14)
Income = 5, 75000 - 99999	-0.237	0.162	-0.248	-0.084	-0.041
	(0.17)	(0.47)	(0.20)	(0.12)	(0.28)
Income = 6, 100000 - 149999	-0.112	-0.198	0.059	-0.172*	-0.170
	(0.20)	(0.23)	(0.15)	(0.10)	(0.16)
Income = 8, I prefer not to say	0.042	0.088	-0.012	0.013	0.089
	(0.14)	(0.16)	(0.12)	(0.08)	(0.10)
Constant	0.156	1.228	-0.346	0.034	0.684
	(0.47)	(0.85)	(0.35)	(0.26)	(0.59)
Observations	76	76	76	76	76
R-squared	0.385	0.447	0.372	0.419	0.442

*Notes: OLS regression result for participants without inconsistent answers for the check questions. Robust standard errors In parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table B3 Regression results for people with expected feeling of real incentive

VARIABLES	Index b	Index a	AA10	AA50	AA90
STEM-B score	0.005	-0.045	0.021*	0.019**	-0.022
	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)
amount of correct CRT questions	0.001	0.111	-0.028	-0.057**	0.073
	(0.04)	(0.07)	(0.03)	(0.02)	(0.04)
Age	0.032	-0.075	0.049	0.043**	-0.026
	(0.03)	(0.06)	(0.03)	(0.02)	(0.04)
Age^2	-0.000	0.001	-0.001	-0.000*	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
gender	0.042	0.116	0.005	-0.002	0.100
	(0.06)	(0.17)	(0.08)	(0.05)	(0.10)
Household number	0.001	-0.101*	0.038	0.020	-0.049
	(0.03)	(0.06)	(0.03)	(0.02)	(0.04)
School level = 2, Higher Professional Education (HBO)	0.041	-0.238	0.096	-0.031	-0.086
	(0.08)	(0.20)	(0.09)	(0.06)	(0.12)
School level = 3, Master's Degree (WO+)	0.080	-0.065	0.067	-0.021	0.037
	(0.07)	(0.20)	(0.08)	(0.05)	(0.11)
School level = 4, Pre-University Education (VWO)	-0.042	0.028	-0.087	0.078	-0.086
	(0.08)	(0.18)	(0.07)	(0.05)	(0.10)
School level = 5, Primary School	-0.025	0.034	-0.079	0.164***	-0.103
	(0.07)	(0.18)	(0.08)	(0.06)	(0.10)
School level = 6, Secondary Vocational Education and Training (MBO)	-0.340***	-0.030	-0.232	-0.281**	-0.130
	(0.11)	(0.27)	(0.17)	(0.12)	(0.14)
School level = 7, Senior General Secondary Education (HAVO)	-0.163	-0.636**	0.121	0.000	-0.415**
	(0.12)	(0.30)	(0.15)	(0.10)	(0.15)
Employment = 4, Student	-0.039	-1.138***	0.455***	-0.002	-0.516**
	(0.14)	(0.32)	(0.15)	(0.10)	(0.19)
Employment = 5, Working full-time	0.051	-0.590*	0.258	0.076	-0.212
	(0.13)	(0.34)	(0.17)	(0.09)	(0.18)
Employment = 6, Working part-time	-0.039	-0.928**	0.373**	-0.053	-0.412**
	(0.13)	(0.33)	(0.17)	(0.10)	(0.18)
Marital status = 2, Living with a partner	-0.165	-0.322	0.037	-0.091	-0.170
	(0.13)	(0.33)	(0.18)	(0.10)	(0.19)
Marital status = 3, Married	-0.150	0.600*	-0.362*	-0.117	0.244
	(0.12)	(0.32)	(0.20)	(0.16)	(0.16)
Marital status = 4, Never been married	-0.188	-0.023	-0.123	0.010	-0.070
	(0.16)	(0.33)	(0.18)	(0.17)	(0.20)
Income = 2, 10000 - 24999	0.040	0.182	-0.017	0.040	0.108
	(0.15)	(0.25)	(0.09)	(0.07)	(0.18)
Income = 3, 25000 - 49999	0.015	0.336	-0.126	0.133	0.123
	(0.18)	(0.29)	(0.09)	(0.10)	(0.21)
Income = 4, 50000 - 74999	-0.292	-0.180	-0.103	-0.155	-0.193
	(0.20)	(0.41)	(0.25)	(0.14)	(0.22)
Income = 5, 75000 - 99999	-0.150	0.069	-0.085	-0.017	-0.055
	(0.13)	(0.23)	(0.09)	(0.06)	(0.16)
Income = 6, 100000 - 149999	-0.139	1.160**	-0.477*	-0.237	0.564*
	(0.25)	(0.45)	(0.25)	(0.22)	(0.28)
Income = 7, 150000 or more	0.174	0.119	0.116	0.078	0.136
	(0.16)	(0.29)	(0.14)	(0.09)	(0.18)
Constant	-0.335	3.122*	-1.497*	-0.894*	1.324
	(0.71)	(1.64)	(0.82)	(0.44)	(1.01)
Observations	45	45	45	45	45
R-squared	0.588	0.549	0.648	0.629	0.470

*Notes: OLS regression result for people who filled in their email, which is expected to give these people a feeling of a real incentive. Robust standard errors In parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Table B4 Regression results (ex) academic subjects

VARIABLES	Index b	Index a	AA10	AA50	AA90
STEM-B score	0.016	0.005	0.003	0.015*	0.005
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
amount of correct CRT questions	0.002	-0.021	0.013	-0.020	-0.006
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)
Age	-0.009	-0.043**	0.015	-0.004	-0.027*
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Age^2	0.000	0.000*	-0.000	0.000	0.000*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
gender	-0.023	0.068	-0.048	-0.005	-0.006
	(0.08)	(0.09)	(0.05)	(0.05)	(0.06)
Household number	-0.011	0.014	-0.014	-0.003	0.000
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
School level = 2, Higher Professional Education (HBO)	-0.050	0.060	-0.064	-0.074	0.011
	(0.07)	(0.12)	(0.06)	(0.05)	(0.07)
School level = 3, Master's Degree (WO+)	-0.023	-0.010	-0.029	-0.027	-0.029
	(0.08)	(0.11)	(0.05)	(0.05)	(0.07)
Employment = 3, Retired	-0.848**	-0.418	-0.219	-0.483***	-0.627**
	(0.39)	(0.31)	(0.19)	(0.18)	(0.29)
Employment = 4, Student	-0.558*	-0.279	-0.151	-0.306**	-0.361
	(0.32)	(0.28)	(0.13)	(0.13)	(0.27)
Employment = 5, Working full-time	-0.498	-0.374	-0.087	-0.221	-0.414
	(0.31)	(0.23)	(0.11)	(0.13)	(0.25)
Employment = 6, Working part-time	-0.539*	-0.451**	-0.077	-0.257**	-0.452*
	(0.31)	(0.22)	(0.10)	(0.12)	(0.25)
Marital status = 2, Living with a partner	0.251	0.129	0.061	0.185	0.154
	(0.22)	(0.22)	(0.16)	(0.13)	(0.12)
Marital status = 3, Married	0.242	0.243	-0.004	0.236*	0.183*
	(0.23)	(0.23)	(0.18)	(0.14)	(0.10)
Marital status = 4, Never been married	0.255	0.067	0.096	0.240	0.127
	(0.23)	(0.23)	(0.17)	(0.15)	(0.12)
Marital status = 5, Widowed	0.117	-0.119	0.053	0.151	-0.015
	(0.24)	(0.24)	(0.17)	(0.14)	(0.15)
Income = 2,. 10000 - 24999	-0.059	-0.014	-0.062	0.058	-0.073
	(0.10)	(0.17)	(0.07)	(0.06)	(0.10)
Income = 3, 25000 - 49999	-0.120	0.225	-0.163	0.007	0.056
	(0.13)	(0.17)	(0.10)	(0.07)	(0.10)
Income = 4, 50000 - 74999	0.040	0.174	-0.048	0.040	0.136
	(0.14)	(0.18)	(0.10)	(0.08)	(0.12)
Income = 5, 75000 - 99999	-0.010	0.228	-0.100	-0.013	0.168
	(0.19)	(0.23)	(0.15)	(0.10)	(0.14)
Income = 6, 100000 - 149999	-0.215	0.086	-0.162	-0.072	-0.058
	(0.18)	(0.24)	(0.17)	(0.08)	(0.15)
Income = 7, 150000 or more	0.427	0.555*	-0.032	0.299*	0.479*
	(0.33)	(0.32)	(0.15)	(0.16)	(0.28)
Income = 8, I prefer not to say	-0.097	0.105	-0.095	-0.030	0.030
	(0.13)	(0.16)	(0.11)	(0.08)	(0.10)
Constant	0.484	1.237**	-0.214	0.053	0.915*
	(0.59)	(0.62)	(0.36)	(0.35)	(0.46)
Observations	112	112	112	112	112
R-squared	0.248	0.188	0.233	0.305	0.203

*Notes: OLS regression result for people with (ex) academic subjects. Robust standard errors In parentheses. *** p<0.01, ** p<0.05, * p<0.1.*

Appendix C

In this section, there will be explained how some of the neo-additive source functions that violate one or more conditions of equation 8 from Wakker (2010). Manually adjusting neo-additive source functions that violate some conditions has been done before by Martinsons (2015, December 18). Therefore, the same approach is used in this thesis.

Violations A – A slope smaller or equal to zero (s ≤ 0)

For neo-additive source functions with a slope smaller or equal to zero, the condition s ≥ 0 is violated. Therefore, these source functions are adjusted in a way that at p = 0.5 the slope is 0.01. This is done in two steps. First the transition point (tp) through which the adjusted neo-additive source function will be fitted is calculated and the slope is adjusted. The transition point is calculated as follows:

$$tp = c + 0.5 * s \tag{9}$$

In the second step the new intercept c' is calculated. C' is calculated as follows:

$$c' = tp - 0{,}5 * 0.01 \tag{10}$$

Table C1 shows the original parameters and the new adjusted parameters.

Table C1 Violation A

Variable	Mean	Std. Dev.	Min	Max
c	.623	.188	.241	.889
d	.548	.114	.418	.851
s	-.171	.121	-.406	-.02
c adj	.533	.143	.19	.727
d adj	.457	.143	.263	.8
s adj	.01	0	.01	.01

Violation B – Slope bigger than 1 with the intercept between 0 and 1 (s > 1 & 0 < c < 1)

Seventeen neo-additive source functions have a slope that is bigger than 1 while having a intercept that is between 0 and 1. To adjust these source functions the intercept is kept fixed while the slope is adjusted. The slope is adjusted with the following calculation:

$$s' = \frac{(1-c)}{1} \tag{11}$$

Table C2 shows the original parameters and the new adjusted parameters after the manual adjustments of the slope.

Table C2 Violation B

Variable	Mean	Std. Dev.	Min	Max
c	.007	.016	0	.057
d	-.016	.04	-.146	0
s	1.009	.03	1	1.125
c adj	.007	.016	0	.057
d adj	0	0	0	0
s adj	.993	.016	.943	1

Violation C – Intercept smaller than zero and slope bigger than 1 (c < 0 & s > 1)

Only seven neo-additive source functions have violations as described above. To manually "put" these source functions within the (0,1) domain, the slope is made equal to 1 and the intercept is made equal to 0. Table C3 shows the original parameters and the new adjusted parameters after the manual adjustments of the intercept and slope

Table C3 Violation C

Variable	Mean	Std. Dev.	Min	Max
c	-.084	.085	-.271	-.022
d	-.014	.047	-.072	.052
s	1.098	.063	1.016	1.219
c adj	0	0	0	0
d adj	0	0	0	0
s adj	1	0	1	1

Violation D – Intercept smaller than zero and slope between 0 and 1 (c < 0 & 0 ≤ s 1 or)

fifteen neo-additive source functions have negative intercept and a slope between 0 and 1 or equal to 1. These source functions are parallel shifted upwards until the intercept will become 0. Table C4 shows the original parameters and the new adjusted parameters after the manual adjustments of the intercept.

Table C4 Violation D

Variable	Obs	Mean	Std. Dev.	Min	Max
c	15	-.035	.042	-.13	-.005
d	15	.077	.147	.005	.581
s	15	.957	.12	.529	1
c adj	15	0	0	0	0
d adj	15	.043	.12	0	.471
s adj	15	.957	.12	.529	1

Violation E – Sum of slope and intercept is bigger than 1 (s + c > 1)

After already adjusting multiple neo-additive source functions manually, only nine source functions have a sum of the slope and intercept that is bigger than 1. These neo-additive source functions are shifted downwards until d is equal to 0. . Table C5 shows the original parameters and the new adjusted parameters after the manual adjustments of the neo-additive source functions.

Table C5 Violation E

Variable	Mean	Std. Dev.	Min	Max
c	.184	.161	.005	.554
d	-.035	.037	-.118	-.004
s	.851	.137	.564	1
c adj	.149	.137	0	.436
d adj	0	0	0	0
s adj	.851	.137	.564	1