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Title:

Which risk/ambiguity attitude components are related to intelligence?

- Probability weighting parameters.

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1. Introduction

The role of intelligence and its connection to our individual differences in preferences and economic behavior has been explored by researchers throughout history. This study examines whether there is a relation between an individual's cognitive ability – intelligence, and their individual parameters of likelihood insensitivity (a) and pessimism (b), which theory uses to describe individual probability weighting, people's non-objective perception regarding probabilities in choices under risk.

More specifically, the main focus of the study is to investigate whether an individual's subjective self-estimated intelligence (SEI) is related to those parameters and whether it is a better indicator compared to a cognitive test score. (As we will see going forward, SEI and IQ test performance are correlated with each other, but are also correlated with various personality traits, with SEI having a multiple times higher correlation. In that sense we are putting forward the hypothesis that likelihood insensitivity and pessimism are related more to personality, rather than cognitive ability.)

So, to look into probability weighting in relation to SEI and cognitive ability we conducted an anonymous three-step survey, in which subjects were asked first to choose between prospects involving different probabilities, then to make an estimation of their own intelligence, and, lastly, to take an Intelligence (IQ) test. All the above variables were also examined against the extra variables of age, gender, level of education and country of origin.

The end results suggest that both likelihood insensitivity (a) and pessimism (b) do not relate with any other variable. The only significant findings were a relation between higher education and higher cognitive ability and the overestimation of intelligence and gender (males). Also, worth noting is that individuals of above average cognitive ability were more accurate in their estimations, and varied in their perception regarding their own intelligence, but people with below average intelligence almost exclusively overestimated their abilities pointing to the presence of the Downing Effect.

2. Literature Review

2.1 Subjective Probability Weighting

Modern Behavioral Economics is usually traced back to the work of Kahneman and Tversky (1979) and their paper introducing Prospect Theory (PT). Their motivation was to provide an alternative to the widely accepted Expected Utility Theory (EUT) developed by Von Neumann and Morgenstern[1] (1944,1947,1953), and as such to offer a new model for choice under risk that considers and treats as systemic the various violations of EUT, such as the Allais (1953) paradox and the certainty effect.

In this paper we will focus on a specific aspect of EUT violations, the nonlinear evaluation of probabilities. Kahneman and Tversky (1979) started the discussion by showing how when people compare probabilities, they tend to overweight the smaller ones and underweight the larger ones. After them more research followed, cementing this original finding and establishing the notion that people treat probabilities non-linearly. And although Prospect Theory addressed initial violations such as the Allais paradox and provided a momentous model for choice under risk, it created some new problems. Specifically, the fact that with nonlinear probabilities, the model occasionally gives predictions that violate monotonicity.

So theory evolved, and new models emerged. First was Rank Dependent Utility (RDU) (Quiggin 1982, Yaari 1987) which introduced ranked outcomes, and then the Cumulative Prospect Theory (CPT) (Starmer and Sugden 1989; Luce and Fishburn 1991; Tversky and Kahneman 1992) was formed to combine everything together. An effort that ultimately led to the Nobel Memorial Prize in Economic Sciences for Daniel Kahneman in 2002.

Starting with RDU, optimism (risk seeking) and pessimism (risk aversion) were used to describe the S-shape of the probability weighting function (Convex for small and concave for larger probabilities) (Fig.2.1) which has been a common empirical finding, going back to Preston and Baratta in 1948.

Abdellaoui (2000) describes the possibility and the certainty effect. When people perceive probability changes, their perception depends highly on the starting and ending probability, rather than on the increase or decrease itself. The possibility effect is the higher emotional impact and weight people have to an increase from 0% to something, rather than an equal increase from a medium starting probability, and that is because they overvalue eliminating the impossibility of that 0%. Similarly, the certainty effect is the overvaluation of achieving the certainty of 100%, and because of that people assign a bigger weight in a probability increment that reaches it, compared to an equal increment from a medium starting probability that does not. Tversky and Kahneman (1992) had also described this phenomenon as "diminishing sensitivity" that occurs when the examined probabilities are distanced from the

[1] The origin of EUT can be traced back to Bernoulli (1738) and his response to the St. Petersburg Paradox.

extremes of 0% (impossibility reference point) and 100% (certainty reference point). The further from these two points, the lower the individual's sensitivity.

The two effects of treating higher and lower probabilities irrationally were also dubbed as lower subadditivity and upper subadditivity and that way the inverse S-shape of the probability weighting function was formalized by Amos Tversky and Peter Wakker.

For gains, a probability weighting function w "satisfies *bounded subadditivity*, or *subadditivity (SA)* for short, if there exist constants ε ≥ 0 and ε' ≥ 0 such that: (4.1) w(q) ≥ w(p + q) - w(p) whenever p + q < 1-ε and (4.2) 1 - w(1 - q) ≥ w(p + q) - w(p) whenever p ≥ ε'. Conditions (4.1) and (4.2) are called *lower SA* and *upper SA*, respectively. […]. The constants ε, ε' are called *boundary constants*, and do not depend on p, q." p and q refer to objective probabilities, while ε and ε' can vary between individuals (Tversky and Wakker 1995 p.1260). The theoretical analysis behind this, "was motivated by the observed pattern of risk seeking, nonlinear preferences, and source dependence" which "suggests an S-shaped weighting function that overweights small probabilities and underweights moderate and high probabilities" (Tversky and Wakker 1995, p. 1255).

The Probability weighting function is often presented as in the graph below (Fig.2.1). Prelec (1998 p.498) summarizes its properties in relation to the diagonal that represents linear probability as:

"*regressive* - intersecting the diagonal from above

asymmetric - with fixed point at about 1/3

s-shaped - concave on an initial interval and convex beyond that"

reflective - assigning equal weight to a given loss-probability as to a given gain-probability."

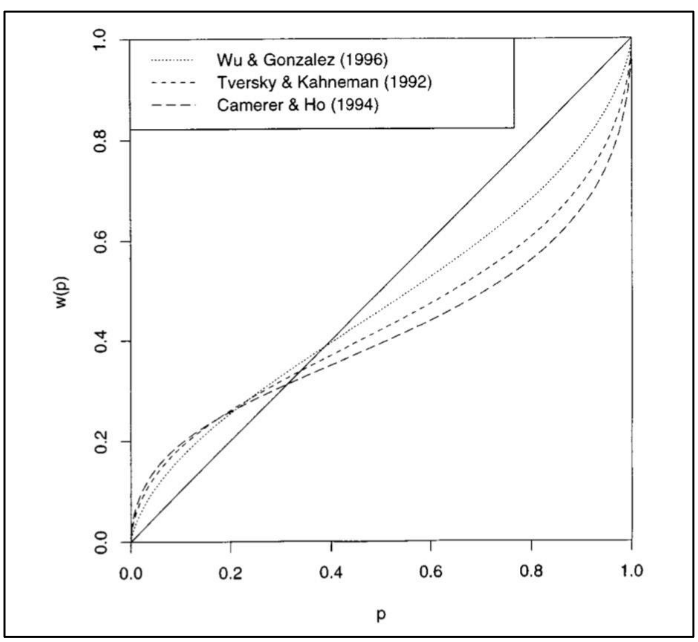


Fig. 2.1 "One-parameter weighting functions estimated by Camerer and Ho (1994), Tversky and Kahneman (1992), and Wu and Gonzalez (1996)" In Wu and Gonzalez (1999 p:132).

Being regressive explains the pattern of risk seeking for gains in small probabilities and losses for large probabilities, and risk aversion for losses for small probabilities and gains for large probabilities. Being asymmetric (with a fixed point around 1/3 probability), shows that people tend to overweight lower probabilities and underweight the rest, limiting the weight of uncertain outcomes relative to certain. Because of that asymmetry, risk aversion for gains is enhanced and so is risk seeking for losses due to reflection. The S-shape shows the preference towards the extreme probabilities of 0% and 100%.

This phenomenon is ultimately important because it helps explain people's attitudes towards situations involving risk, more specifically why people can behave both as risk averse and risk seeking at the same time. For example, the Allais' Paradox manifests itself for gains at a high probability because people underweight the probability of the possible outcome.

For gains at a low probability, overweighting helps explain why people chose to buy lottery tickets or enter a casino (see Garrett and Sobel 1999; Forrest et al. 2002), while for losses at small probabilities people overpay by buying insurance in order to reduce that very small probability to the certainty of 0% (see Cicchetti and Dubin 1994; Sydnor 2010). Segal (1987,1990) also uses probability weighting to explain ambiguity and aversion for compound lotteries and Halevy (2008) links it to intertemporal choice due to the inherent risk of the future.

For our purposes when examining individual probability weighting, denoted $w(p)$ for probabilities p between 0 and 1, we will focus on gains and use the parametric family mentioned by Wakker (2010 p:208) referring to previous work by Goldstein and Einhorn (1987), Lattimore, Baker, and Witte (1992), and Ostaszewski, Green, and Myerson (1998).

$$w(p) = \frac{\mathrm{b}p^{a}}{\mathrm{b}p^{a} + (1-p)^{\alpha}} \qquad a > 0, b > 0$$

The reason is the use of the two parameters 'a' and 'b' who describe likelihood insensitivity (which determines the curvature of the function) and pessimism (which determines the elevation) in order to further interpret the examined phenomenon and the shape of the weighting function.

When a=b=1 then w(p)=p , which is the linear probability function as used in EUT. For a<1 the function takes an inverse S-shape with the curvature increasing as the value of a is lower. Similarly, for a>1 the function gets the S-shape, with the curvature increasing the higher the value of a. The parameter b determines the elevation of the curve. In particular, it determines the intersection point between the probability weighting function and the 45^{o} line that represents linear probability. That intersection point's coordinates are [b/(1+b) , b/(1+b)] and the higher the value of b, the lower that point is in the plane.

Likelihood insensitivity (diminishing sensitivity for probabilities) is the same as bounded subadditivity and the "lack of understanding of risk and uncertainty", and pessimism /optimism are also "closely related to the classical risk aversion and risk seeking" (Wakker 2010, p. 358). Bleichrodt and Pinto (2000, p. 1487) had also described the two parameters as a: "the extent to which people are able to discriminate between differences in probability" and b: "the extent to which people find the chance domain attractive".

Also considering research like Charupat et al.'s (2013) that found evidence connecting probability weighting to emotional balance, and how emotions in general affect people's rational decision making, it is clear that psychological aspects along with cognitive ability influence the phenomenon we study. Rottenstreich and Hsee (2001 p.186) who also had examined the effect of emotions noted that emotionally charged outcomes "elicit greater degrees of hope and fear and, therefore larger jumps at endpoints" , where endpoints refer to the extreme probabilities 0 and 1.

2.2 Cognitive Ability – Intelligence

Measuring Intelligence

The modern study of human intelligence can be traced back to the late 19th century with the core debate being about the effect of nature/genetics and nurture/environment. Among the pioneers was Sir Francis Galton, an English polymath and cousin to Charles Darwin, who among other things discovered the statistical concepts of correlation (Galton 1888) and of 'regression towards the mean' (Galton 1886), both of which were tied to his anthropologic research. In his lab he also originated the use of questionnaires and surveys in order to record individual accounts on how the mind works (see Clauser 2007), and although his use of statistical and psychometric methods to study intelligence was ground breaking, his results were mostly fruitless.

The first intelligence test resembling the ones we use today was developed by someone who had spent some time with Galton, Alfred Binet and his student Theophile Simon in 1905. A year before that, the French Ministry of Public Instruction had commissioned Binet to develop a means to diagnose intellectual disability in primary grade students for the purpose of separating them for specialized classes.

Binet started by making two critical assumptions. The first assumption was that children's intelligence increase by age. Which means that a typical 10-year-old will manage to solve problems that the typical 8-year-old will not, and that is a reality at least until puberty. Therefore, the notion of 'mental age' makes sense, being a term describing the level at which a child operates. Comparing that mental age, to the child's actual chronological age would determine whether that child was advanced or not.

The second and more controversial assumption was that a child's relative intelligence among its chronological age group was fixed throughout its life. That means that a child that underperforms at age 6 relative to its peers, it will continue to underperform till graduation, so it made sense to remove it from the standard curriculum.

So, with the Ministry accepting these assumptions, Binet went to inquire teachers and collect a bunch of problems that children usually encounter in school on a daily basis, like unwrapping sweets and comparing weights of various objects. He finally used those problems as a test to derive the mental age of each child, and then used that age to differentiate the children among each other. That was the Simon-Binet Scale of Intelligence and it was such a success that it drew interest beyond the borders of France and sprung a variety of adaptations. (Antonson 2010, Hunt 2011 pp.4-5)

The most prevalent one was the Stanford-Binet Intelligence test by Louis Terman (1916), an American professor of Stanford University. Terman working with Binet, standardized the test, increased its length and included adults in its measurements. For the final score they used the ratio developed by German psychologist William Stern (1912), the *Intelligence Quotient,* which was calculated as 'mental age ÷ chronological age x100' giving an average IQ score equal to 100. So for example, a child who could read at age 4 when the majority of children learn to read at age 6, would have an IQ score of 150.

I Q	***Classification***
Above 140	"Near" genius or genius.
120–140	Very superior intelligence.
110–120	Superior intelligence.
90–110	Normal, or average, intelligence.
80– 90	Dullness, rarely classifiable as feeble-mindedness.
70– 80	Border-line deficiency, sometimes classifiable as dullness, often as feeble-mindedness.
Below 70	Definite feeble-mindedness.

<u>Table. 1</u> The first IQ Classification System given by Terman (1916, p.79).
Throughout the years, the ranges and the characterizations have been updated and adopted for each individual IQ test out there, but the main point remains roughly unchanged.

Terman then went on to do his '*Genetic Study of Genius'* which is the longest running study in psychology, and aimed to examine the development of 'genius' children into adulthood. His subjects were kids with high Stanford-Binet scores, and although there were hardly any actual geniuses among them, they seemingly overperformed academically and socially later in life (see Terman & Oden 1947) accrediting the IQ tests as predictors of such outcomes. Today, those initial results are highly contested though, from the sample used not being generalized, Terman not being an impartial spectator, and the economic background of each child's family being the major factor (Holahan & Sears, 1995).

David Wechsler (1939) was the one that provided the next major breakthrough, modernizing the IQ score, by introducing 'deviation IQ' as an alternative to 'ratio IQ'. The problem with relying on 'mental age' is that it stops making sense when you start examining adults, and a linear progression of intelligence through age is not the case anymore.

This new IQ is now derived statistically, based on the individual's rank order on the provided test, relative to a group of people with similar characteristics. If Y is the raw score on the test based on correct answers and difficulty, and M and S are the mean and the standard deviation for all the scores among the reference group, then the standard score of the test taker is:

$$z = \frac{Y - M}{S}$$

The IQ score then is calculated as:

$IQ = 15z + 100$

"If the raw scores were normally distributed, then the resulting IQ scores will be normally distributed with a mean of 100 and a standard deviation of 15." (Hunt 2011 p.6)

The way such a test can be created is by running it among large sample sizes of people, representative of the intended population. The samples need to be big enough so as to have distributions for every age group, and for the test to remain relevant it has to constantly be tested against new samples. This massive effort ensures that the only legitimate IQ tests out there are actually a handful.

Over the years the pair of IQ tests that we discussed, have evolved. The modern versions of the Stanford-Binet (currently on its 5th edition) and the Wechsler tests are widely used today to measure various expressions of cognition, from vocabulary to arithmetic, to memory and reasoning et al. "Intelligence testing has been widely used to make important decisions about people's academic and vocational careers. Testing is also used as a guide in medical rehabilitation, such as evaluating the course of treatment following insults to the brain. The tests are also widely used in research on the description, causes, and consequences of being intelligent" (Hunt 2011 p.17).

The term IQ should also be considered anachronistic. Today's tests are referred to as cognitive ability tests, mental processing tests, or tests of multiple cognitive abilities and the labels adopted from the institutions that provide them include the Mental Processing Composite, General Cognitive Index, General Conceptual Ability, Broad Cognitive Ability Composite, Fluid- Crystallized Index etc. Wechsler's scales still yield Full Scale IQs, but the Binet since its 4th edition is using its Standard Age Score Composite (Kaufman 2009, p.12). For our purposes though and for simplicity's sake, we will still use the terms 'IQ and 'IQ test' as it still exists in the public's lexicon despite being technically incorrect.

Finally, it is important to point that the notion of 'intelligence' has a variety of definitions. From "the ability to learn, or understand, or to deal with new or trying information: REASON", to "think abstractly, as measured by objective criteria (such as test)", "mental acuteness: SHREWDENESS", "the act of understanding: COMPREHENSION" and others[2]. And because what constitutes intelligence is such a broad spectrum, when we look to analyze it, we have to accept that we cannot fully encapture it.

Most importantly we need to consider the tautology of intelligence being the ability to do well on intelligence tests. As Boring (1923 p.35) noted a century ago "intelligence as a measurable capacity must at the start be defined as the capacity to do well in an intelligence test. Intelligence is what the tests test." And that is why we differentiate between general intelligence and IQ scores. As Duckworth et al. (2011 p.7716) describe: "IQ scores, in contrast, measure the performance of individuals on tests designed to assess intelligence. That is, IQ is an observed, manifest variable, whereas intelligence is an unobserved, latent variable."

[2] Intelligence. 2019. In Merriem-Webster.com
Retrieved October 20, 2019, from http://www.merriam-webster.com/dictionary/intelligence

Theory of Intelligence

While the development and use if IQ tests was expanding, theory of intelligence was also being established, starting with Charles Spearman's (1904) general-factor theory or g, which states that intelligence is a single mental capacity, with some minor specific factors s. This theory dominated for decades, despite criticisms, most notably by Louis Leon Thurnstone (1938) who advocated for a more detailed definition of s that included notions like "verbal comprehension (V), word fluency (W), number ability (N), spatial ability (S), associative memory (M), perceptual speed (P), and reasoning (R) or induction (I)" (Kaufmann 2009 p.44).

As such for years, the interpretation of IQ scores was that they reflected Spearman's single form of intelligence g. Wechsler himself, despite offering three different IQ tests (Verbal, Performance, and Full-Scale) considered all of them to be a reflection of that same solitary type of intelligence (Kaufman 2009, pp. 44-45). In the end though, "multiple-ability theories finally crashed the IQ party, the most prominent were (a) Guilford's (1967) structure-of-intellect model; (b) brain-based approaches (Luria, 1966; Sperry, 1968) that emphasized two styles of information processing, sometimes referred to as sequential and simultaneous; and (c) the Cattell-Horn theory of fluid intelligence (Gf) and crystallized intelligence (Gc), referred to as Gf-Gc theory (Horn & Cattell, 1966)." (Kaufman 2009, p.48)

Raymond Cattell was a student of Spearman and looked to develop his teacher's theory by dividing General Intelligence (g) in two subcategories (Cattell 1941,1963). The first was Fluid Intelligence (Gf) referring mostly to deduction and reasoning, and relying to biological and neurological factors. And the second being Crystallized Intelligence (Gc) referring to applying acquired knowledge and relying heavily on education. The most critical difference between the two, being that Crystallized Intelligence is more resistant to age, while Fluid Intelligence deteriorates rapidly (see Salthouse 1991, Schaie & Willis 1993, Cacioppo & Freberg 2012 p.448). There's been some studies that indicate Fluid Intelligence could be improved with training (see Jaeggi et al. 2008 and Qiu et al. 2009) but their results have not been really replicated.

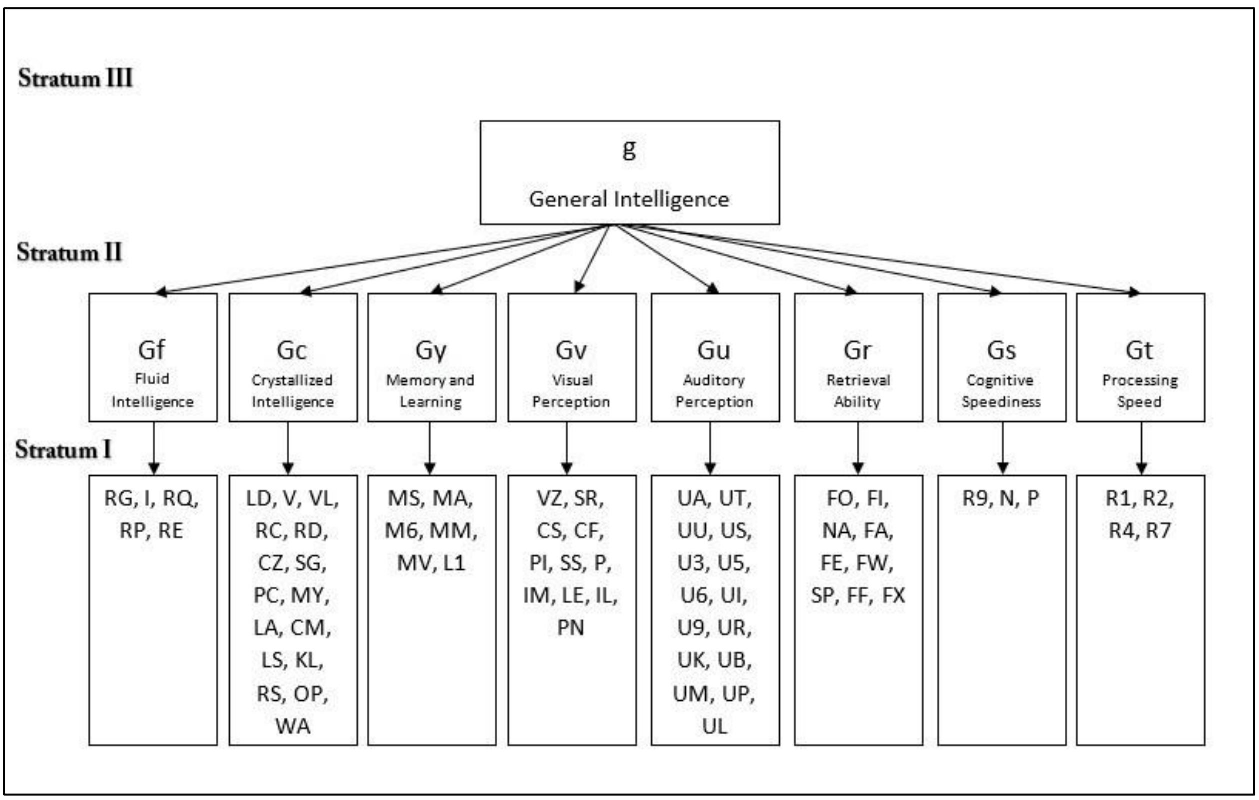
John Horn who in turn was a student of Cattell, strived to do the same as his predecessor and expand the Gf-Gc theory. "He quickly identified four abilities in addition to Gf and Gc (Horn, 1965, 1968): short-term acquisition and retrieval (Gsm), long-term storage and retrieval (Glr), visual processing (Gv), and speed of processing (Gs)[3]. That number would grow to 9 or 10 broad abilities by the mid-1990s (Horn, 1989; Horn & Noll, 1997)." (Kaufman 2009, p.81)

The turning point was when Matarazzo (1972) pointed that the Wechsler test was actually compatible with Horn and Cattell's theory, with the Performance test measuring Fluid Intelligence (Gf) and the Verbal test measuring Crystallized Intelligence (Gc), providing a new interpretation and theoretical foundation to the IQ test. Horn's then later expansion to include more abilities in the model gave the basis for the tests in the late 20th century.

[3] Different abbreviations and symbols have been used for various CHC abilities. The ones shown in parentheses are the ones currently used by most CHC theorists, not necessarily the original symbols.

The prevailing theory of intelligence today is the CHC Theory, a merge of the models by Cattell-Horn and Caroll. John Caroll (1993,1997) had arranged cognitive abilities in a hierarchy (Fig 2.2), where up top (Stratum III) was Spearman's General Intelligence (g). Below that (Stratum II) were eight broad abilities that resembled Horn's (1989) work, and at the bottom (Stratum I) were dozens more that corresponded to detailed characteristics for the second category describing the level of fidelity, mastery and speed over those abilities.

Since the two models were quite similar, the respective scientists decided to combine them in a single theory (Willis et al. 2011 p.45) which was later expanded and revised by Kevin McGrew (see Schneider & McGrew 2012).The success of CHC theory relies on its "remarkably consistent conclusions about the spectrum of human abilities". And because of that consistency it "has formed the foundation for most contemporary IQ tests" (Kaufman, 2009 p.91).



<u>Fig.2.2</u> Adapted from Carroll 1993 p.626

2.3 Demography of Intelligence

In the realm of scientific research, group differences have always been of interest, and the same applies for differences in intelligence between ages, genders, and ethnicities. It is important to note though, that such results are liable to interpretation and in no way pose a basis for sweeping assertations regarding the existence of such differences or their roots.

A reason for that is that performance in cognitive ability tests is also highly influenced by motivation (see Duckworth et al. 2011). Motivation that can be limited by regressive mindsets and discrimination dubbed the 'stereotype threat'. For example, women and African-Americans, affected by stereotypical thinking, expect to perform worse with mathematics, and for that reason alone they may disengage from related tasks and hinder their performance in cognitive ability tests that include them (see Steele and Aronson 1995,1998).

And another good reason that applies to a lot of fields in general, is that the vast majority of them that are done today rely on samples of just college students. And the validity of generalizing from students to the general population should be taken into consideration.

Age

As we mentioned when we discussed the theories of intelligence, age as a factor was a fundamental brick in the formation of those theories. Modern studies like the ones by McArdle et al. (2002) and Schaie (2005) seem to support the notion, although the exact age where people peak can differ. In general, Crystallized intelligence (Gc) seems to increase until middle age and remain relatively constant thereafter, while Fluid Intelligence (Gf) peaks earlier and then on average, declines.

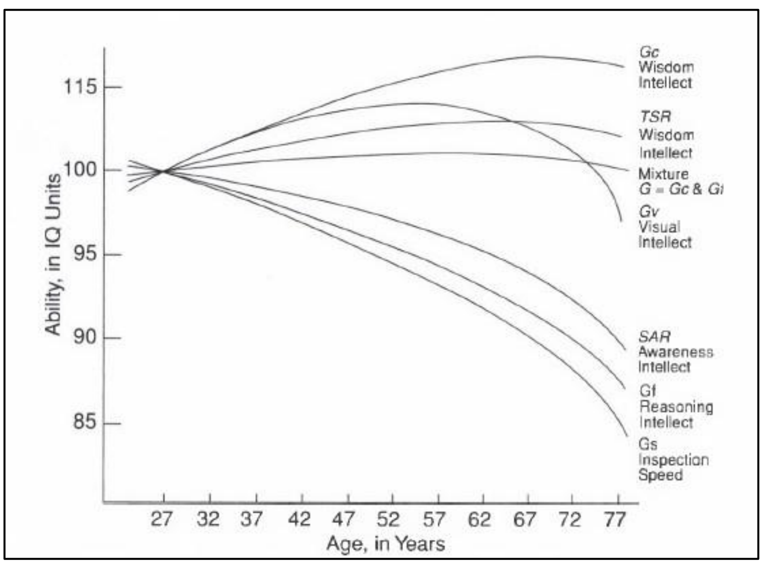


Fig.2.3 "A stylized picture of the age trends for different broad second-level traits in the Gc-Gf model of intelligence. […] From Horn, 1986, p. 52." In Hunt (2011 p.370)

The reasons for the deterioration of Gf could be a general decline in reaction time that happens with age (see Cerella 1985) or by a weakening working memory (see Kramer et al. 2006; Raz et al. 2008). Crystallized Intelligence (Gc), on the other hand, by definition is only strengthened with experience, but is also based on heuristics that can be underestimated in a laboratory setting. It still requires a healthy individual though.

Gender

The various cases presenting differences in intelligence between men and women come from three different types of evidence. “Results from overall scores derived from battery- type tests, such as the IQ score derived from the Wechsler tests; the results from factorial studies in which individual scores are computed for the g factor derived from a variety of test batteries, including both avowed intelligence tests and batteries constructed for research purposes; and the results from studies of individual tests, such as the Raven Matrices tests, that purport to be measures of g.” (Hunt 2011 pp.377-378)

Regarding battery-type tests, the general result is that women outperform men in verbal tasks (ie Hirnstein et al. 2014; Basso et al. 2000) while men do better in spatial tasks (Linn et al.1985, Weiss et al.2009). But of course, these are only indications regarding General Intelligence (g) ability as a whole, since the final result of such tests is influenced by the different weights that are given to the different tasks forming the battery, inadvertently favoring one gender over the other. And especially since such differences are minimal in size, their meaningfulness can be disputed.

The ideal way to observe gender differences in General Intelligence would be to have an accurate sample of a big enough population, and a reliable measure of g. Unfortunately, no such measure exists, and the closer one we have are the progressive matrix tests, like the Raven Matrices (see Bilker et al. 2012).Older studies using Raven Progressive Matrices (RPM) did not observe any gender differences (Court 1983; Raven 2000), but their results were later disputed by Lynn and Irwing (2004,2005) who concluded a slight male advantage. But still that advantage has been argued to be a result of a bias towards spatial reasoning that exists in these tests (Johnson & Bouchard 2005).

The last resort for examination is national surveys, psychometric research studies and laboratory psychology studies. This is where the noteworthy differences appear, although again they regard specific subcategories of intelligence and not General Intelligence.

Hedges and Newell (1995) compared four different national surveys and found that women perform better on reading comprehension, perceptual speed, and associative memory, while men did better with mathematical and spatial tasks (Table 2). Psychometric research in European countries has shown women doing better on language skills and processing speed, while men do better with visual image manipulation and reasoning (Colom & Lynn 2004 for Spain; Strand, Deary, & Smith 2006 for UK) etc. Interestingly in the laboratory, all these results appear amplified (ie Hunt et al 1988; Law Pellegrino and Hunt 1993) and new more practical dimensions are also tested, where men do better in positional awareness and orientation (ie Choi and Silverman 2003) and better comprehend maps (Boardman 1990).

All these findings have been attributed to biological and evolutionary differences between men and women, as well as socioeconomic and cultural differences and they raise interesting questions regarding policy and education. But, as Diane Halpern (2000 p.377) concluded after reviewing the vast amount of literature on gender differences in cognitive ability, those differences do not mean much for the average day-to-day lives of people.

Survey Code	Test Date	N	Reading Comp.	Mathematics	Nonverbal Reasoning	Spatial Ability	Perceptual Speed	Assoc. Memory
Project Talent	1960	73,425	−.15	.12	.04	.13	n.a.	−.32
NLS-72	1972	16,860	−.05	.24	−.22	n.a.	−.23	−.26
HS&B	1980	25,069	.002	.22	n.a.	.25	−.21	−.18
NLSY79	1980	11,914	−.18	.26, .08	n.a	n.a.	−.43, −.23	n.a.
NELS:88	1992	24,599	−.09	.03	n.a.	n.a.	n.a.	n.a.

Table 2. *"Male-female standard deviation unit [d] scores for effect size for different aspects of intelligence from Hedges and Nowell, 1995, Tables 1 and 2." In Hunt (2011 p.387)*

Nationality

Racial and ethnic differences have definitely been observed in research (see Neisser et al. 1996) and should be approached with the same nuance as gender differences. Unfortunately, because of the scale and effort needed for transnational differences, the relevant studies we can draw upon are very limited.

The most critical factor for such a study to be relevant is the use of a single test among all countries, that is free of educational and cultural biases. The two best current approaches are the Culture Fair Intelligence Test (CFIT) by Cattell (1949) and Raven's Progressive Matrices (Raven 1938), but as Aiken (2004 p.242) notes they are commendable efforts but only partially successful in eliminating bias.

The only multinational study ever done with a uniform test appears to be by Vinko Buj (1981) who compared 21 European cities plus Ghana's capital Akkra, using Cattell's Scale CFT3, a non-verbal, culture-fair test. Unfortunately though, "researchers believe the data from this study are of dubious quality: nobody knows the author; he did not work at a university; the way he collected so much data is unknown; the description of samples and testing procedure is scanty; and only one single two-page-long publication exists. The correlations with other measures, except PISA, are good" (Rindermann 2007 p.671).

	Country	Town	No. of subjects	Mean IQ	Standard deviation	Standard error of the mean
1.	Holland	Amsterdam	333	109.4	16.1	0.9
2.	Germany	Hamburg	1,572	109.3	22.4	0.6
3.	Poland	Warsaw	835	108.3	29.7	1.0
4.	Sweden	Stockholm	205	105.8	25.8	1.8
5.	Yugoslavia	Zagreb	525	105.7	34.1	1.5
6.	Italy	Rome	1,380	103.8	35.2	0.9
7.	Austria	Vienna	187	103.5	15.3	1.1
8.	Switzerland	Zurich	163	102.8	19.4	1.5
9.	Portugal	Lisbon	242	102.6	18.7	1.2
10.	Great Britain	London	1,405	102.0	19.3	0.5
11.	Norway	Oslo	100	101.8	11.6	1.2
12.	Denmark	Copenhagen	122	100.7	13.3	1.2
13.	Hungary	Budapest	260	100.5	21.4	1.3
14.	Czechoslovakia	Bratislava	363	100.4	25.9	1.4
15.	Spain	Madrid	848	100.3	34.7	1.2
16.	Belgium	Brussels	247	99.7	23.5	1.5
17.	Greece	Athens	220	99.4	25.6	1.7
18.	Ireland	Dublin	75	99.2	17.3	2.0
19.	Finland	Helsinki	120	98.1	26.6	2.4
20.	Bulgaria	Sofia	215	96.3	34.7	2.4
21.	France	Paris	1,320	96.1	27.1	0.7

Table 3. *IQ values of various European cities according to Buj (1981), for Akkra the score was 82.2*

Another well-known work was in the two books by Richard Lynn and Tatu Vanhanen (2002,2006) where they collected IQ scores for 113 countries and then estimated the scores for another 79 by comparing them to neighboring or similar countries. Their goal was to use that data and contrast them to the economic data of each country and produce correlations between IQ scores and a "Quality of Life Index". More than that they grouped countries by geography and race, and attributed the differences in economic advantage foremost on race and secondary on nutritional and educational factors. Their books have drawn enough criticism as well, for their methodology, their data, and their conclusions (see Barnett and Williams 2004; Ervik 2003; Nechyba 2004; Palairet 2004; Richardson 2004).

Index of Quality of Life	*Correlation with IQ Estimate*
Gross national income/person (adjusted for local purchasing power)	.684
Adult literacy rate	.642
Tertiary education	.746
Life expectancy	.773
Democratization Index	.568

Note: Data selected from Lynn and Vanhanen, 2006, Table 6.1. Figures shown indicate the data based on 113 observed points.

Table 4. "*Correlations between IQ estimates and selected indices of national well-being" in Hunt (2011 p.438)*

The only other relevant studies that have been undertaken include Wicherts, Dolana and Maas (2010) who focused in sub-Saharan Africa and criticized Lynn and Vanhanen for weak IQ estimates and underestimating the effects of education and economy. Further included are Heiner Rindermann (2007) who used the results of international student assessment tests[4] (who all correlate with each other) as indicators of cognitive ability for the population of each country. His final groupings share similarities to those of Lynn and Vanhanen, although his research understandably pointed to the importance of education in economic development.

[4] The tests used are the 'Trends in International Mathematics and Science Study' (TIMSS) and 'Progress in International Reading Literacy Study (PIRLS) by the 'International Association for the Evaluation of Educational Achievement' (IEA), and the 'Programme for International Student Assessment' (PISA) by the 'Organisation for Economic Co-operation and Development' (OECD).

2.4 Bounded Rationality

After looking at the theory for intelligence, it appears its most relevant characteristic is its limits and bounds, which has interesting implications for economics, since the homo-economicus is at the foundation.

Herbert Simon was among the first to combine psychological research with economics (see Simon 1955,1957a,1957b), and offered theories that involved cognitive mechanisms and the use of satisficing[5] in individuals, due to their bounded rationality. Where bounded rationality describes the lack of information, the lack of time and the limited computational abilities in humans, who also have inconsistent utility functions. Satisficing then becomes people's behavior and describes how decision-making falls down to "good enough" choices due to the above limitations.

Simon was the main figure representing this early approach in economics which Sent (2004 p.70) calls the old behavioral economics. In modern behavioral economics today, the focus is on those (systematic) departures from rationality due to the use of heuristics and their resulting biases (e.g. Kahneman & Tversky 1974). A heuristic, is a mental process or technique, alternative to Bayes' rule, that is used during decision making in order to make a choice as effortless as possible, something that reflects back to Simon's idea. As Schoemaker (1982 p.553) notes: people's "failure to optimize appears to be cognitive, rather than motivational".

Heuristics are related to decisions made by our subconsciousness and based on intuition in contrast to conscious and rationality. This dichotomy is known as "dual-process theory" (Sloman 1996) and the two different processes are named System 1 (intuition) and System 2 (reasoning) (Stanovich and West 2000). The reason System 1 often dominates decision making is because of what Kahneman (2003 p.699) calls 'Accessibility', which is "the ease with which particular mental contents come to mind. And a failure in judgment can be the result of System 1 overtaking and System 2 failing to correct".

The heuristics mentioned by Kahneman and Tversky (1974) and relevant in choices under risk, are representativeness, availability and anchoring. Representativeness refers to the tendency to correlate similarity with probability, essentially the use of stereotypes which leads to the biases of base-rate neglect, insensitivity to sample size, gambler's fallacy, the Law of small numbers, misconceptions of regression et al. Availability is the attribution of a higher frequency to things that come easier to mind and is related to Accessibility, and biases due to Availability are illusory correlation, hindsight bias, curse of knowledge, money illusion et al. And finally, adjustment from an Anchor (Anchoring) is the influence of abstract and even irrelevant information- starting points (anchors) in people's predictions. That leads to biases like insufficient adjustment, misevaluation of the probabilities of conjuctive and disjunctive events and biased assessment of subjective probability distributions.

[5] A portmanteau of satisfy and suffice.

2.5 Illusory Superiority

Another interesting aspect of intelligence that also has behavioral undertones is people's perception of their own intelligence. There has been enough research on whether self-estimated intelligence (SEI) is a good proxy for actual IQ scores, and the correlations found range from r=30% to r=50% (see Paulhaus, Lysy & Yik 1998; Furnham & Chamorro-Premuzic, 2004; Chamorro-Premuzic, Furnham, & Moutafi, 2004).

The majority of SEI research though has been focused on gender differences and the fact that women are more modest than men in their estimates. Apparently, men on average overestimate their intelligence by 5 IQ points points while women tend to underestimate theirs by a comparable margin (see Furnham 2001; Furnham, A., Moutafi, J. & Chamorro-Premuzic, T. 2005; Furnham, Shahidi & Baluch 2002). Many studies have also been done in many nations, and one (von Stumm, Chamorro-Premuzic & Furnham 2009) has made a between-countries comparison, examining the effect of culture, along with gender.

When we examined the gender differences in cognitive ability tests, we noted how women perform better in verbal tests, while men perform better in mathematical and spatial tests and it appears that this fact has been ingrained in people's perceptions. When people are asked to assess their intelligence, these three dimensions are what people appear to consider the most, and because men do better in both mathematical and spatial tasks, intelligence appears to be viewed as 'male-normative' (Storek & Furnham 2013 p.665).

But knowing that the IQ score is actually a positioning of one's cognitive ability in a distribution of a population, an overestimated score implies that people hold themselves higher not just in general, but also in relation to others. Illusory superiority (Van Yperen & Buunk, 1991) is a cognitive bias in psychology wherein a person over-evaluates their own attributes, in relation to the same attributes of others, "be it personality traits, abilities, conformity to group norms or life circumstances" (Hoorens 1993 p.117).

Explanations for why people give high SEI can vary, depending on whether the estimation was given before or after a cognitive ability test, but generally people tend to overvalue their positive behaviors and characteristics (Alicke & Govorun 2005) an effect related to egocentrism (Kruger 1999). Giladi and Klar (2002) interestingly suggest that humans tend to elevate any individual against the aggregate in general, and not only just when evaluating themselves.

But regarding over-evaluation of cognitive ability specifically, two effects are particularly interesting. The Dunning-Kruger effect (see Kruger & Dunning 1999) by which people tend to underestimate their own incompetence, and the Downing Effect (see Davidson and Downing 2000) by which people with below-average IQ tend to overestimate it, while people with above-average IQ tend to underestimate it. And although there has been no research whatsoever about SEI in relation to probability weighting, there has been enough that links it to personality traits.

2.6 Personality

Whether personality and intelligence are related is a question that has been examined for decades (see Hofstee 2001), and although in theory they appear unrelated, personality traits have been shown to be related to the performance in cognitive ability tests, and through them correlated to intelligence (Brebner & Stough, 1995; Eysenck, 1994; Zeidner & Matthews, 2000). Despite that, various meta-analytical studies have shown only a slim relationship between personality traits and intelligence at best (Ackerman & Heggestad 1997).

Similar research to that has been done on the relationship between self-estimated/self-assessed intelligence and personality traits (Furnham et al 2001,2005; Chamorro-Premuzic et al. 2005), with a focus on the "NEO Personality Inventory" by Costa and McCrae (1992)[6] which is a personality test based on the 'Big Five' Personality theory (Digman 1990; Goldberg 1993). According to this theory, an individual's overall personality is shaped by five distinct characteristics: Neuroticism (lack of emotional stability, irritability, moodiness), Extraversion (being outgoing and social), Openness (being open to new experiences), Agreeableness (being friendly, compassionate and cooperative) and Conscientiousness (reliability, being organized and methodical) .

The general results again are correlations between SEI and the 'Big Five' personality traits that are significant but modest in size, but for our purposes we will concentrate on the results of the study by Chamorro-Premuzic et al. (2005), the reason being that these researchers not only tested SEI against personality traits, but they also included a cognitive ability test, the 'Raven's Standard Progressive Matrices' that gauge fluid Intelligence (Gf) (Raven, Raven & Court 1998). Their goal was to test what influences SEI scores and they concluded that SEI is "a mediating construct between personality and psychometric intelligence" and "may be influenced by both non-cognitive (e.g.,modesty, assertiveness, anxiety, impulsiveness) and cognitive (Gf and Gc) variables." (p.1525)

As shown on Table.5 below (instead of SEI, they used SAI – Self-assessed Intelligence) they found significant correlations between Cognitive ability (Gf) and SEI ($r = 0.22$, $p = 0.01$) which as we have mentioned is a common finding. Of the Big Five factors, Openness correlated significantly with both Gf ($r = 0.21$, $p = 0.01$) and SEI ($r = 0.20$, $p = 0.01$) and Neuroticism correlated significantly with SEI ($r = 0.20$, $p = 0.01$). Nevertheless, the correlations between SEI and Agreeableness and Extraversion were not significant.

Beyond the initial Big Five, they delved into some of their sub-facets and for them, cognitive ability correlated significantly with aesthetics ($r = 0.20$, $p = 0.01$), ideas ($r = 0.17$, $p = 0.03$) and values ($r = 0.21$, $p = 0.01$) (all under Openness). Other subfacets were not significantly correlated with Gf. SEI on the other hand correlated significantly with anxiety ($r = 0.23$, $p = 0.003$), self-consciousness ($r = 0.16$, $p = 0.04$), and vulnerability ($r = 0.16$, $p = 0.04$) under Neuroticism, activity ($r = 0.17$, $p = 0.03$) under Extraversion, and ideas ($r < 0.001$) and values ($r = 0.20$, $p = 0.01$) under Openness. Gender and Age were not significantly correlated with either Cognitive ability or SEI.

[6] The current version is the NEO PI-3 (McCrae, Costa & Martin 2005).

T. Chamorro-Premuzic et al. / Personality and Individual Differences 38 (2005) 1517–1528 1521

Table 1
Correlations between Gf, SAI, the Big Five, sex and age

	SAI	Gf
SAI		.22**
Anxiety	−.23**	−.08
Anger-hostility	−.08	−.01
Depression	−.15	.02
Self-conscious	−.16*	.01
Impulsiveness	−.07	−.05
Vulnerability	−.16*	.06
<u>Neuroticism</u>	−.20*	−.01
Warmth	−.01	−.07
Gregariousness	−.05	−.04
Assertiveness	.14	−.01
Activity	.17*	.00
Excitement seek	.13	.03
Positive emotions	−.02	−.00
<u>Extraversion</u>	.08	−.02
Fantasy	.13	.08
Aesthetics	.06	.20**
Feelings	.05	.13
Actions	.10	.06
Ideas	.29**	.17*
Values	.20*	.21**
<u>Openness</u>	.20*	.21**
Trust	.02	.12
Straightforward	−.12	−.03
Altruism	.03	−.01
Compliance	−.02	.08
Modesty	−.15	−.03
Tender-mind	−.03	.00
<u>Agreeableness</u>	−.08	.01
Competence	.15	−.01
Order	−.07	.04
Dutifulness	.10	−.01
Achievement-striv	.07	−.04
Self discipline	.08	−.01
Deliberation	−.01	−.05
<u>Conscientiousness</u>	.07	−.02
Sex	.02	−.00
Age	.04	.01

* $p < .05$.
** $p < .01$.

<u>Table 5.</u> The correlations between the Big Fife personality traits and their sub-facets, with Self-assessed Intelligence (SAI) and Cognitive Ability (Gf) (Chamorro-Premuzic et al. 2005 p.1521).

As such we can clearly notice that although SEI and Cognitive Ability are significantly correlated with eachother, SEI has a much larger correlation (in magnitude and in significance) with the majority of the personality traits, which intuitively makes sense, since SEI is a subjective measurement that could vary based on personality.

2.7 Bringing it all together

There have been a number of studies examining the relation of cognitive ability and choice under risk especially regarding risk aversion. Lilleholt (2019) identified 150 of them and concluded that “there exists a weak, but significant negative relationship between cognitive ability and risk aversion in the domain of gains. However, no relationship was observed in the mixed domain or in the domain of losses.” (p.234).

Unfortunately for probability weighting there are very few studies that examine its relation with cognitive ability, especially for likelihood sensitivity and optimism. Going back to the earliest studies, the comparisons are mostly made using education as a proxy for numeracy, since education and numeracy are positively correlated, with higher education leading to higher numeracy (see Peters, Baker, Dieckmann, Leon & Collins, 2010). This literature shows that lower numeracy is related with more incoherence in judging probabilities (see Winman et al., 2014; Lindskog et al. 2015) and more nonlinear probability weighting functions (Millroth & Juslin 2015; Patalano et al. 2015). But those studies used evaluation of prospects and not choice, which is a distinction that can make a difference (Lichtenstein & Slovic 2006).

Some studies like by Bruine de Bruin et al. (2000), Petrova et al.(2014) and Traczyk & Fuławka (2016) came to similar results but used actual numeracy tests like the “Berlin Numeracy Test” by Cokely et al. (2012), with the latter two studies also confirming the effect of emotions on probability weighting. Petrova et al. (2014) showed how both hope and fear cause overweighting for small probabilities and Traczyk & Fuławka (2016) how incidental negative affect increases the curvature of the probability weighting function.

But even after we accept education (and numeracy) as a stand in for cognitive ability, that ought to be a subcategory of Crystallized Intelligence (Gc). Maybe we could refer to studies that compare age to Probability Weighting, and make the assumption that age can be used as a proxy for Fluid Intelligence (Gf), but beyond that we found only a handful of studies that deliberately examined probability weighting and gave their participants cognitive ability tests that capture Gf.

The first by Renato Frey, Rui Mata and Ralph Hertwig (2015), they “used the digit–symbol substitution task (DSST;Wechsler, 1981) as a measure of fluid cognitive abilities. In addition, they used a vocabulary test (spot-a-word; Lehrl, 1977) as a measure of crystallized abilities, which tend to increase across life span (e.g., see Park et al., 2002). Finally, they also assessed participants’ numerical abilities using a general numeracy scale (Lipkus, Samsa, & Rimer, 2001).”(p.63). But in the end, they only reported how probability weighting related with the age of the participants (younger people underweighted small probabilities, while older people had a more linear approach), and how cognitive ability had a minor effect on the effort they had to make between choices.

More interestingly in the paper by Mukherjee (2011), he used the Rational-Experiential Inventory (REI) questionnaire (Epstein et al. 1996) to measure the rational (system 2) and experiential (system 1) parts of his participants’ thinking process, along with a probability weighting questionnaire. In addition to that he had two treatment groups that had those questionnaires but one was also given an ‘affective priming’ questionnaire and the other a ‘cognitive load’ manipulation. The former included emotionally charged questions and the latter a memory task.

His results showed a significant positive correlation of higher ‘system 1’ thinking and overweighting of small probabilities, but no significant effect of ‘system 1’ on large probabilities. On the other hand, ‘System 2’ thinking had no systematic effect on probability weighting whatsoever. The use of affective priming and cognitive load was in order to “enhance System 1 access” to the thought process, which could be interpreted as a shift from Crystallized (Gc) to Fluid Intelligence (Gf). In this case, similarly as before, greater overweighting of small probabilities was recorded, but no change on the underweighting of larger ones. Affective ‘system 1’ thinking appears to increase the curvature and the elevation of the probability weighting function, and that increase in elevation cancels out the overall effect for larger probabilities.

In the end, cognitive ability has been only lightly studied in conjunction with probability weighting and theory suggests as we showed that it could be related with any bias whatsoever due to bounded rationality. Similarly, because Self-estimated Intelligence has been shown to be correlated with Intelligence, it is worth examining how the two will fare next to each other as predictors of the probability weighting parameters.

As we saw in the study by Chamorro-Premuzic et al. (2005), SEI’s correlation with the majority of the Big Five personality traits is much bigger in magnitude and in significance, compared to cognitive ability. So assuming that likelihood insensitivity, pessimism and individual perception towards probabilities can also stem from personality, rather than cognitive ability, we can expect to also find more significant correlations in our study as well.

In essence, because SEI is much easier to assess, it is loaded with its own biases, and it is a better indicator of personality, we expect it to be not only a more practical measurement, but quite possibly a more accurate estimator for the probability weighting parameters that are the focus of our study. And more than just SEI, we will examine how the level of overestimation of cognitive ability (SEI -IQ) relates to the same parameters, since that measurement is a better reflection and a more accurate indication of irrationality.

3. Research

As we mentioned, the purpose of this thesis is to examine the relationship between cognitive ability and self-estimated intelligence SEI and the parameters of likelihood insensitivity (a) and pessimism (b).For that reason, we constructed an online questionnaire to collect data on preferences under risk, individual self-estimated intelligence (SEI), actual levels of intelligence (IQ), and generic demographical information (gender, age, education, country of origin) among various individuals.

Specifically, the survey was structured in four distinctive parts presented in the same order for every participant. Every following part was made accessible after the completion of the previous part, and that was done in order to control the available information and limit any biases that could arise if the questionnaire was presented whole (to see the complete questionnaire go to Chapter 7).

3.1 Introduction – Personal Information

First the participants were presented with an introductory page, informing them about the nature and the goal of the study, asking them to click next in the end if they agreed to partake.

After they accepted, they were asked some general information about themselves: their gender (male – female), their age, their level of education (Primary, Secondary, Bachelor's, Master's, PhD) and their country of origin.

This information is relevant since as we mentioned before, demographical differences have been shown to be linked to cognitive performance and risk attitudes, so this data will provide satisfactory control to our research.

After this information was filled out, the participants moved on to the next part of the survey by again clicking "next".

3.2 Preferences

In this part, the goal was to assess the individual's probability weighting, using an array of choice lists based on the work by Tversky and Fox (1995) and Brandstätter et al. (2002) asking for the certainty equivalents for different prospects to gain €100 in the form of lottery tickets of varying probabilities. Starting from €100 at 2% probability, to 5%, 10%, 50%, 90%, 95% and finally 98%. We used seven prospects in order to more thoroughly examine the preferences at the fringes of very low and very high probabilities and as such get a more accurate measurement of each person's probability weighting function.

Every choice list provided thirteen (13) options for each participant starting from €0 guaranteed to €100 guaranteed, using increments in-between that varied between prospects and providing smaller differences in the amounts that were close to the expected value of each prospect. That was done again to pinpoint more accurately each certainty equivalent. The choice then was made by clicking the preferred option between the prospect and each amount of guaranteed money (see Table 3.1). The final CE value was then calculated as the average between the two guaranteed amounts of the choices where the participant made the switch from preferring the prospect to preferring the money.

Now imagine you were given the choice between a free lottery ticket with 2% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 2%
€0.5 guaranteed	○ ○	€100 with probability 2%
€1 guaranteed	○ ○	€100 with probability 2%
€1.5 guaranteed	○ ○	€100 with probability 2%
€2 guaranteed	○ ○	€100 with probability 2%
€3 guaranteed	○ ○	€100 with probability 2%
€5 guaranteed	○ ○	€100 with probability 2%
€10 guaranteed	○ ○	€100 with probability 2%
€20 guaranteed	○ ○	€100 with probability 2%
€40 guaranteed	○ ○	€100 with probability 2%
€60 guaranteed	○ ○	€100 with probability 2%
€80 guaranteed	○ ○	€100 with probability 2%
€100 guaranteed	○ ○	€100 with probability 2%

<u>Table 3.1.</u> The first choice list in the survey.

This procedure then produced 13 combinations of preferences described by probabilities and money for each participant. These combinations then were used to derive that participant's a and b parameters' values. In order to do that we assumed a simple power utility function u(x) [which Wakker (2008) has shown is a good fit for experimental and observational data] along with the probability weighting function w(p) we mentioned earlier.

$$u(x) = x^c \ , \ c>0 \qquad (1)$$

$$w(p) = \frac{bp^a}{bp^a + (1-p)^a} \ , \ a>0 \ b>0 \qquad (2)$$

For each (CE,p) combination then, there is u(CE) = w(p)u(100) =>

$$CE = 100\left(\frac{bp^a}{bp^a + (1-p)^a} \right)^{1/c} \qquad (3)$$

Using iterative methods in R for all those (CE,p) combinations the function (3) was solved for each combination. For each person, the average values of a, b and c out of these iterations were then used as their individual parameters in the dataset, in order to compare and contrast against each participant and the group as whole.

3.3 Self Estimated Intelligence - SEI

The part following the choice lists was to inquire the participants on their estimation about their own intelligence. Here, they were presented with a typical graph of a standard normal distribution N(0,1) partitioned by σ and the percentages associated with that, followed by a short explanation of how people's intelligence in a population fits such a distribution.

Next, the participants were asked where do they believe they place in a distribution like that. And to answer, a slider was put that started at 0 and went from -4 to +4 (the same range as was shown in the graph) with 2 decimals accuracy.

3.4 Baddeley's Reasoning Test - IQ

After self-estimating their intelligence levels, the last part was for the participants to actually test themselves using a grammatical reasoning test developed by Baddeley et al (1968).

It is important to note that although this test is not technically an IQ test, it has been shown through extensive research that it gives results that highly correlate with other more thorough and legitimate intelligence tests, especially those designed to measure fluid intelligence (Gf) (see Baudson & Preckel 2016; Furnham & Chamorro-Premuzic 2006/2008; Furnham & McClelland 2010). And since it only takes three minutes to complete, it is as an efficient way to gauge cognitive ability for the purposes of this research.

So, this part of the questionnaire started with instructions regarding the test and how it works taken verbatim from the original paper. The test presents sentences that make a statement followed by a pair of letters (AB or BA). Those statements either describe accurately that following pair or not, and the purpose of the participant is to answer for every sentence by clicking on either True or False.

Specifically the subjects had 3 minutes to answer as many questions they could from a total of 64 that were all the possible combinations of the following six binary conditions: (1) Positive or Negative, (2) Active or Passive, (3) True or False, (4) Precedes or Follows, (5) A or B mentioned first, (6) Letter pair AB or BA.

For example:

1. A follows B-BA (Answer: True)
2. B precedes A-AB (Answer: False)
3. A is followed by B-AB (Answer: True)
4. B is not followed by A-BA (Answer: False)
5. B is preceded by A-BA (Answer: False)
6. A does not precede B-BA (Answer: True)

Etc.

After reading the instructions the participants clicked next to start the test and were instantly presented with a 3-minute countdown clock and all the questions in a row. The order of the questions was randomized for each person, and their final score was the total number of correct answers they managed to get before the time ran out.

With a minimum score of 0 and a maximum of 64, that score number falls exactly within the SEI range of (-4,+4) used in the previous question by subtracting 32 from the score and dividing by 8 [IQ= (test score-32)/8]. This way we can compare between the two numbers for SEI and IQ.

After the three minutes were up, the test was over and the subjects were transferred to a new page thanking them for their participation and giving them the option to download a document with the whole survey and their answers.

4. Results

4.1 Participants

demographics

In order to get enough participants, the survey was uploaded online in various boards and fora, while friends and family were also asked to contribute. While many people volunteered, there are also some people that chose to participate because they were also looking for participants in their own research projects so they expected a quid pro quo exchange. Regardless of that, no financial incentives were offered at any point to any participant.

In total n=117 individuals took part in this survey. Out of them 64 (54.70%) were female and 53 (45.30%) were male (Table 4.1), with an average age of 35 years (minimum was 19 years, and the maximum was 71) (Table 4.2).

gender	Freq.	Percent	Cum.
female	64	54.70	54.70
male	53	45.30	100.00
Total	117	100.00	

Table 4.1 The frequencies for the two genders.

Variable	Obs	Mean	Std. Dev.	Min	Max
age	117	35.18803	13.53217	19	71

Table 4.2 Summary for the age of the participants.

edu	Freq.	Percent	Cum.
Bachelor	62	52.99	52.99
Master	25	21.37	74.36
Primary	2	1.71	76.07
Secondary	28	23.93	100.00
Total	117	100.00	

Table 4.3 The frequencies of the different education levels (it is 0 for PhD).

Most of them (52.99%) held a Bachelor's degree, while none had a PhD. (Table 4.3)

And although 20 different countries of origin were reported, the vast majority of people (71.80%) were from the USA or an english speaking country in general (USA, UK, Australia and Cyprus combined were 82.91% of the total) (Table 4.4) which is relevant since the entire survey was done in English.

country	Freq.	Percent	Cum.
AR	1	0.85	0.85
AU	2	1.71	2.56
BE	1	0.85	3.42
CA	1	0.85	4.27
CH	1	0.85	5.13
CL	1	0.85	5.98
CU	1	0.85	6.84
CY	1	0.85	7.69
DE	1	0.85	8.55
GR	3	2.56	11.11
IN	2	1.71	12.82
IQ	1	0.85	13.68
IS	1	0.85	14.53
IT	1	0.85	15.38
JP	1	0.85	16.24
MU	1	0.85	17.09
PK	1	0.85	17.95
PL	2	1.71	19.66
UK	10	8.55	28.21
US	84	71.79	100.00
Total	117	100.00	

<u>Table 4.4</u> The frequencies of all the different countries of origin.

cognitive ability

Regarding cognitive ability, as mentioned before, a population would be expected to have a score that follows a standard normal distribution. The sample in this survey instead had an average score of -0.52 points ranging from -3.625 to 3.375. Similarly, the SEI reported in the sample was 1.24 on average, ranging from -1.74 to 4. By converting the IQ and SEI values to the

(0,64) scale ($\bar{x}^* = 8\bar{x} + 32$) we can easily calculate the rate at which people overestimated their abilities Accu = $\frac{SEI-IQ}{IQ}$. On average, people overestimated them by 91.63% (Table 4.5,4.6, 4.7).

Variable	Obs	Mean	Std. Dev.	Min	Max
IQ	117	-.5202991	1.456995	-3.625	3.375
SEI	117	1.244444	1.114732	-1.74	4
Accu	117	$\boxed{.9162876}$	1.300753	-.4745098	7

Table 4.5 Summary for the values of IQ and SEI.

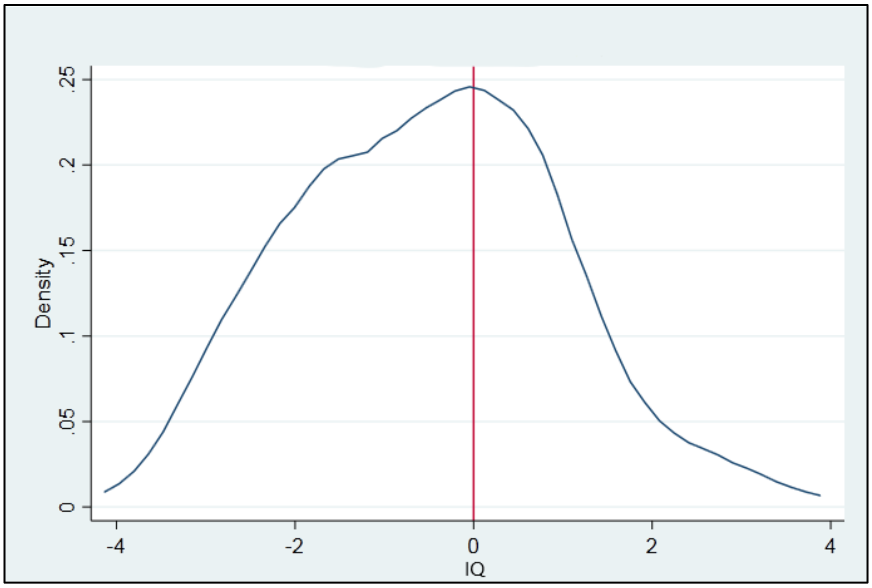


Table 4.6 Distribution fit for IQ results.

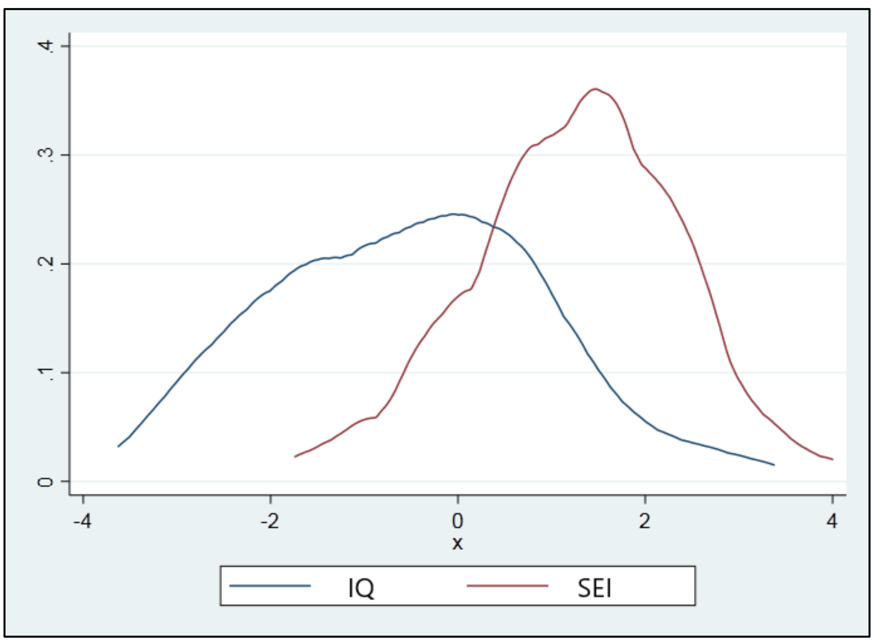


Table 4.7 Distribution fit of IQ compared to SEI.

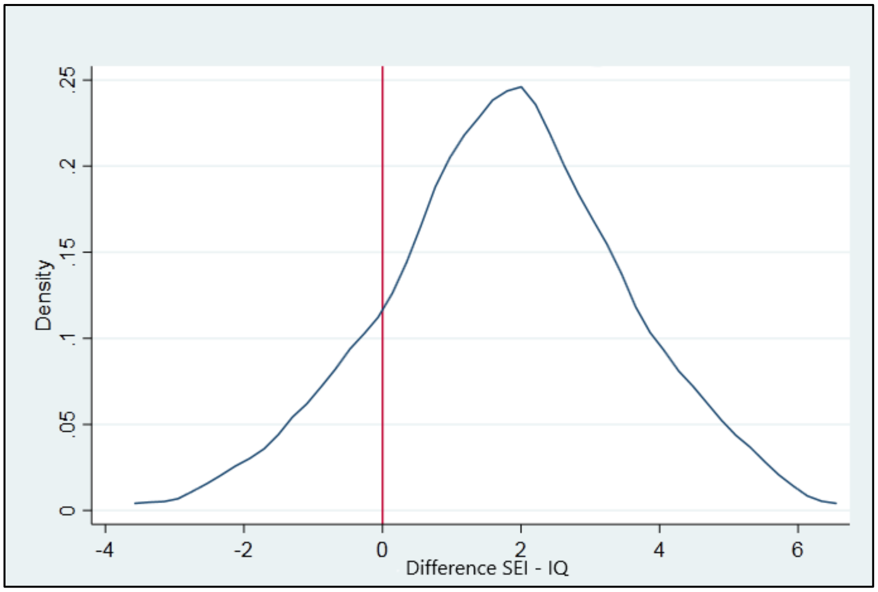


Table 4.8 Distribution fit for the difference between SEI and IQ. A perfect estimation would have given a difference of 0 between SEI and the IQ test score. No participant managed a perfect 0.

Despite the prevalent overestimation by the sample, there were some individuals (14.53%) who underestimated their abilities (Difference <0). Interestingly almost all of them were of above average intelligence (IQ>0). That shows how people with lower ability (IQ<0) overwhelmingly overestimated it while people with higher ability (IQ>0) were more varied in their estimations (see Table 4.9). This is a finding that hints at the appearance of the Downing effect which states that people of lower intelligence tend to overestimate it compared to people of higher intelligence who tend to underestimate it.

At this point it would have been interesting to also have asked the participants how well they thought they performed in the Baddeley's Reasoning Test and based on the answers derive whether the Dunning-Kruger effect was also manifested, since it similarly reflects illusory superiority related to performance on cognitive tasks. This is a topic for future research.

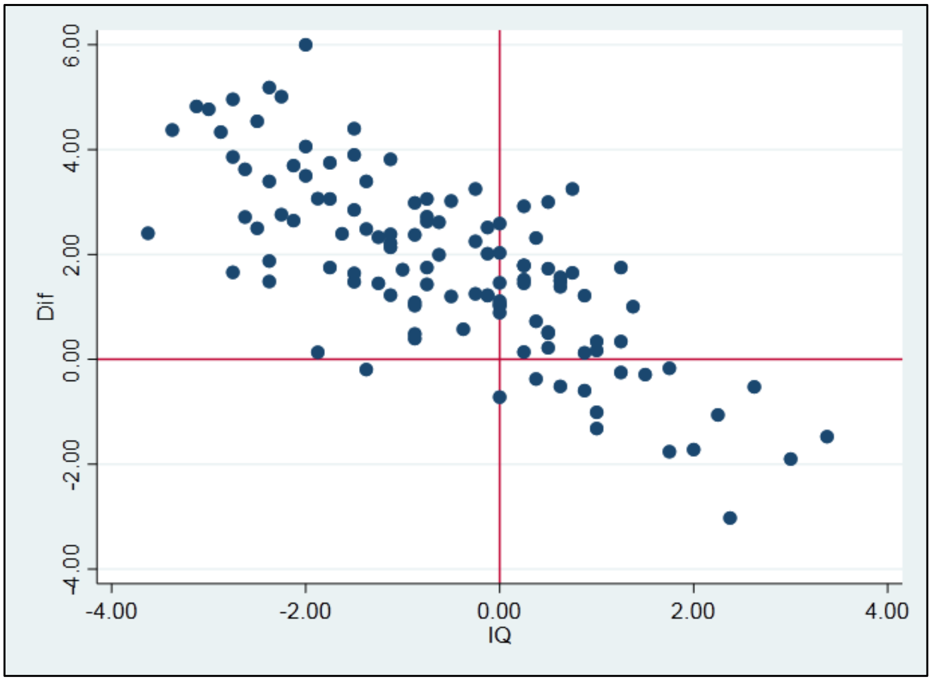


Table 4.9 Scatterplot of Dif = SEI – IQ.

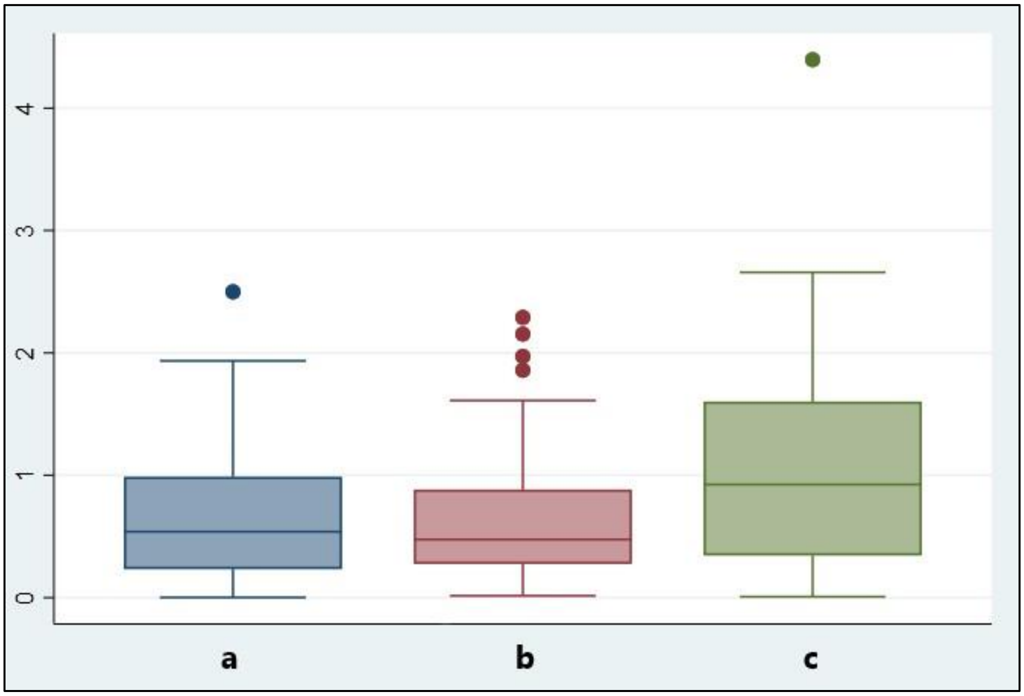
probability weighting

And last are the probability weighting parameters that were derived from the choice lists that the participants provided. Unfortunately, not all of them were fully completed and as such the observations derived now are less than the total sample size.

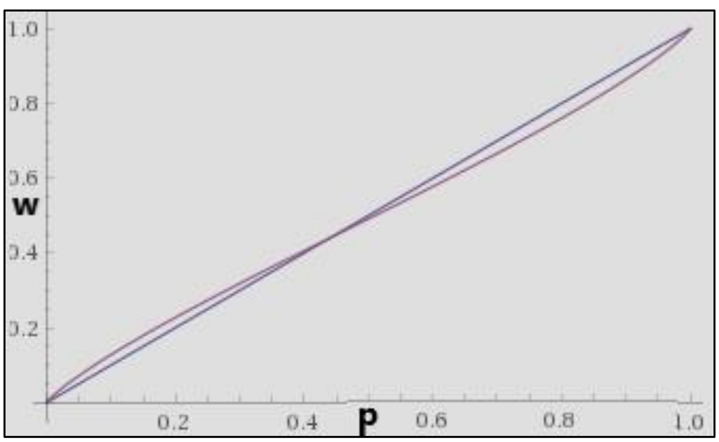
For likelihood insensitivity (a) there were 93 observations with an average value of 0.858, while for pessimism (b) there were 94 observations with an average value of 0.966 (table 4.10, Figure 4.1). Since a<1 but not by a lot, that means that the average person in the sample is described by a slight inverse-S curvature in their weight probability function (Figure 4.2). Since both values (especially b) are so close to 1, that shows a sample where the average person is close to perfectly rational in their choices.

Variable	Obs	Mean	Std. Dev.	Min	Max
a	93	.8583852	.9505221	.0004421	5.621597
b	94	.965813	.9440036	.0035059	5.019426
c	92	1.236692	1.154622	.0069286	6.629444

Table 4.10 Summary of parameters a, b and c.



<u>Fig 4.1</u> Mean estimates of a, b and c.



<u>Fig 4.2</u> The red line represents the probability weighting function w(p) of the average participant, while the blue line represents linear probability (w=p, a=1,b=1).

4.2 Analysis

In order to analyze the data and test for the effects of the various variables we used a series of robust OLS regressions. We opted for robust regressions in order to weigh the observations based on their behavior, and as such account for outliers without excluding them from our analysis, but also not treating them equally. That is a compromise because we have no compelling reason to suggest they were data entry errors.

Furthermore, to make use of the personal/demographical data we turned them into numerical variables. Specifically, gender (0: female, 1: male), education (1: primary, 2: secondary, 3: Bachelor, 4: Master) and country (0: non-english 1: english as official language).

We first run the cognitive ability (IQ) scores against all the demographical variables using a linear regression (table 4.11). The model's ability to predict cognitive ability was low (R^2 = 6%) and not significant (p=0.09). From all the independent variables only education (edu) had a significant effect (p=0.047) and a positive coefficient, indicating a positive effect of extra education on the performance people have on a cognitive ability test, like the one we used. Of course, such a relationship can also be explained in reverse, and people with higher cognitive ability tend to pursue or achieve higher levels of education.

Linear regression

Number of obs	=	117
F(4, 112)	=	2.04
Prob > F	=	0.0941
R-squared	=	0.0600
Root MSE	=	1.4376

IQ	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
gender	-.4738265	.2688889	-1.76	0.081	-1.006595	.0589424
age	-.0007733	.0095379	-0.08	0.936	-.0196714	.0181249
edu	.3598062	.1791068	2.01	0.047	.0049291	.7146834
country	.0728906	.3400649	0.21	0.831	-.6009044	.7466857
_cons	-1.396773	.7723655	-1.81	0.073	-2.927116	.1335707

<u>Table 4.11</u> First OLS regression output. Dependent variable is the cognitive ability (IQ) score, and the independent variables are gender, age, education and country. Only education had a significant effect.

Then we tested the values at which people estimated their intelligence to be (SEI) against IQ, gender, age, education and country (table 4.12). In this case, the model's predictability was low (R^2 =11.17%) but significant (p=0.015). In this case the IQ scores had a significant effect (p=0.043) and a positive coefficient, which is expected for people with higher cognitive ability to also tend to evaluate themselves higher. The interesting finding is that the effect of gender was also significant (p=0.002) and with a positive coefficient, which indicates that men gave higher cognitive ability estimations (SEI) compared to women. Something which is not justified, since as we found earlier, differences in gender did not produce differences in IQ scores.

Linear regression

Number of obs	=	117
F(5, 111)	=	2.96
Prob > F	=	0.0151
R-squared	=	0.1117
Root MSE	=	1.074

SEI	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IQ	.1428885	.0697146	2.05	$\boxed{0.043}$	.0047443	.2810327
gender	.6519933	.2017488	3.23	$\boxed{0.002}$	.2522147	1.051772
age	.0051756	.0078378	0.66	0.510	-.0103556	.0207068
edu	.1256917	.1231808	1.02	0.310	-.1183993	.3697827
country	.0351726	.2482032	0.14	0.888	-.4566586	.5270038
_cons	.442607	.5861628	0.76	0.452	-.7189137	1.604128

<u>Table 4.12</u> *Second OLS regression output. Dependent variable is the self-estimated intelligence score (SEI), and the independent variables are IQ, gender, age, education and country. IQ and gender had a significant effect.*

The third regression was to test the difference (Dif) between SEI and IQ against the other variables (table 4.13). In this case the model was significant (p=0.00), with high predictability (R^2=61.62%). The IQ score had a significant effect (p=0.00) with a negative coefficient, which means that people with higher cognitive ability tend to be more accurate and even underestimate their ability (and people with lower ability tend to overestimate it). And the effect of gender was also significant (p=0.002) with a positive coefficient, which means that men tend to overestimate their ability more than what women do.

```
Linear regression                               Number of obs     =        117
                                                F(5, 111)         =      34.09
                                                Prob > F          =     0.0000
                                                R-squared         =     0.6162
                                                Root MSE          =      1.074
```

Dif	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IQ	-.8571115	.0697146	-12.29	0.000	-.9952557	-.7189673
gender	.6519933	.2017488	3.23	0.002	.2522147	1.051772
age	.0051756	.0078378	0.66	0.510	-.0103556	.0207068
edu	.1256917	.1231808	1.02	0.310	-.1183993	.3697827
country	.0351726	.2482032	0.14	0.888	-.4566586	.5270038
_cons	.442607	.5861628	0.76	0.452	-.7189137	1.604128

<u>Table 4.13</u> Third OLS regression output. Dependent variable is the difference SEI - IQ, and the independent variables are IQ, gender, age, education and country. IQ and gender had a significant effect.

The next regression we run was in order to test how the same variables relate to people's accuracy to estimate their own cognitive ability (table 4.14). For this test we used the absolute difference between the self-estimation and the actual score for people's cognitive ability:

$AD = |SEI - IQ| \geq 0$

The lower its value the more accurate was people's estimation. AD = 0 would mean the individual was perfectly accurate.

This model was significant (p=0.00) with relatively high predictability (R^2=40.71%). The IQ score had a significant effect (p=0.00) with a negative coefficient, which means that people with higher cognitive ability gave better estimations for it. And the effect of gender was also significant (p=0.023) with a positive coefficient, which means that the men were less accurate than the women in their estimations.

```
Linear regression                               Number of obs     =        117
                                                F(5, 111)         =      11.38
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4071
                                                Root MSE          =     1.0452
```

AD	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IQ	-.5302737	.078883	-6.72	$\boxed{0.000}$	-.6865856	-.3739618
gender	.4551025	.1970651	2.31	$\boxed{0.023}$	.0646049	.8456002
age	.0084944	.0070306	1.21	0.230	-.0054373	.022426
edu	.0838431	.1128123	0.74	0.459	-.1397021	.3073882
country	.269742	.2567793	1.05	0.296	-.2390834	.7785674
_cons	.8026144	.5573167	1.44	0.153	-.3017459	1.906975

<u>Table 4.14</u> Fourth OLS regression output. Dependent variable is the estimation accuracy AD, and the independent variables are IQ, gender, age, education and country. IQ and gender had a significant effect.

Lastly, in the same way, we tested the probability weighting parameters a and b against all the previously mentioned variables IQ, SEI, AD, gender, age, edu and country (table 4.15). For both parameters, the models had low predictability and were not significant (p_a= 0.81, R_a^2 = 6.44% and p_b= 0.11, R_b^2 = 12.40%) and no variable had any significant effect. Despite that, we notice certain tendencies:

- The coefficients of all the variables have the same sign for both a and b, indicating the same positive or negative relationship, except for country which suggests that being from an English speaking country has a positive effect on likelihood insensitivity (a) and a negative on pessimism (b).
- IQ, SEI and age have a negative coefficient, implying a negative relationship with the examined variables and AD,gender,edu have a positive coefficient.
- IQ and SEI had coefficients (not significant) that were roughly equal in magnitude on their effect on (a) and (b).

Linear regression						
				Number of obs	=	93
				F(7, 85)	=	0.53
				Prob > F	=	0.8118
				R-squared	=	0.0644
				Root MSE	=	.95653

a	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IQ	-.1042276	.079055	-1.32	0.191	-.2614102	.052955
SEI	-.119778	.1249176	-0.96	0.340	-.3681477	.1285917
AD	.0307181	.1075525	0.29	0.776	-.183125	.2445613
gender	.1259116	.2590658	0.49	0.628	-.3891805	.6410038
age	-.0004706	.0085745	-0.05	0.956	-.0175189	.0165778
edu	.1470372	.1409508	1.04	0.300	-.1332108	.4272852
country	.1472868	.2730367	0.54	0.591	-.3955832	.6901568
_cons	.3093522	.63517	0.49	0.627	-.9535359	1.57224

Linear regression						
				Number of obs	=	94
				F(7, 86)	=	1.74
				Prob > F	=	0.1097
				R-squared	=	0.1240
				Root MSE	=	.9188

b	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
IQ	-.0801	.0869708	-0.92	0.360	-.2529922	.0927923
SEI	-.107381	.1239791	-0.87	0.389	-.3538432	.1390812
AD	.0848188	.1170768	0.72	0.471	-.1479221	.3175597
gender	.2792757	.2280891	1.22	0.224	-.1741504	.7327019
age	-.0053904	.0055133	-0.98	0.331	-.0163505	.0055698
edu	.1939605	.1599641	1.21	0.229	-.1240377	.5119586
country	-.2272511	.2905462	-0.78	0.436	-.8048378	.3503356
_cons	.5890168	.6348548	0.93	0.356	-.6730327	1.851066

<u>Table 4.15</u> Two OLS regressions output for each dependent variable a and b. The independent variables are IQ, SEI,AD, gender, age, education and country. Neither regression produced a significant effect.

5.Discussion

5.1 Limitations

It is worth mentioning some limitations of this study, which can point to interesting future research possibilities.

First, the overwhelming majority of people who answered our questionnaire, were from a single country (USA), and although the variation in age, gender and education was acceptable, it is possible that cultural effects influenced the results. Most people being Americans may lessen the distortion of the Baddeley test being in English and intended for English participants only, but the original test is also supposed to be taken using pen and paper, which in our case did not happen. Using a computer and relying on an internet connection has quite possibly resulted in underestimated IQ scores.

Then there is the limited measurement of intelligence. We elaborated in the literature review on all the different reflections of intelligence, and in the end, we used a proxy of an IQ test to measure a specific dimension of intelligence. Ideally, this study would have been done with a reputable IQ test that measures as many facets of General Intelligence as possible.

Furthermore, there is the concern of motivation, which as we mentioned can have a dampening effect on the results of an intelligence test. For logistical reasons we did not offer any monetary compensation to participants, but it would be interesting to see how the results would have been different if we had.

Also, the questionnaire we used was presented in four parts that were fixed in sequence. That has the inherent problem of each part influencing the answers on the part that followed. The most critical choice was to have the IQ test after the self-estimation of intelligence, and that was done in order to get a SEI value that is least biased as possible. Of course, by having SEI before, we expected to capture a general sense of intelligence overconfidence, but by having SEI after (or maybe a question asking people how they think they did in the test) the value would have been influenced by overconfidence over the specific task.

Lastly, we did mention briefly how probability weighting can be influenced by emotions, but in the end, we chose to not examine emotional intelligence.

5.2 Conclusion

This thesis sought to examine the relationship between probability weighting, cognitive ability, and self-perception of intelligence (SEI), of which not much is known in the literature. More specifically, we wanted to find possible connections with the parameters of likelihood insensitivity and pessimism that dictate the form of the probability weighting function.

Past literature shows that cognitive ability is correlated with self-estimated Intelligence (SEI) and we expect it to also be related with probability weighting (and most known biases for that matter) due to bounded rationality. Research on SEI until today has been limited to gender differences and personality traits and SEI has been shown to be correlated with both. In this spirit we tested how SEI would fare against a cognitive ability score in relation to probability weighting, essentially indulging the thought of likelihood insensitivity and pessimism being projections of personality rather than only cognitive ability limitations.

Using a sample of 117 people who answered our online questionnaire that asked their perceptions on their own intelligence and then tested them using a cognitive ability test, we found no significant correlation of the examined parameters with either cognitive ability (IQ), or self-estimated intelligence (SEI), or the difference between the two (SEI-IQ).

Despite the limitations and the results of this thesis, we believe that the findings still make an important empirical contribution on the study of risk attitudes, and the novelty of introducing SEI in it can open new paths for future research. What makes SEI a promising concept in economics and individual behavior in general is its clear relation with both cognitive ability and personality, and for that reason it can be a fruitful avenue to explore.

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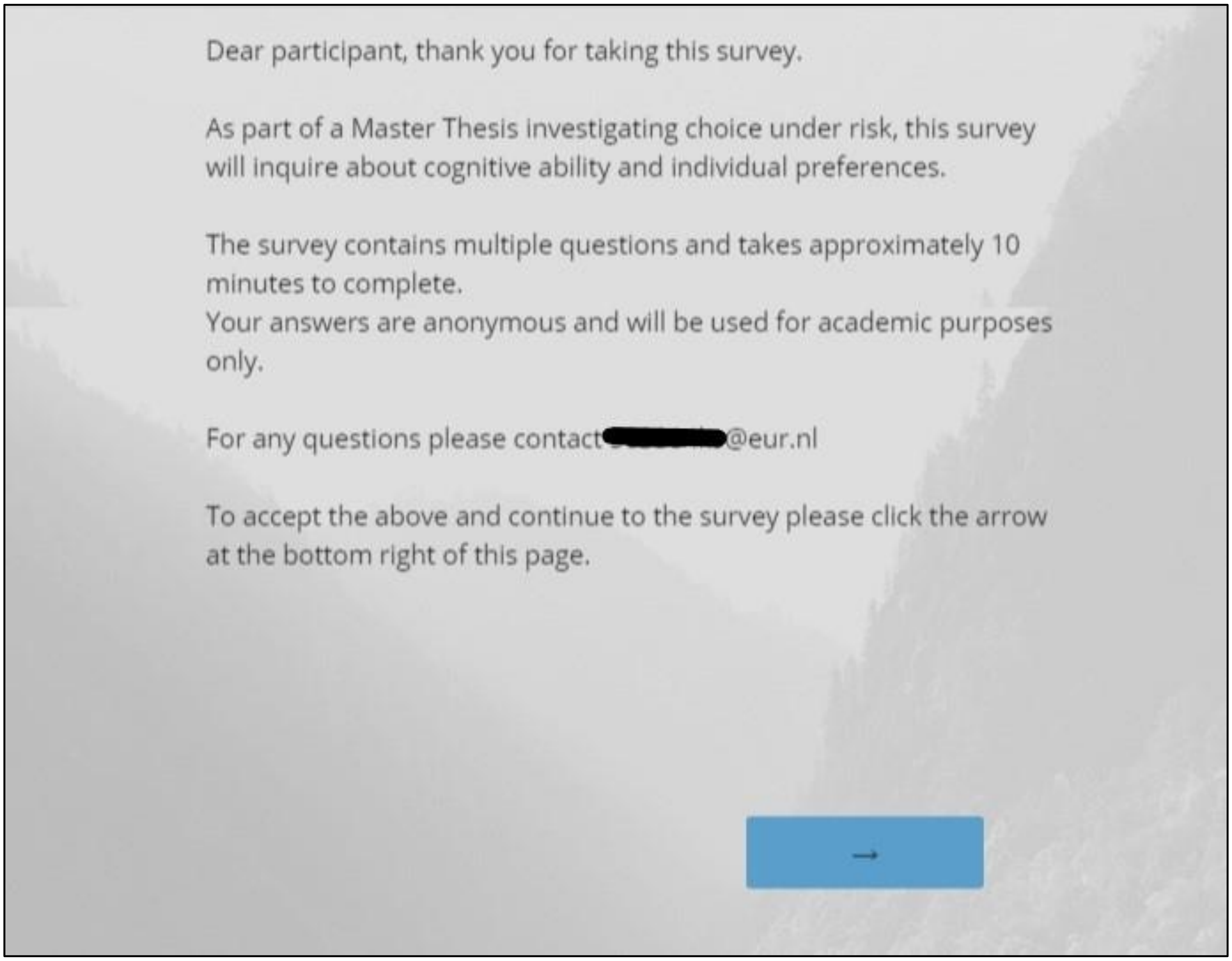
7. The Full Questionnaire:

7.1 Introduction – Page 1



Dear participant, thank you for taking this survey.

As part of a Master Thesis investigating choice under risk, this survey will inquire about cognitive ability and individual preferences.

The survey contains multiple questions and takes approximately 10 minutes to complete.
Your answers are anonymous and will be used for academic purposes only.

For any questions please contact [redacted]@eur.nl

To accept the above and continue to the survey please click the arrow at the bottom right of this page.

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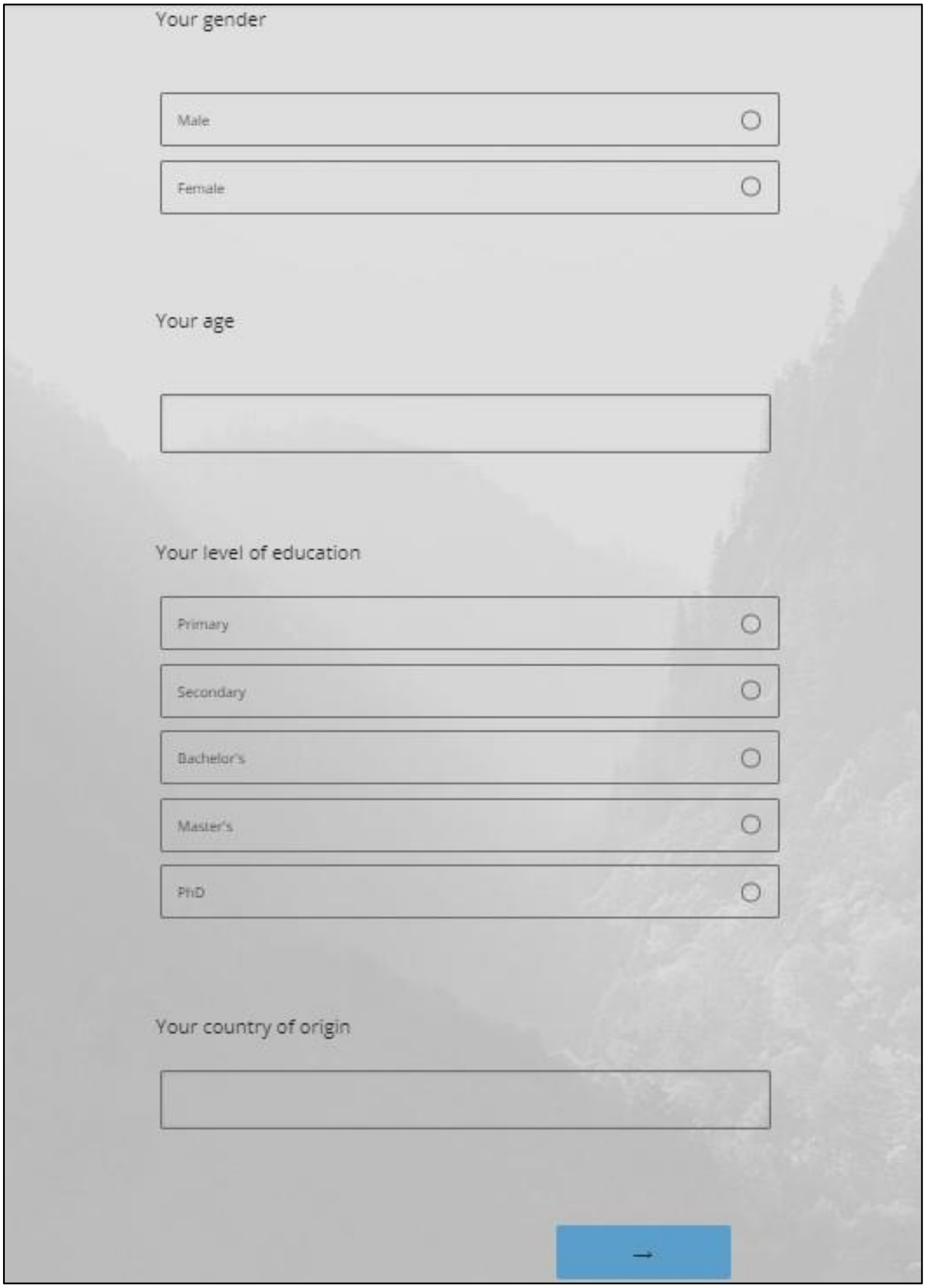
7.2 Personal Information – Page 2



Your gender

Male

Female

Your age

Your level of education

Primary

Secondary

Bachelor's

Master's

PhD

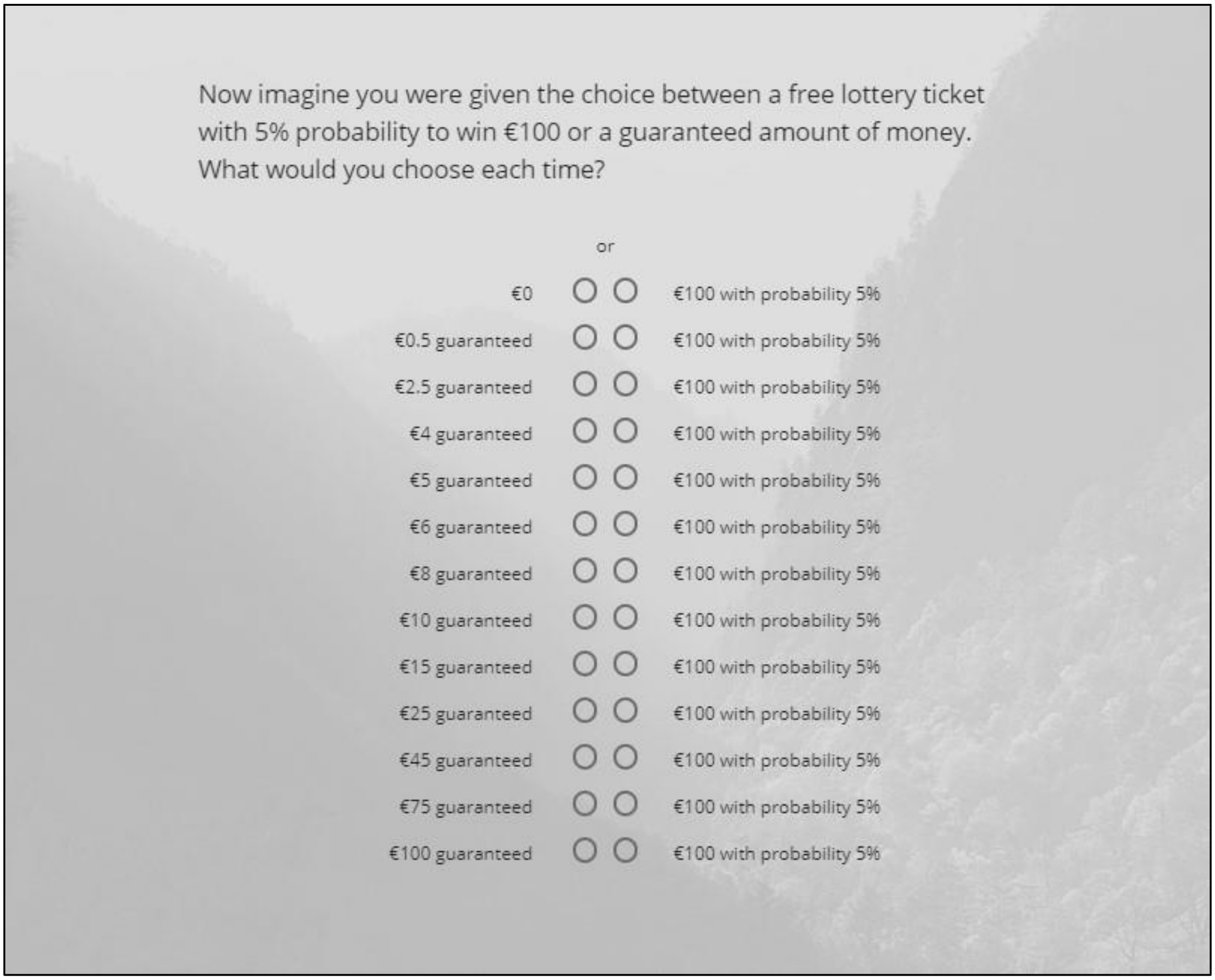
Your country of origin

→

7.3 Choice Lists – Page 3

Now imagine you were given the choice between a free lottery ticket with 2% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 2%
€0.5 guaranteed	○ ○	€100 with probability 2%
€1 guaranteed	○ ○	€100 with probability 2%
€1.5 guaranteed	○ ○	€100 with probability 2%
€2 guaranteed	○ ○	€100 with probability 2%
€3 guaranteed	○ ○	€100 with probability 2%
€5 guaranteed	○ ○	€100 with probability 2%
€10 guaranteed	○ ○	€100 with probability 2%
€20 guaranteed	○ ○	€100 with probability 2%
€40 guaranteed	○ ○	€100 with probability 2%
€60 guaranteed	○ ○	€100 with probability 2%
€80 guaranteed	○ ○	€100 with probability 2%
€100 guaranteed	○ ○	€100 with probability 2%

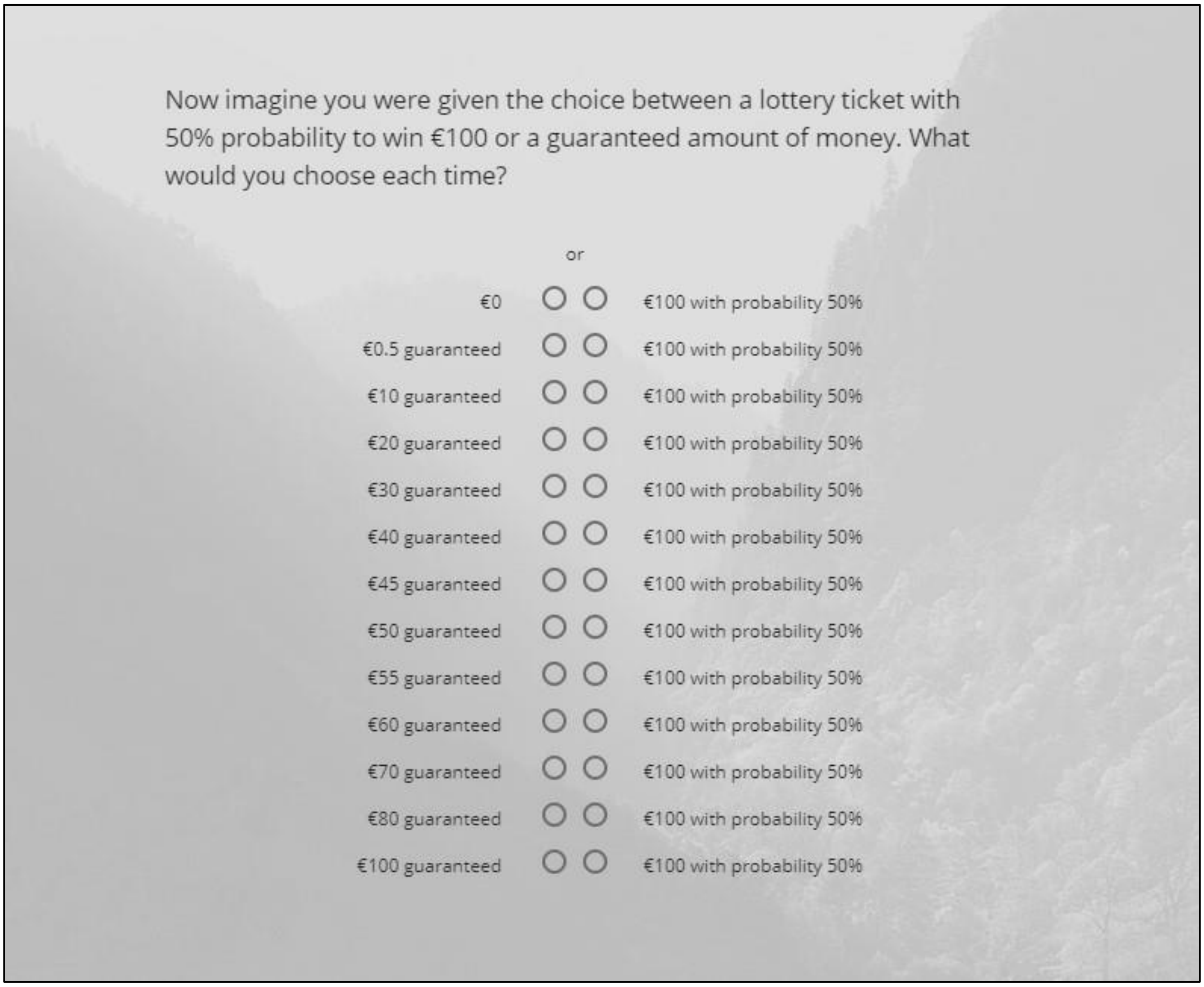


Now imagine you were given the choice between a free lottery ticket with 5% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 5%
€0.5 guaranteed	○ ○	€100 with probability 5%
€2.5 guaranteed	○ ○	€100 with probability 5%
€4 guaranteed	○ ○	€100 with probability 5%
€5 guaranteed	○ ○	€100 with probability 5%
€6 guaranteed	○ ○	€100 with probability 5%
€8 guaranteed	○ ○	€100 with probability 5%
€10 guaranteed	○ ○	€100 with probability 5%
€15 guaranteed	○ ○	€100 with probability 5%
€25 guaranteed	○ ○	€100 with probability 5%
€45 guaranteed	○ ○	€100 with probability 5%
€75 guaranteed	○ ○	€100 with probability 5%
€100 guaranteed	○ ○	€100 with probability 5%

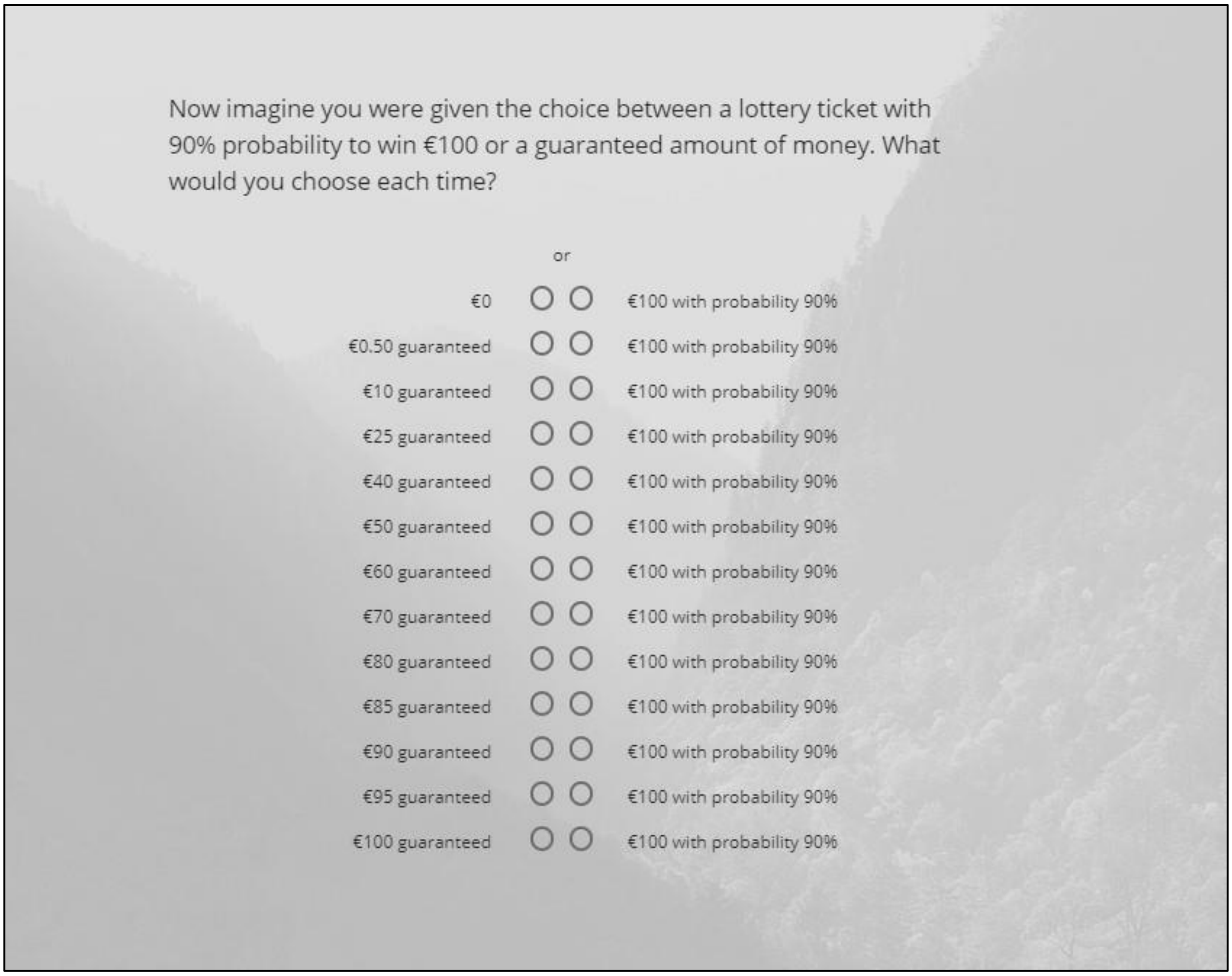
Now imagine you were given the choice between a lottery ticket with 10% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 10%
€0.5 guaranteed	○ ○	€100 with probability 10%
€4 guaranteed	○ ○	€100 with probability 10%
€7.5 guaranteed	○ ○	€100 with probability 10%
€9 guaranteed	○ ○	€100 with probability 10%
€10 guaranteed	○ ○	€100 with probability 10%
€12 guaranteed	○ ○	€100 with probability 10%
€15 guaranteed	○ ○	€100 with probability 10%
€25 guaranteed	○ ○	€100 with probability 10%
€40 guaranteed	○ ○	€100 with probability 10%
€60 guaranteed	○ ○	€100 with probability 10%
€80 guaranteed	○ ○	€100 with probability 10%
€100 guaranteed	○ ○	€100 with probability 10%



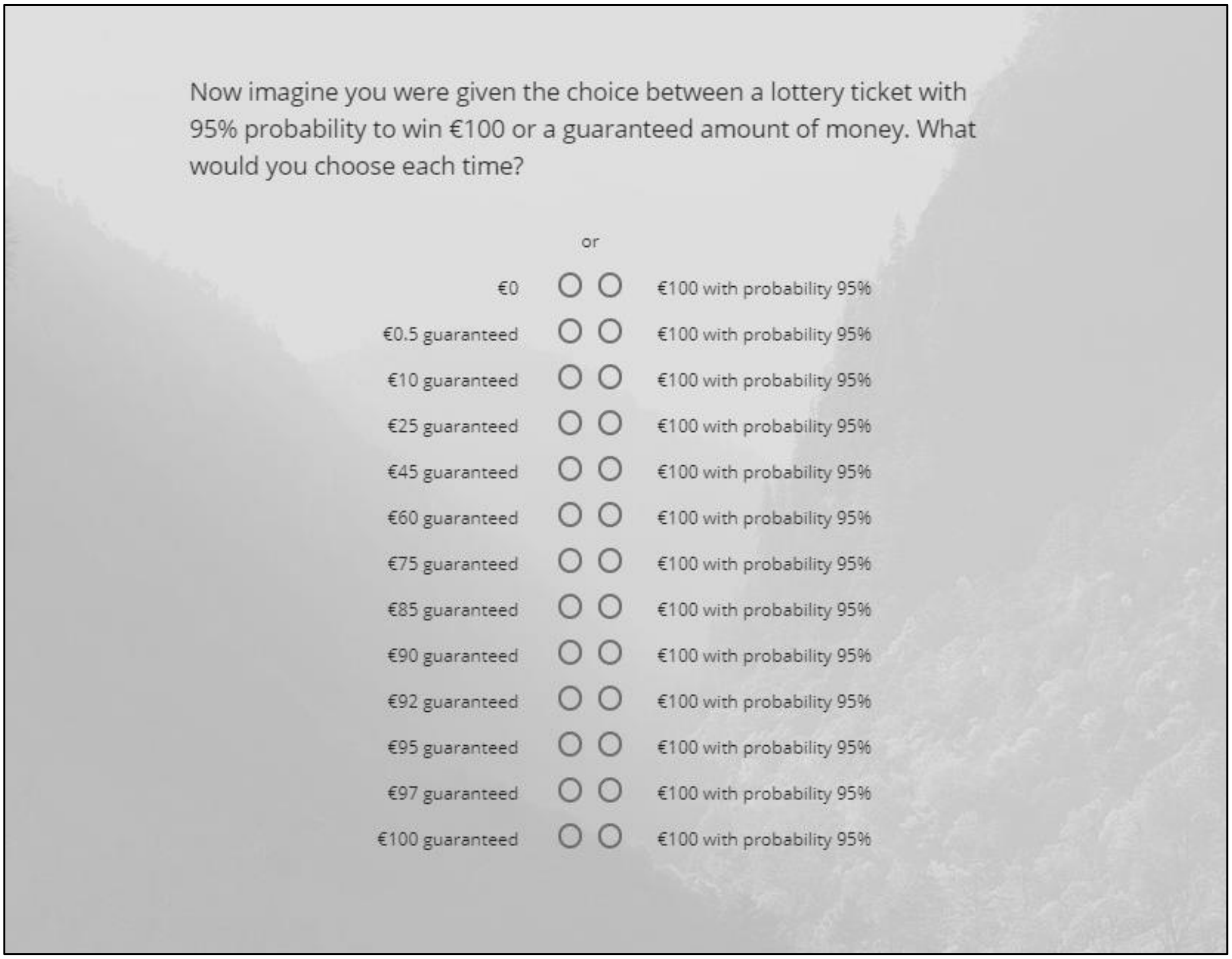
Now imagine you were given the choice between a lottery ticket with 50% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 50%
€0.5 guaranteed	○ ○	€100 with probability 50%
€10 guaranteed	○ ○	€100 with probability 50%
€20 guaranteed	○ ○	€100 with probability 50%
€30 guaranteed	○ ○	€100 with probability 50%
€40 guaranteed	○ ○	€100 with probability 50%
€45 guaranteed	○ ○	€100 with probability 50%
€50 guaranteed	○ ○	€100 with probability 50%
€55 guaranteed	○ ○	€100 with probability 50%
€60 guaranteed	○ ○	€100 with probability 50%
€70 guaranteed	○ ○	€100 with probability 50%
€80 guaranteed	○ ○	€100 with probability 50%
€100 guaranteed	○ ○	€100 with probability 50%



Now imagine you were given the choice between a lottery ticket with 90% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 90%
€0.50 guaranteed	○ ○	€100 with probability 90%
€10 guaranteed	○ ○	€100 with probability 90%
€25 guaranteed	○ ○	€100 with probability 90%
€40 guaranteed	○ ○	€100 with probability 90%
€50 guaranteed	○ ○	€100 with probability 90%
€60 guaranteed	○ ○	€100 with probability 90%
€70 guaranteed	○ ○	€100 with probability 90%
€80 guaranteed	○ ○	€100 with probability 90%
€85 guaranteed	○ ○	€100 with probability 90%
€90 guaranteed	○ ○	€100 with probability 90%
€95 guaranteed	○ ○	€100 with probability 90%
€100 guaranteed	○ ○	€100 with probability 90%



Now imagine you were given the choice between a lottery ticket with 95% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 95%
€0.5 guaranteed	○ ○	€100 with probability 95%
€10 guaranteed	○ ○	€100 with probability 95%
€25 guaranteed	○ ○	€100 with probability 95%
€45 guaranteed	○ ○	€100 with probability 95%
€60 guaranteed	○ ○	€100 with probability 95%
€75 guaranteed	○ ○	€100 with probability 95%
€85 guaranteed	○ ○	€100 with probability 95%
€90 guaranteed	○ ○	€100 with probability 95%
€92 guaranteed	○ ○	€100 with probability 95%
€95 guaranteed	○ ○	€100 with probability 95%
€97 guaranteed	○ ○	€100 with probability 95%
€100 guaranteed	○ ○	€100 with probability 95%

Now imagine you were given the choice between a lottery ticket with 98% probability to win €100 or a guaranteed amount of money. What would you choose each time?

	or	
€0	○ ○	€100 with probability 98%
€0.5 guaranteed	○ ○	€100 with probability 98%
€20 guaranteed	○ ○	€100 with probability 98%
€40 guaranteed	○ ○	€100 with probability 98%
€60 guaranteed	○ ○	€100 with probability 98%
€70 guaranteed	○ ○	€100 with probability 98%
€80 guaranteed	○ ○	€100 with probability 98%
€90 guaranteed	○ ○	€100 with probability 98%
€95 guaranteed	○ ○	€100 with probability 98%
€97 guaranteed	○ ○	€100 with probability 98%
€98 guaranteed	○ ○	€100 with probability 98%
€99 guaranteed	○ ○	€100 with probability 98%
€100 guaranteed	○ ○	€100 with probability 98%

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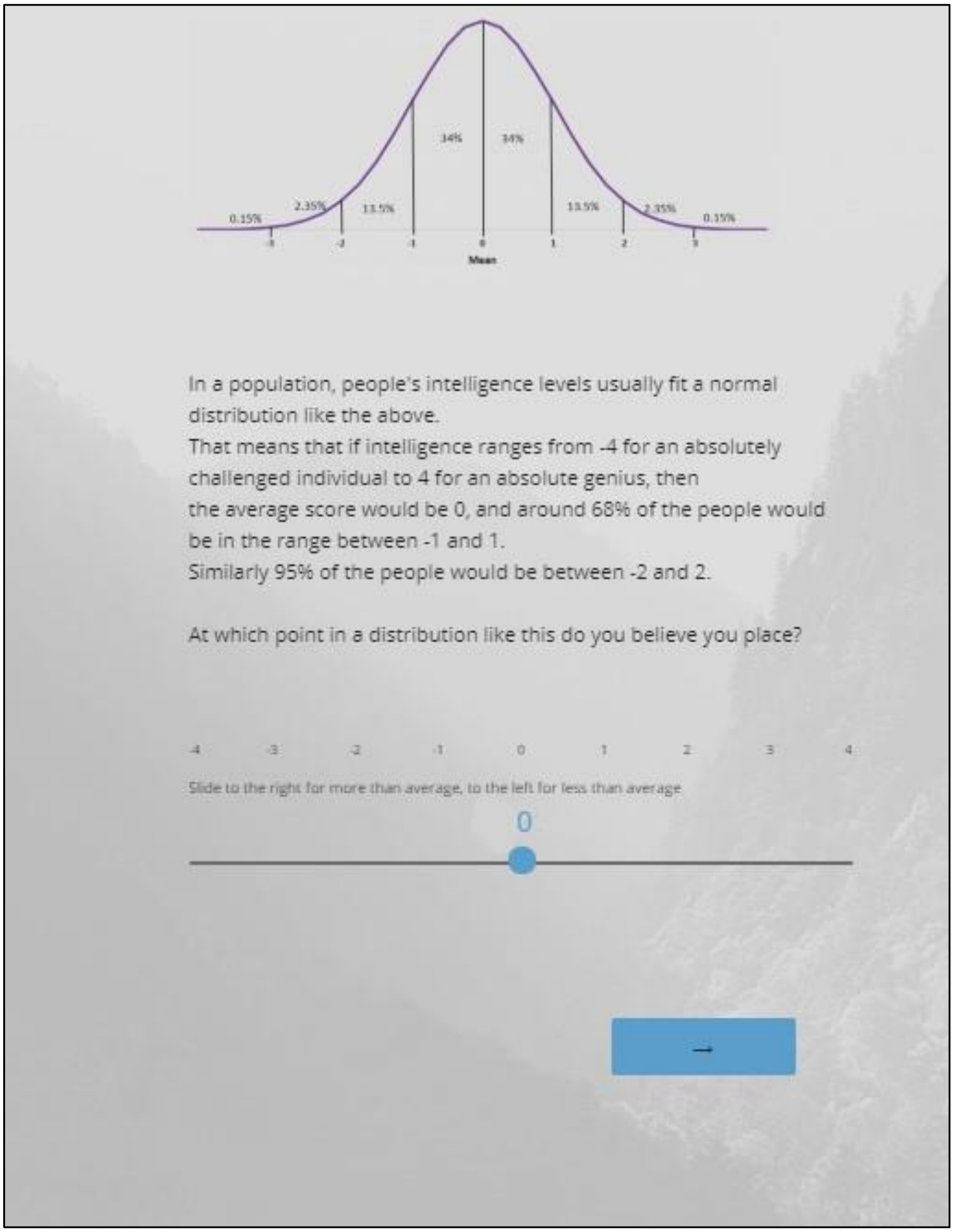
7.4 SEI – Page 4


0.15%
2.35%
13.5%
34%
34%
13.5%
2.35%
0.15%
-3
-2
-1
0
1
2
3
Mean
In a population, people's intelligence levels usually fit a normal distribution like the above.
That means that if intelligence ranges from -4 for an absolutely challenged individual to 4 for an absolute genius, then the average score would be 0, and around 68% of the people would be in the range between -1 and 1.
Similarly 95% of the people would be between -2 and 2.
At which point in a distribution like this do you believe you place?
-4 -3 -2 -1 0 1 2 3 4
Slide to the right for more than average, to the left for less than average
0
→

7.5 Test Instructions – Page 5

Ok, now one last step is left.
In the following test there are a number of short sentences each followed by a pair of letters (AB or BA).

The sentences claim to describe the order of the two letters, i.e., to say which comes first.
They can do this in several different ways.
Thus the order AB can be correctly described by saying either
(1) A precedes B, or (2) B follows A, or (3) B does not precede A,or (4) A does not follow B.
All these are correct descriptions of the pair AB but are incorrect when applied to the other pair, BA.
Your job is to read each sentence and to decide whether it is a true or false description of the letter pair which follows it.
If you think that the sentence describes the letter pair correctly click the first choice (labeled "True").
If you think the sentence does not give a true description of the letter order, click the second ("False").

This is illustrated in examples 1 and 2 below.
When you have read 1 and 2, think about examples 3,4, 5, and 6.

Examples:

1. A follows B-BA
   True
2. B precedes A-AB
   False
3. A is followed by B-AB
   True or False?
4. B is not followed by A-BA
   True or False?
5. B is preceded by A-BA
   True or False?
6. A does not precede B-BA
   True or False?

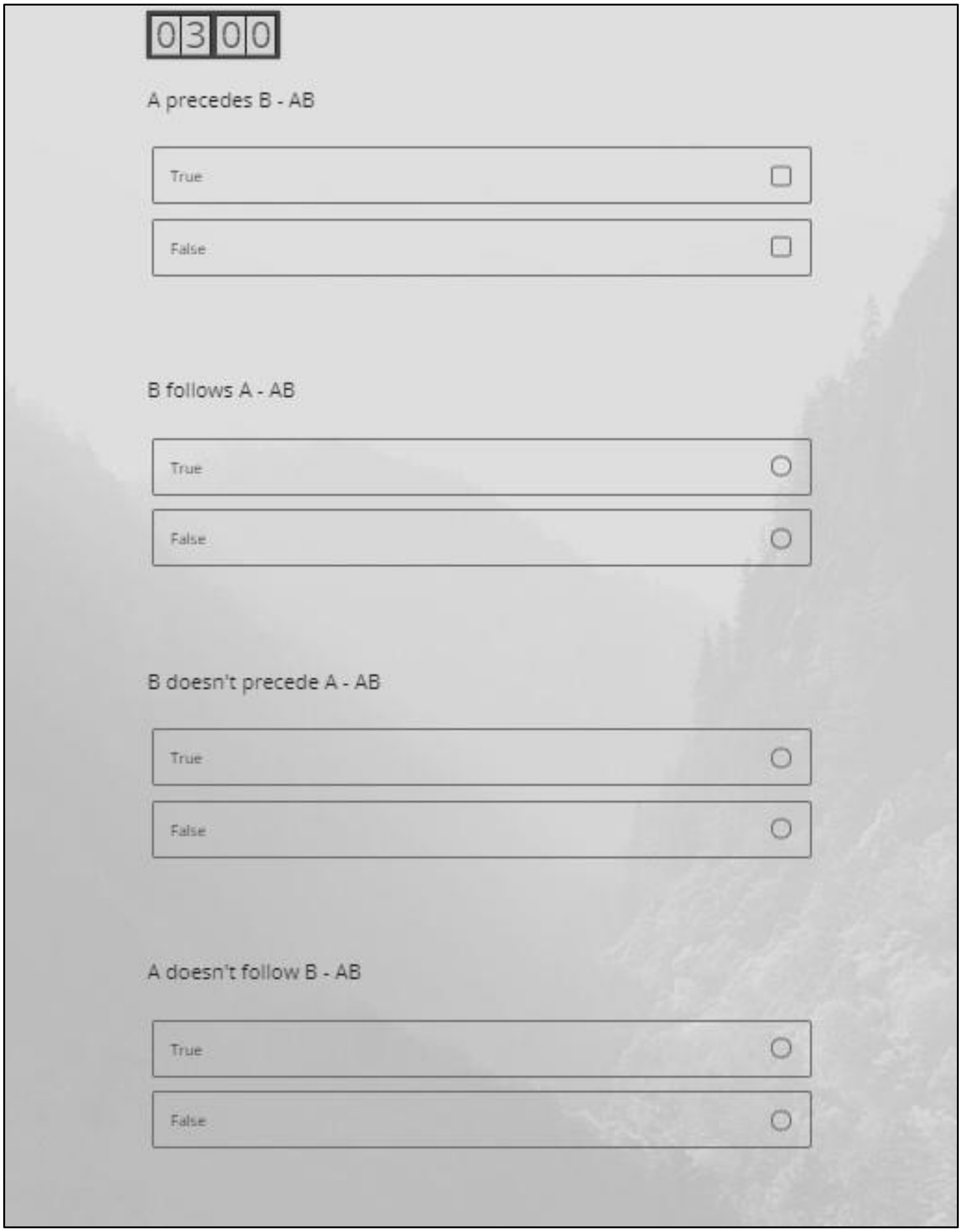
When you start the main test, work as quickly as you can without making mistakes.
Start with the first sentence and work systematically through the test.
You will have 3 minutes to answer as many as possible.

Click the bottom right arrow to start. Good luck!

→

7.6 Baddeley Test – Page 6

(The order is randomized for every participant)



0300

A precedes B - AB

- True
- False

B follows A - AB

- True
- False

B doesn't precede A - AB

- True
- False

A doesn't follow B - AB

- True
- False

B is not followed by A - AB

- True
- False

B is not followed by A - BA

- True
- False

B is not preceded by A - AB

- True
- False

B is not preceded by A - BA

- True
- False

B follows A - AB

- True
- False

B follows A - BA

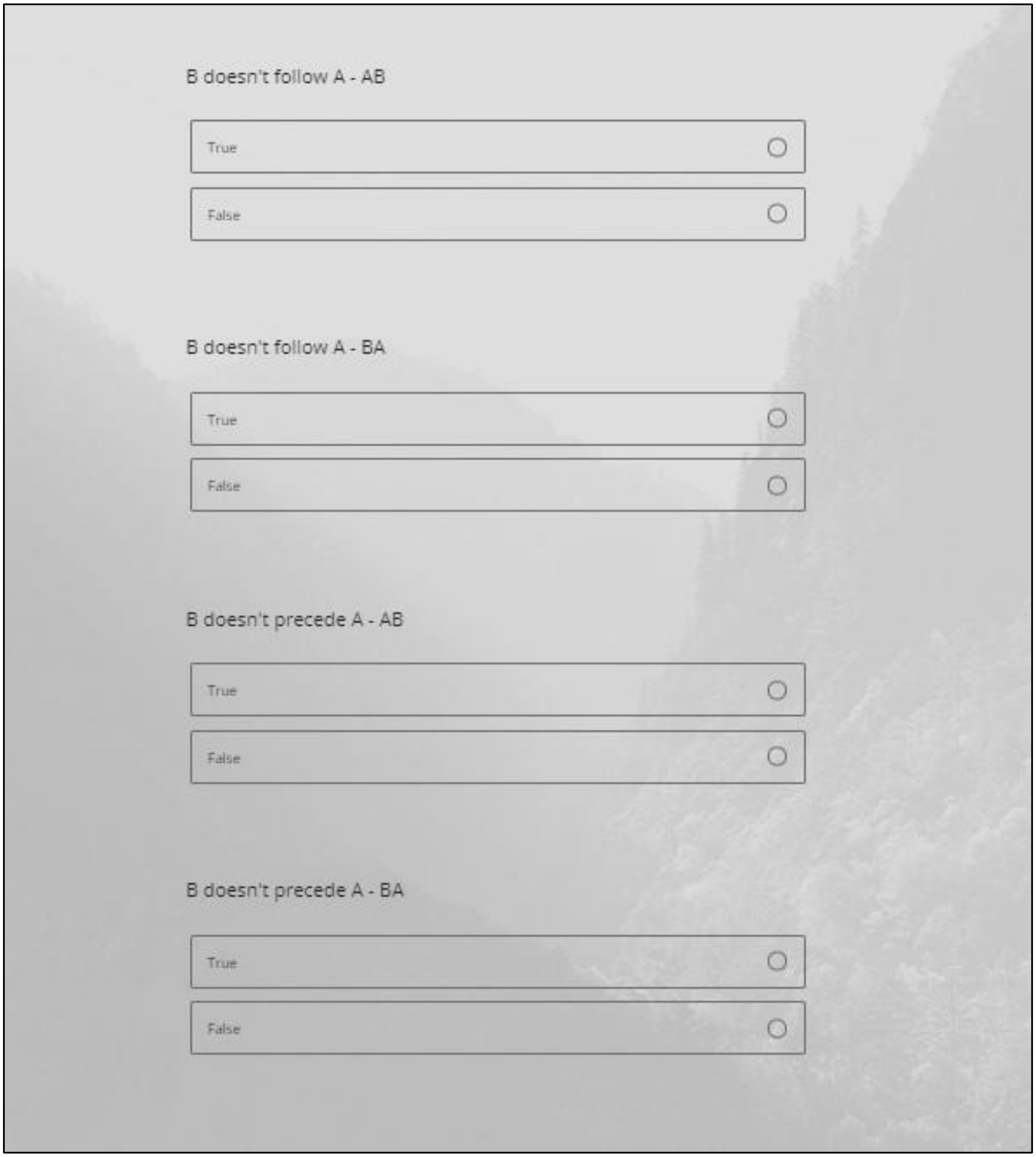
- True
- False

B is followed by A - AB

- True
- False

B is followed by A - BA

- True
- False



B doesn't follow A - AB

True

False

B doesn't follow A - BA

True

False

B doesn't precede A - AB

True

False

B doesn't precede A - BA

True

False

A is preceded by B - AB

True

False

A is preceded by B - BA

True

False

A precedes B - AB

True

False

A precedes B - BA

True

False

A is not followed by B - AB

- True
- False

A is not followed by B - BA

- True
- False

A is not preceded by B - AB

- True
- False

A is not preceded by B - BA

- True
- False

A follows B - AB

- True
- False

A follows B - BA

- True
- False

A is followed by B - AB

- True
- False

A is followed by B - BA

- True
- False

A doesn't follow B - AB

- True
- False

A doesn't follow B - BA

- True
- False

A doesn't precede B - AB

- True
- False

A doesn't precede B - BA

- True
- False

B is preceded by A - BA

- True
- False

A is followed by B - BA

- True
- False

A is not preceded by B - BA

- True
- False

B is not followed by A - BA

- True
- False

A is preceded by B - BA

- [ ] True
- [ ] False

B is followed by A - BA

- True
- False

B is not preceded by A - BA

- True
- False

A is not followed by B - BA

- True
- False

A is preceded by B - AB

- True
- False

B is followed by A - AB

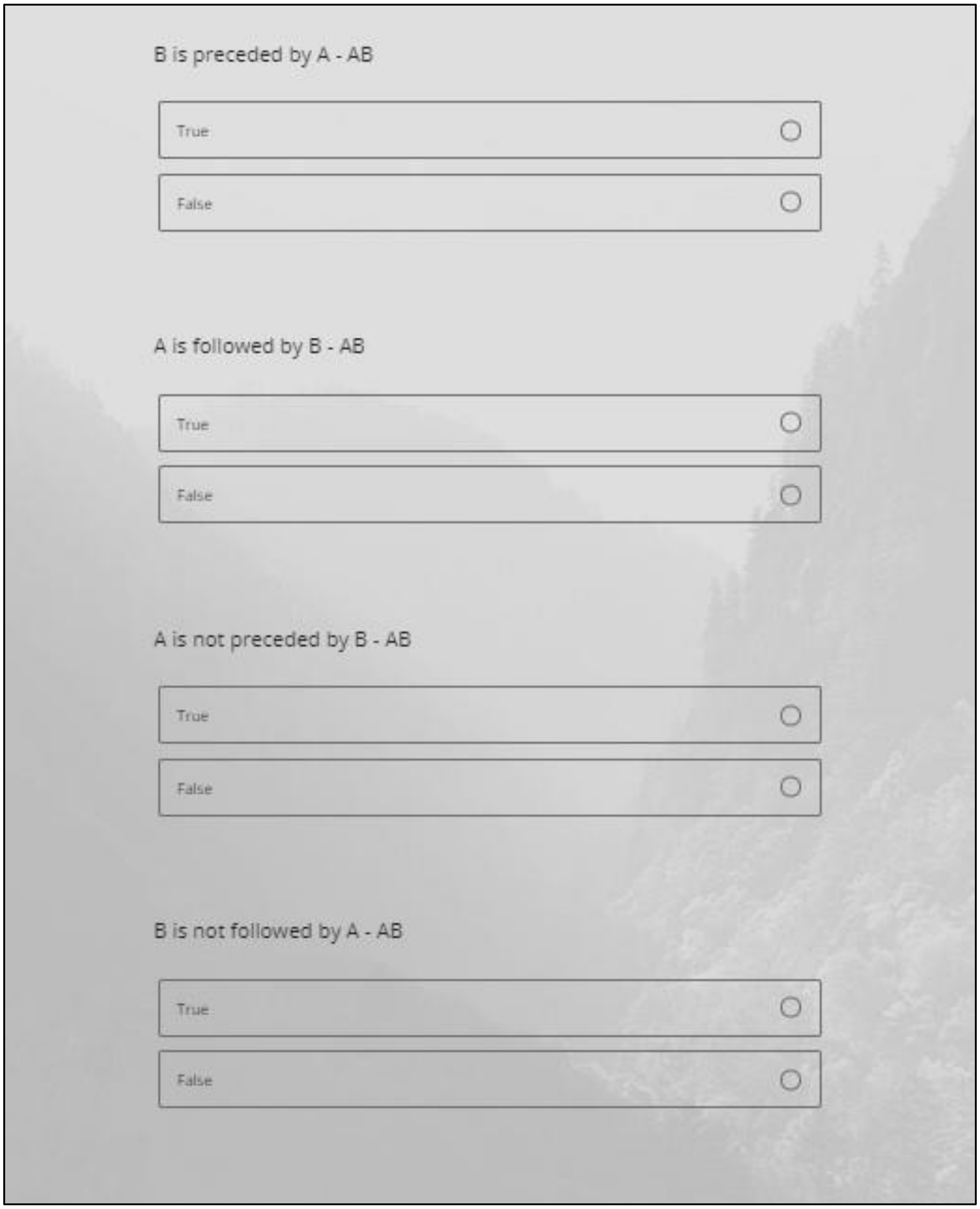
- True
- False

B is not preceded by A - AB

- True
- False

A is not followed by B - AB

- True
- False



B is preceded by A - AB

True

False

A is followed by B - AB

True

False

A is not preceded by B - AB

True

False

B is not followed by A - AB

True

False

A precedes B - BA

- True
- False

B follows A - BA

- True
- False

B doesn't precede A - BA

- True
- False

A doesn't follow B - BA

- True
- False

B precedes A - BA

- True
- False

A follows B - BA

- True
- False

A doesn't precede B - BA

- True
- False

B doesn't follow A - BA

- True
- False

B precedes A - AB

- True
- False

A follows B - AB

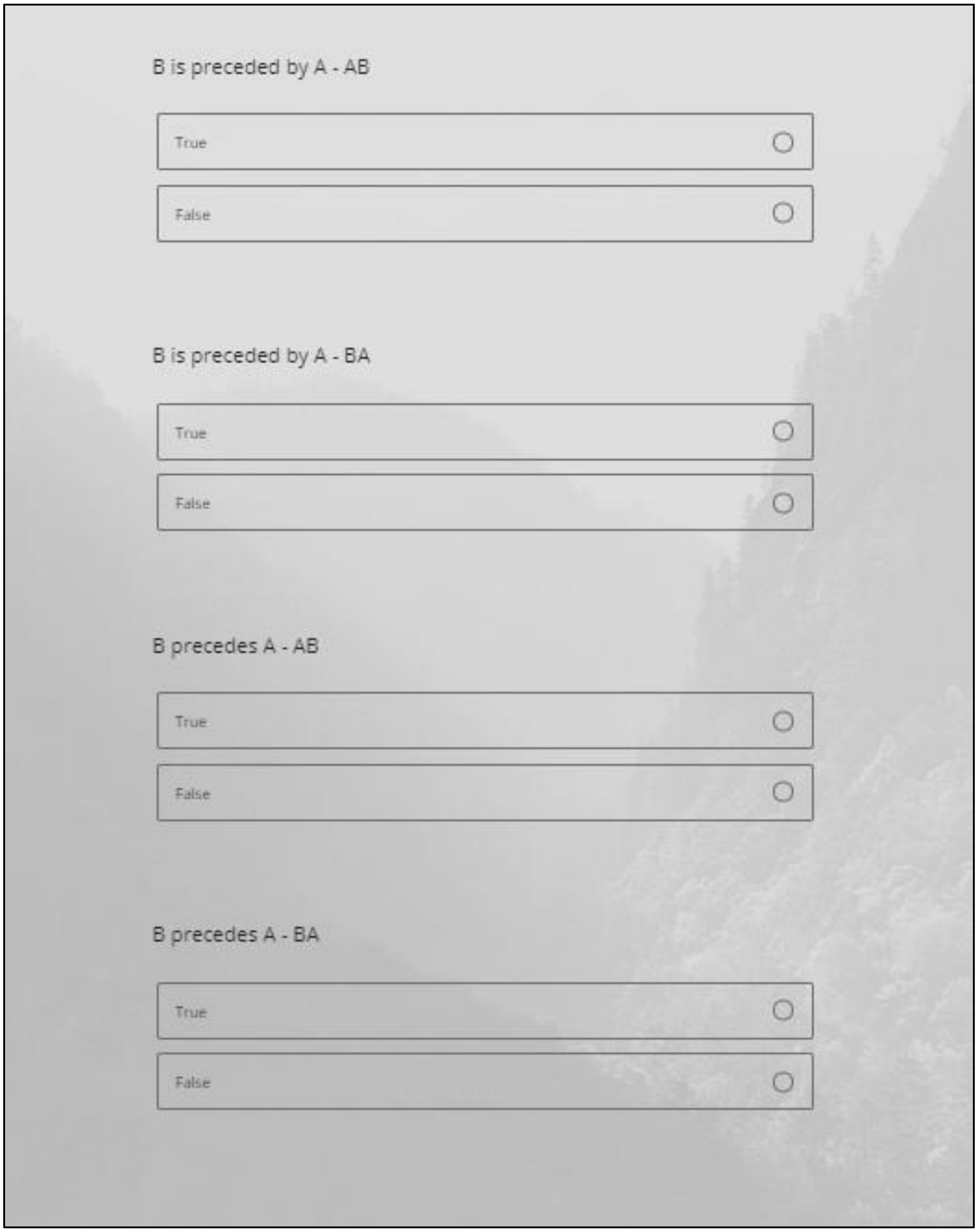
- True
- False

A doesn't precede B - AB

- True
- False

B doesn't follow A - AB

- True
- False



B is preceded by A - AB

True

False

B is preceded by A - BA

True

False

B precedes A - AB

True

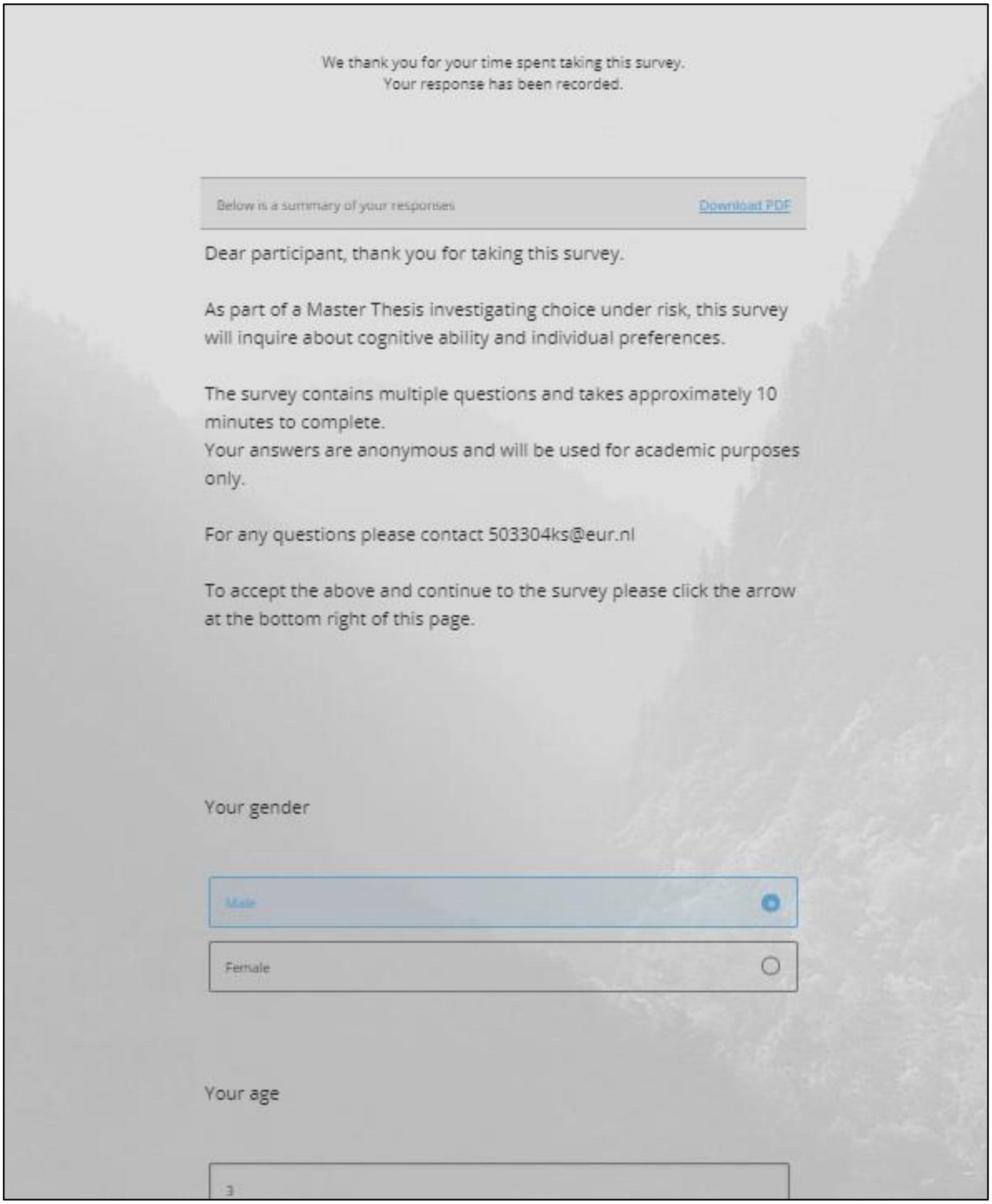
False

B precedes A - BA

True

False

7.7 Completion – Page 7



We thank you for your time spent taking this survey.
Your response has been recorded.

Below is a summary of your responses   Download PDF

Dear participant, thank you for taking this survey.

As part of a Master Thesis investigating choice under risk, this survey will inquire about cognitive ability and individual preferences.

The survey contains multiple questions and takes approximately 10 minutes to complete.
Your answers are anonymous and will be used for academic purposes only.

For any questions please contact 503304ks@eur.nl

To accept the above and continue to the survey please click the arrow at the bottom right of this page.

Your gender

Male

Female

Your age

3