UNIVERSITY OF CAMBRIDGE

Succeeding in a Nebulous World:
A statistical and machine learning analysis of the impact of three dimensions of cognition on success in entrepreneurship.

Table of contents

Table of contents

Table of tables

Table of tables

Table of Figures

Table of Figures

Table of Abbreviations

AIC	Akaike Information Criterion
AUT	Alternate Uses Test
CRT	Cognitive Reflection Test
DF	Degrees of Freedom
NDM	Naturalistic Decision Making
PCA	Principal Component Analysis
RF	Random Forest
RSS	Residual Sum of Squares
TT	Tumour Test; referring to Duncker's radiation problem (1945) and Gick and Holyoak's (1983) adjustments

1 Introduction: Succeeding in a nebulous world

For well over a century, business schools, the US military, and renowned corporations have measured individuals' intelligence to evaluate their potential. Intelligence is a good predictor of academic achievement and problems where goals, context, and the variables of the equation are clear (e.g. Jensen, 1998), but it fails to predict success when these factors are more ambiguous, especially in settings characterised by unknown unknowns (Loch et al., 2006; Wideman, 1992), also referred to as unforeseen contingencies (Schrader, Riggs and Smith, 1993) or wicked problems (Rittel and Webber, 1973). For these environments, increases in intelligence above a threshold do not add explanatory power (Gould, 1996; Sternberg, 2004). Problems associated with unknown unknowns may require different cognitive abilities beyond intelligence.

Finding a measure to predict an individual's ability to solve problems characterised by unknown unknowns has substantial implications for business and management. Managers, executives, and entrepreneurs all share a common reliance on their ability to solve problems characterised by unknown unknowns; it is a fundamental determinant of their output, and their success. Venture capital could be allocated more efficiently, CEOs could be selected more effectively, and entire innovation teams could be better assembled, if a reliable predictor of the ability to solve problems characterised by unknown unknowns existed. This study is concerned with developing such a measure.

The existing literature studies the impact of individual factors on performance, such as logical thinking – the ability to use one's deliberate cognitive system to solve a task (e.g. Frederick, 2005; Gould, 1996; Jensen, 1998; Spearman, 1903; Willingham, 1974) – and creativity – the ability to produce ideas that are novel and useful (e.g. Baron, 2004; Sternberg, 2004; Ward, 2004). However, research remains scarce on how these individual factors interact and contribute to problem-solving ability in settings characterised by unknown unknowns. This study seeks to understand how individual factors and the combined contributions of those factors relate to a representative example of solving problems characterised by unknown unknowns: entrepreneurship.

The prediction of entrepreneurial success is not new. Sternberg (1994, 2004) shows how logical thinking, creativity, and practical intelligence contributes to entrepreneurial success, where practical intelligence refers to the capacity to understand complex mechanisms embedded in real world examples (Lave, 1988; Nunes, 1994). Baron (1998) and Ward (2004) study how entrepreneurial ability might be a consequence of the ability to think creatively. Frederick (2005) demonstrates how the ability to think logically results in different time and risk preferences. Still, it remains unclear whether logical thinking ability leads to better problem-solving in environments with unknown unknowns. For entrepreneurship, a practice characterised by unknown unknowns, many researchers seek to explain success through a set of personality traits and social factors (e.g. Baum & Bird, 2010; Baum et al., 2011; Frese & Gielnik, 2014; Jin & Kirsch, 2015; Shaver & Scott, 1991), as opposed to a set of cognitive abilities.

In addition to creativity and logic, there exists a considerable body of research on analogical thinking: the ability to draw connections from one piece of information to another by means of abstraction (Gassmann & Zeschky, 2008; Gick & Holyoak, 1983). This research primarily addresses the cognitive mechanisms of analogical thinking itself (Gick & Holyoak, 1983; Keane,

1987) and how the practice of analogical thinking helps in product innovation and entrepreneurship (Dahl & Moreau, 2002; Garbuio et al., 2018; Gassmann & Zeschky, 2008). Yet whether an individual's ability to think analogically correlates with their ability to effectively navigate settings characterised by unknown unknowns is yet to be investigated. Given that research demonstrates a clear link between success in different environments characterised by unknown unknowns and the practice of analogical thinking (Dahl & Moreau, 2002; Garbuio et al., 2018; Gassmann & Zeschky, 2008), it is not far-fetched to assume that individuals' analogical thinking abilities might explain success in those environments as well.

This study sheds light on how the cognitive predisposition of an individual contributes to her or his success in effectively navigating settings characterised by unknown unknowns. The cognitive dimensions of logic, creativity, and 'analogic' have been chosen as they can be tested easily and conveniently. Analogical thinking in particular might be an overlooked dimension, although it is easy to measure and might contribute greatly to success in managing settings of unknown unknowns. While the results of this study are likely to be transferrable to dealing with any sort of problem involving unknown unknowns, this study focusses on one of the problems most characterised by unknown unknowns: launching, and succeeding with, an entrepreneurial venture.

2 Theory

2.1 Facets of uncertainty

Uncertainty can be grouped into different levels of complexity. Its simplest form is risk. Risk involves a number of possible outcomes and a known probability assigned to each of the possible outcomes. Next to risk, *Knightian uncertainty* – or *ambiguity,* or *known unknowns* – defined by a situation where the possible outcomes are known, but probabilities cannot be assigned (Loch et al., 2006). Such situations are clearly more difficult to deal with and require the usage of proxies such as Savage's (1972) subjective probabilities. For example, one can intuitively guess that it is less likely for Apple, compared to a newly founded start-up, to lose all of its enterprise value within the next year. Lastly, *unknown unknowns* (Loch et al., 2006) extend Knightian uncertainty by adding uncertainty to the possible outcomes. When an entrepreneur starts a firm, the number of possible outcomes cannot be clearly defined. For example, while Nokia once manufactured boots and tyres, it later became a world leader in the telephone market (e.g. Treuren, 2003).

This type of uncertainty plagues many high-level decision makers in politics and business and is especially characteristic of entrepreneurship (Loch et al., 2006). Despite the wide agreement on the importance and prevalence of 'unk-unks', the extant research primarily studies the application of modern models of management, and of thinking in general (e.g. Crossan et al., 2005; Loch et al., 2006; McGrath & MacMillan 2000). There is little focus on cognitive capabilities beyond IQ, despite the finding that IQ tends to lack explanatory power within such a context (e.g. Gould, 1998; Simonton, 2006).

2.2 Entrepreneurship, a setting characterised by unknown unknowns

In the context of entrepreneurship, Drucker (1985, p. 189) famously stated:

> "*When a new venture does succeed, more often than not it is in a market other than the one it was originally intended to serve, with products and services not quite those with which it had set out, bought in large part by customers it did not even think of when it started, and used for a host of purposes besides the ones for which the products were first designed.*"

Drucker's comments clearly articulate how the process of entrepreneurship may be understood as a process of navigating a setting of unknown unknowns. Loch et al. (2006) show that in such environments, traditional project management fails to produce the desired results (pp. 33). Moreover, Rittel and Webber (1973) refer to the notion of rationality and efficiency as not being sufficient for dealing with such settings. The question remains: Which ways of thinking and which cognitive abilities will be useful for navigating and solving problems in such environments?

2.3 Logical Thinking

Research on logic and intuition has been mostly concerned with either the distinction between these two factors or how each one may contribute to success within different contexts. Kahneman and Tversky's Dual Systems Theory (Kahneman, 2011; Tversky & Kahneman, 1974) is perhaps the most well-known explanation of what distinguishes intuition from logic. They refer to logical thinking as System 2, which is a cognitive process which is slow, thoughtful, and deliberate. Logic's contribution to success in specific areas has been mostly investigated by psychologists and in research on IQ tests (e.g. Hudson, 1966; Jensen, 1996; Sternberg, 1999; 2004). System 1 refers to intuitive decisions that are executed by the sub-conscious in an automatic and fast manner, which is prone to *biases*. As a result of these biases, it is often proposed that those who perform well on cognitive reflection tests, and thus avoid biases, a simple proxy for IQ, also perform well at problem-solving (Kahneman, 2011).

In contrast, many argue that real world problem-solving is too complex to be solved through the application of System 2. Rittel and Webber (1973) observe that "[for wicked problems] *our intelligence is insufficient to our tasks"* (p.160). Moreover, Sternberg (1999, 2004) argues that practical intelligence, alongside analytical and creative intelligence, may be necessary in such environments. Gary Klein (1989, 2015) furthermore argues that expert decision-making in applied settings relies on highly intuitive heuristic processes he calls "natural decision-making". More specifically, researchers of natural decision-making define intuition as an agglomeration of patterns discovered through experience, which can intuitively be accessed by the expert decision maker (e.g., Klein, Calderwood, & Clinton-Cirocco, 2010; Klein, Orasanu, Calderwood, & Zsambok, 1993). Though seemingly at odds, Kahneman and Klein (2009) find that the benefits of both intuitive and logical decision-making processes are contingent on the setting (p. 524). Environments characterised by unknown unknowns, such as *stock markets*, *politics*, and *entrepreneurship*, benefit from rational, or System 2, decision-making processes.

Entrepreneurship clearly falls within the realm of being characterised by unknown unknowns (Kahnemann, 2011; Kahneman & Klein, 2009; Klein 2015). Thus, despite the popular belief, or at least inclination, to downplay logical thinking within the realm of entrepreneurship, it is likely to, at least partially, contribute to success.

It can thus be proposed:

H1,a: Entrepreneurs are more likely to perform well in logical thinking tasks than non-entrepreneurs.

The question remains as to whether logical thinking offers the full picture. For example, increased cognitive reflection often leads to slower decision-making (Bert et al., 2014), as individuals try to consider all possible input and output variables. It could thus be argued that most successful entrepreneurs have a certain level of intelligence, but that a high level of intelligence might reduce their ability to successfully start a venture.

H1,b: Exceptional logical thinking ability is as common with entrepreneurs as it is with non-entrepreneurs.

2.4 Creative Thinking

Research on creative thinking is concerned with how creative people are and behave (Barron, 1955; Feist, 1998), how creativity can be improved (Amabile, 1996; Scott et al., 2004), and its role in success, for instance in entrepreneurship (e.g. Ward, 2004). Moreover, in different contexts, people's creative thinking abilities improve. This may concern, specifically, their motivation (Elkind et al, 1970), the level of trust among team members (Gong et al., 2012), or their visual environment (Studente et al., 2016).

An idea is considered creative if it is both useful and novel (George & Wiley, 2018). However, while coming up with ideas which are *novel* is an outcome of a divergent thinking process – i.e.

generating as many as different bits of information as possible – coming up with an idea which is useful is likely a convergent thinking task, i.e. combining several bits of information to form one final result (Guilford, 1967). This study is concerned with the role of novelty or divergent thinking, as it is associated more with subconscious thought as opposed to the slow and deliberate process of logical thought (Kahneman, 2011).

As with logical thinking ability, success in the workplace has also been attributed to creativity (e.g. Tierney, Farmer, & Graen, 1999; Torrance, 1972). Sternberg (1999, 2004) and Ward (2004) argue that creativity plays a major role in entrepreneurial success. Ward, for example, justifies this conclusion by arguing that novel and useful ideas are the lifeblood of entrepreneurship. Theoretically, entrepreneurs confronted with problems characterised by unknown unknowns have to map possible solutions quickly, identify their effectiveness, and test them (e.g. Sadler-Smith, 2015). While identifying the effectiveness of solutions is primarily a logical task, their generation in the first place is inherently creative. This is important for a variety of entrepreneurial tasks: for example, the ability to market products in new ways which appeal to customers, to design new, creative product features, or to sell a new product to new audiences requires divergent thinking.

One could argue that divergent thinking prevents entrepreneurs from converging to a solution. However, research shows clear links between creativity and logical thinking (Kaufman & Pluncker, 2011; Schubert, 1973; Sternberg, 1999), the latter of which uses convergent thinking ability (Webb et al., 2017). Furthermore, experts in design thinking stress the importance of generating quantitatively as many ideas as possible during the ideation phase of the design thinking process (e.g. Kudrowitz, 2010). Greater quantity leads to a synthesis of higher quality, and thus ultimately to better products. It can be assumed that entrepreneurs who can generate more ideas are better at opportunity recognition and validation, at generating more ideas quantitatively and assessing them to recognise an opportunity, and also during opportunity exploitation, by consistently generating more options which can be assessed.

It can thus be proposed:

> H2: Entrepreneurs are more likely to perform well in creative thinking tasks than non-entrepreneurs.

2.5 Analogical Thinking

Research on analogical thinking is mostly concerned with how analogical thinking helps in finding a solution to a problem, for example in the field of product innovation (e.g. Gassman et al., 2008), new product ideation (e.g. Dahl and Moreau, 2002), or entrepreneurship (e.g. Garbuio et al., 2018). It is recognised in those papers that knowledge about another domain from which an analogy can be drawn, as well as the process of abstraction itself, contribute to the quality of an individual's faculty for analogical thinking. Analogical thinking, in turn, is a symbol of successful innovation practice, according to Gassman et al. (2008).

Also, many scientists study the cognitive process of analogical thinking itself (Gentner, 1983; 1993; Gick and Holyoak, 1983; Keane, 1987). It is argued that analogical reasoning is conducted through abstraction, both vertically – between analogues – and horizontally within an analogue (Hesse, 1970), and on different levels of depth for both processes (Kintsch and van Dijk, 1978; van Dijk, 1980). Gick and Holyoak (1983) call such an abstract construct a schema. A schema is an abstraction of Analogue A to such an extent that it only counts the similarities to Analogue B, but not the differences. An analogue is thus always more similar to its schema than to another analogue. Seeing connections between two analogues by creating the right schemas is thus not a mere act of abstraction; it is an ordered, focused act of abstraction which keeps the goal in mind. Gick and Holyoak test different forms of analogical thinking by adapting Duncker's (1945) radiation problem with two further stories. While Duncker's radiation problem alone tests the ability to both come up with analogues to draw from and then make a conclusion based on self-retrieved analogues, Gick and Holyoak provide two further stories which already function as analogues and offer help in composing a viable schema.

It comes as a surprise that, even though models for assessing an individual's ability to conduct analogical reasoning exist, and links have been drawn between the usage of analogical thinking and entrepreneurship (e.g Dahl and Moreau, 2002; Gassman et al., 2008), no study known to the author has yet been conducted which links an individual's cognitive analogical thinking ability to entrepreneurial success.

Assuming that analogical thinking ability determines entrepreneurial success is intuitive. Analogical thinking might not only help in discovering and exploiting opportunities, but also in communicating them effectively. According to Gick and Holyoak's (1983) argumentation, finding schemas which map similarities between different markets and products can likely lead to innovation in one market inspired by innovation in another market. One would have to come up with a schema which is abstract enough to allow one to recognise the similarities, but in a second step add concrete attributes to the schema to make it applicable to the target market. Proposals such as a 'Google for education' – a product that arranges educational content based on personal consumption behaviour and other personal attributes – may not only be an applicable schema, but also help employees and investors understand the nature of the product quicker. As within successful R&D practice, where a successful strategy is to transfer ideas from one discipline to another (Cummings and Teng, 2003), the same principle is expected to apply to entrepreneurship.

Moreover, analogical thinking is recognised as a useful practice in solving problems characterised by unknown unknowns, such as product innovation or launching new ventures (Dahl and Moreau, 2002; Garbuio et al., 2018; Gassmann et al., 2008). For example, seeing how Amazon digitized and centralized the ordering of books might motivate an entrepreneur to digitize and centralize the ordering of food. The schema is here to completely digitize the ordering process, but not to centralize it, as ordering will be dependent on local restaurants. It can hence be concluded that entrepreneurs who develop these schemas in a useful manner tend to be more successful.

It can thus be proposed:

> H3: Entrepreneurs are more likely to perform well in analogical thinking tasks than non-entrepreneurs.

2.6 Stages of entrepreneurship

Every entrepreneur moves from an idea stage to an execution stage in her or his venturing process. This has been described differently by many authors, for example by moving from *value creation* to *sustainable venture creation* (Lackeus, 2015), from *opportunity recognition* to *opportunity exploitation* (Sadler-Smith, 2015), or from *opportunity identification* to *refinement* *of business concept* to *survival and growth* (Frese, 2007). Usually, there is a step in the process where the opportunity is identified and validated, and one in which the opportunity is exploited in order to grow and scale the venture sustainably. While both phases are characterised by unknown unknowns, the later stages can be argued to be less chaotic or involve fewer unknown unknowns than the former. It is in the interest of this study to separately evaluate the efficacy of cognitive *creative*, *logical*, and *analogical* ability in these two phases.

This study synthesises the above steps into opportunity recognition, opportunity validation, and scaling, which is most similar to Frese's (2007) three step process. It is assumed that out of a random sample, fewer than all people will be able to recognise an opportunity; out of all those individuals, fewer than all will be able to validate their opportunities, and fewer again will be able to scale effectively.

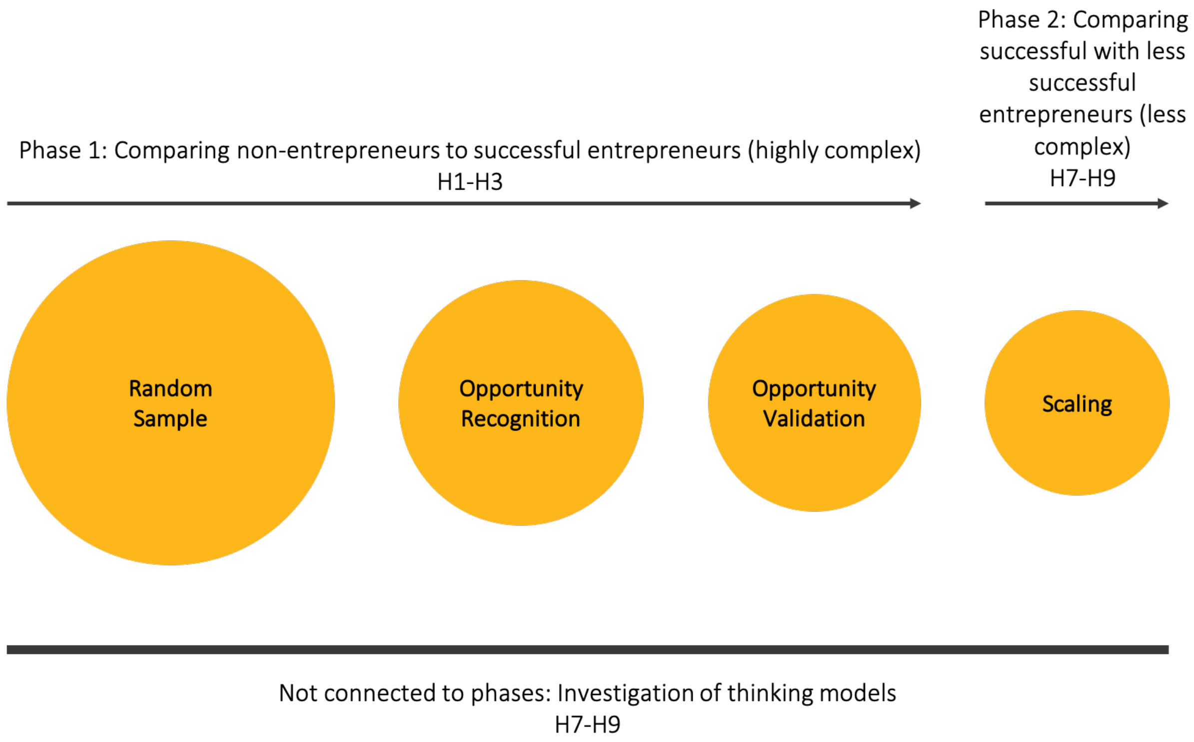


Figure 1: Stages of entrepreneurship inspired by Lackeus (2015), Sadler-Smith (2015), and Frese (2007)

The above distinction between phases of success is crucial, as both phases involve different phenomena. To build a working product and sell it initially, which involves many unknown unknown factors, is different to taking a working idea and scaling it (Lackeus, 2015; Sadler-Smith, 2015). This is often why start-ups are founded by one person and scaled by another. Wasserman (2008) describes this dilemma in detail, emphasising that many start-ups, when entering their growth stage, should focus on employing a new CEO with a different personality and abilities. As such, this study expects to find differences in the cognitive abilities within the group of successful entrepreneurs. Despite the positive effect of analogical and creative thinking ability on both stages of entrepreneurship, it is believed that the importance of these cognitive abilities is greater in the early stages of entrepreneurship. This results in the following hypotheses:

> H4: Entrepreneurs with greater logical thinking ability are more likely to report more revenue, receive more funding, or have more employees.
>
> H5: Entrepreneurs with greater creative thinking ability are more likely to report more revenue, receive more funding, or have more employees.
>
> H6: Entrepreneurs with greater analogical thinking ability are more likely to report more revenue, receive more funding, or have more employees.

2.7 Dependence

2.7.1 Logic and Creativity

The *creative act* has been described by Ward (1994), who examined people's ability to come up with novel animals that live on another planet. The proximity of the drawings of those animals to earthly animals suggests that creative thinking starts by beginning with a base, e.g.

a known animal; structuring that base in categories, e.g. size, colour, form; and creating relevant sub-categories which will be shuffled until a new model exists. High creativity is expected if a person was able to think about many different forms, many different colours, or many different sizes, or all at the same time, giving many different variants for each category. Ward (1994) describes this as a logical task. In Ward's task, individuals seem to begin with attributes of animals they know and then apply some form of logic to their creative process by altering categories in a structured manner. This would suggest that the number of categories one can come up with is creative, but, subsequently, the ability to think logically allows the individual to produce more creative outcomes by altering categories in a structured manner.

In contrast, it is often argued that especially intelligent, logically-thinking people lack creativity (e.g. Kaufman and Pluncker, 2011). Moritz et al. (2014) furthermore show that decision speed negatively correlates with increased logical thinking ability. Consequently, divergent thinking ability and creativity may also be negatively affected, as individuals with especially high-level logical thinking ability may generate creative solutions at slower speed. At one point, one might expect a curvilinear relationship between results on the Alternate Uses Test and the Cognitive Reflection Test.

It can thus be proposed:

> H7: The ability to think logically and the ability to think creatively follow an inversed U-shaped relationship.

2.7.2 Analogy in relation to logic and creativity

Analogical thinking is different to logical thinking (Gick and Holyoak, 1983). To conduct logical thinking, individuals must activate their System 2. However, in analogical thinking, one has to generate possible analogies and draw links between them in a 'fuzzier', less logical manner. For example, in the tumour test, which can be found in Appendix A, subjects have to kill a tumour by splitting and merging rays, as one single ray is too strong. A story about firemen who put out a fire by throwing buckets of water simultaneously prompts many problem solvers to find the solution to the TT. The analogy is not perfect, as a single, huge bucket of water could have put out the fire as well; still, any structural imperfections of the stories, which have been pointed out before (Holyoak and Thagard, 1989; Keane, 1987), do not seem to hinder individuals in finding the solution. The 'fuzzy logic' approach of separating and throwing water simultaneously helps individuals to solve that problem. Simultaneously, the individual has to abstract the problem to such an extent, i.e. a schema (Gick and Holyoak, 1983), so that similarities between both can found. As a result of its 'fuzzy logical' character, analogical thinking is treated separately to logic and creativity in this study.

However, analogical thinking is likely still linked to logical thinking; as analogical thinking depends on abstraction, it is only reasonable to assume that logical thinking plays an important role in it. The step involved in drawing an analogy between two analogues is to produce a schema. The most effective schema would be one that maximizes the similarities between the two analogues. This form of thinking is clearly performed by System 2 (Kahneman, 2011).

Drawing an analogy between two objects requires a process similar to the one described by Ward (1994). In both analogical and creative thinking, the object needs to be abstracted to an appropriate schema (Gick and Holyoak, 1983). Yet, for creativity alone, the construction of the schema may be arbitrary, and all that counts is a certain amount of abstraction followed by exchanging one categoric object with another. For analogical thinking, on the other hand, that process has to be organized and goal oriented. For example, Gick and Holyoak explain that an analogy between two stories can only be found if the goal is understood. To solve Duncker's (1945) famous radiation problem, one has to take the secondary military story they provide as a helpful, analogous hint as both a problem in its own right and as the source of a potential solution to the overarching radiation problem, rather than as a mere anecdote about a populist hero. This, as well as the ability to abstract, is a logical thinking ability. The pure ability to think divergently should, therefore, not help to build schemas for different analogies, as this can be seen as a mostly convergent, logical act. This can be tested via Duncker's (1945) radiation problem: Individuals who only solved the task after having read one of the additional stories need to only perform convergent thinking, as opposed to those individuals who solved the task straight away by coming up with information from which analogies can be drawn themselves, displaying an ability to think divergently. One would thus expect that only when accounting for the divergent part of solving Duncker's radiation problem can a meaningful relationship between creativity and analogical thinking ability be recognised. It can hence be proposed:

> H8: The ability to think creatively only correlates with analogical thinking ability if the divergent part of analogical thinking ability is included.

This adds to Gentner's (1983, 1993) research on analogical thinking, which proposes that there is a difference between surface and structural similarities. In his MAC/FAC model ('Many Are Called, but Few Are Chosen'), Gentner proposes that access to stored structures is primarily similarity-driven when solving a task like Duncker's radiation problem. What is mostly neglected, however, is that those who solve the problem without any hints may apply analogical thinking as well, not necessarily deriving the solution purely logically. Generating possible analogues oneself from which one can draw from later may be a primarily creative task. Hence, it seems as if the measures of logical, analogical, and creative thinking ability are different pieces necessary to solve the puzzle of problem-solving in environments with unknown unknowns. A simple problem can be completely mapped and solved by logical thinking ability. A problem in environments with unknown unknowns, in contrast, has an undefined state space. By producing a schema between a known, solved problem or area and the complex problem, the possibility of success is likely to increase, as many unknown factors can be automatically eradicated through the analogy. Creative thinking ability is likely to increase the number of possible analogues one can draw the analogy from, whereas logical thinking is likely to increase the quality of the schema and the likelihood of seeing a connection between the schemas. It can thus be expected that people who score relatively highly in both divergent and convergent thinking tasks will be more likely to solve an analogous problem-solving task. One component without the other is expected to be unconducive to entrepreneurship. It can thus be proposed:

> H9: Great analogical thinking ability is more likely given the presence of both logical and creative thinking ability.

3 Model and Data

3.1 Empirical model

This study investigates three different areas as illustrated in the table below.

Table 1: Empirical Model of the Thesis

Subject	Hypotheses	Method	Sample
The importance of logical, creative, and analogical thinking ability in differentiating successful entrepreneurs from non-entrepreneurs	H1-H3	***Comparison and classification***: Mann-Whitney U test, (multivariate) probit regression, random forest classifier, Chi-squared test	All surveyed participants
The importance of logical, creative, and analogical thinking ability in differentiating entrepreneurs among each other on success metrices	H4-H6	***Regression:*** Linear regression	Entrepreneurs only
The interrelations of logical, creative, and analogical thinking ability	H7-H9	**Comparison and regression:** Multivariate and polynomial regressions	All surveyed participants

Anyone who has validated an opportunity has been classified as a successful entrepreneur, and for all successful entrepreneurs, success metrics such as revenue and funding, as well as the overall number of employees – adjusted for time since entering operation – have been used to compare the level of success in scaling between each other. According to the differentiation introduced in chapter 2.6, all entrepreneurs are, as such, successful entrepreneurs according to the success criteria introduced later in this chapter. In all three cases, the respondents' logical, creative, and analogical thinking abilities are the independent variables meant to predict different dependent variables. In the first part of this study (H1-H3), successful entrepreneurs will be compared to a random sample. This part addresses issues of comparison and classification. An appropriate analysis method is regressing the test scores against a binary dependent variable which indicates successful entrepreneurship. In the second part (H4-H6), the dependent variables are continuous success metrics. Thus, linear regression models are used for analysis. The third part (H7-H9) uses polynomial and multivariate regressions to detect any non-linear relationships between the three dimensions of successful entrepreneurship. In this part, the cognitive dimensions will be both dependent and independent variables in order to predict the dependencies of those variables. The following chapters explore the surveyed data and the methods used for analysis in more depth.

3.2 Cognitive Reflection Test

The Cognitive Reflection Test (CRT), first introduced by Frederick (2005), measures people's ability to perform System 2 thinking. The test measures whether people use their System 2 when an immediate intuitive solution comes to mind. Another benefit of the CRT is that it highly and significantly correlates with several intelligence tests, such as SAT, ACT, WPT, and NFC. Frederick (2005) demonstrates in his seminal paper on cognitive reflection – in which he addresses the question "is the Cognitive Reflection Test just another IQ test?" – that there is vast overlap between different IQ tests, and that mere usage of System 2 is just as good a predictor of behaviour – often even a better one – as specific IQ tests (pp. 33). It is heavily g-loaded – that is, it represents Spearman's intelligence factor g to a great extent (Jensen, 1998) – and will function as a good predictor of entrepreneurs' logical thinking ability. The Cognitive

Reflection Test (CRT) is preferred in this study because it measures the degree to which a person is cognitively reflective, not innate intelligence, a still vaguely described concept which is subject to much criticism (e.g. Gould, 1996; Grissmer, 2000).

This study adds an adaption of Frederick's questions by Thomson and Oppenheimer (2016) to measure respective CRT results more granularly. An additional question has been added that seeks to explore how participants answer questions which are not fully specified. Specifically, it measures whether participants will be able to formulate abstract responses. This question is not used for the calculation of the CRT scores, as it does not measure cognitive reflection directly, but is used for the machine learning classification and clustering models (see Appendix A for all questions).

> *A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball.*
>
> *How much does the ball cost?*
>
> *_____ $*

The intuitive answer is 0.10 while the correct answer is 0.05. Participants' answers are assessed and measured on correctness. For the CRT, a compound score with a minimum of 0 and a maximum of 7 is calculated. The dummy question is investigated separately.

3.3 Alternate Uses Test

The Alternate Uses Test (AUT), introduced by Guilford (1967) in his book *The Nature of Human Intelligence*, is a widely adopted divergent production test to test the quantity and quality of ideas produced. It is used for many measures of creativity and shows slight correlations with

IQ, between 0.2 and 0.3 depending on the context (Schubert, 1973; Richards, 1976; Sternberg, 1999b).

In this study, people were presented with the following task:

> *"Please list as many uses as you can think of for **a chair**.*
>
> *(A new text box will appear after each use you enter)*
>
> *Once 2 minutes have passed the survey will proceed to the next section."*

Participants' answers were recorded and assessed for fluency measures which count the overall use cases an individual could generate (Shah et al., 2003; Jennings, 2009; Bennetts et al., 2017). The number of use cases was counted to result in a compound score between 0 and 30.

3.4 Tumour Test

The tumour test (TT) was first introduced by Duncker (1945) as the *radiation problem*. Later, Gick and Holyoak (1983) extended Duncker's radiation problem by providing two analogical stories which might help the subject derive a solution by drawing an analogy. It has been shown that, based on the remoteness of the analogies (Keane, 1987), the difficulty of finding a solution varies, measured by the percentage of people able to solve the problem. This study refers to Duncker's adjusted radiation problem as the 'tumour test' (TT), which includes the two hints introduced by Gick and Holyoak (1983) to test subjects' ability to think analogically. The question is given below, and the full test – including the stories – can be found in Appendix A.

> *"Suppose you are a doctor faced with a patient who has a malignant tumor in his stomach. It is impossible to operate on the patient, but unless the tumor is destroyed the patient will die. There is a kind of ray that can be used to destroy the tumor. If the rays reach it all at once at a sufficiently high intensity, the tumor will be destroyed. Unfortunately, at this intensity the healthy tissue that the rays pass through on the way to the tumor will also be destroyed. At lower intensities the rays are harmless to healthy tissue, but they will not affect the tumor either. What type of procedure might be used to destroy the tumor with the rays, and at the same time avoid destroying the healthy tissue?"*

Participants are scored based on the degree of intervention they receive prior to solving the test. Someone who solves the test without any hint receives a 4; a 3 if solved after reading the first story; a 2 if solved after reading the second story; a 1 if solved after she or he is explicitly asked to use the stories as a hint; and a 0 if she or he is unable to arrive at a correct solution. If respondents later revise their original answer after reading one of the stories, they are given a score as if they had only answered after reading the relevant story. Moreover, individuals are asked to explain their way of arriving at their solution. This is important to differentiate those answers derived analogically from those derived logically.

3.5 Data and Sample

Data was collected from non-entrepreneurs and entrepreneurs through an online survey. The former was attained from English-speaking countries solely by using the online service Mechanical Turk (MTurk), and comprises 677 respondents. The latter was collected through entrepreneurial networks, including the MSt in Entrepreneurship at the University of

Cambridge, the Kairos Society, and various venture capital companies, including Wave Ventures, Redstone VC, and First Momentum VC. The data set comprises 191 individuals. Any collected data was manually checked for validity and classified as successful entrepreneurship using predefined criteria. Criteria for successful entrepreneurship were whether the entrepreneur has received funding, generates revenue or profit, employs more than one person, or has received access to a prestigious venture program. Thus, only successful entrepreneurs were termed entrepreneurs in this study; when hypotheses 1-3 refer to entrepreneurs, they refer to successful entrepreneurs in the terms of this study. Any individual who did not meet these criteria was moved into the non-entrepreneurs group. Especially in the group 'MSt in Entrepreneurship at University of Cambridge', many individuals were moved into the non-entrepreneurs category.

Candidates who did not read carefully were filtered out through attention verification tests. 15 out of the 199 entrepreneurs were filtered out through the verification tests, while 236 out of the 677 respondents from the MTurk set were removed. Candidates must have completed 100% of the survey for their data to be analysed. 186 individuals from MTurk and 100 entrepreneurs did not complete the survey fully. If candidates answered the AUT with meaningless use cases such as "usecase 1" or "usecase 2", their data was filtered out. Not providing any answers to the AUT or the CRT similarly resulted in an exclusion from the final data set. For the CRT in particular, leaving any of the questions blank resulted in being removed from the data set. This further resulted in the removal of two entrepreneurs and 32 individuals from the MTurk set. Answering any of the tests in a manner that indicated lack of attention or understanding of the question, such as providing a number greater than 48 in the third CRT question, resulted in removal from the data set. This further resulted in the removal of two entrepreneurs and 32 individuals from the MTurk set. Individuals who failed to provide any insight towards the TT, that is, at least indicate what could be similar between the three scenarios, were filtered out as well. This removed four entrepreneurs and 25 individuals from the MTurk set. Finally, all entrepreneurs who did not meet the criteria for being successful entrepreneurs were moved to the non-entrepreneurs MTurk set. 14 entrepreneurs were moved. None of the moving was conducted on a case-by-case basis.

Eventually, the overall sample consisted of 266 individuals, comprising 56 successful entrepreneurs and 210 non-entrepreneurs. The median completion time of the remaining set was 14.6 minutes. Participants' age was collected in interval steps. Three individuals were below the age of 19, nine individuals were above the age of 60, and most individuals were between the age of 31 and 40. Data on gender, ethnicity, or other background data was not collected. The 56 successful entrepreneurs were usually in seed or series A stage, and in 90% of the cases had fewer than 50 employees. The non-entrepreneurs sample included aspiring entrepreneurs, students, and otherwise employed adults of all age groups.

During the survey, the following data was collected for purposes of analysis.

Entrepreneur status

The status of being classified as a successful entrepreneur is treated as a qualitative, nominal variable. All individuals not classified as successful entrepreneurs were uniformly classified as non-entrepreneurs in the data set. Thus, both unsuccessful entrepreneurs as well as non-entrepreneurs are classified as non-entrepreneurs in this study. This is particularly useful for later classification and regression, especially for t-testing, probit regression, and random forests applied to the data set.

Test scores

For comparing successful entrepreneurs to non-entrepreneurs, this study uses data retrieved from the CRT, AUT, and TT. As mentioned above, each of the tests offer a certain score, ranging from zero to seven for the CRT, from zero to 25 for the AUT, and from zero to four for the TT. None of the test scores can be treated as belonging to the ratio scale family, as a meaningful zero point cannot be set which allows multiplication, division, and calculation of the mean. A zero point can be calculated, but it does not signal a complete absence of cognitive reflection for the CRT nor a complete absence of creativity for the AUT. Thus, a CRT score of 6 is not twice as good as a CRT score of 3. Hence, CRT and AUT data can be treated as belonging to the interval scale, as a clear order can be imposed on test scores and on the number of correct or incorrect answers or generated use cases, respectively. The scores can be compared with GRE, SAT, or GMAT scores, which are also treated as interval data (Salkind, 2010). For example, an AUT score of 5 can be compared to an AUT score of 10 in terms of the number of use cases found. TT data can also be treated as an interval scale, as only one question is answered, but an appropriate score is assigned depending on the number of hints used to answer the question. The reverse frequency of hints needed to solve the problem represents the score of the TT. Consequently, all of the test scores will be used to calculate mean scores and standard deviations.

Success measures

Three main success measures are taken into account: revenue, funding, and number of employees. All of the success measures are ratio scale data, as a meaningful zero point can be set. Revenue and funding received will be treated as continuous variables, and number of employees as a discrete variable. However, entrepreneurs who have been operating longer are expected to record higher revenues, more funding, and a higher number of employees on average. Therefore, the number of months passed since the beginning of a venture's operation are included in a crucial fourth discrete variable. All success factors are divided by this variable to enable a fairer assessment of entrepreneurial success. The mean values of the success measures are shown in the following table:

Table 2: Overview of success metrices and their mean scores in the sample

Metric	Mean
Revenue in £	308 873.2
Funding in £	404 045.3
Employees	8.7

Control variables

A number of control variables are considered (see Appendix A for the full list). Individuals are assessed on their core strengths, their own judgement about their thinking type, the number of times they have switched their occupation, their conduciveness towards feedback, and the frequency of their networking efforts. The numbers were treated as nominal and ordinal scale only and were solely used for the machine learning model in this thesis.

3.6 Methods

Differentiating successful entrepreneurs from non-entrepreneurs

Hypotheses H1-H3 focus on opportunity recognition and validation. This study uses the Mann-Whitney U test to compare the test scores between entrepreneurs and non-entrepreneurs, as well as specific subsets. The non-parametric test for comparison is preferred, given the nature of the data which will be more closely examined in the following chapter. Moreover, the test scores can be regressed against the binary variable using a probit regression (Long and Freese, 2001). A probit regression is used to assign probabilities to changes in the independent variables. Additionally, a model using a logit link function for the logistic regression was compared to an inverse normal link function. As the results did not differ, probit regression was chosen as the major tool for differentiation (See Appendix B for details). Subsequently, a multivariate probit regression was applied to a series of ANOVAs (Analysis of Variance) to test whether a combination of the test scores can improve upon the single use of any of the predictors to classify successful entrepreneurship (Long and Freese, 2001). Lastly, additional data (including core strengths, networking behaviour, switches of occupation, self-judgement of thinking type, importance of feedback to that individual, and an additional question which asked individuals to answer an unsolvable question) are used to classify entrepreneurs. A random forest model is generated to help in further classifying entrepreneurs successfully.

To generate further insight into the relationships between the three dimensions of cognitive ability and increased interpretability, three groups for major comparison are constructed: low scorers, medium scorers, and high scorers. For the CRT, individuals with three or fewer correct answers are categorised as low scorers, individuals with four to six correct answers as medium scorers, and individuals with seven correct answers as high scorers. For the AUT, individuals who generate 12 use cases or more are classified as high scorers, individuals with seven or more use cases medium scorers, and all other individuals are categorised as low scorers. For each group, a category is found that is roughly the same size. For example, as only 20 individuals solved the TT without any hint, the respective categories for high CRT and AUT scores correspond approximately to this group size. Criteria that lead to exactly similar group sizes could not be generated, as a one-point increase in test scores leads to several more individuals being added to the group. For each of the groups, a Chi-squared test is performed to compare the differences in proportions of successful entrepreneurs to non-entrepreneurs (Backhaus, Erichson, Plinke, and Weiber, 2016).

Table 3: Number of individuals represented in the groups 'low scores', 'medium scores', and 'high scores' for all test scores

	Low	Medium	High
CRT	111	139	16
AUT	144	102	20
TT	190	56	20

Comparing entrepreneurs among each other

To assess whether the test scores are related to a greater level of success, a linear regression is used to regress the test scores against the adjusted success measure. A linear regression model is especially useful in this case because of the interpretability of the R^2 and p-value (Backhaus et al., 2016).

Investigating non-linear behaviour of the three cognitive dimensions

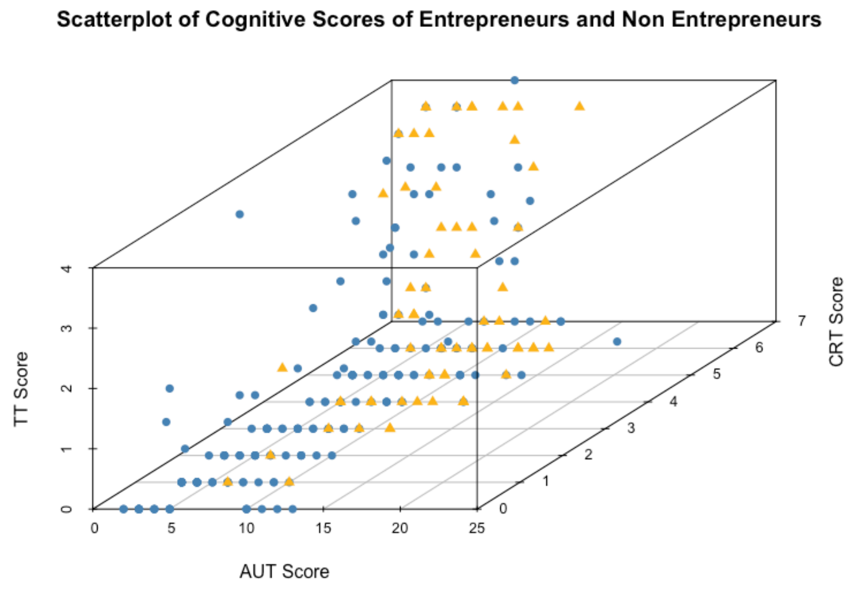
To investigate whether the CRT and AUT scores follow an inverse U-shaped relationship, a linear and a series of polynomial regressions are fitted to the data. Polynomial regressions up to a quartic model are fitted and compared to each other through ANOVAs. In order to test whether the divergent part of analogical thinking – that is, all test scores of four in the TT – leads to correlation between CRT and TT performance, two multivariate linear regressions are compared. One includes all scores of four, and one includes the entire data set. Finally, to test whether high-level analogical thinking ability is accompanied by both high-level creative and logical thinking ability, subsets with both high CRT and AUT scores were compared to subsets with both low scores and high scores in only one of the categories. The subsets’ TT performance was compared using Mann-Whitney U tests.

4 Results and Interpretation

4.1 Successful Entrepreneurs and Non-Successful Entrepreneurs: A predictive model

4.1.1 Results

The test results of the entrepreneurs are illustrated in the graph below, enabling an intuitive understanding of the data. Successful entrepreneurs, marked as yellow triangles in the data set, seem to be significantly more frequent among high TT scorers and significantly less frequent among low scorers in all of the tests. Whether these observations are significant and how they differ in magnitude will be discussed in the following paragraph.



C

Figure 2: Three-dimensional scatterplot of test score data; AUT scores are plotted along the X-axis, TT scores along the Y-axis and CRT scores along the Z-axis; successful entrepreneurs are indicated in yellow, non-successful entrepreneurs are indicated in blue

Non-normality of data

The Shapiro-Wilk Test for all three samples indicates high non-normality:

Table 4: P-value of Shapiro-Wilk Test of test scores

	P-value
CRT	$2.2 \bullet 10^{-16}$
AUT	$6.5 \bullet 10^{-10}$
TT	$9.1 \bullet 10^{-11}$

The low p-values in the test scores result from the light-tailed distributions; only few non-severe outliers could be found. Consequently, whenever possible, non-parametric methods such as the Whitney U test were used. However, the multivariate probit regression, which assumes a normal distribution, can be used without further concerns, as no major differences between the logistic and probit regression models arise. All graphical test data and residuals can be found in Appendix C.

Independent two-group Mann-Whitney U tests

All test scores differ significantly from each other, as demonstrated by conducting three independent two-group Mann-Whitney U tests. The mean values have to be interpreted with caution, as the two samples compared to each other follow a non-normal distribution. Given the light-tailed behaviour of the test score data, there are no outliers to distort the mean values. Therefore, mean scores are still included in the table on the next page.

Table 5: Mean scores of entrepreneurs vs non-entrepreneurs, percentage increase of mean scores, and p-values of Mann-Whitney U test of test scores

	Mean	P-value
Entrepreneurs	CRT: 5.13 AUT: 8.48 TT: 1.30	
Non-entrepreneurs' share in category	CRT: 3.41 AUT: 6.19 TT: 0.51	CRT: $8.0 * 10^{-8}$ *** AUT: $1.2 * 10^{-7}$ *** TT: $6.8 * 10^{-5}$ ***
Percentage increase	CRT: 50% AUT: 43% TT: 155%	

The results indicate significant differences in the two groups based on the non-parametric Mann-Whitney U test. Successful entrepreneurs seem to be more likely than non-entrepreneurs to score highly in logical, creative, and analogical thinking ability. The relative difference is greatest for the TT, followed by the CRT and the AUT.

Single factor probit regression

The probit regression corroborates the above results and adds further interpretability. In the following table, the estimate of the increase in z-value, the p-value testing the log odds and odds ratios, the residual deviance, the Akaike Information Criterion (AIC), the R^2, and the p-value of the R^2 are presented. The AIC and residual deviance are included to compare the performance of the models both among each other and to the multivariate probit regression, which is similar to performing an ANOVA on a probit regression model. Moreover, McFadden's Pseudo R^2 and respective p-values (McFadden, 1973) were calculated. To calculate McFadden's R^2, his proposed formula $\frac{1-\ln(L_{mod})}{\ln(L_0)}$ has been used, where L_{mod} represents the model with the explained variables and L_0 the null model. These two extra outcomes have been used to offer an estimate of the fit of the model.

The regression model exhibits the following behaviour, where Y is a binary term indicating the presence of successful entrepreneurship and X the vector or regressors, in this case the CRT, AUT or TT score. β was estimated by maximum likelihood using the software R. The equation is $Y = \begin{cases} 1 & if\ X^T\beta + \varepsilon > 0 \\ 0 & otherwise \end{cases}$ (equation 1) where $\Pr(Y = 1 \mid X) = \Phi(X^T\beta)$ and where Pr denotes probability and Φ stands for the cumulative distribution function of the standard normal distribution. For each vector *X*, a vector β has been fit to create the below table.

Table 6: Coefficients, p-value, residual deviance, AIC, McFadden's Pseudo R^2, and p-value of McFadden's Pseudo R^2 of probit regression fitted to test score data

	Coefficient	p-value	Residual deviance	AIC	R^2	p-value R^2
CRT	0.28513	$8.31 \cdot 10^{-8}$ ***	239.51	244	0.13	4.75e-09
AUT	0.13501	$3.66 \cdot 10^{-6}$ ***	250.15	254	0.08	1.16e-06
TT	0.25678	$7.25 \cdot 10^{-5}$ ***	258.11	262	0.06	7.50e-05

The coefficients represent the increase in z-value estimates for the probability distribution of being a successful entrepreneur per one-point increase in test scores. They can be used to calculate the probabilities of individuals classifying as entrepreneurs. A CRT score of 7 compared to a CRT score of 0 increases the likelihood of being an entrepreneur by 46.5%. An AUT score of 12 compared to an AUT score of 0 increases the likelihood of being a successful entrepreneur by 40.0% according to the model. Lastly, a TT score of 4 compared to a TT score of 0 increases the likelihood by 35.0%. This further validates the hypothesis of entrepreneurs having higher creativity, higher cognitive reflection, and higher analogical thinking abilities. The p-value indicates that the observed relationship is highly significant. The residual deviance, AIC, and R^2 can be used to determine the fit of the model. According to these criteria the CRT offers the greatest predictive power, as it presents the highest R^2 and the lowest residual deviance and AIC. The p-value of the respective R^2 indicates that all calculated R^2 values offer a reliable, significant estimation of the fit of the models. Consequently, H1a (***), H2 (***), and H3 (***) are confirmed.

Multivariate probit regression

To assess the individual contributions to the overall classification, a multivariate probit regression is conducted, providing the following results. The model is the multivariate version of equation 1 where β_1, β_2, and β_3 indicate the individual coefficients of the CRT, AUT, and TT respectively.

Table 7: Coefficients, p-value, residual deviance, AIC, McFadden's Pseudo R^2, and p-value of McFadden's Pseudo R^2 of probit regression fitted to test score data

	Coefficient	p-value	Residual deviance	AIC	R^2	p-value R^2
CRT	0.23801	4.03e-05 ***	220.21	228	0.20	1.37e-11
AUT	0.11265	3.31e-04 ***				
TT	0.13830	4.81e-02 **				

In this model, the coefficients of the scores can be added to offer a compound estimate of the probability of an individual being a successful entrepreneur. According to the model, an individual with high scores in all of the tests, namely 7 in the CRT, 12 in the AUT, and 4 in the TT, can be considered 78.5% more likely to be a successful entrepreneur than an individual who scores zero in all of the tests. Moreover, the decrease in the coefficient and p-value of the TT score also indicates that TT scores can be predicted partly by AUT and TT scores. This is especially true for the few people who score highly on both the TT and AUT, as will be seen in subsequent chapters of this dissertation. As can be seen compared to the individual regressions conducted above, the lower residual deviance, the lower AIC, the greater pseudo-R^2, and the lower p-value for the respective pseudo-R^2 all indicate a greater model fit with greater predictive power. A value of 0.20 for McFadden's R^2 is considered an excellent fit for empirical models (Hensher and Stopher, 1979).

To summarise these results, all individuals are ordered and plotted against the likelihood of being a successful entrepreneur predicted by the multivariate probit analysis.

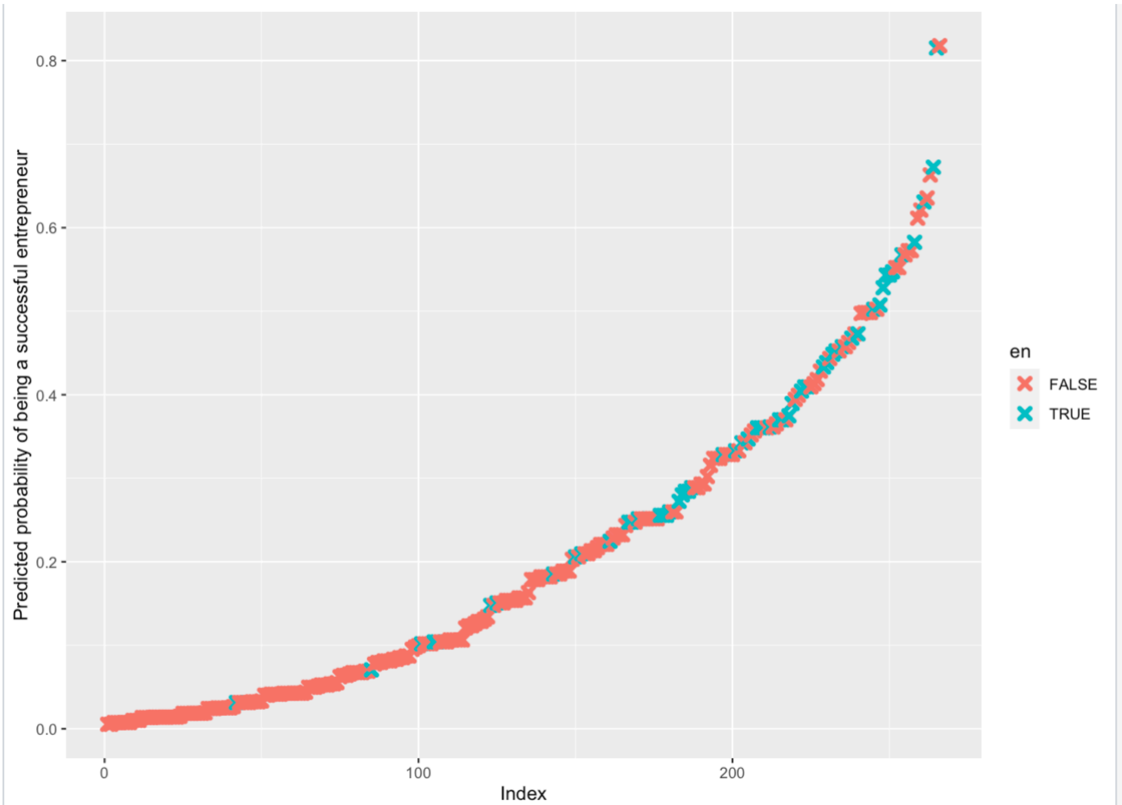


Figure 3: Predicted probability of being a successful entrepreneur based on multivariate probit regression model plotted for each participant in the survey; entrepreneurs are marked in blue, non-entrepreneurs are marked in red

What can be seen from this graph is that the model does indeed predict an increasing likelihood of being an entrepreneur for someone who scores highly in all dimensions. However, a significant number of non-entrepreneurs score highly on the test as well. The greatest differentiator, in fact, is a low score in all of the tests. This will be further investigated in the next chapter. Further polynomial multivariate probit regressions are fitted and can be found in Appendix D. None of the polynomial models outperformed the linear multivariate regression according to the AIC.

Predicting successful entrepreneurship via advanced classification models

In addition to the multivariate probit regression, which seems beneficial in defining a range in which people are unlikely to become successful entrepreneurs, a random forest model is fitted which takes into account further periphery data of the entrepreneurs discussed in chapter 3.5 and the additional CRT dummy question whose relation to other test scores is described in Appendix E. The first random forest model was built on the entire data set. 500 trees are constructed, and the number of variables tried at each split is three. The confusion matrix and the model can be found below. The out-of-bag error for this model was 15.8%.

Table 8: Confusion matrix of first random forest model: False indicates that individuals belong to the group of non-entrepreneurs, true indicates that individuals belong to the group of successful entrepreneurs; the horizontal axis indicates true labels, the vertical axis indicates random forest predictions

	False	True	Class error
False	202	6	2.9%
True	33	23	58.9%

This is an especially strong predictor in terms of classifying non-successful entrepreneurs, while successful entrepreneurs are still classified correctly in slightly less than half of the cases. A graphical representation using an inverse proximity matrix for Euclidean distances is presented below. The axes are thus similar to that of a Principal Component Analysis.

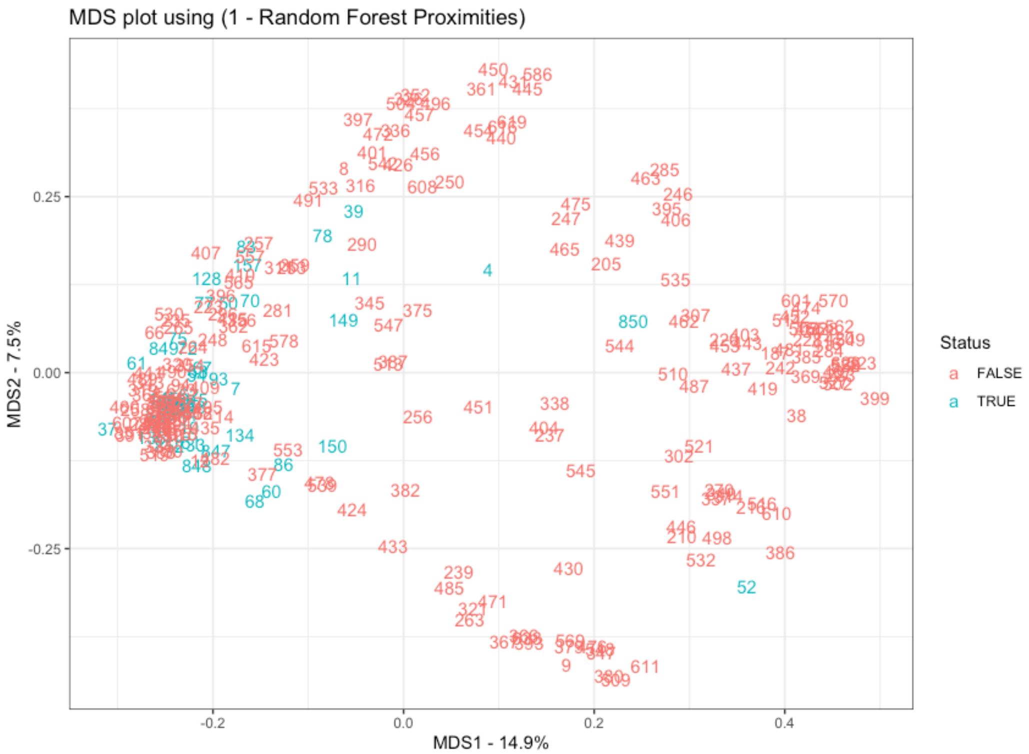


Figure 4: MDS plot as inverse proximity plot of successful entrepreneurs (blue, true) versus non-entrepreneurs (red, false); the two axes are the two dimensions accounting for the greatest variation (indicated as percentage points on each of the axes)

To prevent the misclassification of many successful entrepreneurs as non-entrepreneurs, a second random forest with similar parameters but an evenly distributed sample is built which includes as many non-entrepreneurs as entrepreneurs. The sample comprises all of the successful entrepreneurs and a randomly selected group of non-entrepreneurs. R’s set.seed(10) function is used for the randomisation. The confusion matrix reads as follows with an out-of-bag error estimate of 32.1%.

Table 9: Confusion matrix of second random forest model containing as many entrepreneurs as non-entrepreneurs: False indicates that individuals belong to the group of non-entrepreneurs, true indicates that individuals belong to the group of successful entrepreneurs; the horizontal axis indicates true labels, the vertical axis indicates random forest predictions

	False	True	Class error
False	46	16	25.8%
True	20	30	40.0%

Upon first examination the results seem poor, but after further graphical cluster analysis three distinct groups emerge. The labelling of true or false is based on random forest predictions.

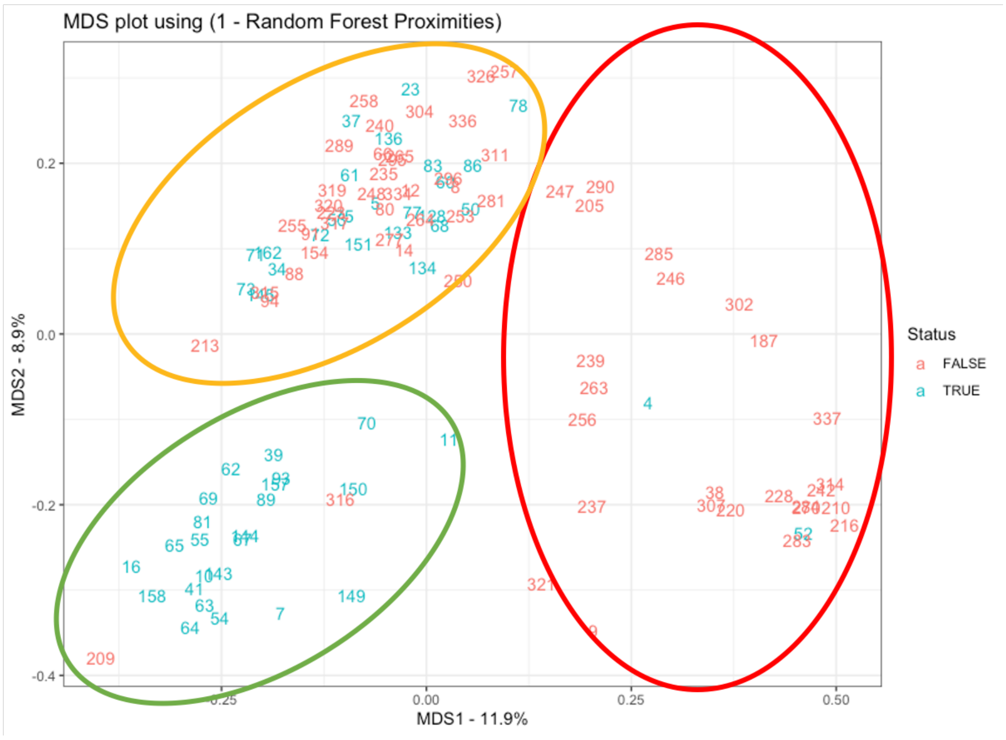


Figure 5: MDS plot as inverse proximity plot of successful entrepreneurs (blue, true) versus non-entrepreneurs (red, false); the two axes are the two dimensions accounting for the greatest variation (indicated as percentage points on each of the axes)

The green, red, and yellow clusters offer further interpretability. Individuals in the green cluster are very likely to be successful entrepreneurs and individuals in the red cluster are very unlikely to be successful entrepreneurs. It is the yellow cluster which adds ambiguity to the classification algorithm, which cannot discriminate between the three distinct clusters. However, human investigation of the data or K-means analysis can be of help to determine an individual's success potential. The three distinct clusters emerge consistently when a random forest model is generated. The table below shows other random forests which were generated by the same data. Cross-validation has not been performed as, for random forests, the out-of-bag-error gives an unbiased estimate of the error rate; each tree is built by way of a different bootstrap sample (Breiman, 2001).

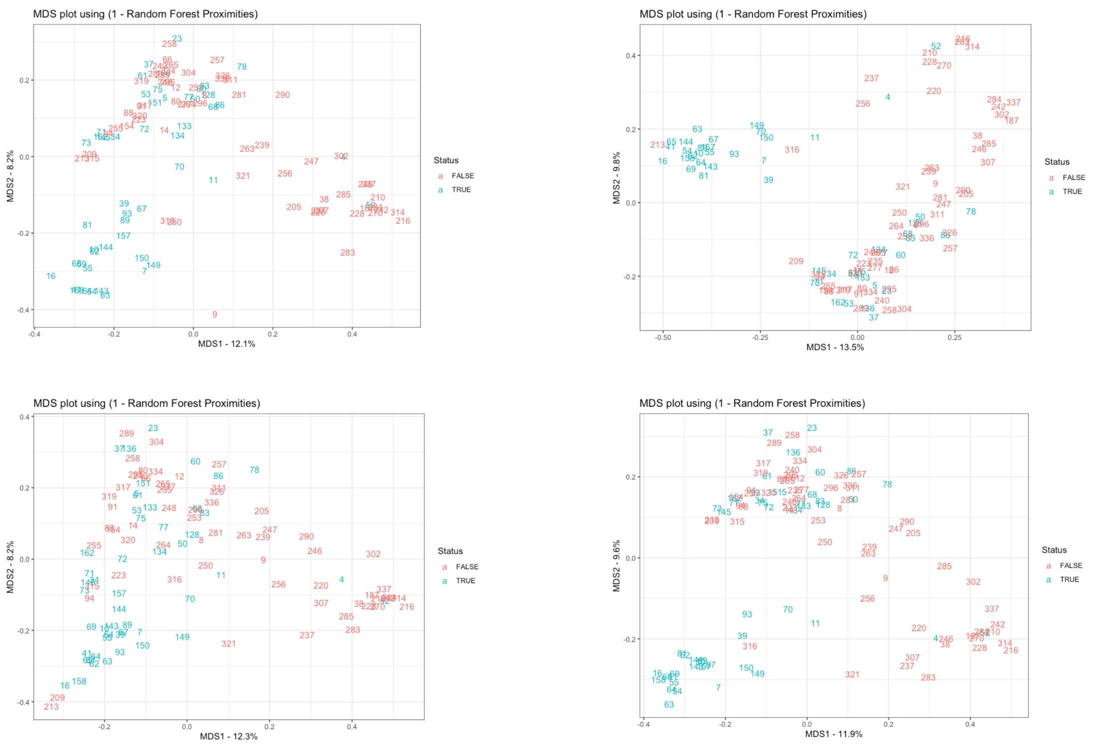


Figure 6: Overview of four randomly generated random forest models to classify data ceteris paribus for all input variables to the first random forest model

The predictive power of these non-linear models invites further analysis of the three cognitive dimensions and their relation to entrepreneurship.

Digging deeper: Odds and probabilities of entrepreneurs belonging to each category

The logistic and probit regressions belong to the family of generalised linear models. The question remains as to whether a low score in the tests is as indicative of the absence of successful entrepreneurship as a high score is indicative of the presence of successful entrepreneurship. The plotted histograms below offer a first indication.

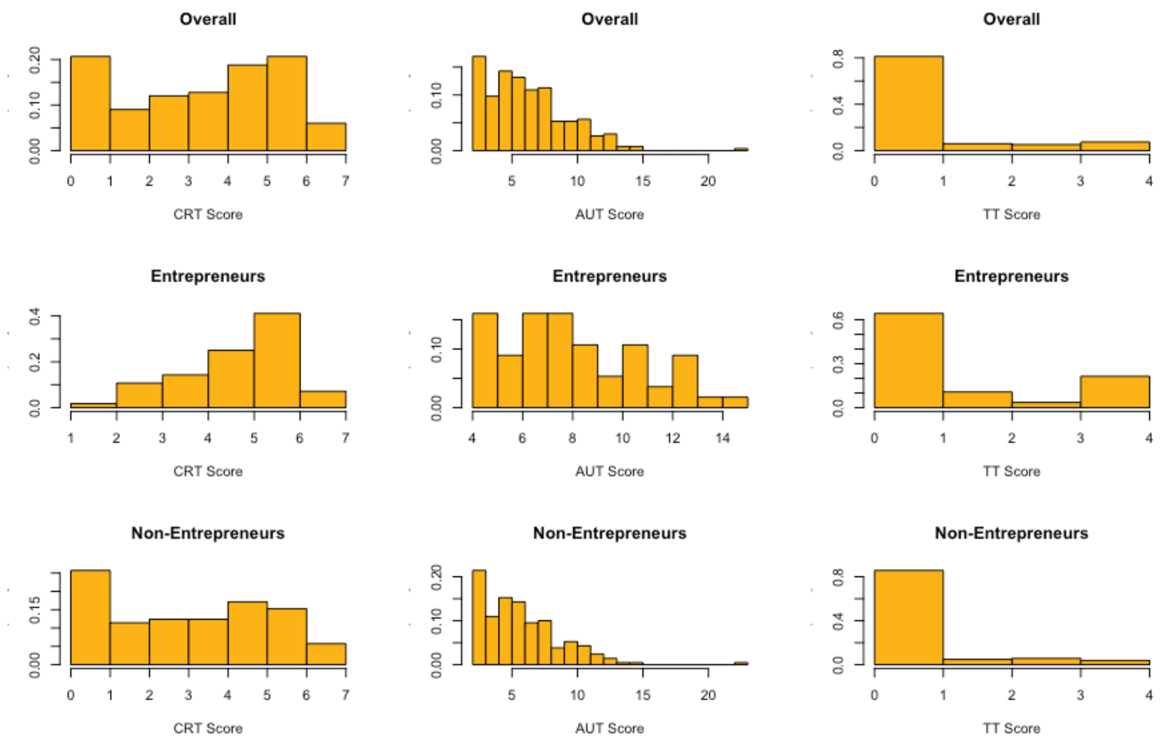


Figure 7: Histograms of overall sample (top), successful entrepreneurs (middle), and non-entrepreneurs (bottom) of CRT scores (left), AUT scores (middle), and TT scores (right)

Upon examining the histograms, it becomes immediately apparent that entrepreneurs seem to be less likely to have low scores in the AUT, CRT, and TT, and seem significantly more likely to score highly in the TT. To confirm this assumption, three groups for each of the three cognitive dimensions were constructed. The following table and graph summarise the percentage of successful entrepreneurs and non-entrepreneurs in each respective category.

Table 10: Percentages, percentage increases, and p-values of successful entrepreneurs versus non-entrepreneurs belonging to the categories 'low scores', 'medium scores', and 'high scores' for CRT, AUT, and TT scores

	Low	Medium	High
Entrepreneurs' share in category	CRT: 12.5% AUT: 25.0% TT: 51.8%	CRT: 80.4% AUT: 58.9% TT: 26.8%	CRT: 7.1% AUT: 16.1% TT: 21.4%
Non-entrepreneurs' share in category	CRT: 49.5% AUT: 61.9% TT: 76.7%	CRT: 44.8% AUT: 32.9% TT: 19.5%	CRT: 5.7% AUT: 5.2% TT: 3.8%
Relative increase (decrease) in %	CRT: (296.0%)*** AUT: (147.6%)*** TT: (48.1%)***	CRT: 79.5%*** AUT: 79.3%*** TT: 37.2%	CRT: 25.0% AUT: 206.8%** TT: 462.5%***
P-value of difference compared to rest of sample	CRT: $9.15 \cdot 10^{-6}$ AUT: $1.21 \cdot 10^{-5}$ TT: $1.13 \cdot 10^{-3}$	CRT: $4.83 \cdot 10^{-6}$ AUT: $1.54 \cdot 10^{-3}$ TT: 0.29	CRT: 0.72 AUT: 0.015 TT: $7.9 \cdot 10^{-5}$

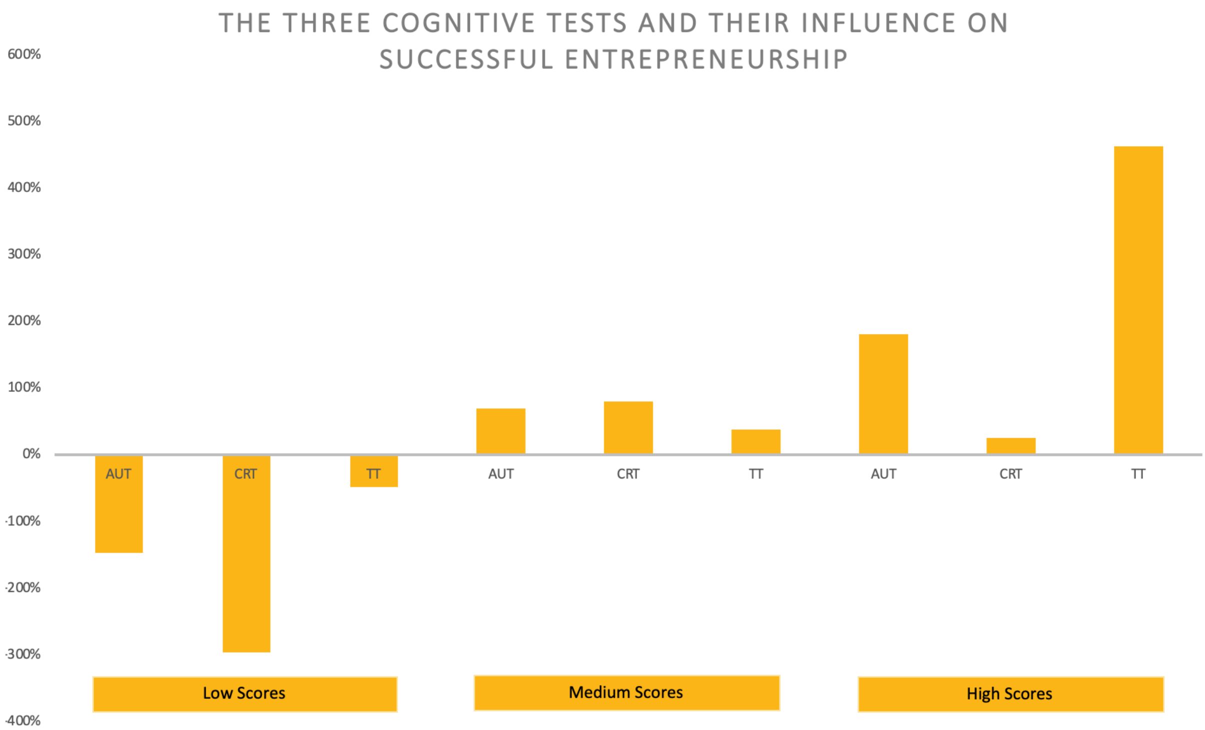


Figure 8: Graphical representation of differences in the likelihood of belonging to the groups 'low scores', 'medium scores', and 'high scores' for successful entrepreneurs versus non-entrepreneurs

Three key differences are of especially high magnitude: Entrepreneurs are 147.6% less likely to be low AUT scorers and 296% less likely to be low CRT scorers. On the other hand, they are 462.5% more likely to be exceptional analogical thinkers and 206.8% more likely to be exceptional creative thinkers. They are only 25% more likely to be exceptional logical thinkers. This allows for a first general classification: Entrepreneurs seem to be less likely to be non-intelligent and non-creative and more likely to be very good in analogical and creative thinking. This probabilistic argument is derived from the probability calculated from the odds ratio of successful entrepreneurs belonging to each of the nine categories. This is a frequentist interpretation of the data (Neyman, 1977), which will be later commented on in more detail.

The question of the significance of these results remains. To test the significance, a Chi-squared test is implemented which used the frequency of successful entrepreneurs belonging to a respective group and the frequency of all other successful entrepreneurs not belonging to the group as a base population. The null hypothesis which is to be rejected by the Chi-squared test is that the respective proportion of the base population is different to those of the non-entrepreneurs. The respective p-values are indicated in Table 17 above.

This differs from the typical procedure of performing a Chi-squared test across all frequencies to obtain how proportions across the groups of 'low', 'medium' and 'high' scores differ between entrepreneurs and non-entrepreneurs. This study follows a more specific approach to obtain a respective p-value for each of the percentage differences. The trade-off to this approach is that some significant differences are not revealed. For example, the p-value of medium TT scores indicates no significant difference. The true reason, however, is that although entrepreneurs are indeed more likely to score a medium score, the data was distorted by most entrepreneurs achieving the high score. The order of the factors 'low', 'medium', and 'high' is thus lost. Still, the more conservative approach was chosen here to reveal critical significant differences specifically, such as the difference in high TT scores. This confirms hypothesis H1b (***), as entrepreneurs are not more frequent within the high intelligence cluster. However, both high-level creative thinking ability and high-level analogical thinking ability remain strong predictors of successful entrepreneurship.

4.1.2 Interpretation: Predicting success

The presented data suggest a clear distinction between the cognitive abilities of successful entrepreneurs and non-entrepreneurs. Upon more exact inspection, an especially strong relationship can be found: Low scores in all of the cognitive abilities are significantly less common among successful entrepreneurs. In other words: Entrepreneurs are significantly less likely to exhibit low scores in all of the tests. As a result, low cognitive abilities in all three dimensions, individually and in an amplified manner combined, are indicative of a person not being a successful entrepreneur. The multivariate probit regression allows for a general classification of whether an individual has the potential to be a successful entrepreneur. It is especially interesting to see in the multivariate regression model that low scorers are almost never represented among the successful entrepreneurs. The data is so evident that it could be argued that the very few entrepreneurs represented in these areas are either partnered by a strong co-founder or have been lucky with their ventures. High scores in all three of the tests seem to be indicative of successful entrepreneurship. However, while low scorers are unlikely to be successful entrepreneurs, scoring high on all of the dimensions does not suffice to separate a successful entrepreneur from a non-entrepreneur.

The first random forest models classified non-entrepreneurs correctly in 97% of all cases, which is a predictor strong enough to appeal to venture capitalists and renowned accelerators. The second random forest model could be used to cluster aspiring entrepreneurs as high potential, low potential, or ambivalent cases. Individuals belonging to the red cluster may be classified as low potential, and thus unlikely to succeed. They might need further training in both creative and analogical thinking, as logical thinking is mostly stable over time. Individuals belonging to the green cluster might be considered to exhibit high potential, with a high likelihood of succeeding. Individuals within the yellow area might be considered ambiguous cases. From a frequentist perspective, they are approximately as likely to succeed as to fail in solving problems characterised by unknown unknowns. Should the model of this dissertation extend to all uncertain environments, such a random forest may also be used for identifying promising new managers and academics. Lastly, the yellow, ambiguous cluster might be due to personal preferences. Because cognitive ability is mostly a measure of potential, many individuals in the ambiguous cluster may have the potential but not the desire to start a firm.

The difference in predictive power between the linear models and the random forest model may be a result of the non-linear behaviour of the three cognitive dimensions. All linear models predict that an increase in all of the dimensions will lead to an equal increase in the likelihood of being a successful entrepreneur. Comparing low, medium, and high scorers among each other revealed that this is not the full picture. The mere presence or absence of low logical ability seems to be the major differentiator between entrepreneurs and non-entrepreneurs; subsequently, high creative thinking ability and especially high analogical thinking ability make the difference. The difference in mean scores thus results from different statistical properties. For CRT scores, such differences result to a great extent from the absence of low CRT scores in the successful entrepreneurship group. For the AUT scores, differences result from both the absence of low scores and the presence of high scores. For the TT scores, differences result mostly from the presence of high scores. This cements the theory that, beyond a certain threshold of IQ or logical thinking ability, other cognitive predispositions, such as high levels of creative and analogical thinking ability, account for the major differences in performance.

4.2 Comparing successful entrepreneurs among each other

4.2.1 Results

Three Kendall-Theil-Siegel linear non-parametric regressions are performed with test scores regressing against each of the adjusted success measures, including revenue, funding, and employees divided by the months since the entrepreneurial venture began operating. Data is reduced to 37 individuals who provided truthful answers on their success metrics. Individuals who reported higher profit than revenue, for example, were filtered out. For each of the regressions, the number of individuals is reduced further if partial information is missing (for example, less data about funding than revenue growth is provided). The regression reports p-values and mean absolute deviation, the latter of which offers a robust estimate for variability, and yields the following results, displayed in the table below.

The regression model follows the classical linear slope $Y = X^T\beta + \varepsilon$ (equation 2) of typical regression models. Compared to equation 1, Y is continuous and β was fitted by minimising median deviations instead of mean deviations.

Table 11: Coefficient, Medium Absolute Deviation, p-value and predicted success metrics in pound for revenue and funding comparing maximum achieved score (7 for CRT, 23 for AUT, 4 for TT) to minimum scores for 5 years of operation of Kendall-Theil-Siegel linear

	Success Metric	Coefficient	MAD	P-value	Increase in success metric according to criteria above
CRT	Revenue	1229	1806	$8.22 \bullet 10^{-7}$ ***	516 180 £
CRT	Funding	1782	2814	$3.56 \bullet 10^{-5}$ ***	748 440 £
CRT	Employees	0.07	0.06	$1.12 \bullet 10^{-4}$ ***	29.4
AUT	Revenue	108.6	808.8	0.20	149 868 £
AUT	Funding	515.38	1029.7	$1.57 \bullet 10^{-2}$ **	711 224 £
AUT	Employees	0.02	0.04	0.13	27.6
TT	Revenue	-22.4	1415.5	0.856	-5.376 £
TT	Funding	170.4	1890.5	0.11	40 869 £
TT	Employees	0.04	0.07	$5.0 \bullet 10^{-2}$ **	9,6

The results indicate that CRT scores are significantly related to adjusted success measures. There is also slight evidence that a relationship between TT scores, AUT scores and success measures exists. Adjusted success measures are difficult to interpret, as the division of the respective success measures by the months since start of operation reduces the interpretability of the coefficient. One can think of the coefficient as a one-point score increase in the respective test score, leading to an average increase in an additional *£X* per month. For example, comparing a CRT score of 0 to a CRT score of 7 yields (approximately) an additional £149 688 in funding received per year, which is equivalent to £748 440 for entrepreneurs who have been in operation for exactly 5 years. This is calculated by multiplying the coefficient with 7 for the score dimension and 12 and 5 for the time dimension respectively. This leads to the conclusion that both TT and AUT scores follow a significant relationship with one of the success metrics, but the magnitude to which the success metric is influenced is only considerable for AUT scores. Hypotheses 4 (***), 5 (**) and 6 (**) can thus be confirmed.

4.2.2 Interpretation: Differences in Opportunity Validation and Scaling

The results suggest that individuals with high levels of cognitive reflection, and thus high intelligence, are much more likely to convince investors, generate revenue, and hire employees. As cognitive reflection was expected to be especially useful as problems and settings become narrower, its influence during the scaling phase of the venture was expected to be especially great. These results confirm this hypothesis. TT scores seem to be significantly connected to the adjusted number of employees. However, the connection is weak and needs further investigation. Since only 37 data points remained and data was self-reported, stronger and more significant correlations may be observed once more data is collected. Moreover, the regressions of AUT scores against success measures yielded low p-values and relatively great coefficients. This suggests that creativity plays a role in predicting later-stage success of entrepreneurs. More data will be especially helpful in investigating non-linear relationships between the measures. It is plausible that, at some point, a negative relationship between cognitive reflection and success measures might be observed.

4.3 In-depth effects of the three dimensions and their relation

4.3.1 Results

Intelligence and creativity in relation

It is often claimed that high intelligence is accompanied by low creativity. This would imply that the two factors are negatively correlated: However, this is not the case. It is instead proposed that the factors follow an inversely-shaped U curve. A polynomial regression was conducted to see whether AUT scores could predict CRT scores. A quadratic regression did indeed predict polynomial results, with a p-value of 9e-06 and an R^2 of 0.085. A series of ANOVAs was conducted to test whether the additional fit from the model beats the linear regression; the quadratic regression does perform better than the linear, cubic, and quartic regressions. Hypothesis 7 (***) can thus be confirmed.

Table 12: RDF, RSS, DF, F, and P-value of Quadratic, Cubic, and Quartic regression compared to linear regression model of CRT scores versus AUT scores

Model	Residual DF	RSS	DF	F-value	P-value
Linear (X)	264	1112.8			
Quadratic (X^2)	263	1084.3	1	6.9141	0.009059 ***
Cubic (X^3)	262	1077.2	1	1.7186	0.191020
Quartic (X^4)	261	1074.6	1	0.6291	0.428395

Analogical thinking ability and creativity in relation

It has been proposed that a significant relationship between TT scores and AUT scores prevails only during the divergent thinking part of the TT. Generally, there is a significant relationship between TT scores and AUT scores, even when accounting for logical thinking ability as a potential moderator. As can be seen below, when comparing the general multivariate linear regression with all data in Table 13 to that which only considers TT scores of 3 or lower in Table 14, the relationship between AUT scores and TT scores fades in significance. Hypothesis 8 (***) can thus be confirmed.

Table 13: Coefficients, std. error, and p-value of multivariate linear regression fitting CRT and AUT scores to TT scores

	Coefficient	Std. Error	P-value
Inctercept	-0.29112	0.19491	0.1365
CRT score	0.17659	0.03532	1.05e-06 ***
AUT score	0.04517	0.02393	0.0602 *

Table 14: Coefficients, std. error, and p-value of multivariate linear regression fitting CRT and AUT scores to TT scores excluding all TT scores equal to 4

	Coefficient	Std. Error	P-value
Intercept	-0.11542	0.13732	0.401
CRT score	0.10291	0.02521	6.07e-05 ***
AUT score	0.02224	0.01722	0.198

Significance of CRT, AUT and TT scores in relation to each other

It could be shown that CRT and AUT seem to predict TT scores to some extent. This section aims to examine this relation more closely. There is indeed a positive correlation between TT scores and CRT scores of 0.33 and a positive correlation between TT and AUT scores of 0.19.

Table 15: Correlation matrix of test scores

	CRT score	AUT score	TT score
CRT score	1.0000000	0.2460223	0.3263736
AUT score	0.2460223	1.0000000	0.1862318
TT score	0.3263736	0.1862318	1.0000000

Moreover, one would expect TT scores to be fundamentally higher throughout the sample as CRT and AUT scores rise. Especially as CRT and AUT are partially negatively correlated, only two individuals were found who had both a high CRT and a high AUT score according to the criteria above – a CRT score of 7 and an AUT score above 12 – which were individually achieved by 20 individuals each. Therefore, the criteria have been eased to an AUT score of 8 or higher and a

CRT score of 6 or higher for means of illustration. The criteria are robust to the mean TT score, which remains significantly higher when the criteria are adjusted.

Table 16: Mean TT scores and proportion of entrepreneurs for all data and different sub-groups

	Mean TT score	% of individuals in group being successful entrepreneurs
All data	0.68	21%
CRT above 5 and AUT above 7	1.34	50%
All other tested individuals	0.59	17%
Percentage increase	127%*** ($p = 1.48 \bullet 10^{-3}$)	138%*** ($p = 5.63 \bullet 10^{-5}$)

The stark difference in mean TT scores has to be interpreted with caution because of the non-normality of the sample data. However, as none of the data exhibits long-tailed behaviour, the mean scores are still a meaningful measurement of comparison. To test whether the increase in scores is significant, an independent sample Mann-Whitney U test was performed to compare the data non-parametrically. It is noteworthy to say that within the presence of both high CRT and high AUT, high TT performance seems to be likely. The proportions of non-entrepreneurs and entrepreneurs of all data versus the group with high CRT and AUT scores have been compared using a Chi-squared test, which indicates high significance. The difference in significance has strong implications for successful entrepreneurship: Individuals who score higher in both categories are 138% more likely to be successful entrepreneurs. Hypothesis 9 (***) can thus be confirmed.

The results with regard to entrepreneurship are even clearer if high scorers in all of the dimensions are taken into account, as can be seen in the table below. This is because, as seen in the multivariate probit regression, TT scores are explained to some extent by logical and creative thinking but still contribute significantly to the prediction model.

Table 17: Percentage of individuals in group being successful entrepreneurs for all data and different sub-groups

	% of individuals in group being successful entrepreneurs
All data	21%
CRT above 5, AUT above 7, and TT above 1	62%
All other tested individuals	19%
Percentage increase to all data	195%*** ($p = 3.33 \bullet 10^{-3}$)

Moderately high scores in all three dimensions increase the likelihood of successful entrepreneurs in the sample greater than high individual scores. For example, In comparison, only 6% of all individuals achieved a CRT score of 7 or higher, but the share of entrepreneurs among them is only 25%, which is roughly equal to the share of the entrepreneurs in the overall sample.

4.3.2 Interpretation: Towards Cognitive Generalists – A Call for Cognitive Triathletes

The inverse U-shaped relationship between logical and creative thinking can be interpreted in two ways: Either a high-level logical thinking ability makes it generally less likely for that individual to perform well in creative tasks, as the two dimensions are competing with each other; or high-level logical thinking ability encourages individuals to pursue less creative thinking and more logical thinking. The two assumptions lead to very different implications for entrepreneurship or – in a broader context – dealing with unknown unknowns, as people with relatively high-level logical and creative thinking abilities were significantly more likely to be entrepreneurs. The former interpretation – that logic competes with creativity – implies that those individuals who generally score well in both categories have a better genetic or cognitive predisposition towards being successful entrepreneurs. They should be sought out by venture capitalists and angel investors. The latter interpretation – that logical thinkers deliberately favour logic over creativity – implies that cognitive specialism could be overcome by a balanced education in both creative and logical thinking, especially as creative thinking processes are usually undervalued in education (Kaufman and Pluncker, 2011). There is not yet a great deal of research on analogical thinking ability, but the results suggest that individuals should balance their logical, creative, and analogical thinking abilities to maximise their potential of succeeding as entrepreneurs. In all cases, there is clear evidence that, in terms of predicting successful entrepreneurship, the presence of moderately high levels of ability in all of the dimensions outperforms a very high ability in one of the dimensions.

Secondly, the mechanisms behind analogical thinking have now, to some extent, been demystified. It was shown that creative thinkers seem to be especially likely to solve the TT immediately. This further validates the hypothesis that solving analogical problems is split into two parts: In the first part, an individual generates several analogies that can be used for converging on a potential solution. This part is mainly divergent and seems to be related to the ability to think divergently or creatively. In the second part, the individual finds a schema (Gick and Holyoak, 1983; Keane, 1987), which is mostly a logical, convergent mechanism. As predicted, when excluding the divergent part in the TT, i.e. all scores of four, the significant relationship between creative and analogical thinking ability lessened. The implications of this are discussed in the next chapter.

5 General Discussion

5.1 Contributions to academia

The study primarily examines the cognitive processes and capabilities that contribute to an individual's ability to operate in a nebulous world – often referred to in the relevant research as an environment of unknown unknowns (Loch et al., 2006). The study's results establish that three cognitive processes – *logical*, *creative*, and *analogical* thinking – positively increase the likelihood of successfully navigating a specific use case of such nebulous environments: entrepreneurship. To date, research on unknown unknowns has often focussed on the application of specific methods and principles, such as certain analogical thinking methodologies (e.g. Garbuio et al., 2018; Gassmann and Zeschky, 2008) and project management practices (e.g. Crossan et al., 2005; Loch et al., 2006; McGrath and MacMillan 2000). Cognitive performance is rarely taken into account. The cognitive dimension of this study adds to these research streams and may be of help to design superior methods and project management practices. Especially the finding about the relevance of analogical thinking should inspire researchers to develop methods that involve analogical thought processes.

The relation of the three components to successful entrepreneurship furthers research on analogical thinking ability, intelligence, and creativity collectively. While most researchers investigate and summarize the relationships between logical thinking and creativity (e.g. Jauk et al., 2013; Kaufman and Pluncker, 2011; Schubert, 1973), the fact that the presence of both creativity and logical thinking ability seems to be necessary for successful entrepreneurship adds to the literature's impact and scope. Moreover, the advancement of the logical-creative model by a third dimension, analogical thinking, which offers additional explanatory power, may be especially useful in research situations where logical and creative thinking ability fail to provide an answer. Research on the psychology of success (e.g. Baum et al., 2011) and new venture growth (e.g. Baum and Bird, 2010; Frese and Gielnik, 2014; Jin and Kirsch, 2015) may especially benefit from the findings in this paper.

Moreover, next to the collective contributions of the variables, the in-depth analysis of the individual contributions of each of the cognitive dimensions broadens current research assumptions as well.

The study adds to research on the individual relation between logical thinking and entrepreneurship or, in general, problem-solving in environments characterised by unknown unknowns. It has been shown that logical thinking ability increases success in entrepreneurship up to a certain threshold but fades in significance once this level has been reached, implying a degressive or even polynomial relationship. Once an individual has reached this threshold of logical thinking ability, creative thinking ability and analogical thinking ability add additional explanatory power. This extends Kahneman and Klein's (2009) claim that the logical thinking style generally predicts success in uncertain environments.

The results confirm Sternberg's (1999a, 2004) and Ward's (2004) theories of the role of creativity in entrepreneurship, as higher levels of creativity were shown to be a predictor of success. In addition, this study extends these findings by investigating the relationships between creativity and logical thinking ability. Especially when creative thinking ability is paired with logical thinking ability, the chances of success increase. Moreover, prior research finds a positive linear relationship between creativity and logical thinking ability – up to a certain point, after which correlation seems to average zero (e.g. Schubert, 1973; Kaufman and Pluncker, 2011; Jauk et al., 2013). This study, however, establishes an inverse U-shaped relationship between the two variables.

Moreover, the study adds to the literature on analogical thinking. This study advances Gick and Holyoak's (1983), Gentner's (1983, 1993), and Keane's (1987) research on analogies, by defining analogical thinking ability as an important factor in entrepreneurship as well as explaining its divergent and convergent parts. This study is the first known to the author to implement Duncker's (1945) radiation problem as an effective measure of analogical thinking ability instead of a measure to investigate analogies in general. Prior to this, the problem was mainly used to describe the cognitive mechanisms behind logical thinking. This also extends Gassmann's approach, who argued that there is merely a step of abstraction, followed by steps of analogising and adapting to build a solution (Gassmann and Zeschky, 2008). Gassmann and Zeschky's steps might be extended to include a preliminary step, one that is primarily creative and that focusses on which solutions in the solution space are considered in the first place. These results also contribute further insights into existing empirical psychological research (Gentner, 1983; 1993; Gick and Holoyoak, 1983; Holyoak and Thagard, 1989; Keane, 1987), which suggests that analogical problem-solving, in the absence of deliberately presented analogous stories, depends on creative thinking and the ability of individuals to generate analogues themselves. In reality, unlike in the TT, entrepreneurs are not presented with helpful narrative hints. This is a potential explanation of why scores of four in the TT were especially likely among entrepreneurs.

This study incorporates non-linear and machine learning methods of analysis to gain insights into how or whether we can predict who might be a successful entrepreneurs, which are usually not incorporated in research on success in relation to intelligence and creativity (e.g. Baum and Bird, 2011; Gould, 1996; Jensen, 1998; Schubert, 1973).

Furthermore, methodologically, comparing undoubtedly successful entrepreneurs to a set of non-entrepreneurs by means of binary regression and sample tests appears to be a fruitful approach to assessing entrepreneurial success. Comparing success metrices such as the revenues and profits of different ventures is difficult, as entrepreneurs sometimes value social goals over financial goals, work on their business part-time, or pass their ventures on to new CEOs. Future research could focus on comparing successful entrepreneurs to non-entrepreneurs by means similar to this study. The separation model was inspired by Lackeus (2015), Sadler-Smith (2015), and Frese (2007). Future work would benefit from agreeing on a mutual terminology for these stages.

5.2 Contributions to practical matters

The findings of this study are expected to be of particular interest to three main stakeholder groups: investors, educators, and entrepreneurs. The three dimensions offer a concise, accessible model, which can be used by investors for better venture pre-selection. The linear models used in this study classified the 150 weakest performers correctly as non-successful entrepreneurs in 96% of all cases. Moreover, the non-linear random forest with all data predicted non-successful entrepreneurs correctly in 97% of all cases across the entire data set. Especially for early venture capitalists and angel investors with high deal-flow, a preselection mechanism with these levels of accuracy could be of high relevance. Furthermore, the second random forest model of this study generated clusters in which entrepreneurship seems to be especially likely. This could represent a further tool in identifying high-potential entrepreneurial candidates. By comparing over 20 instances of expert prediction versus algorithm prediction in healthcare, Meehl (1954) was able to demonstrate that algorithms almost exclusively outperformed expert decisions in the long run. As 96% of investors were categorised as highly overconfident in a study conducted by Zacharakis and Sheperd (2001), adhering to algorithmic pre-selection may offer a competitive edge to those who can accept and systematically erase their biases through machine prediction.

Also, educators may be encouraged by this study to focus on the improvable dimensions of intelligence presented in this study. Even though logical thinking ability is not thought to change over time (Stagnaro et al., 2018), creativity is trainable both from a neurological (Lopata et al., 2017) and purely empirical perspective (Epstein et al., 2008). Analogical thinking ability is expected to be trainable, as the application of analogical thinking methodologies has been shown to increase innovation and entrepreneurship (Garbuio et al., 2018; Gassmann and Zeschky, 2008). While logical thinking, the untrainable part of this dissertation's equation, seems to be overemphasized in education, the clear consequence of these results is that education should focus more on the trainable parts: creativity and analogical thinking. Hopefully, the importance of analogical thinking established by this study will function as a signal to educators to promote the practice of analogical thinking methodologies, and indeed more widespread encouragement of the solving of problems characterised by unknown unknowns by providing meaningful analogies to accompany the solving of the task.

Especially early stage entrepreneurs may find these findings useful and may use this study as an impetus to focus on their creative and analogical problem-solving processes when building a new venture. While the importance of the two dimensions remains partly opaque for venture scaling, their contribution to venture building has been shown to be undeniably significant.

5.3 Limitations and Future Work

The main impetus of this study was to use entrepreneurship as a proxy for uncertain environments, which entail problems involving many unknown unknowns. As the insights gained in this study are naturally limited to the context of entrepreneurship, there should be a fundamental interest in research to test similar effects in business, politics, and academia. It is to be expected that, whenever an individual is successful in dealing with unknown unknowns, their performance in the tests used here will be similar to those of successful entrepreneurs. However, this assumption should be thoroughly tested. The non-linear relationship reported in the study may hold true for Jensen (1996), who shows that IQ positively relates with occupational success, socioeconomic status, and eminence.

Those with especially high levels of occupational success, socioeconomic status, and eminence may be cognitive triathletes who perform well across all dimensions but are not among the very highest in any of the single dimensions. The explanatory power that IQ lacks as a single predictor might rise significantly when also assessing creativity and analogical thinking ability. Moreover, Simonton (2006) reports that IQ scores predict a US president's effectiveness to some extent. As US presidents operate under conditions of high uncertainty, the measures reported in this study may contribute additional explanatory power to such a prediction model.

Further research could focus especially on identifying environments characterised by unknown unknowns in which the findings of this study hold true. Furthermore, researchers are invited to point out differences in cognitive dimensions that may be useful in different environments according to the model used in this study. Those differences can be used to describe the best strategies to cope in such environments. Moreover, the participants of this study were drawn from two groups: A broad population of people from all over the world in all kinds of circumstances was compared to a more homogenous group of successful entrepreneurs. How other specific groups perform in the tests conducted in this study should also be investigated. How would Ivy League students perform? How will academics do? Answering those questions will shed light on whether the effects found in this study also help to distinguish entrepreneurs from other successful individuals; the expectation should be that those successful individuals will score better in logical thinking tests and worse in tests of creativity and analogical thinking.

A low number of entrepreneurs (37) were classified as truthfully answering questions on success measures, which did not allow for representative regressions. This is especially true with regard to the contribution of all three dimensions. A larger, more comprehensive survey should be conducted which, ideally, uses secondary data as a metric of success.

Analogical thinking could be partly explained by creative and logical thinking. Yet, the author believes there are fundamentally different mechanisms at play. Future research that seeks to understand the processes that enable analogical thinking would be of great interest.

6 Summary and Conclusion

This study was concerned with investigating three dimensions of cognitive ability and their impact on effectively navigating a setting characterised by unknown unknowns, specifically in the context of entrepreneurship. The first part of this study established that successful entrepreneurship can be predicted by cognitive predisposition. The random forest model classified non-entrepreneurs successfully in 97% of all cases across the entire data set with an overall out-of-bag-error of 15.8%. A second random forest model was able to identify clusters of almost exclusively successful entrepreneurs. The second part of this study demonstrated that high-level logical thinking ability increases entrepreneurs' yearly funding strongly and revenue growth slightly. High-level analogical thinking ability is also significantly correlated with revenue growth. The third part of this study demonstrated that logical and creative thinking ability follow an inverse U-shaped relationship. Analogical thinking can partly – albeit not fully – be predicted by creative and logical thinking. Moderate performance in all dimensions is a better predictor of success than especially high performance in any one of the dimensions. Entrepreneurs were 296% less likely to have below-average logical thinking abilities and 148% less likely have below-average creative thinking abilities. They were 207% more likely to have high-level creative thinking abilities and 463% more likely to have high-level analogical thinking abilities. They were 25% – an insignificant factor in this context – more likely to have high logical thinking ability.

These findings suggest that successful entrepreneurship can be predicted based on cognitive performance. Venture capitalists might be especially interested in applying machine-supported pre-selection mechanisms according to this model. Entrepreneurs, educators, and any other individuals dealing with highly uncertain environments characterised by unknown unknowns may take these findings on analogical and creative thinking ability – which can be trained – as encouragement to focus on developing these abilities further. Moreover, all kinds of renowned admission programs related to the settings of this study might better focus on achieving a good balance in all three cognitive dimensions rather than overly emphasising the IQ component. It seems that 'cognitive triathletes' outperform 'cognitive marathon runners'. Especially analogical thinking ability, and its high impact on venture success, should be subject to further research both in terms of a better understanding of its theoretical underpinnings and of its relevance in different domains.

Bibliography

Amabile, T. M. (2018) *Creativity in Context: Update to the Social Psychology of Creativity*. Routledge.

Backhaus, K. *et al.* (2016) *Multivariate Analysemethoden: Eine anwendungsorientierte Einführung*. 14th edn. Gabler Verlag. doi: 10.1007/978-3-662-46076-4.

Baron, R. A. (1998) 'Cognitive mechanisms in entrepreneurship: Why and when enterpreneurs think differently than other people', *Journal of Business Venturing*, 13(4), pp. 275–294. doi: 10.1016/S0883-9026(97)00031-1.

Baron, R. A. (2000) 'Psychological Perspectives on Entrepreneurship: Cognitive and Social Factors in Entrepreneurs' Success', *Current Directions in Psychological Science*, 9(1), pp. 15–18. doi: 10.1111/1467-8721.00050.

Barron, F. (1955) 'The disposition toward originality', *The Journal of Abnormal and Social Psychology*, 51(3), pp. 478–485. doi: 10.1037/h0048073.

Baum, J. R., Bird, B. J. and Singh, S. (2011) 'The Practical Intelligence of Entrepreneurs: Antecedents and a Link with New Venture Growth', *Personnel Psychology*, 64(2), pp. 397–425. doi: 10.1111/j.1744-6570.2011.01214.x.

Bennetts, C. *et al.* (2017) 'Comparing Facets of Divergent Thinking in Engineering Freshmen and Upperclassmen', in. *ASME 2017 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, American Society of Mechanical Engineers Digital Collection. doi: 10.1115/DETC2017-67604.

Billingsley, P. (1995) *Probability and Measure*. Wiley.

Bibliography

Breiman, L. (2001) 'Random Forests', *Machine Learning*, 45(1), pp. 5–32. doi: 10.1023/A:1010933404324.

Crossan, M. *et al.* (2005) 'Time and Organizational Improvisation', *The Academy of Management Review*, 30(1), pp. 129–145. doi: 10.2307/20159099.

Cummings, J. and Teng, B.-S. (2003) 'Transferring R&D Knowledge: The Key Factors Affecting Knowledge Transfer Success', *Journal of Engineering and Technology Management*, 20, pp. 39–68. doi: 10.1016/S0923-4748(03)00004-3.

Dahl, D. W. and Moreau, P. (2002) 'The Influence and Value of Analogical Thinking during New Product Ideation', *Journal of Marketing Research*, 39(1), pp. 47–60. doi: 10.1509/jmkr.39.1.47.18930.

Drucker, P. F. (1985) *Innovation and Entrepreneurship*. Taylor & Francis Ltd - M.U.A. Available at: https://www.dawsonera.com/abstract/9780080549415 (Accessed: 15 July 2020).

Duncker, K. (1945) 'On problem-solving', *Psychological Monographs*. Edited by L. S. Lees, 58(5), pp. i–113. doi: 10.1037/h0093599.

Epstein, R., Schmidt, S. M. and Warfel, R. (2008) 'Measuring and Training Creativity Competencies: Validation of a New Test', *Creativity Research Journal*, 20(1), pp. 7–12. doi: 10.1080/10400410701839876.

Feist, G. J. (1998) 'A Meta-Analysis of Personality in Scientific and Artistic Creativity', *Personality and Social Psychology Review*, 2(4), pp. 290–309. doi: 10.1207/s15327957pspr0204_5.

Frederick, S. (2005) ‘Cognitive Reflection and Decision Making’, *Journal of Economic Perspectives*, 19(4), pp. 25–42. doi: 10.1257/089533005775196732.

Frese, M. (2009) *Toward a Psychology of Entrepreneurship: An Action Theory Perspective*. Now Publishers Inc.

Frese, M. and Gielnik, M. M. (2014) ‘The Psychology of Entrepreneurship’, *Annual Review of Organizational Psychology and Organizational Behavior*, 1(1), pp. 413–438. doi: 10.1146/annurev-orgpsych-031413-091326.

Furnham, A. *et al.* (2008) ‘Personality, hypomania, intelligence and creativity’, *Personality and Individual Differences*, 44(5), pp. 1060–1069. doi: 10.1016/j.paid.2007.10.035.

Garbuio, M. *et al.* (2018) ‘Demystifying the Genius of Entrepreneurship: How Design Cognition Can Help Create the Next Generation of Entrepreneurs’, *Academy of Management Learning & Education*, 17(1), pp. 41–61. doi: 10.5465/amle.2016.0040.

Gardner, H. (2011) *Frames of Mind: The Theory of Multiple Intelligences*. Hachette UK.

Gassmann, O. and Zeschky, M. (2008) ‘Opening up the Solution Space: The Role of Analogical Thinking for Breakthrough Product Innovation’, *Creativity and Innovation Management*, 17(2), pp. 97–106. doi: 10.1111/j.1467-8691.2008.00475.x.

Gentner, D. (1983) ‘Structure-mapping: A theoretical framework for analogy’, *Cognitive Science*, 7(2), pp. 155–170. doi: 10.1016/S0364-0213(83)80009-3.

Gentner, D., Rattermann, M. J. and Forbus, K. D. (1993) ‘The Roles of Similarity in Transfer: Separating Retrievability From Inferential Soundness’, *Cognitive Psychology*, 25(4), pp. 524–575. doi: 10.1006/cogp.1993.1013.

George, T. and Wiley, J. (2019) ‘Fixation, flexibility, and forgetting during alternate uses tasks’, *Psychology of Aesthetics, Creativity, and the Arts*, 13(3), pp. 305–313. doi: 10.1037/aca0000173.

Gick, M. L. and Holyoak, K. J. (1983) ‘Schema induction and analogical transfer’, *Cognitive Psychology*, 15(1), pp. 1–38. doi: 10.1016/0010-0285(83)90002-6.

Gong, Y. *et al.* (2012) ‘Unfolding the Proactive Process for Creativity: Integration of the Employee Proactivity, Information Exchange, and Psychological Safety Perspectives’, *Journal of Management*, 38(5), pp. 1611–1633. doi: 10.1177/0149206310380250.

Gottfredson, L. S. (2004) ‘Social Consequences of Group Differences in Cognitive Ability’, p. 43.

Gould, S. J. (1996) *The Mismeasure of Man*. Revised, Expand. New York: W W Norton & Co.

Guilford, J. P. (1956) ‘The structure of intellect’, *Psychological Bulletin*, 53(4), pp. 267–293. doi: 10.1037/h0040755.

Guilford, J. P. (1957) ‘Creative abilities in the arts’, *Psychological Review*, 64(2), pp. 110–118. doi: 10.1037/h0048280.

Guilford, J. P. (1967) *The nature of human intelligence*. New York, NY, US: McGraw-Hill (The nature of human intelligence).

Hensher, D. and Stopher, P. R. (eds) (1979) *Behavioural travel modelling*. London: Croom Helm.

Hesse, M. B. (1970) *Models and Analogies in Science*. New edition. Notre Dame, Ind.: University of Notre Dame Press.

Holyoak, K. J. and Koh, K. (1987) ‘Surface and structural similarity in analogical transfer’, *Memory & Cognition*, 15(4), pp. 332–340. doi: 10.3758/BF03197035.

Holyoak, K. J. and Thagard, P. (1989) ‘Analogical Mapping by Constraint Satisfaction’, *Cognitive Science*, 13(3), pp. 295–355. doi: 10.1207/s15516709cog1303_1.

Hudson, L. (1966) *Contrary Imaginations: A Psychological Study of the English Schoolboy*. Routledge.

Jauk, E. *et al.* (2013) ‘The relationship between intelligence and creativity: New support for the threshold hypothesis by means of empirical breakpoint detection’, *Intelligence*, 41(4), pp. 212–221. doi: 10.1016/j.intell.2013.03.003.

Jennings, K. E. (2009) ‘Early results with faceted classification of “alternate uses” test responses’, in *Proceedings of the seventh ACM conference on Creativity and cognition*. Berkeley, California, USA: Association for Computing Machinery (C&C ’09), pp. 383–384. doi: 10.1145/1640233.1640312.

Jensen, A. (1998) ‘The g factor: the science of mental ability’, *Choice Reviews Online*, 36(04), pp. 36-2443-36–2443. doi: 10.5860/CHOICE.36-2443.

Jin, B. and Kirsch, D. A. (2015) ‘Entrepreneurial Growth as a Process: Mechanism-Based Theorizing’, in *Entrepreneurial Growth: Individual, Firm, and Region*. Emerald Group Publishing Limited (Advances in Entrepreneurship, Firm Emergence and Growth), pp. 63–94. doi: 10.1108/S1074-754020150000017010.

Kahneman, D. (2012) *Thinking, Fast and Slow*. 2nd edn. Penguin.

Kahneman, D. and Klein, G. (2009) 'Conditions for intuitive expertise: A failure to disagree.', *American Psychologist*, 64(6), pp. 515–526. doi: 10.1037/a0016755.

Kaufman, J. C. and Plucker, J. A. (2011) 'Intelligence and creativity', in *The Cambridge handbook of intelligence*. New York, NY, US: Cambridge University Press (Cambridge handbooks in psychology), pp. 771–783. doi: 10.1017/CBO9780511977244.039.

Keane, M. (1987) 'On retrieving analogues when solving problems', *The Quarterly Journal of Experimental Psychology Section A*, 39(1), pp. 29–41. doi: 10.1080/02724988743000015.

Knight, F. H. (1921) *Risk, Uncertainty and Profit*. Boston: Houghton Mifflin. Available at: http://cambridge-primo.hosted.exlibrisgroup.com/primo-explore/openurl?genre=book&sid=wiley&aufirst=F.H.&aulast=Knight&date=1921&btitle=Risk,%20Uncertainty%20and%20Profit&pub=Houghton%20Mifflin&vid=44CAM_PROD&institution=44CAM&url_ctx_val=&url_ctx_fmt=null&isSerivcesPage=true (Accessed: 15 July 2020).

Kudrowitz, B. M. (Barry M. (2010) *Haha and aha! : creativity, idea generation, improvisational humor, and product design*. Thesis. Massachusetts Institute of Technology. Available at: https://dspace.mit.edu/handle/1721.1/61610 (Accessed: 13 August 2020).

Lave, J. (1988) *Cognition in Practice: Mind, Mathematics and Culture in Everyday Life*. Cambridge University Press.

Loch, C., De Meyer, A. and Pich, M. T. (2006) *Managing the Unknown*. Available at: https://www.dawsonera.com/readonline/9781118276730 (Accessed: 23 June 2020).

Long, J. S. and Freese, J. (2001) *Regression models for categorical dependent variables using Stata*. College Station, Tex: Stata Press.

Lopata, J. A., Nowicki, E. A. and Joanisse, M. F. (2017) 'Creativity as a distinct trainable mental state: An EEG study of musical improvisation', *Neuropsychologia*, 99, pp. 246–258. doi: 10.1016/j.neuropsychologia.2017.03.020.

McFadden, D. (1973) 'Conditional logit analysis of qualitative choice behaviour', in *Frontiers in Econometrics*. New York: Academic Press, pp. 105–142.

McGrath, R. G. and MacMillan, I. C. (2000) *The Entrepreneurial Mindset: Strategies for Continuously Creating Opportunity in an Age of Uncertainty*. Harvard Business Press.

Meehl, P. E. (1954) *Clinical versus statistical prediction: A theoretical analysis and a review of the evidence*. Minneapolis, MN, US: University of Minnesota Press (Clinical versus statistical prediction: A theoretical analysis and a review of the evidence), pp. x, 149. doi: 10.1037/11281-000.

Moritz, B., Siemsen, E. and Kremer, M. (2014) 'Judgmental Forecasting: Cognitive Reflection and Decision Speed', *Production and Operations Management*, 23(7), pp. 1146–1160. doi: 10.1111/poms.12105.

Nunes, T. (1994) 'Street intelligence', *Encyclopedia of human intelligence*. 2nd edn.

Okuda, S. M., Runco, M. A. and Berger, D. E. (1991) 'Creativity and the Finding and Solving of Real-World Problems', *Journal of Psychoeducational Assessment*, 9(1), pp. 45–53. doi: 10.1177/073428299100900104.

Richards, R. L. (1976) ‘A Comparison of Selected Guilford and Wallach-Kogan Creative Thinking Tests in Conjunction With Measures of Intelligence*’, *The Journal of Creative Behavior*, 10(3), pp. 151–164. doi: 10.1002/j.2162-6057.1976.tb01018.x.

Rittel, H. W. J. and Webber, M. M. (1973) ‘Dilemmas in a general theory of planning’, *Policy Sciences*, 4(2), pp. 155–169. doi: 10.1007/BF01405730.

Rousseeuw, P. J. and Leroy, A. M. (2003) *Robust Regression and Outlier Detection*. 1st Edition. Wiley-Interscience.

Sadler-Smith, E. (2016) ‘The role of intuition in entrepreneurship and business venturing decisions’, *European Journal of Work and Organizational Psychology*, 25(2), pp. 212–225. doi: 10.1080/1359432X.2015.1029046.

Salkind, N. (2010) *Encyclopedia of Research Design*. 2455 Teller Road, Thousand Oaks California 91320 United States: SAGE Publications, Inc. doi: 10.4135/9781412961288.

Savage, L. J. (1972) *The Foundations of Statistics*. Courier Corporation.

Schmider, E. *et al.* (2010) ‘Is It Really Robust?’, *Methodology: European Journal of Research Methods for the Behavioral and Social Sciences*, 6, pp. 147–151. doi: 10.1027/1614-2241/a000016.

Schubert, D. S. P. (1973) ‘Intelligence as Necessary but Not Sufficient for Creativity’, *The Journal of Genetic Psychology*, 122(1), pp. 45–47. doi: 10.1080/00221325.1973.10533169.

Scott, G., Leritz, L. E. and Mumford, M. D. (2004) 'The effectiveness of creativity training: A quantitative review', *Creativity Research Journal*, 16(4), pp. 361–388. doi: 10.1080/10400410409534549.

Shah, J. J., Smith, S. M. and Vargas-Hernandez, N. (2003) 'Metrics for measuring ideation effectiveness', *Design Studies*, 24(2), pp. 111–134. doi: 10.1016/S0142-694X(02)00034-0.

Shanahan, M. and Treuren, G. (2003) *Globalisation: Australian Regional Perspectives*. Wakefield Press.

Shaver, K. and Scott, L. (1991) 'Person, Process, Choice: The Psychology of New Venture Creation', *Entrepreneurship Theory and Practice*, 27.

Simonton, D. K. (2006) 'Presidential IQ, Openness, Intellectual Brilliance, and Leadership: Estimates and Correlations for 42 U.S. Chief Executives', *Political Psychology*, 27(4), pp. 511–526.

Snowden, D. (2005) 'Multi-ontology sense making: a new simplicity in decision making', *Journal of Innovation in Health Informatics*, 13(1), pp. 45–53. doi: 10.14236/jhi.v13i1.578.

Sommer, S. C. and Loch, C. H. (2015) 'Project Management Under High Uncertainty', in *Wiley Encyclopedia of Management*. American Cancer Society, pp. 1–12. doi: 10.1002/9781118785317.weom130035.

Spearman, C. (1961) *'General Intelligence' Objectively Determined and Measured*. East Norwalk, CT, US: Appleton-Century-Crofts (Studies in individual differences: The search for intelligence), p. 73. doi: 10.1037/11491-006.

Stagnaro, M., Pennycook, G. and Rand, D. G. (2018) *Performance on the Cognitive Reflection Test is Stable Across Time*. SSRN Scholarly Paper ID 3115809. Rochester, NY: Social Science Research Network. doi: 10.2139/ssrn.3115809.

Sternberg, R. J. (1999a) *Handbook of Creativity*. Cambridge University Press.

Sternberg, R. J. (1999b) 'The Theory of Successful Intelligence', *Review of General Psychology*, 3(4), pp. 292–316. doi: 10.1037/1089-2680.3.4.292.

Sternberg, R. J. (2004) 'Successful intelligence as a basis for entrepreneurship', *Journal of Business Venturing*, 19(2), pp. 189–201. doi: 10.1016/S0883-9026(03)00006-5.

Studente, S., Seppala, N. and Sadowska, N. (2016) 'Facilitating creative thinking in the classroom: Investigating the effects of plants and the colour green on visual and verbal creativity', *Thinking Skills and Creativity*, 19, pp. 1–8. doi: 10.1016/j.tsc.2015.09.001.

Thomson, K. S. and Oppenheimer, D. M. (2016) 'Investigating an alternate form of the cognitive reflection test', *Judgment and Decision Making*, 11(1), p. 15.

Tierney, P., Farmer, S. M. and Graen, G. B. (1999) 'An examination of leadership and employee creativity: the relevance of traits and relationships.', *Personnel Psychology*, 52(3), pp. 591–620. doi: 10.1111/j.1744-6570.1999.tb00173.x.

Torrance, E. P. (1972) 'Career Patterns and Peak Creative Achievements of Creative High School Students Twelve Years Later', *Gifted Child Quarterly*, 16(2), pp. 75–88. doi: 10.1177/001698627201600201.

Tversky, A. and Kahneman, D. (1974) 'Judgment under Uncertainty: Heuristics and Biases', *Science*, 185(4157), pp. 1124–1131. doi: 10.1126/science.185.4157.1124.

Ward, T. B. (1994) ‘Structured Imagination: the Role of Category Structure in Exemplar Generation’, *Cognitive Psychology*, 27(1), pp. 1–40. doi: 10.1006/cogp.1994.1010.

Ward, T. B. (2004) ‘Cognition, creativity, and entrepreneurship’, *Journal of Business Venturing*, 19(2), pp. 173–188. doi: 10.1016/S0883-9026(03)00005-3.

Wasserman, N. (2008) ‘The Founder’s Dilemma’, *Harvard Business Review*, 1 February. Available at: https://hbr.org/2008/02/the-founders-dilemma (Accessed: 13 August 2020).

Webb, M. E. *et al.* (2017) ‘The contributions of convergent thinking, divergent thinking, and schizotypy to solving insight and non-insight problems’, *Thinking & Reasoning*, 23(3), pp. 235–258. doi: 10.1080/13546783.2017.1295105.

Willingham, W. W. (1974) ‘Predicting Success in Graduate Education’, *Science*, 183(4122), pp. 273–278.

Zacharakis, A. L. and Shepherd, D. A. (2001) ‘The nature of information and overconfidence on venture capitalists’ decision making’, *Journal of Business Venturing*, 16(4), pp. 311–332. doi: 10.1016/S0883-9026(99)00052-X.

Appendix A – Questionnaire as Displayed on Qualtrics (Desktop Preview View)

Timing

These page timer metrics will not be displayed to the recipient.

First Click	0 seconds
Last Click	0 seconds
Page Submit	0 seconds
Click Count	0 clicks

A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball.
How much does the ball cost?
______ $

If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
______ minutes

How many cubic feet of dirt are there in a hole that is 3' deep x 3' wide x 3' long?
______ feet

In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?
______ days

David had 15 marbles. He lost some of them. How many marbles does David have now?
______ marbles

If you're running a race and you pass the person in second place, what place are you in?
______ place

A farmer had 15 sheep and all but 8 died. How many are left?
______ sheep

Emily's father has three daughters. The first two are named April and May. What is the third daughter's name?
____

>>

Timing

These page timer metrics will not be displayed to the recipient.

First Click	0 seconds
Last Click	0 seconds
Page Submit	0 seconds
Click Count	0 clicks

00 13

Please list as many uses as you can think of for **a chair**.
(A new text box will appear after each use you enter)
Once 2 minutes have passed the survey will proceed to the next section.

1

Add an additional response below

2

Add an additional response below

3

Add an additional response below

4

Add an additional response below

5

Add an additional response below

6

Add an additional response below

7

Add an additional response below

8

Add an additional response below

9

Add an additional response below

10

Add an additional response below

11

Add an additional response below

12

Add an additional response below

13

Add an additional response below

14

Add an additional response below

15

Add an additional response below

16

Add an additional response below

17

Add an additional response below

18

Add an additional response below

19

Add an additional response below

20

Add an additional response below

21

Add an additional response below

22

Add an additional response below

23

Add an additional response below

24

Add an additional response below

26

Add an additional response below

25

Add an additional response below

27

Add an additional response below

29

Add an additional response below

30

>>

Main task:
Suppose you are a doctor faced with a patient who has a malignant tumor in his stomach. It is impossible to operate on the patient, but unless the tumor is destroyed the patient will die. There is a kind of ray that can be used to destroy the tumor. If the rays reach it all at once at a sufficiently high intensity, the tumor will be destroyed. Unfortunately, at this intensity the healthy tissue that the rays pass through on the way to the tumor will also be destroyed. At lower intensities the rays are harmless to healthy tissue, but they will not affect the tumor either. What type of procedure might be used to destroy the tumor with the rays, and at the same time avoid destroying the healthy tissue?

Source: [1]

Attention verification:
The problem described above relates to:

- ○ Someone who broke their arm.
- ○ A patient with a tumor who cannot be operated on.
- ○ A doctor who might die.

Appendix A – Questionnaire as Displayed on Qualtrics (Desktop Preview View)

Do you have a solution to the main task? Can you kill the tumor and save the patient?

- ○ Yes
- ○ No

>>

Please briefly describe your solution, or if you changed your mind and no longer believe you have an answer please leave the text box empty and continue.

>>

Please read through the story below and answer the verification question. If you answer it correctly, you will proceed.

One night a fire broke out in a woodshed full of timber on Mr. Johnson's place. As soon as he saw flames he sounded the alarm, and within minutes dozens of neighbors were on the scene armed with buckets. The shed was already burning fiercely, and everyone was afraid that if it wasn't controlled quickly the house would go up next. Fortunately, the shed was right beside a lake, so there was plenty of water available. If a large volume of water could hit the fire at the same time, it would be extinguished. But with only small buckets to work with, it was hard to make any headway. The fire seemed to evaporate each bucket of water before it hit the wood. It looked like the house was doomed.

Just then the fire chief arrived. He immediately took charge and organized everyone. He had everyone fill their bucket and then wait in a circle surrounding the burning shed. As soon as the last man was prepared, the chief gave a shout and everyone threw their bucket of water at the fire. The force of all the water together dampened the fire right down, and it was quickly brought under control, Mr. Johnson was relieved that his house was saved, and the village council voted the tire chief a raise in pay.

Source: [2]

Attention verification:
The story above involves:

○ A fire that broke out in a large city.

○ A crew of fireman with trucks and equipment who quickly put out a terrible fire.

○ A fire in a woodshed that was put out by throwing buckets of water on it.

>>

Do you have a solution to the main task? Can you kill the tumor and save the patient?

- ○ Yes
- ◉ No

>>

Please read through the story below and answer the verification question. If you answer it correctly, you will proceed.

A small country was ruled from a strong fortress by a dictator. The fortress was situated in the middle of the country, surrounded by farms and villages. Many roads led to the fortress through the countryside. A rebel general vowed to capture the fortress. The general knew that an attack by his entire army would capture the fortress. He gathered his army at the head of one of the roads, ready to launch a full-scale direct attack. However, the general then learned that the dictator had planted mines on each of the roads. The mines were set so that small bodies of men could pass over them safely, since the dictator needed to move his troops and workers to and from the fortress.

However, any large force would detonate the mines. Not only would this blow up the road, but it would also destroy many neighbouring villages. It therefore seemed impossible to capture the fortress. However, the general devised a simple plan. He divided his army into small groups and dispatched each group to the head of a different road. When all was ready he gave the signal and each group marched down a different road. Each group continued down its road to the fortress so that the entire army arrived together at the fortress at the same time. In this way, the general captured the fortress and overthrew the dictator.

Source: [2]

Attention verification:
The story above involves:

- ○ A general who sought to overthrow a dictator.
- ○ An army that built roads in order to access an enemy territory.
- ○ A prince who needed to rescue someone from a castle.

>>

Survey Powered By Qualtrics

Please reflect on the main task, and the two subsequent stories. Think of how the principles applied in story 1 and story 2 might be applied to solve the main task. How would you solve the problem described in the **main task**, i.e., how you would seek to kill the tumor and save the patient.

>>

Survey Powered By Qualtrics

What are the similarities between the main task and the two subsequent stories?

>>

Survey Powered By Qualtrics

Please provide answers to the following questions. Answers are anonymised as truthful self-reporting is critical to this study.

Are you (or have you ever been) the founding shareholder of a legal entity with a business purpose?

- Yes
- No

>>

Survey Powered By Qualtrics

Appendix A – Questionnaire as Displayed on Qualtrics (Desktop Preview View)

As an entrepreneur, which of the following describes your funding strategy?

- ○ Grow through the funds generated from the business, i.e., "bootstrapping"
- ○ Growth through external investors
- ○ Other

Which of the options below most closely characterises your reason for starting your business?

- ○ Recognition
- ○ Money (wealth)
- ○ Impact on society
- ○ Other

Of the three options below, which one is your primary strength?

- ○ Leadership and internal relations
- ○ Sales and public (external) relations
- ○ Solving challenging problems

For the most successful business you have had, please answer the following:

Number of months since incorporation	
What currency were revenue and profit recorded in?	
revenue per year (in last year or when you exited) Please provide the amount and the currency.	
Profit per year at peak. Please provide the amount and the currency	
Your involvement as a percent of your time. For example 25%	
Total amount of funding received. Amount and currency	
Number of employees in the last	

Number of employees in the last year you were involved	
revenue growth in the last three years	

If you had to choose one of the following categories to describe yourself, which would it be?

- ○ Analytical, mathematical and/or logical
- ○ Intuitive, artistical and/or unsystematic

Which of the following industries do you work in, or are you closest to?

- ○ Aerospace
- ○ Agriculture
- ○ Automotive
- ○ Chemics
- ○ Defense
- ○ Education
- ○ Electronics
- ○ Energy
- ○ Entertainment
- ○ Finance
- ○ Food
- ○ Health
- ○ Hospitality
- ○ Insurance
- ○ Media
- ○ Petrolium
- ○ Real Estate

- ○ Robotics
- ○ Software
- ○ Sport
- ○ Telecommunications
- ○ Transport
- ○ Water
- ○ Other

How often have you switched your occupation?

- ○ Never
- ○ 0-3 times
- ○ 4-6 times
- ○ 7 times or more

When you performed a certain task, how strongly do you want others to let you know what you did well and what needs improving?

- ○ Extremely important
- ○ Very important
- ○ Moderately important
- ○ Slightly important
- ○ Not at all important

How often are you exposed to other people who you don't have a prior acquaintance with?

- ○ Daily
- ○ 4-6 times a week

○ 2-3 times a week

○ Once a week

○ Never

Which age bracket are you in?

○ 1-16

○ 17-18

○ 19-21

○ 22-25

○ 26-30

○ 31-40

○ 41-50

○ 51-60

○ 61+

>>

Appendix A – Questionnaire as Displayed on Qualtrics (Desktop Preview View)

Additional note: The CRT questions stem from the following sources.

Table 18: Question catalogue of CRT questions including source, intutive answer and correct answer

Question	Source	Intuitive Answer	Correct Answer
A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? ______ $	Frederick (2005)	0.10	0.05
If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ______ minutes	Frederick (2005)	100	5
In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ______ days	Frederick (2005)	24	47
How many cubic feet of dirt are there in a hole that is 3' deep x 3' wide x 3' long? ______ feet	Thomson and Oppenheimer (2016)	27	0
If you're running a race and you pass the person in second place, what place are you in? ______ place	Thomson and Oppenheimer (2016)	1	2
A farmer had 15 sheep and all but 8 died. How many are left? ______ sheep	Thomson and Oppenheimer (2016)	7	8
Emily's father has three daughters. The first two are named April and May. What is the third daughter's name? _______	Thomson and Oppenheimer (2016)	June	Emily

Appendix A – Questionnaire as Displayed on Qualtrics (Desktop Preview View)

David had 15 marbles. He lost some of them. How many marbles does David have now? ______ marbles	Own collection	-	15-x

Additional note: Periphery data was treated as indicated below.

Table 19: Overview of periphery data collected and used for random forest modelling

Question	Answer Choices	Scale
Off the three options below, which one is your primary strength?	- Leadership and internal relations - Sales and public (external) relations - Solving challenging problems	Nominal
If you had to choose one of the following categories to describe yourself, which would it be?	- Analytical, mathematical and/or logical - Intuitive, artistical and/or unsystematic	Nominal
How often have you switched your occupation?	- Never - 1-3 times - 4-6 times - 7 times or more	Ordinal
When you performed a certain task, how strongly do you want others to let you know what you did well and what needs improving?	- Extremely important - Very important - Moderately important - Slightly important - Not at all important	Ordinal
How often are you exposed to other people who you don't	- Daily - 4-6 times a week - 2-3 times a week	Ordinal

have a prior	-	Once a week
acquaintance with?	-	Never

Appendix B – R Output of Probit Regression vs Logistic Regression

```
> ##Multi Probit Regression
>
> probit <- glm(tag ~ TT_score + CRT_score + AUT_score, family = binomial(link =
"probit"), data = data)
> summary(probit)

Call:
glm(formula = tag ~ TT_score + CRT_score + AUT_score, family = binomial(link =
"probit"),
    data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8457  -0.6858  -0.3708  -0.1480   2.6304

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.77384    0.35841  -7.739 1.00e-14 ***
TT_score     0.13830    0.06999   1.976 0.048149 *
CRT_score    0.23801    0.05797   4.105 4.03e-05 ***
AUT_score    0.11265    0.03138   3.590 0.000331 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 273.80  on 265  degrees of freedom
Residual deviance: 220.21  on 262  degrees of freedom
AIC: 228.21

Number of Fisher Scoring iterations: 6

> ll.null <- probit$null.deviance/-2 #calculating McFadden's Pseudo R^2
> ll.proposed <- probit$deviance/-2
> (ll.null - ll.proposed) / ll.null
[1] 0.1957238
>
> 1 - pchisq(2*(ll.proposed - ll.null), df=(length(probit$coefficients)-1)) #calculating the resp.
p-value
[1] 1.373457e-11
> predict(probit, data.frame(CRT_score = 7, AUT_score = 12, TT_score = 4), type =
"response") -
+   predict(probit, data.frame(CRT_score = 0, AUT_score = 0, TT_score = 0), type =
"response")
        1
0.7845797
```

```
> ##Multi Logistic Regression
>
> logistic <- glm(tag ~ TT_score + CRT_score + AUT_score, data = data)
> summary(logistic)

Call:
glm(formula = tag ~ TT_score + CRT_score + AUT_score, data = data)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.69989  -0.24452  -0.10304   0.06094   0.96365

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.178636   0.061846  -2.888 0.004196 **
TT_score     0.047005   0.019483   2.413 0.016525 *
CRT_score    0.044460   0.011679   3.807 0.000175 ***
AUT_score    0.028421   0.007612   3.734 0.000231 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for gaussian family taken to be 0.1385969)

    Null deviance: 44.211  on 265  degrees of freedom
Residual deviance: 36.312  on 262  degrees of freedom
AIC: 235.18

Number of Fisher Scoring iterations: 2

>
> ll.null <- logistic$null.deviance/-2 #calculating McFadden's Pseudo R^2
> ll.proposed <- logistic$deviance/-2
> (ll.null - ll.proposed) / ll.null
[1] 0.1786486
>
> 1 - pchisq(2*(ll.proposed - ll.null), df=(length(logistic$coefficients)-1)) #calculating the
resp. p-value
[1] 0.04816425
> predict(logistic, data.frame(CRT_score = 7, AUT_score = 12, TT_score = 4), type =
"response") -
+   predict(logistic, data.frame(CRT_score = 0, AUT_score = 0, TT_score = 0), type =
"response")
        1
0.8402888
```

Appendix B – R Output of Probit Regression vs Logistic Regression

Graphical Comparison

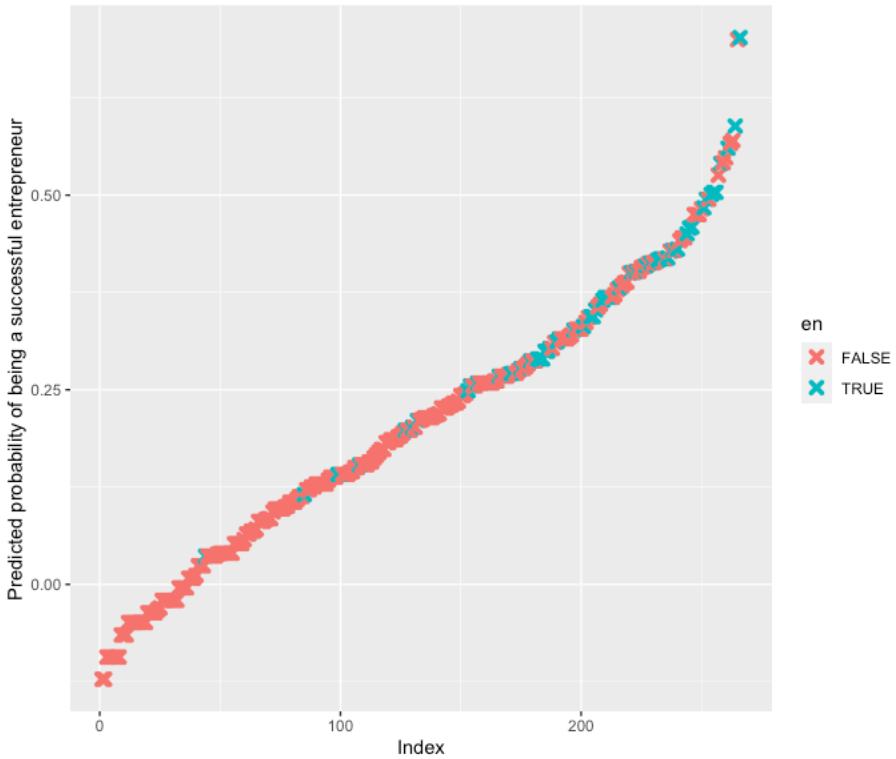


Figure 9: Predicted probability of being a successful entrepreneur based on multivariate probit regression model plotted for each participant in the survey; entrepreneurs are marked in blue, non-entrepreneurs are marked in red

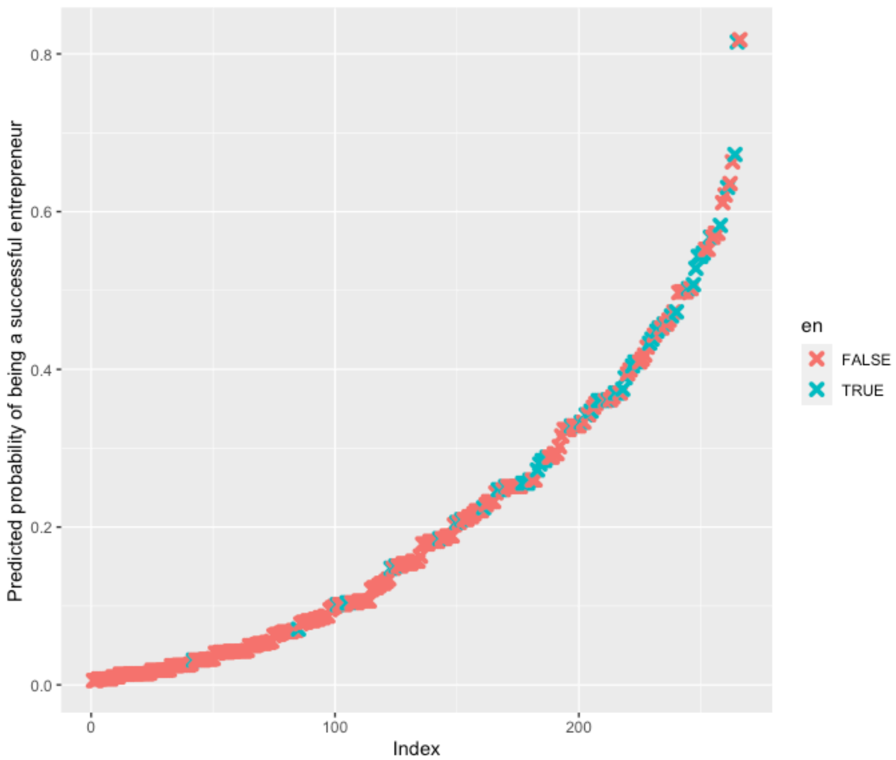


Figure 10: Predicted probability of being a successful entrepreneur based on multivariate logistic regression model plotted for each participant in the survey; entrepreneurs are marked in blue, non-entrepreneurs are marked in red

Appendix C – Non-Normality of Data

Comparing successful entrepreneurs to non-entrepreneurs

The Shapiro-Wilk Test for all three samples indicates high non-normality:

Table 20: P-value of Shapiro-Wilk Test of test scores (similar to table 4)

	P-value
CRT	$2.2 \bullet 10^{-16}$
AUT	$6.5 \bullet 10^{-10}$
TT	$9.1 \bullet 10^{-11}$

These results were expected, as capping of the test scores leads to evidently light-tailed distributions. Moreover, the distribution of test scores is expected to be fundamentally different. Test scores, boxplots, and QQ plots are plotted and visualised below to further investigate this behaviour. Technically, scatter and QQ plots use residual data. For reasons of comparability in the below figure, independent variables are presented, as no visual differences will arise for independent t-tests.

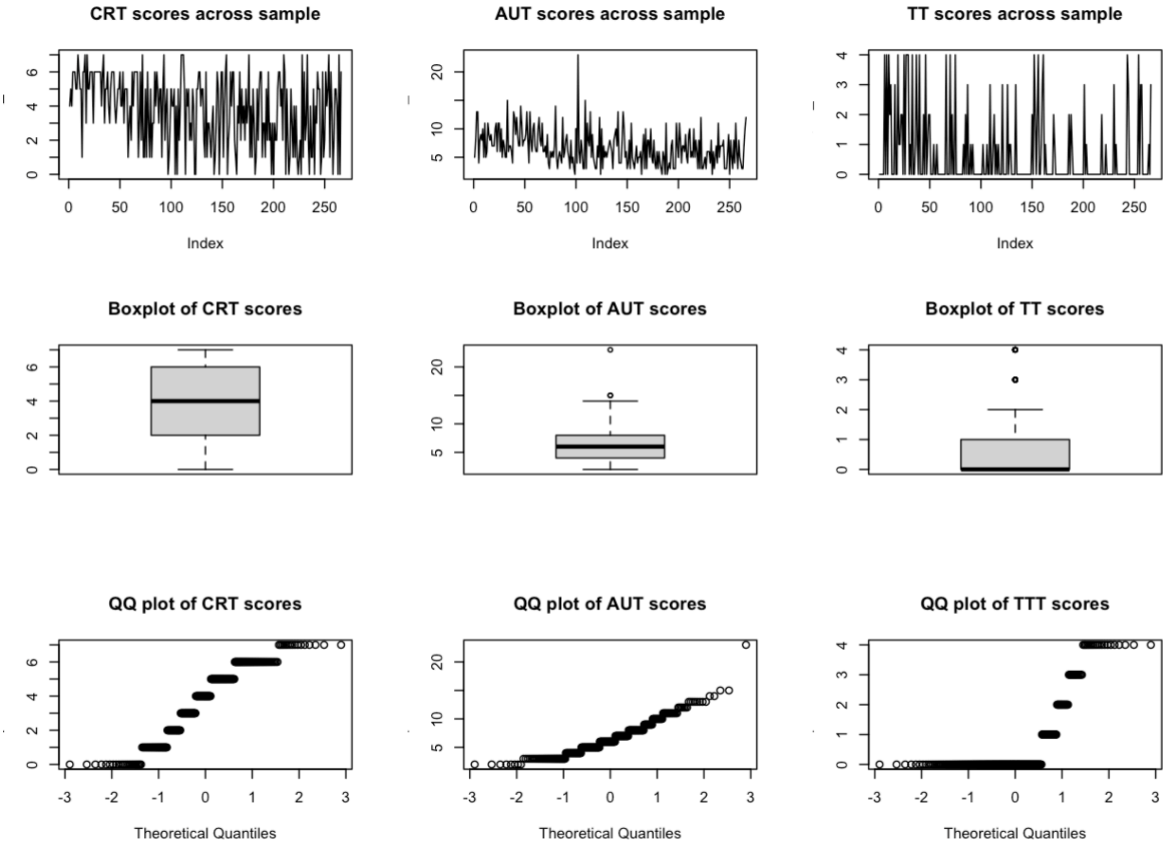


Figure 11: Scatterplots (top), boxplots (middle), and QQ plots (bottom) of CRT scores (left), AUT scores (middle), and TT scores (right); theoretical quantiles are on the x-axis, observed quantiles are on the y-axis

As the test scores are capped, there is little room for outliers. The boxplots reveal that only one evident outlier can be found in the AUT scores, which is almost 6 standard deviations away from the mean, with an AUT score of 23. The boxplot of the TT scores reveals that the median is zero, as more than half of all individuals were not able to solve the TT. This results in a mean of 0.68 and standard deviation of 1.25. Consequently, all test scores of four and three are classified as outliers. TT scores of four are 2.66 standard deviations away from the mean. The Quantile-Quantile (QQ) plots, however, indicate that the majority of data follows a normal distribution besides the light tails of the distribution, which is due to all but the AUT scores being capped. All CRT and AUT test score data besides high AUT scores seem to be light-tailed. For parametric analysis, the AUT outlier should be removed. Moreover, the high TT scores show an especially strong deviation from the mean. The subsets have different sample sizes. For better understanding of the sample, the entrepreneurs' data is moved to the left in the index plots. Means and quantiles also differ between the two sets.

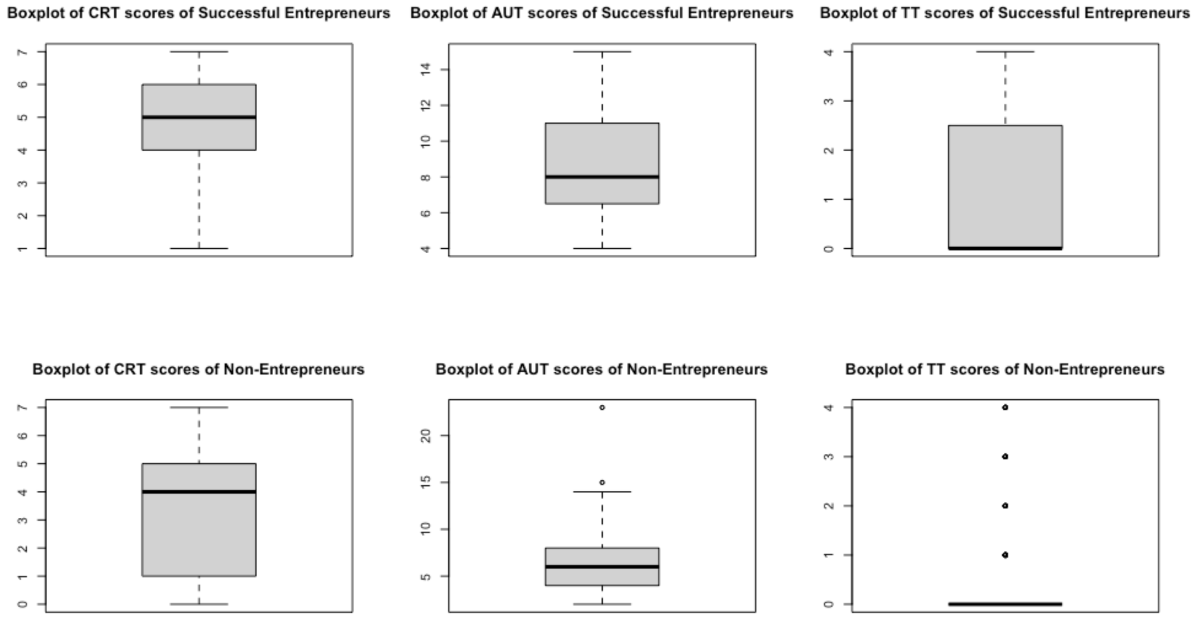


Figure 12: Boxplots of entrepreneurs (top) and non-entrepreneurs (bottom) of CRT scores (left), AUT scores (middle), and TT scores (right)

It could be argued that the capped scores still lead to distributions which allow for parametric regression as outliers cannot pass a certain threshold of standard deviations. Also, a sample size of 266 allows for the application of the central limit theorem (Billingsley, 1995). However, a more conservative, non-parametric approach will be used to compare successful entrepreneurs and non-entrepreneurs to ensure the absolute validity of any measured outcomes.

Comparing successful entrepreneurs among each other

In order to compare successful entrepreneurs among each other, three linear regressions were performed, with test scores regressing against the adjusted success measures including revenue, funding, and employees divided by the months since the entrepreneurial venture began operating. The performed regression's residual values did not follow a normal distribution, as can be seen when investigating the residual plots below. The spikes in residual plots and the heavy right tails of the distributions are evident.

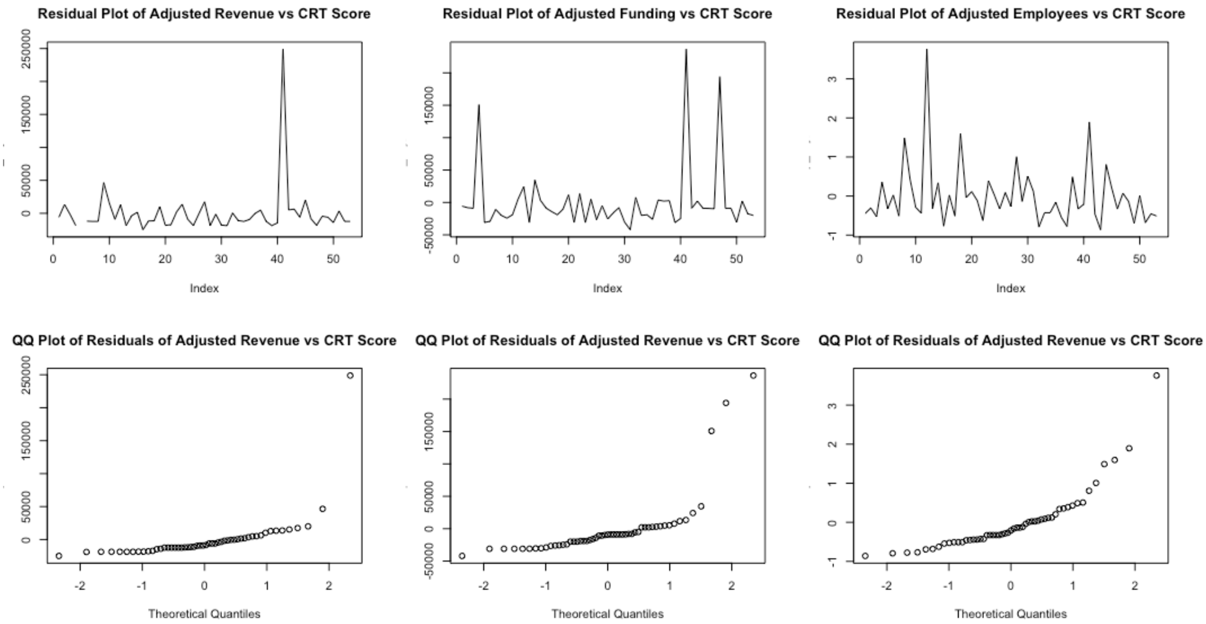


Figure 13: Residual plots (top) and QQ plots (bottom) of adjusted revenue (left), adjusted funding (middle), and adjusted employees(right) of linear regression fit to success metrices vs CRT score

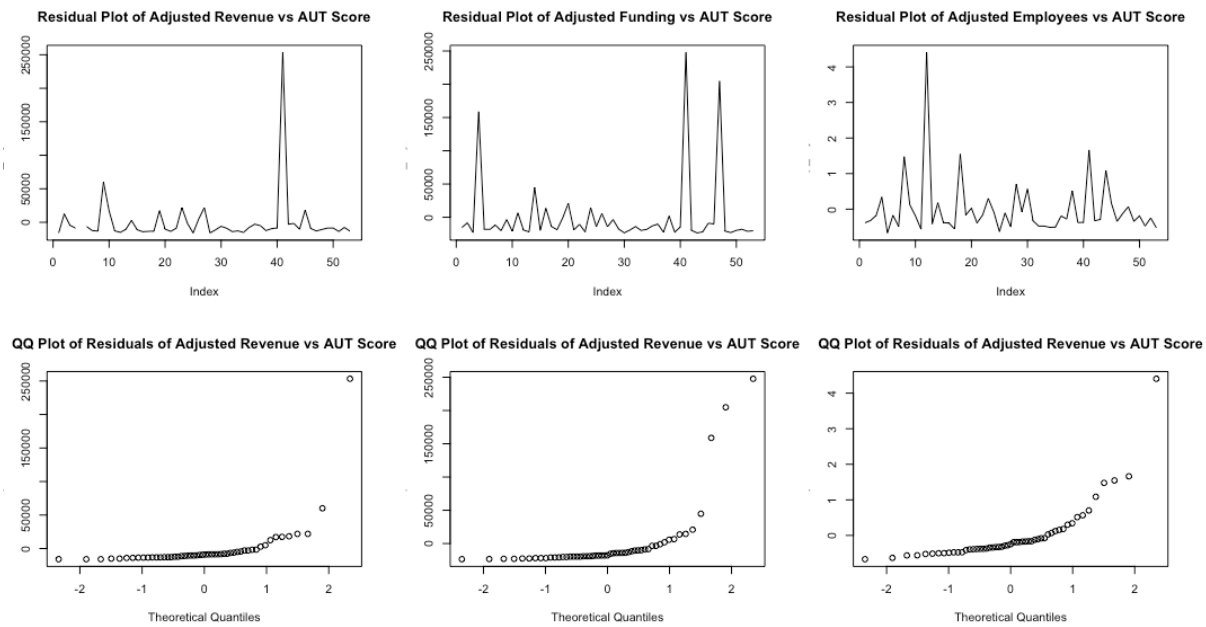


Figure 14: Residual plots (top) and QQ plots (bottom) of adjusted revenue (left), adjusted funding (middle), and adjusted employees(right) of linear regression fit to success metrices vs AUT score

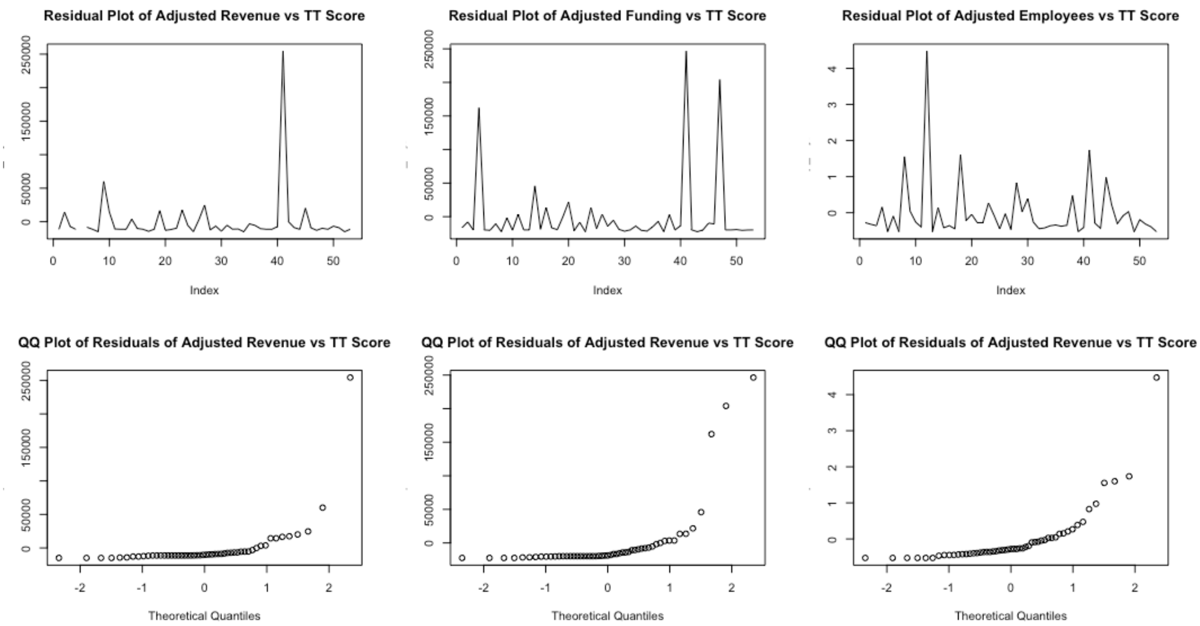


Figure 15: Residual plots (top) and QQ plots (bottom) of adjusted revenue (left), adjusted funding (middle), and adjusted employees(right) of linear regression fit to success metrices vs TT score

Consequently, dependent variables have been logged. The resulting residuals for logged success metrics are not normally distributed according to the Shapiro-Wilk normality test.

Table 21: P-values of Shapiro Wilk Test for linear regression of test scores against logged success metrices

	P-value
CRT vs adjusted logged revenue	$2.4 \bullet 10^{-6}$
CRT vs adjusted logged funding	$5.5 \bullet 10^{-4}$
CRT vs adjusted logged employees	$3.5 \bullet 10^{-6}$
AUT vs adjusted logged revenue	$3.1 \bullet 10^{-6}$
AUT vs adjusted logged funding	$1.2 \bullet 10^{-5}$
AUT vs adjusted logged employees	$7.5 \bullet 10^{-7}$
TT vs adjusted logged revenue	$1.1 \bullet 10^{-5}$
TT vs adjusted logged funding	$4.6 \bullet 10^{-6}$
TT vs adjusted logged employees	$3.0 \bullet 10^{-7}$

Appendix C – Non-Normality of Data

The graphical data can be examined below. The data appears to be much closer to a normal distribution, but QQ plots still indicate non-normality, with heavy tails on the right side of the distributions. Consequently, a non-parametric approach has been chosen for this data.

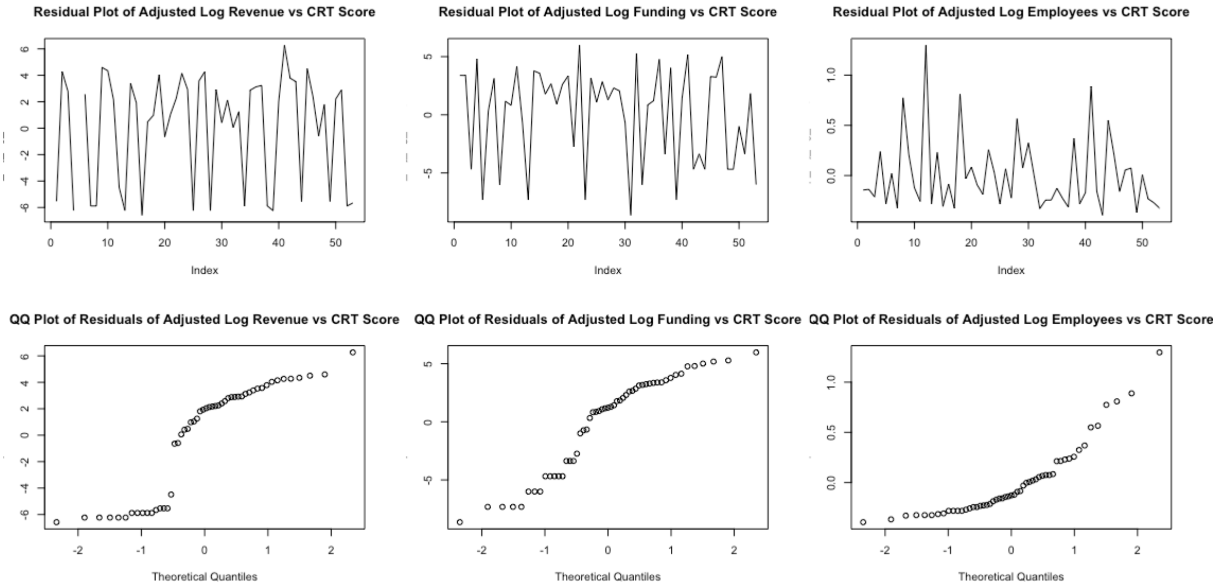


Figure 16: Residual plots (top) and QQ plots (bottom) of logged adjusted revenue (left), logged adjusted funding (middle), and logged adjusted employees(right) of linear regression fit to logged success metrices vs CRT score

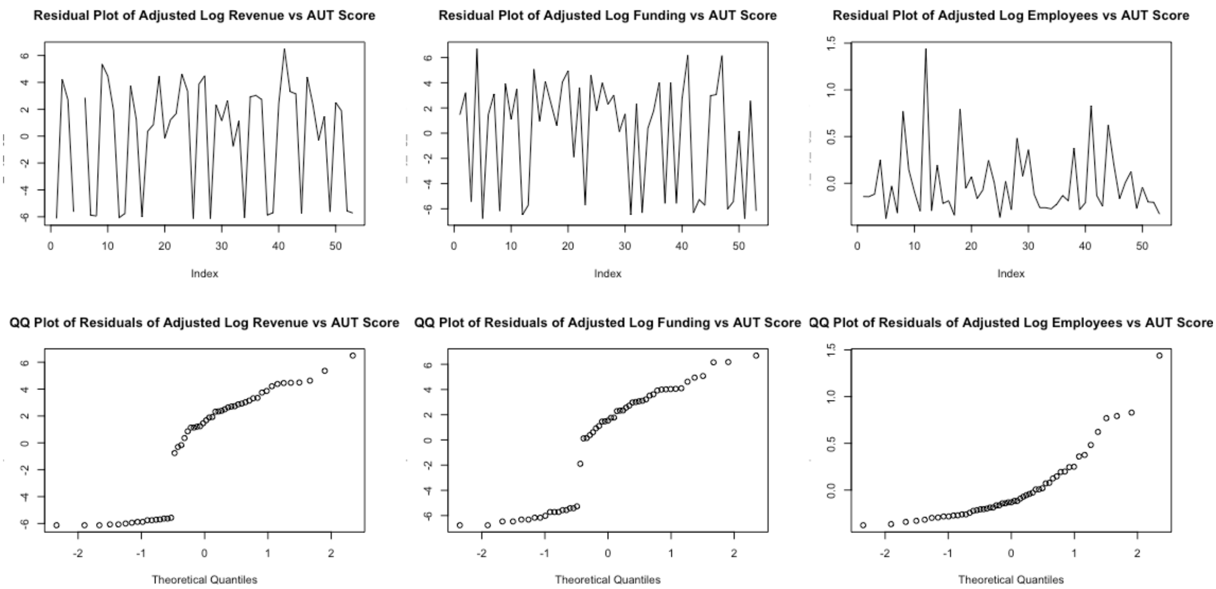


Figure 17: Residual plots (top) and QQ plots (bottom) of logged adjusted revenue (left), logged adjusted funding (middle), and logged adjusted employees(right) of linear regression fit to logged success metrices vs AUT score

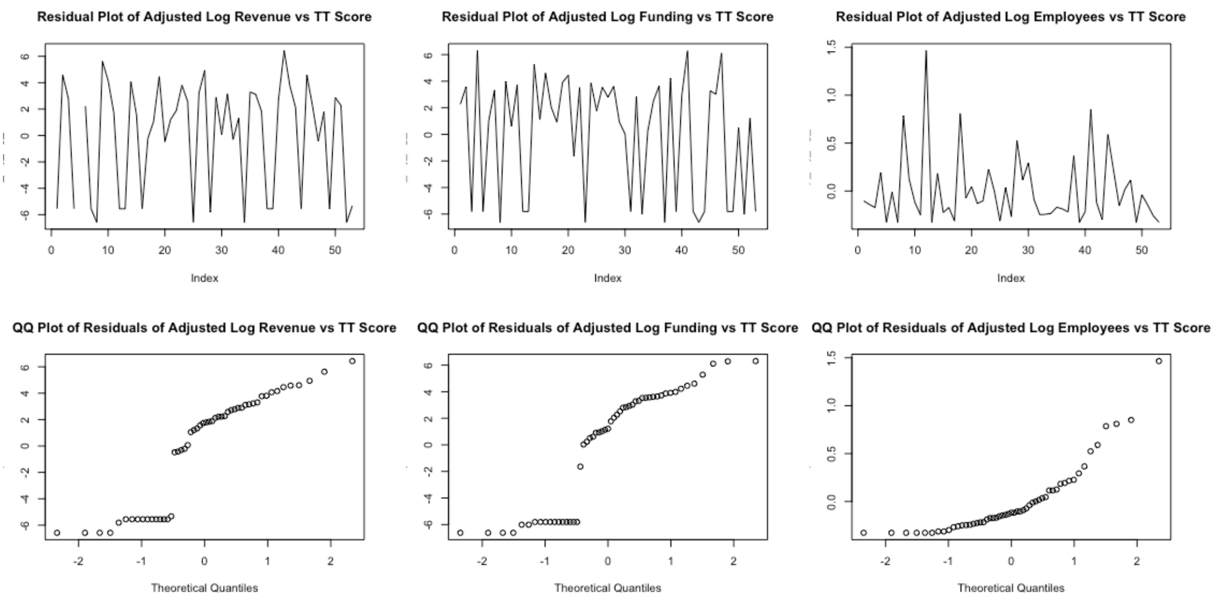


Figure 18: Residual plots (top) and QQ plots (bottom) of logged adjusted revenue (left), logged adjusted funding (middle), and logged adjusted employees(right) of linear regression fit to logged success metrices vs TT score

Comparing test scores

Again, the Shapiro-Wilk Test exhibits high non-normality.

Table 22: P-values of Shapiro Wilk Test of test scores fitted to each other

	P-value
CRT vs AUT	$5.3 \bullet 10^{-9}$
CRT vs TT	$2.2 \bullet 10^{-16}$
AUT vs CRT	$4.6 \bullet 10^{-6}$
AUT vs TT	$2.2 \bullet 10^{-16}$
TT vs CRT	$1.1 \bullet 10^{-6}$
TT vs AUT	$4.8 \bullet 10^{-10}$

Upon graphical investigation of the residual plots, the observed high non-normality does not result from the presence of any outliers. Only one outlier can be identified for the residual plots involving the AUT. For 266 data points, this accounts for minimal difference in the observed residuals. When regressing CRT scores against AUT scores and TT scores against AUT scores, the difference between mean and median is 0.35 and 0.477 respectively. Hence, for purposes of interpretability, parametric regression is chosen for analysing the interrelation of the three dimensions.

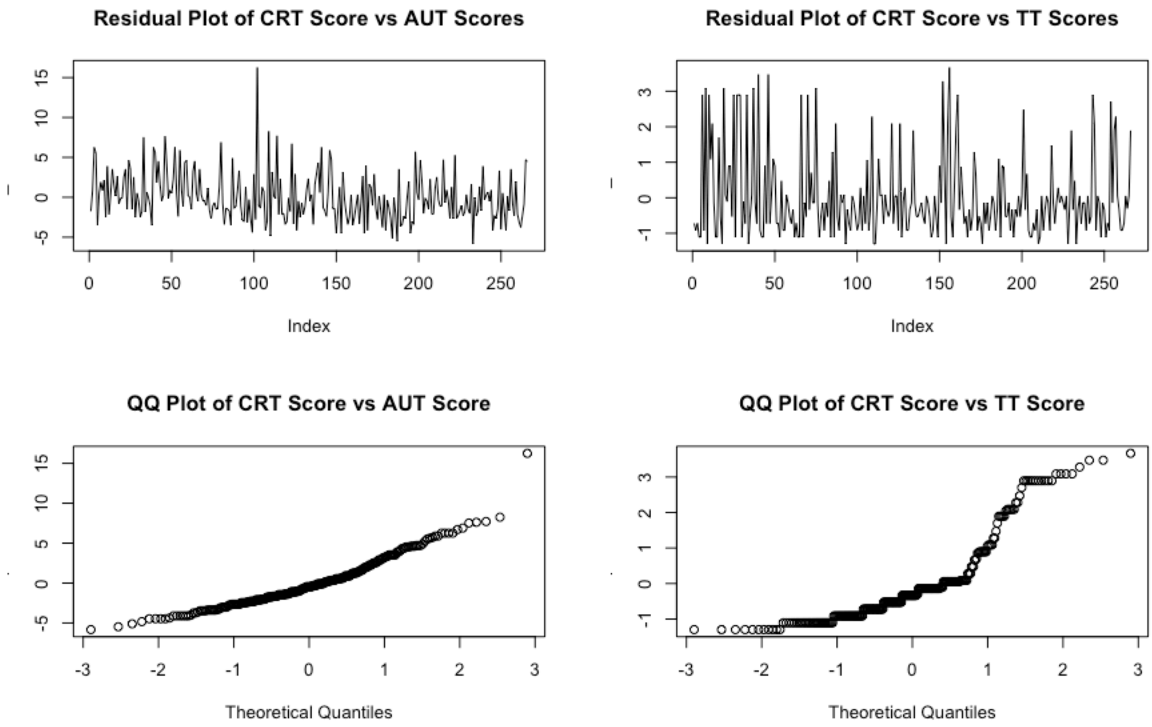


Figure 19: Residual plots (top) and QQ plots (bottom) of linear regression fit to CRT score vs AUT score (left) and CRT score vs TT score (right)

Appendix C – Non-Normality of Data

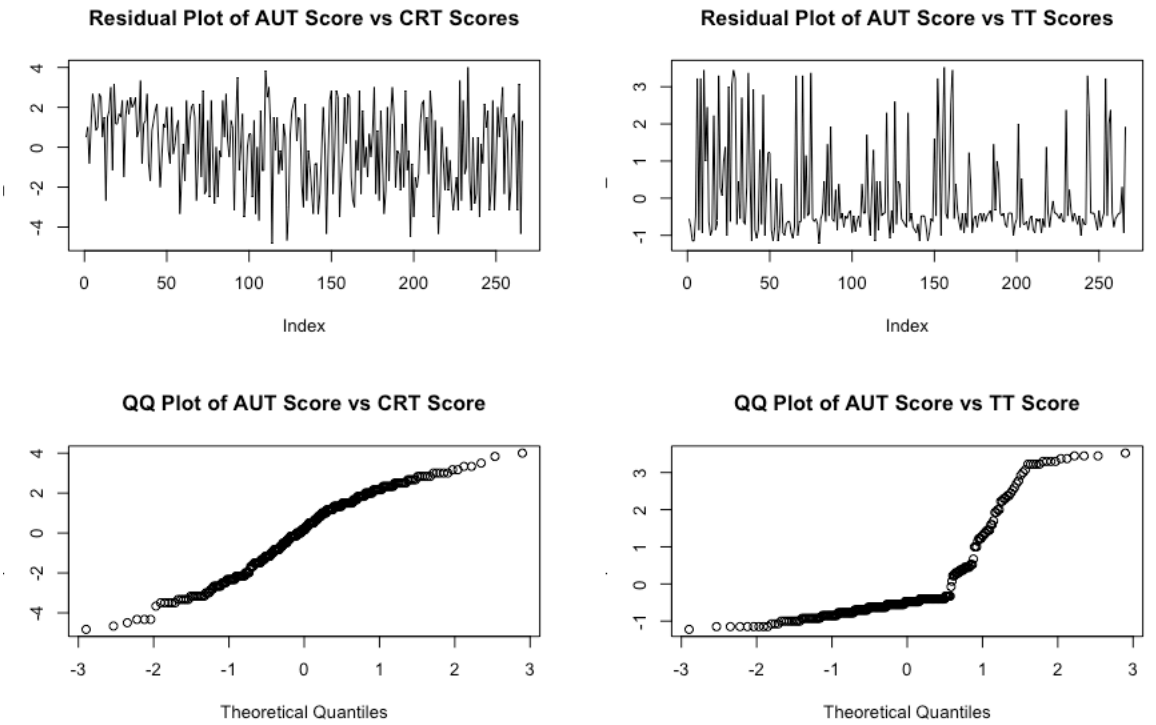


Figure 20: Residual plots (top) and QQ plots (bottom) of linear regression fit to AUT score vs CRT score (left) and AUT score vs TT score (right)

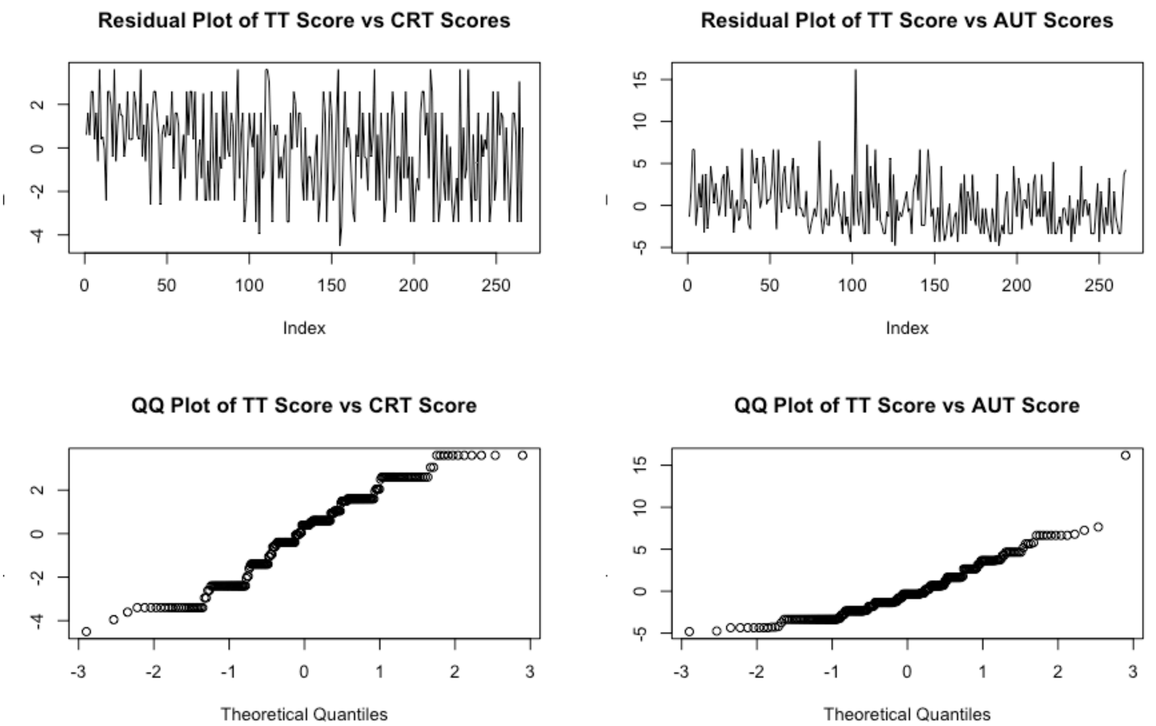


Figure 21: Residual plots (top) and QQ plots (bottom) of linear regression fit to TT score vs CRT score (left) and TT score vs AUT score (right)

Appendix D – R output of Comparison of Multivariate Polynomial Probit Regressions of Test Scores versus Entrepreneurship

The R output of a series of multivariate polynomial regressions of test scores versus a binary variable indicating entrepreneurship is included below. Both the summary of the models and the ANOVA is listed.

```
> for(i in 1:4) {
+   polyprobit <- glm(tag_entrepreneur_factor ~ polym(TT_score, AUT_score, CRT_score,
degree=i, raw=TRUE), family = binomial(link = "probit"), data = data)
+   poly_anova <- c(poly_anova, polyprobit)
+   print(summary(polyprobit))
+ }

Call:
glm(formula = tag_entrepreneur_factor ~ polym(TT_score, AUT_score,
    CRT_score, degree = i, raw = TRUE), family = binomial(link = "probit"),
    data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8457  -0.6858  -0.3708  -0.1480   2.6304

Coefficients:
                                                              Estimate Std. Error z value Pr(>|z|)
(Intercept)                                                   -2.77384    0.35841  -7.739 1.00e-14 ***
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.0  0.13830    0.06999
1.976 0.048149 *
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.0  0.11265    0.03138
3.590 0.000331 ***
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.1  0.23801    0.05797
4.105 4.03e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 273.80  on 265  degrees of freedom
Residual deviance: 220.21  on 262  degrees of freedom
AIC: 228.21

Number of Fisher Scoring iterations: 6


Call:
glm(formula = tag_entrepreneur_factor ~ polym(TT_score, AUT_score,
    CRT_score, degree = i, raw = TRUE), family = binomial(link = "probit"),
    data = data)

Deviance Residuals:
```

```
    Min        1Q    Median       3Q       Max
-1.30626  -0.73430  -0.30197  -0.02292   2.95117

Coefficients:
                                                          Estimate Std. Error z value Pr(>|z|)
(Intercept)                                              -5.026235   1.368633  -3.672  0.00024 ***
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.0  0.042438
0.465941   0.091  0.92743
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.0.0  0.044088
0.073010   0.604  0.54593
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.0  0.446826
0.197564   2.262  0.02372 *
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.1.0 -0.006232
0.024626  -0.253  0.80022
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.2.0 -0.015714
0.008239  -1.907  0.05648 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.1  0.802966
0.383854   2.092  0.03645 *
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.1 -0.004242
0.059787  -0.071  0.94344
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.1 -0.010363
0.025735  -0.403  0.68717
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.2 -0.060624
0.036170  -1.676  0.09372 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 273.80  on 265  degrees of freedom
Residual deviance: 210.79  on 256  degrees of freedom
AIC: 230.79

Number of Fisher Scoring iterations: 7


Call:
glm(formula = tag_entrepreneur_factor ~ polym(TT_score, AUT_score,
    CRT_score, degree = i, raw = TRUE), family = binomial(link = "probit"),
    data = data)

Deviance Residuals:
    Min        1Q    Median       3Q       Max
-1.41844  -0.72580  -0.21921  -0.08944   2.81379

Coefficients:
                                                          Estimate Std. Error z value Pr(>|z|)
(Intercept)                                              -2.3796426 2.3409624  -1.017   0.3094
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.0  0.7353892
2.3557937   0.312   0.7549
```

```
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.0.0 -1.0573091
0.6272664  -1.686   0.0919 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)3.0.0  0.1895891
0.0905652   2.093   0.0363 *
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.0  0.0177931
0.8236207   0.022   0.9828
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.1.0 -0.3257567
0.2567383  -1.269   0.2045
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.1.0  0.0616576
0.0336482   1.832   0.0669 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.2.0 -0.0067377
0.0755155  -0.089   0.9289
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.2.0  0.0051301
0.0094830   0.541   0.5885
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.3.0  0.0002155
0.0017741   0.121   0.9033
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.1 -0.7086443
0.9607897  -0.738   0.4608
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.1  0.7366640
0.6641613   1.109   0.2674
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.0.1 -0.0851942
0.0757590  -1.125   0.2608
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.1  0.2141184
0.1606570   1.333   0.1826
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.1.1  0.0031567
0.0265260   0.119   0.9053
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.2.1 -0.0049221
0.0099418  -0.495   0.6205
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.2  0.1004993
0.2350586   0.428   0.6690
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.2 -0.0438100
0.0568690  -0.770   0.4411
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.2 -0.0167291
0.0150269  -1.113   0.2656
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.3 -0.0030672
0.0198113  -0.155   0.8770
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 273.80  on 265  degrees of freedom
Residual deviance: 197.36  on 246  degrees of freedom
AIC: 237.36

Number of Fisher Scoring iterations: 8


Call:
glm(formula = tag_entrepreneur_factor ~ polym(TT_score, AUT_score,
    CRT_score, degree = i, raw = TRUE), family = binomial(link = "probit"),
```

```
    data = data)

Deviance Residuals: 
     Min        1Q    Median        3Q       Max  
-1.45154  -0.63858  -0.19315  -0.00016   2.44098  

Coefficients:
                                                                              Estimate Std. Error z value Pr(>|z|)  
(Intercept)                                                                 -1.911e+01  1.278e+01  -1.496   0.1348  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.0  1.502e+01  1.040e+01   1.443   0.1489  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.0.0 -2.651e+00  4.530e+00  -0.585   0.5584  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)3.0.0 -5.306e-01  1.249e+00  -0.425   0.6710  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)4.0.0  2.686e-01  1.572e-01   1.709   0.0875 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.0  8.172e+00  5.521e+00   1.480   0.1388  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.1.0 -5.364e+00  3.229e+00  -1.661   0.0967 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.1.0 -3.558e-01  4.784e-01  -0.744   0.4570  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)3.1.0  5.582e-02  5.678e-02   0.983   0.3255  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.2.0 -1.407e+00  8.923e-01  -1.577   0.1148  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.2.0  1.470e-01  1.433e-01   1.026   0.3048  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.2.0  3.463e-02  2.015e-02   1.719   0.0856 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.3.0  1.020e-01  6.398e-02   1.594   0.1109  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.3.0 -1.329e-03  4.565e-03  -0.291   0.7710  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.4.0 -2.825e-03  1.734e-03  -1.629   0.1033  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.1  2.669e+00  4.934e+00   0.541   0.5885  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.1 -6.885e-01  4.124e+00  -0.167   0.8674  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.0.1  1.399e+00  9.328e-01   1.500   0.1336  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)3.0.1 -3.093e-01  1.622e-01  -1.907   0.0565 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.1 -7.487e-01  1.346e+00  -0.556   0.5781  
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.1.1  1.647e+00  9.157e-01   1.799   0.0720 .
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.1.1 -7.201e-02  6.476e-02  -1.112   0.2661  
```

polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.2.1 9.324e-02 1.184e-01 0.788 0.4310
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.2.1 -3.849e-02 1.942e-02 -1.982 0.0474 *
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.3.1 -2.033e-03 4.644e-03 -0.438 0.6616
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.2 -5.078e-01 1.227e+00 -0.414 0.6790
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.2 -9.601e-01 9.575e-01 -1.003 0.3160
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)2.0.2 6.190e-02 8.999e-02 0.688 0.4915
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.2 4.015e-02 1.909e-01 0.210 0.8335
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.1.2 -7.748e-02 5.927e-02 -1.307 0.1911
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.2.2 -4.975e-03 1.048e-02 -0.475 0.6350
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.3 8.253e-02 2.030e-01 0.407 0.6843
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)1.0.3 6.658e-02 7.031e-02 0.947 0.3437
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.1.3 -3.589e-05 1.340e-02 -0.003 0.9979
polym(TT_score, AUT_score, CRT_score, degree = i, raw = TRUE)0.0.4 -5.036e-03 1.399e-02 -0.360 0.7188

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 273.80 on 265 degrees of freedom
Residual deviance: 181.91 on 231 degrees of freedom
AIC: 251.91

Number of Fisher Scoring iterations: 11

Appendix D – R output of Comparison of Multivariate Polynomial Probit Regressions of Test Scores versus Entrepreneurship

```
> anova(poly_anova)

Analysis of Deviance Table

Model 1: tag_entrepreneur_factor ~ TT_score + CRT_score + AUT_score
Model 2: tag_entrepreneur_factor ~ polym(TT_score, AUT_score, CRT_score,
    degree = 2, raw = TRUE)
Model 3: tag_entrepreneur_factor ~ polym(TT_score, AUT_score, CRT_score,
    degree = 3, raw = TRUE)
Model 4: tag_entrepreneur_factor ~ polym(TT_score, AUT_score, CRT_score,
    degree = 4, raw = TRUE)
  Resid. Df Resid. Dev Df Deviance
1       262     220.21
2       256     210.79  6   9.4169
3       246     197.36 10  13.4344
4       231     181.91 15  15.4417
```

Appendix E – Testing Abstraction

An eighth CRT dummy question was added which did not contribute to the CRT score. It was used to determine whether ability to formulate abstract answers mediates the relationship between analogical thinking and the other cognitive questions. The question reads:

> *"David had 15 marbles. He lost some of them. How many marbles does David have now?"*

Upon further investigation of the data, it has become apparent that successful entrepreneurs were able to answer the question in a much more abstract manner. Answers from successful entrepreneurs included: '*between 2 and 13*', '*15-n; n<=13*', '*some marbles*', '*15-some*', while answers of the non-entrepreneurs included '13', '0' 'no idea', and 'can't say'.

The question was regressed against the nominal variable status of successful entrepreneurship using a probit regression, yielding the following results:

Table 23: Probit regression output of extra question vs entrepreneurship status

Test	Coefficient	p-value	Residual deviance	AIC	R^2	p-value R^2
Extra Question	0.4918	6.7e-03***	266.48	270	0.03	6.9e-02

Afterwards, a multiple probit regression was applied which included the CRT, AUT and TT scores. The p-value of the extra question was reduced to 5.2e-02*; the AIC decreased from 228 to 226; the residual deviance decreased from 220 to 216. This suggests that the question does add additional information, albeit very little compared to regressions without the cognitive dimensions.

The residual deviance and AIC were generated using a series of multivariate probit regression, including the extra question but omitting each of the CRT, AUT and TT.

Table 24: AIC and Residual deviance of multivariate regression considering test scores and extra question missing each test scores, the extra question, both TT and the extra question, and none of the parameters

Test	AIC	Residual deviance
Missing CRT	241.45	233.45
Missing AUT	238.85	230.85
Missing TT	227.86	219.86
Missing Extra Question	228.21	220.21
Missing both TT and Extra Question	230.1	224.1
Comparison: All factors included	226.41	216.41

The results are similar to an ANOVA for a multivariate probit regression and indicate that there is minimal difference between the TT and the extra question in additional explanatory power. If both questions are missing, the AIC and residual difference rise quite considerably. This is not supported, however, by the correlation matrix below, which indicates a weak correlation between TT scores and the extra question. The weak correlation with all test scores may indicate that this variable measures another dimension altogether.

Table 25: Correlation matrix of test scores including extra question

Test	CRT Score	AUT Score	TT Score	Extra Question
CRT Score	1.00	0.25	0.33	0.19
AUT Score	0.25	1.00	0.19	0.04

TT Score	0.33	0.19	1.00	0.10
Extra Question	0.19	0.04	0.10	1.00