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Revisiting image theory: decision styles, temptations and image theory's compatibility test

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**Revisiting Image Theory:
Decision Styles, Temptations and Image Theory's Compatibility Test**

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A thesis submitted in partial fulfilment of the requirements of
Sheffield Hallam University
in Collaboration with Munich Business School
for the degree of Doctor of Business Administration

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ABSTRACT

This thesis project revisits the compatibility test, Image Theory's screening process to form decision choice sets, and considers its elements and mechanisms in the light of three aspects: first, it investigates how the affect heuristic influences the compatibility screening. In this context, the claim of earlier research that only criteria violations are considered during the option screening process is reconsidered; second, a structural model is evaluated establishing links between a decision-maker's decision styles and the variables defining the compatibility test; and third, a neural network is created and tested to predict even irrational choice of decision-makers for a specific screening situation and based on their compatibility test in- and outputs.

741 participants of two populations were administered three online questionnaires to collect required data. 40 questionnaire items have been used to identify the participants decision styles. The participants were tasked to select companies as potential acquisition targets and, thus, performed a compatibility test based on criteria and their importance weights provided by the researcher. Companies met and failed to meet the criteria to differing extent. Two temptation alternatives that outperformed all other companies in the most important criteria multiple times and failed to meet all others were administered to the participants. Based on what companies were selected, the participants rejection threshold and their inconsistent choices were determined.

The research provides evidence that the claim of earlier research that Image Theory's compatibility screening process relies only on criteria violations is untenable. Further, a structural equation model was confirmed establishing links between participants' decision styles and the variables defining their compatibility screenings. Eventually, a neural network was generated, trained and tested that correctly predicted with close to 90% reliability a participant's choices, even the objectively irrational ones.

It is recommended that future research further develops the idea of neural networks mimicking human decision behaviour.

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Abbreviations

Abbreviation	Meaning
ACP	: Administrative and Consent Part
AI	: Artificial Intelligence
a_{ij}	: Salience value of attribute A_j in decision alternative D_i
a_{ni}	: $i = 1, 2, \dots, 5$, variables ANXIOUS_1, ANXIOUS_2, ANXIOUS_3, ANXIOUS_4, and ANXIOUS_5
A_j	: Attribute or criterion j that describe a decision alternative D_i
ANOVA	: Analysis of Variance
anxi, anx_s	: ANXIOUS style for the Base (anxi) and for the Student Sample (anx_s) respectively
AUC	: Area Under Curve
a_{vi}	: $i = 1, 2, \dots, 5$, variables AVOIDANT_1, AVOIDANT_2, AVOIDANT_3, AVOIDANT_4, and AVOIDANT_5
avo _i , avo _s	: AVOIDANT style for the Base (avo _i) and for the Student Sample (avo _s) respectively
$a_{\lambda j}$: Salience value of the attribute A_i in the tempting alternative D_λ
$a_{\lambda \tau}$: Salience value of the super attribute A_τ in the tempting alternative D_λ
B_s	: Net benefit when implementing strategy S
b_j	: target or To-Be-Met values for a criterion j
B_s^{opt}	: Maximal net benefit when implementing strategy S^{opt}
CEO	: Chief Executive Officer
CEST	: Cognitive-Experiential Self-Theory
CFA	: Confirmatory Factor Analysis
CFI	: Comparative Fit Index

Abbreviation	Meaning
C_s	: Cost (effort, time, money, etc.) to implement strategy S
DBA	: Doctor of Business Administration
de_i	: $i = 1, 2, \dots, 5$, variables DEPENDENT_1, DEPENDENT_2, DEPENDENT_3, DEPENDENT_4, and DEPENDENT_5
depe, dep_s	: DEPENDENT style for the Base (depe) and for the Student Sample (dep_s) respectively
D_i	: Decision alternative i
DS_{IC}	: Discriminant score of the best discriminant analysis for the choice set variable INCONCIS
DS_{NC}	: Discriminant score of the best discriminant analysis for the choice set variable NUMCOMP
DS_{TH}	: Discriminant score of the best discriminant analysis for the choice set variable THRESHOLD
DSQ	: Decision-Making Styles Questionnaire
D_λ	: Tempting decision alternative
EFA	: Explorative Factor Analysis
fMRI	: functional Magnetic Resonance Imaging
GDMS	: General Decision-Making Style inventory
IBM SPSS	: Software tool provided by IBM for statistical processing of data in social science
I_i	: Incompatibility score of decision alternative D_i
in_i	: $i = 1, 2, \dots, 5$, variables INTUITIVE_1, INTUITIVE_2, INTUITIVE_3, INTUITIVE_4, and INTUITIVE_5
intu, int_s	: INTUITIVE style for the Base (intu) and for the Student Sample (int_s) respectively
I_λ	: Incompatibility score of the tempting decision alternative D_λ

Abbreviation	Meaning
KMO	: Kaiser-Mayer-Olkin
M&A	: Merger and Acquisition
ma _i	: i = 1, 2, ..., 5, variables MAXIMISING_1, MAXIMISING_2, MAXIMISING_3, MAXIMISING_4, and MAXIMISING_5
maxi, max_s	: MAXIMISING style for the Base (maxi) and for the Student Sample (max_s) respectively
MPlus	: Software tool provided by Muthén & Muthén for statistical analysis with latent variables
PCA	: Principle Component factor Analysis
P _{sc}	: Subjective probability that the selected strategy S will lead to the best or correct decision alternative
P _{sc} ^{opt}	: Subjective probability related to the selection of S ^{opt}
ra _i	: i = 1, 2, ..., 5, variables RATIONAL_1, RATIONAL_2, RATIONAL_3, RATIONAL_4, and RATIONAL_5
rati, rat_s	: RATIONAL style for the Base (rati) and for the Student Sample (rat_s) respectively
re _i	: i = 1, 2, ..., 5, variables REGRET_1, REGRET_2, REGRET_3, REGRET_4, and REGRET_5
regr, reg_s	: REGRET style for the Base (regr) and for the Student Sample (reg_s) respectively
RMSEA	: Root Mean Square Error of Approximation
ROC	: Receiver Operating Characteristics
S	: Decision strategy applied during Image Theory's profitability test to select the best decision alternative
SEM	: Structural Equation Model
S ^{opt}	: Strategy S for which the total benefit B _s becomes optimal (maximal): B _s ^{opt}

Abbreviation	Meaning
sp_i	: $i = 1, 2, \dots, 5$, variables SPONTANEOUS_1, SPONTANEOUS_2, SPONTANEOUS_3, SPONTANEOUS_4, and SPONTANEOUS_5
spon, spo_s	: SPONTANEOUS style for the Base (spon) and for the Student Sample (spo_s) respectively
SRMR	: Standardised Root Mean Residual
TLI	: Tucker-Lewis-Index
T_n	: Rejection threshold of decision-maker n
U_c	: Subjective utility that would be gained by the decision-maker if the best or correct decision alternative is selected
U_f	: Subjective utility that would be gained by the decision-maker if a suboptimal or false decision alternative is selected
U_s	: Total subjective utility when implementing strategy S
U_{sc}	: Subjective expected utility of a specific strategy S leading the best or correct decision alternative
U_{sf}	: Subjective expected utility of a specific strategy S leading a suboptimal or false decision alternative
v_{ij}	: Compatibility value of attribute A_j for decision alternative D_i , can take the value 0 (non-violation) or 1 (violation)
VMPC	: Ventro-Medial Prefrontal Cortex
w_j	: Importance weight of attribute A_j
w_τ	: Importance weight of the super attribute A_τ

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1 INTRODUCTION

1.1 Setting the scene

Decision taking is a complex task and to answer the question 'how human beings take decisions' is a long existing human endeavour. Even more though, early or first-generation research in decision-making focused on the question how to find the best option amongst a set of decision alternatives. This led to the creation of numerous normative theories such as utility theory (Bernoulli, 1738), Bayes Theory (Hartigan, 1983), Game Theory (von Neumann & Morgenstern, 1944) and prospect theory (Kahneman & Tversky, 1979).

More recent research (Tversky, 1969; Kahneman, Slovic & Tversky, 1982, Thaler 2005) has casted some doubt on basic assumptions of these normative theories. Normative paradigms that have proved to be at least on 'shaky grounds', if valid at all, are that, first, the decision-maker acts rationally, second, all relevant information to select the best alternative is readily available to and, third, can be processed by the cognitive capacities of the decision-maker (within the required time and budget constraints). Further, normative theories mostly assume that no interaction takes place between the decision-maker and the decision outcome once the decision has been taken. Clearly, this is only valid in classical 'role-the-dice' or 'lottery' decisions that certainly do not represent the overwhelming majority of real-life decisions.

This is not the only criticism of normative decision theories. They appear to be far-fetched and 'wooden' when it comes to incorporating real-life behaviour, let alone affect, emotions, ethics and social responsibility. In many cases "*subjects just do not follow expectation models*" (Hershey & Shoemaker, 1980, p. 417) or as Schwab et al. (1979) put it: "... *there is a nagging suspicion that expectancy theory overintellectualizes the cognitive processes people go through when choosing alternative actions*".

Etzioni (1988, p. 21) provided the following advice: "Those who study behaviour in general, economic behaviour in particular, should give up the assumption of a mono-utility world, propelled by one motive, ... , and recognize in their paradigm at least two

irreducible sources of valuation of ‘utility’: pleasure and morality’. Based on the works of Etzioni (1988), Prelec (1991) in his research, identified three characteristics of a decision situations that classic normative utility based theories had difficulties to cope with: First, the temporal mismatch; that is, the time of decision-making and harvesting the benefit of that decision are recognisably distinct; second, the saliency mismatch describing the situation when the consequence of a decision alternative can be described precisely and imagined clearly whilst other options are vague or blurry; and, third, the scale mismatch introducing the possibility that a given alternative has only considerable impact either when chosen or implemented repeatedly, or when others select this alternative as well.

“The story of behavioural decision theory has been a growing realization that [utility theory] often does not describe the decision-making process ... The dramatic tension has been provided by [utility theory’s] remarkable ability to hang on despite mounting doubts about its descriptive competence” (Fischhoff, Goitein, & Shapira, 1983, p. 185).

The author of this thesis was keen to find a theory that would accommodate real-life decision making even to the expense of not providing guidance on how to find the best decision alternative in a specific decision situation; a broader theory that would not be confined to only one social science. He is of the belief that understanding how human beings take decisions will itself amend individual decision-making in the sense of finding the best possible option available.

The search of the author led him to Beach & Mitchell’s Image Theory (Beach, 1990) a two-step descriptive decision theory. A centre piece of Image Theory is a screening process referred to as compatibility test that reduces the available decision options to a set of alternatives (choice set). These alternatives or options, at first glance, appear to achieve the desired result when implemented. When applying the compatibility test, decision-makers compare desired values for criteria of differing importance to them with the actual salience of these criteria in the decision alternatives considered. An alternative is rejected if the sum of a sufficient number of its differently weighted criteria values fail to meet the decision-maker's rejection threshold. Research of Beach and Strom (1989) as well as of Ordóñez et al. (1999) claim that in the context of the

compatibility test, criteria violations appear to dominate the screening process and, thus, the acceptance or rejection of a decision alternative.

Further, and more interestingly, the above researchers state that achieving a criterion does not contribute to the result of the compatibility test and cannot compensate the failure to meet other criteria. It was this statement that draw the author's attention: would it be possible to provide evidence of the contrary? What if an alternative fails to meet the desired values for all but the one criterion; the criterion for which the alternative outperforms all other alternatives multiple times and that would be of utmost importance to the decision-maker? Would it possible to seduce the decision-makers to allow this tempting alternative, this temptation, in their choice sets even though it does not meet their rejection thresholds and would therefore be deemed as an irrational choice, as an inconsistency, by an objective outside party? These questions can be encapsulated in the first research question:

1. How is Image Theory's compatibility test influenced by tempting decision alternatives?

Presenting relevant literature (i.e. Slovic et al., 2007) and testing the related hypothesis (hypothesis 1) will be a first aim of this thesis.

A second set of hypotheses (hypothesis 2 to 4) that will be developed and tested in the frame of this research project is linked to relations between the elements defining the decision-makers' compatibility tests and their decision style profiles. Those elements or choice set variables are the decision-maker's rejection threshold, the number of alternatives in the choice set and the number of inconsistent choices. That is, the number of alternatives that meet the rejection threshold but have not been selected or those that do not meet this threshold but became part of the choice set.

For the purpose of this thesis, a decision-maker's decision style profile shall be defined as the salience of eight decision styles: rational, intuitive, spontaneous, anxious, avoidant, regret, dependent, and maximising. The author relies on the work of Dewberry et al. (2013) who researched the relationship between these eight decision styles and their categorisation in three process styles: a regulatory process style that deals with decision anxiety based on Lerner and Keltner's Appraisal Theory (Lerner & Keltner, 2000,

2001; Lerner et al., 2003; Lerner et al., 2007), and two cognitive process styles, System 1 and System 2, that bridge into dual processing theories (for an overview see Stanovich & West, 2000).

In the context of researching links between one's decision style profile and the elements of the compatibility test, the first questions that spring to one's mind could be: will more spontaneous decision-makers select more or less decision alternatives forming their choice sets? Will a rational decision-maker be less victim to inconsistent choices than an intuitive individual? Or, more generally, how does the decision-maker's decision profile influence the choice set variables of the compatibility test? Could the choice set variables be predicted if the salience of the decision styles of the decision-maker is known? These questions can be summarised in the second research question setting the scene of what should be further achieved with this thesis:

2. How does the decision style profiles of decision-makers influence the elements of the compatibility test, that is, their rejection thresholds, the number of alternatives surviving the compatibility screenings and the number of their inconsistent choices? If the assumed influence exists, is it possible to predict the elements of compatibility test with sufficient reliability?

Testing related hypothesis required the author to, first, provide evidence that the model developed by Dewberry et al. (2013) is valid in the context of this thesis as well (hypothesis 2), second, determine potential links between a decision-maker's decision style profile and the choice set variables (hypothesis 3), before, third, trying to predict these choice set variables for decision-makers based on the knowledge about their decision style profile (hypothesis 4).

To test the hypotheses of this research project, the author chose to conduct an online survey that consisted of two main parts. A first one to determine the participant's decision style profile and a second one to require them perform a compatibility test in a specific decision situation.

For the first part, the author relied on previous research (Scott & Bruce, 1995; Schwartz et al., 2002; Leykin & DeRubeis, 2010) when operationalising the variables by selecting

questionnaire items to determine the decision and, thus, the process styles of the participants.

In the second part, the participants assumed the role of a CEO of an investment company seeking to acquire an additional company to be added to its portfolio of companies. In this specific decision situation, the participants' task was to select acquisition targets (companies) to form a 'shortlist' based on criteria provided by the researcher.

Researching the links between decision styles and the applicability of Image Theory appears to be uncharted territory. However, the work of Galotti et al. (2006) claimed that "*decision-making styles seem not to affect either the information gathering or the decision-structuring phases of decision-making...*" (Galotti et al., 2006, p.637). Galotti and her colleagues used only the decision styles introduced by Scott and Bruce (1995) without considering potential interaction amongst them. Further, the Galotti et al. (2006) study relied on 133 participants, a relatively small sample size, in particular when trying to detect potentially weak relations; Dewberry et al. (2013) based their research on 629 participants.

Eventually, an element of Galotti's work appears to be a source of potential bias: The 133 participants had to select which college majors they were currently considering. The research relied on a survey that "*was used to provide a systematic way for the participants to describe the options under active consideration, as well as the criteria the participant reported using to evaluate those options ...*" (Galotti, 2006, p. 634). The whole process of the compatibility test seemed to be systematic, and, thus, rather formal, relying on a worksheet that had to be worked through in a structured and well organised way. Providing this kind of structure and guidance when performing the compatibility test might influence what decision style the participant might put at work, i.e. participants might prefer using the rational decision style instead of the spontaneous or intuitive styles. Previous research of Ordóñez et al. (1999) confirmed already that instructions provided by the researcher might influence the outcome of the compatibility test. Therefore, less instructions might be preferable.

The assumption that too much guidance and instructions might hamper the decision-makers to activate the decision styles 'natural' to them in a specific decision situation

and the findings of Hodgkinson et al. (2008) who found in an fMRI study that the "...*locus of the X-system* [the intuitive brain system]... *is a network of neural structures consisting of the basal ganglia, ventro-medial prefrontal cortex (VMPC), nucleus accumbens, amygdala and lateral cortex...* [and that this X-system] ... *is located in neural substrates that are slow to form, slow to change and relatively insensitive to explicit feedback from others*" (Hodgkinson et al., 2008. p. 11) led the author to compare the interaction of the various decision styles with the principle of artificial neural networks, or short neural networks.

Neural networks mimic the structure and processes of the human brain which learns by strengthening or weakening the links (synapses) between numerously connected but very simple processing units. In brain science, these processing units are called neurons and have a cell body as well as axons and dendrites which are 'wires' that transport messages to the next neurons or receive signals from other neurons. The information transfer is triggered by stimuli and relies on electrochemical processes. A neuron can either transmit or receive information that in return might be of an activating or dampening nature. If the stimuli received reach a certain threshold, the neuron 'fires' a signal to other neurons. This electrical signal has to cross a small gap between one neuron and the next and is referred to as synapses. The more often a neuron transmits information to a specific other neuron, the stronger grows the synapse between the two neurons. Human beings "learn" as these synapse modifications occur.

Learning is an important feature of artificial neural networks that are algorithms relying on certain input data and providing an interpretable output (result). Learning in this context, is achieved by modifying the weight allocated to each link between the neurons that are also referred to as nodes or perceptrons in the context of artificial neural networks. A node of a neural network receives signals (values) from other nodes of the network. These values are multiplied by the related weights and, subsequently, the results for all links are summed up. If the total of this sum reaches the threshold of an activation function, the node of the neural network 'fires' a signal (a value) to the next nodes that it is connected with. Typically, a neural network exists of at least two layers (group of nodes), one input layer where the values of the independent variables are entered, and an output layer that provides an interpretable result. More complex networks make use of hidden layers, that is, groups of nodes that are allocated between

the input and the output layer. A more detailed description of neural networks in social science is provided by Garson (1998).

Neural Networks have been used widely in research projects in economics and business as well as in sociology and psychology (for an extensive list of research projects, see Garson, 1998, p. 17 - 22)

This research project hypothesises that the various decision styles represent the nodes of a neural network that might be triggered by certain events external or internal to the decision-maker. The activation of one or more decision styles would then potentially increase or dampen the activity of other decision styles. The sum of those decision style activities would aggregate in the three process styles that would in return influence the choice set variables depending on the strength of the received signals.

On one side, this concept of interacting decision styles led to the definition of the structural model describing the impact of the decision and process styles on the choice set variables, that will be discussed further in the chapter HYPOTHESES. On the other side, the thought of decision and process styles acting as a neural network that excel when designed for non-linear classification or prediction tasks (Garson, 1998, p. 81), generated further questions: Is it possible to predict whether a specific decision alternative will be accepted or rejected by a decision-maker? Is the data collected with the surveys of this research project sufficient to generate, train and test a neural network that holds enough predictive capability to reliably address this task? Again, these questions can be summarised in the third research question:

3. Is it possible to reliably predict the choice of a decision-maker with regards to a specific decision alternative based on the concept of neural networks?

This took the author to postulate the fifth and last hypothesis of this thesis: a neural network can reliably predict the choices of participants based on the data gathered in the current research project. If not falsified, this hypothesis promises to release far-ranging implications for management practice leading to the justification and the author's motivation to conduct this research project. Both shall be discussed in the next chapter.

1.2 Developing the research topic: justification and motivation

The motivation as well as the justification that led to the undertaking of this research project is closely linked to the author's DBA journey and the management experience he has had during his professional career.

As manager and CEO, the author is used to taking decisions himself and therefore holds a natural interest to understand his and others' decision-making. Based on his positivistic nature, the author initially wanted to research the development of a system of company key performance indicators that would enable any CEO to take better decisions. But during the course of the DBA programme when confronted with the content of the various learning modules and whilst discussing with his peer students, the definition of what constitutes a right or wrong decision became more and more blurred. The main driver for the difficulty to separate right from wrong was the literature dealing with heuristics and biases (Kahneman, Slovic, & Tversky, 1982; Gilovich, Griffin, & Kahneman, 2002; Thaler, 2005; Bazerman & Moore, 2013) that nurtured doubt in the author's mind about rationality in managerial and general decision-making. It appeared that other factors than rationality play at least an equally important role in the decision process. But if rationality is not the benchmark and, thus, right and wrong is more of a subjective than an objective in nature, normative decision theories have to fail at least in some decision situations; a conclusion that is supported by relevant literature (see chapter Setting the scene) and was confirmed by the author's own managerial experience that allowed him to observe other decision-makers who perceptively took the "wrong" decision even though the rational alternative should have been bluntly obvious - at least seen from the authors (subjective) point of view. This demonstrates already the mind shift that the author was subject to during his DBS studies.

The conclusion of potentially failing normative theories led the author, first, to believe that descriptive decision theories that are not burdened with right or wrong judgments might be the better alternatives to change individual decision-making, and, second, to generate a desire to investigate the impact of those above mentioned other factors on the decision process. Apparently, and as the work of Dewberry et al. (2013) hinted on already when discussing regulatory and cognitive process styles, there appear to be two

sets of factors influencing decision-making: external factors that define the decision situation itself, i.e. general constraints, such as, time and budget constraints or commitments made to others; and internal factors that appear to be the decision-makers cognitive predisposition, i.e. if decision-makers tend to rely on rationality or intuition during the decision process, or how they respond to the presence and consequences of external factors.

Based on the finding that normative theories might fail in day-to-day decision-making, the author reviewed the literature for descriptive theories and found Beach and Mitchell's (1987) Image Theory that provided a fertile ground for quantitative research stemming from a positivistic stream of research with its screening process to form the choice set (compatibility test) expressed in a very simple equation (see equation 1, page 18).

As the biases and heuristic research demonstrates, the above mentioned cognitive predisposition are in constant interaction or competition with each other that leads in combination with external factors to an additional twist in the decision-making process. Therefore, and under the impression of the biases and heuristics literature, the author became interested how the compatibility test is impacted by biases and heuristics. Thinking of the compatibility test as being non-compensatory, as claimed by the relevant literature (Beach & Strom, 1989; Ordonez, Benson, & Beach, 1999) appeared to be suspicious to the author based on his own experience: if there was one alternative that promised to be 'mind-blowing' in one specific, very desired and thus important attribute, would this 'super-feature' cure the failure of, let's say, all other features to meet the minimum desired requirement? For the author, this was a nagging question requiring an answer since providing evidence that the compatibility test might not always be non-compensatory would develop further Image Theory and, thus, constitute a contribution to knowledge.

Further, having the very simple equation of the compatibility test in mind and reviewing Dewberry et al.'s (2013) work that bridges the gap between internal factors, that is, the regulatory framework and cognitive predispositions of decision-makers, and decision styles, the author identified the requirement and generated the desire to research the links between decision and process styles on one side and the quantitative elements of

Image Theory's compatibility test. No other research project that the author was able to find had this done before and, therefore, the author would venture in unchartered territory - for the author an exciting thought.

If links between decision and process styles and the elements of the compatibility test existed, then the following might be possible: first, predicting a decision-maker's threshold to refuse or accept a given decision alternative in the choice set; second, predicting the number of inconsistent choices inside or outside the choice set; and, third, predicting the number of alternatives that made it into the choice set and of those that didn't. Predicting these elements that define decision-makers' choice sets, could help these individuals to understand their decision process, and, consequently, amend it.

At this point in the process of developing the research topic, the author questioned himself if it was possible not only to predict the elements defining a decision-maker's choice set but also to potentially predict whether a specific alternative would be accepted in the choice set. If this was possible, it would unfold tremendous practical implications: first, objectively irrational choices could be predicted; second, time and money could be saved in the business context, if a specific alternative could be ruled out before its evaluation; and, third, expert systems could be developed that contain the (decision) knowledge of a large number of experts without doing lengthy, structured interviews with these as is the case today.

In summarising this chapter it can be stated that in developing and undertaking this research project, the author was motivated to further develop or even start three streams of research: first, the impact of biases and heuristics on the input (incompatibility threshold) and outcome (number of alternatives in the choice set and related inconsistencies) of the compatibility test; second, the impact of external and internal factors on those elements of the compatibility test; and, third, researching the possible prediction of choices, even irrational ones. The contribution to knowledge of all three topics as well as potential practical implications of the second (management training) and third one (expert systems) justifies undertaking this research project.

1.3 Structure of the thesis

In complementing the introductory chapter, the author would like to provide the subsequent structure of this thesis.

The next chapter LITERATURE REVIEW presents and discusses the relevant literature on Image Theory, on the concept of the affect heuristic that seems to play a major part when considering tempting decision alternatives, on research providing insight on human beings' decision and process styles, and on dual processing theories that appear to be the foundation for research on decision and process styles as well as for the affect heuristic.

The subsequent chapter HYPOTHESES raises relevant questions as a result of the literature review and formulates the five hypothesis of this thesis that have already been briefly touched on.

The chapter METHOD details the research approach that the authors has taken to potentially falsify the hypotheses. This chapter will start with the epistemological position of the author, discusses briefly ethical considerations on which this research project was based, before describing in detail the research design as well as the operationalisation of the variables, the populations and samples used, and the cleaning process that the collected data was subject to. Eventually, the chapter closes in answering how and what statistical methods were used to test each of the five hypotheses.

The RESULTS chapter provides in detail the findings for each hypothesis, before the chapter GENERAL DISCUSSION summarises this discussion and extends it by sharing potential implications for management practice where relevant and by providing limitations of the research project, suggestions for future research projects, and a focus on what this research contributes to the body of scientific knowledge.

Cited literature can be found under the section REFERENCES. Additional, relevant information that could not be provided in the main body of the thesis text has been regrouped and attached in the APPENDICES section. Lists of the tables, figures, abbreviations, and equations has been added right after the list of content above.

2 LITERATURE REVIEW

2.1 Introduction

This literature review will focus on the main areas that are important for the research undertaken in the context of this thesis.

The next subchapter will provide a detailed discussion of Image Theory, a descriptive decision theory proposed by Beach and Mitchell (Beach & Mitchell, 1987; Beach, 1990), as well as related research on the applicability of Image Theory and its building blocks. Image Theory is the basis for all hypotheses developed and researched in this thesis; thus, it was given a dominant role when composing this literature review.

The following subchapter Research on Temptation - the Affect Heuristic will then describe the concept of the affect heuristic and related topics and research. The very first hypothesis is dealing with the potential role of the affect heuristic when performing Image Theory's compatibility test, the screening process to reduce the number of alternatives during a decision situation and to form the choice set containing candidates for potential implementation.

The third and last major part of this literature review is devoted to the research on different decision and related process styles. First, research on the various decision styles is presented and discussed before the concept of the process styles is introduced. Second, and in full appreciation of the process styles' importance, a brief overview of their foundation, the dual process theories, is provided next. The third part of the literature review introduces then the work of Dewberry et al. (2013) which plays a major role for this research project. These researchers' endeavours to provide a general structure organising the eight decision styles and, in particular, regrouping them in one regulatory and two cognitive process styles, forms the basis for testing hypothesis 2 to 5.

Eventually, the literature review closes with a summary of the reviewed literature encapsulating the main schemes important to the research of this thesis.

2.2 Image Theory

Following Beach et al. (1988) and in response to Fischoff et al.'s (1983, p. 185) provocative statement regarding the classic, utility-based theories' weakness of "*descriptive competence*", two developments could be observed: First, researchers try to "*tinker... with traditional theory – by altering definitions or axioms in an attempt to make the theory fit the data...*" (Beach, Smith, Lundell, & Mitchell, 1988, p. 18). Beach et al. (1988) consider prospect theory (Kahneman & Tversky, 1979) as one of the most famous examples of such endeavours. Second, Beach et al. (1988) saw a new stream of theory development unfolding seeking to approach decision-making in an entirely new way rooted strongly in cognitive and social psychology.

Image Theory, developed by Beach and Mitchell (Beach & Mitchell, 1987; Beach, 1990), is a child of this new research stream. It is a descriptive decision theory predominantly occupied with individual decision behaviour; although a version of Image Theory that deals with the decision-making in organisations has been developed as well (Mitchell, Rediker, & Beach, 1986; Weatherly & Beach, 1996; Gilliland, Benson, & Schepers, 1998; Beach & Connolly, 2005). However, in terms of reviewing the literature for the present research project, the author will focus on research regarding Image Theory as a descriptive theory of individual decision-making.

The review of the literature on Image Theory is structured in four subchapters.

- First, a *Description of Image Theory* is provided to set the scene for the research testing the theory;

Subsequently, research work on Image Theory was broadly split in three categories that form the subsequent subchapters:

- *Research on the application of Image Theory;*
- Testing and, thus, further development of Image Theory's compatibility test (*Research on Image Theory's Compatibility Test*), and
- *Linking Image Theory to other theories and models;*

2.2.1 Description of Image Theory

In contrast to other normative decision theories, Image Theory (Beach, 1990) is a descriptive theory that describes how human beings take decisions. It is based on the concept that decision-makers use three different schematic knowledge structures to organise their thinking about decisions (Beach & Mitchell, 1998) and, eventually, to take or reject decision alternatives.

These three knowledge structures are referred to as the value images, the trajectory images and the strategic images.

Value images represent the principles of the decision-makers that guide their behaviour. The foundations of these principles are laid early in an individual's life and change less and less the older the person gets. Value images build the very basis to decide whether a goal or an action plan of a particular decision alternative is 'right' or 'wrong'. The decision-makers generally reject a goal or action plan that violates their value images. Value images allow the introduction of concepts with which traditional utility-based decision theories might face problems, such as, social responsibility or the situational mismatches (Prelec, 1991) described earlier.

The second image category, the trajectory images, consists of previously adopted goals. Goals represent the decision-maker's perception or view of a desired future. Goals in this respect are decision-makers' imagination what they might achieve or become in the future.

Eventually, plans that have previously been adopted and are a sequence of events or actions of how to implement or to achieve these goals form the last image category of Image Theory, the strategic images. Components of these plans are called tactics. Further, the decision-makers' projections of the adopted plans allow them to make a forecast of what will happen if a specific plan is implemented. By comparing the results of this projection to the previously adopted goals, a decision can be taken whether or not a plan will lead to the desired outcome, and if the continued pursue of this plan will eventually violate the decision-maker's images.

Figure 1 (see next page) shows the three image categories in a graphical representation focusing on the likelihood of being changed over time: value images represent the very

core of the decision-maker's knowledge structure and, consequently, are rarely modified or changed.

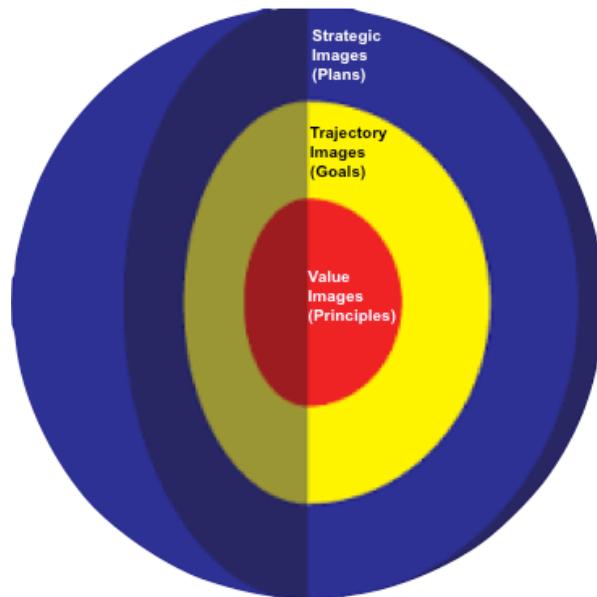


Figure 1:

Decision-maker's knowledge structure consisting of three image categories

Goals build the next layer of the knowledge sphere that are abandoned or modified from time to time either by a – even though rarely occurring – change of the value images or by an event external to the decision-maker. Plans representing the third and most outer layer of the sphere and their adoption, rejection or modification is dependent on either the underlying goals or values or events that drive the decision-maker to either pursue or abandon a previously adopted plan.

When human beings are confronted with a decision situation, they will first retrieve contextual information of their memory. This means they will search their sphere of image categories for previously adopted and implemented goals and plans that have performed well or poorly in the past in comparable situations. If a present situation can be matched with plans and goals previously implemented or pursued, the present situation is referred to as 'recognised'. There is a high likelihood that plans and goals that have served well in the past will be used again in a recognised situation. The set of images of the three categories used in a specific decision situation is called by Beach and Mitchell (1998) the 'working images' forming the decision-maker's decision frame. This decision frame plays an important role during the decision process. Decision problems

that are misframed by decision-makers might lead to wrong or suboptimal decisions, since these decision-makers have ‘forgotten’ to consider certain aspects of the decision problem. That is, they potentially have not retrieved all values, plans and goals that are relevant to the decision situation.

Following Beach and Mitchell (1998) the decision process of Image Theory (see Figure 2) knows two types of decisions, adoption and progress decisions, as well as two kinds of tests that are applied by the decision-makers to eventually find their preferred decision alternatives, the compatibility test and the profitability test.

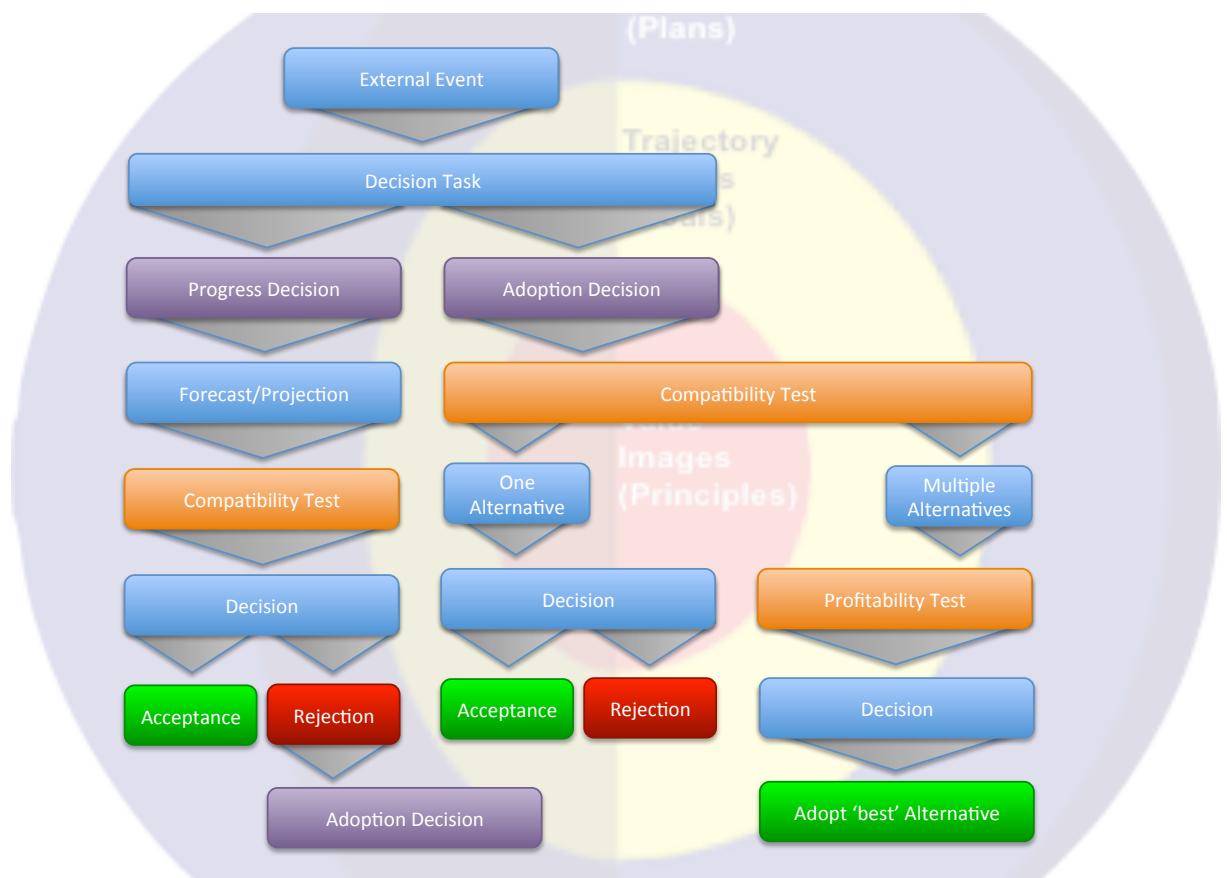


Figure 2:

The decision processes of Image Theory (source: Alexander Müller)

The first decision type, the adoption decision is applied to determine whether or not to adopt a presented goal or decision for pursuit or implementation. Adaption decisions follow a two-step process that splits the decision problem in a screening decision and a choice decision.

The screening decision reduces the number of considered decision alternatives by applying the compatibility test that will be explained later. If the screening process produces only one alternative, the choice decision becomes trivial. If, however, the compatibility test produces more than one suitable decision alternatives, a subsequent choice decision identifies the best one. The ‘best’ alternative implies that it is deemed to produce the most profitable outcome that doesn’t violate the frame provided by the ‘working images’. Most profitable is this alternative that provides the highest utility to the decision-maker. To identify the most profitable alternative, the profitability test is invoked, but only in the case of more than one alternative surviving the compatibility test.

The second decision type is the progress decision. It is linked to the already explained interaction of previously adopted plans and goals that are in the process of being implemented or pursued. This interaction produces a forecast of the future (sometimes referred to as the projected image) that allows the decision-maker to determine if the currently implemented plan will produce the intended result. That is, whether or not the current plan will achieve the desired goal. By using the compatibility test, the current plan can either be rejected or confirmed. If the plan is rejected it might be replaced with an entirely new plan or with a modified plan both requiring an adaption decision. If no plan can be found, the underlying goal might be changed or replaced by an entirely new or modified goal.

Both adoption and progress decision rely on the application of the compatibility test, which is the first of two tests that are known by Image Theory. The compatibility test is used in two ways: during the screening phase of adoption decisions to reduce the number of possible decision alternatives to a set of the assumingly most attractive ones (referred to as choice set) or during a progress decision to either reject or confirm further implementation of a plan or further pursuit of a goal. The core element of the compatibility test is the rejection threshold that is used to either reject a decision alternative or let it pass to become a member of the choice set. Latter is the set of decision alternatives that appear most promising to the decision-maker to bear the most profitable result (‘best fit’) if implemented.

For each decision alternative D_i of a set of n decision alternatives, an incompatibility I_i can be calculated being the measure for how much this decision alternative violates the 'working images' of the decision-maker. The incompatibility I_i of each decision alternative D_i can be formalised to:

$$I_i = \sum_{i=1}^n \sum_{j=1}^m w_j v_{ij} \quad (1)$$

In equation (1) w_j is the importance weight of a specific attribute A_j of m attributes of the decision alternatives. It is a measure of how important this attribute is to the decision-maker. An important attribute A_j of a decision alternative that does not meet the expectation of decision-makers, which means it violates their 'working images', will contribute more to the Incompatibility than an attribute that is considered less important and, thus, has a lower w_j value. Whether or not a given attribute A_j of the decision alternative D_i violates the 'working images' is expressed in equation (1) by the attribute compatibility value v_{ij} . It is 0 if the attribute a_{ij} does not violate the working images and assumes the value -1 if the attribute does not meet the expectation of the decision-maker. This implies that the Incompatibility I_i is negative in value; the more negative it is, the more attributes violate the 'working images', the decision frame, of the decision-maker. Calculating the Incompatibility I_i with a negative value underlines the rejecting character of the incompatibility score.

The incompatibility I_i as calculated by equation (1) is the basis of the compatibility test: If the incompatibility I_i assumes such a (negative) value that it is below the rejection threshold, the decision alternative D_i is rejected by the decision-maker and will not become a part of the choice set and, thus, will not be considered further in the decision process.

Beach and Strom (1989) could not initially confirm the existence of importance weight w_j assuming that all attributes of a decision alternative are equally important to the decision-maker. However, later research (Beach, Puto, Heckler, & Marble, 1996) suggested that differential and not unit weighting is applied in the compatibility test.

The second and last test applied in the frame of Image Theory is the profitability test. It is applied only during adoption decisions and aims to identify and select the decision alternative providing the highest utility to the decision-maker.

The profitability test as defined by Image Theory is not a firm process expressible in an equation as the compatibility test; rather it is made of a number of decision strategies or tools that the decision-maker is mastering. For a specific decision problem, the decision-makers will select one or several of the decision strategies available to them to eventually identify the best alternative. Beach and Mitchell (1978) defined a framework of how decision-makers select a decision strategy. Following the two authors decision strategies can be split in three categories: aided-analytic strategies, unaided-analytic strategies and nonanalytic strategies.

Aided-analytic strategies are based on a procedure, process or protocol that the decision-maker has to follow, i.e. the calculation of a net present value of a given decision alternative. This category of decision strategies always requires tools such as paper and pencil, a calculator or a computer. The large number of normative decision models would fall into this category. Obviously, the underlying process, protocol or procedure has to be cognitively mastered by decision-makers and they must be able to interpret related results. Therefore, aided-analytic decision strategies always require training of the decision-maker and their implementation is effortful and time consuming.

Unaided-analytical decision strategies do not require any tools as those described in the previous paragraph. Nevertheless, these strategies are still based on a prescriptive process that is run entirely in the mind or the decision-maker. An example of such a strategy would be the approximation of subjective expected utility calculation. "*In these strategies, the decision-maker attempts to think about the outcomes that could result from available choices as well as the chances of those outcomes occurring and then choose the alternative that seems in some rough way to offer the best potential*" (Beach & Mitchell, 1978, p. 441). Further research (Tversky, 1967; Shanteau & Anderson, 1969; Holmstrom & Beach, 1973; Mitchell & Knudsen, 1973; Shanteau, 1974; Gray, 1975) suggests that these unaided-analytic strategies are indeed applied in the decision process. There are a variety of strategies that fall in this category, i.e. Simon's (1957) 'satisficing strategy' where the decision-maker chooses the first decision alternative that satisfies a certain attribute. The 'lexicographic strategy' (Tversky, 1969), the 'aspect strategy' (Tversky, 1972) and other strategies (Coombs, 1964; Dawes, 1964 and Einhorn, 1970; Payne, Bettman, & Johnson, 1993) would also qualify as unaided-analytic decision strategy. Obviously, unaided-analytic strategies require less effort and are less time

consuming. In return, they are also less precise and prone to select suboptimal alternatives.

The last category of decision strategies is the nonanalytic ones. These are the easiest and simplest strategies that one can apply in a decision situation and, since they are nonanalytic, they miss any scientific or logical foundation. Examples for such decision strategies which, most likely are simple decision rules, are flipping a coin or the equally famous as childish ‘eeny, meeny, miney, mo ...’. However, they are applied in some specific decision situations. Amongst the nonanalytic strategies one might find as well very simple decision rules, such as, ‘I will not eat the same dish for dinner as I had for lunch’ or ‘I will not drink alcohol before 4 pm’.

Evidently, the various categories of decision strategies vary a great deal in how much effort is spent to identify the final choice; in how much the strategy is founded in logic and science; and in how much time their application requires. The question then arises what strategies are applied in what decision situations. Beach and Mitchell (1978) answer this question by linking the strategy selection to the characteristics of the decision task on one side and of the decision-makers on the other. The characteristics of the latter are defined as their knowledge, ability and motivation.

The decision task can be further broken down in the decision problem itself and the environment in which the decision will be made. Questions that relate to the characteristics of the decision problem are: How familiar or unfamiliar is the decision-maker with the decision problem? Is the decision problem clear to the decision-maker or does it hold a lot of ambiguity? How complex is the decision problem, i.e. how many alternatives need to be considered, how much information is available, how many criteria need to be evaluated? How stable is the decision problem, i.e. do its parameters change over time and how difficult are these changes to predict? The decision environment plays an important role as well. Answers to the following questions are required: Can the decision be reversed or is it irreversible? How significant is the impact of the decision outcome, i.e. will the outcome change the decision-maker’s life? Will the decision-maker be held accountable for the outcome of the decision? Are there any external constraints, such as time constraints or budgets that are not to be exceeded?

Beach and Mitchell (1978) continue to develop an equation to calculate decision task demand as the weighted sum of the demands resulting from the decision problem and the decision environment. Further, they provide seven statements that tie the decision-maker's characteristics to the decision task demand.

Christensen-Szalanski (1978) has developed the ideas of Beach and Mitchell (1978) further. Based on his assumption that the "*selection mechanism consists of a simple cost-benefit analysis... [that] the strategy that appears to offer the greatest expected net gain is the one selected*" (Christensen-Szalanski, 1978, p. 307), he developed a mathematical model for the decision strategy mechanism of profitability test selection.

The Christensen-Szalanski (1978) model as shown in Figure 3 is based on the following assumptions: A chosen decision strategy S can either lead to the selection of the correct (best) or to a false (suboptimal) decision alternative. Provided that the pay offs or losses of the decision alternatives are explicit, a subjective utility U_c can be defined that would be harvested if the strategy S yields the correct or best decision alternative. Equally, a subjective utility U_f can be determined if a false or suboptimal decision alternative is the result of the application of strategy S.

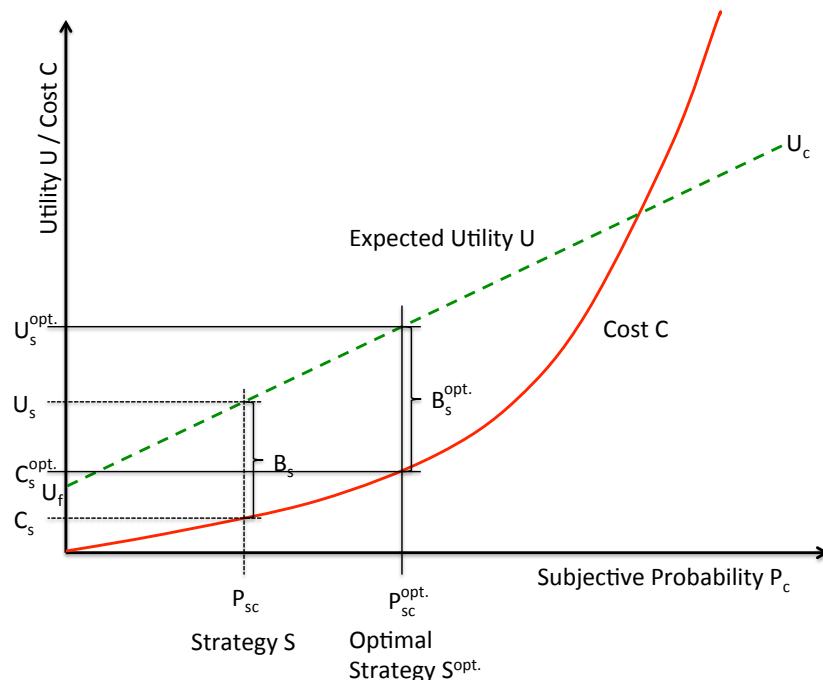


Figure 3:

Christensen-Szalanski model for the strategy selection of the profitability test

Further, a subjective probability P_{sc} exists for each decision strategy S available to the decision-maker. P_{sc} is the subjective probability that the strategy S will lead to the best (correct) decision alternative. If P_{sc} is defined as probability that the chosen strategy S will lead to the best alternative, $(1 - P_{sc})$ will be the probability that the same strategy will identify a false or suboptimal solution. Thus, the subjective expected utility U_{sc} of a specific strategy S leading to the best alternative is:

$$U_{sc} = P_{sc} U_c \quad (2)$$

And, consequently, the subjective utility U_{sf} of the same strategy S identifying a suboptimal alternative is:

$$U_{sf} = (1 - P_{sc}) U_f \quad (3)$$

Further, C_s is the cost (effort, money, time, etc.) that the application of the chosen decision strategy S will cause when implemented. The decision-maker knows this cost C_s , at least as a rough order of magnitude. The function of C_s over the probability P_c is not a straight line but a parabolic curve. This means an increase in C_s is positively accelerated in P_c . That is, for more complex strategies a slight increase in probability to produce the best alternative will lead to a larger increase in cost for the decision-maker. The Christensen-Szalanski model assumes further, that the application of aided-analytic decision strategies will lead to higher probabilities P_c , but will consume more resources as well, cause higher cost.

The sum of (2) and (3) will result in the total subjective utility U_s and in the benefit B_s when considering the cost C_s to implement the strategy S :

$$U_s = P_{sc} (U_c - U_f) + U_f \quad (4)$$

or respectively

$$B_s = U_{sc} + U_{sf} - C_s = P_{sc} (U_c - U_f) + U_f - C_s \quad (5)$$

Christensen-Szalanski's (1978) model drives the decision-maker to choose the strategy S^{opt} that relates to the P_{sc}^{opt} for which the benefit $B_s^{opt}(P_{sc}^{opt})$ becomes maximal. Obviously, the benefit function, the cost curves, U_c and U_f vary from decision-maker to decision-maker as well as from decision task to decision task. A further discussion of

these variations cannot be presented in this paper since it would significantly broaden the scope of this literature review.

Whilst the compatibility test has been intensively researched over last 30 years, the selection mechanism of the profitability test to select a suitable decision strategy allowing the identification of the ‘best’ alternative has not been considered for further research. In the framework of Image Theory’s evolution, only the work of Beach & Mitchell (1978) and the above presented work of Christensen-Szalanski (1978) deserve mentioning. However, Beach (1998, p. 142) expressed his discontent about Christensen-Szalanski’s subjective expected utility model to select a strategy for the profitability test. After all, Image Theory is a descriptive theory and the author tends to join Beach in his criticism: “*Given that image theory is proposed as an alternative to normative theory, it seems almost perverse to incorporate the mainstay of normative theory, maximization of subjective expected utility, as the main mechanism for strategy selection*” (Beach, 1998, p. 267).

Since a selection strategy that eliminates the perceived weaknesses as just described by quoting Beach, has not been found, the review of relevant literature continues with discussing research aiming to provide evidence to the application of Image Theory in real-life decision-making.

2.2.2 Research on the application of Image Theory

Nelson and Puto (1998) and Nelson (2004) researched Image Theory in the context of value-laden customer decision processes. As part of their research they modelled a decision framework that combined all three images, the decision-maker’s principles, goals, and plans, in a decision situation impacted by the social responsibility exercised by an environmentally friendly consumer. The structural model of the researcher saw social responsibility and environmental values impacting consumer’s principles which in return generated specific goals. These goals are influenced by environmental concerns and perceived consumer effectiveness. The goals lead to planned actions that manifest themselves in the commitment to environmentally friendly behaviours, the usage of screening tactics emphasising highly on the environmental attributes of the product. The researchers obtained statistically acceptable support for their structural model and

concluded, thus, that Image Theory provides "*the basis for organizing and structuring knowledge in a more realistic and descriptive manner than traditional decision theory.*" (Nelson & Puto, 1998, p. 208).

Stevens (1998) applies in her paper the elements of Image Theory (that is, the value images, or principles, the trajectory images or goals, and the strategic images or plans) to the decision situation of selecting a certain job offer amongst a range of job opportunities. She describes a two-stage process that first sees the compatibility test reducing the number of job options by evaluating those against criteria of different importance to the job seeker. The result is a choice set containing those job opportunities that have survived the compatibility test and that are then subject to the profitability test to select the winning alternative, that is, the job that the job seeker would accept. Stevens substantiates her model by citing data of earlier research (Osborn, 1990). In this context, she confirms two features of Image Theory. First the application of the compatibility test, and its important feature that rejections are only based on criteria violation that cannot be compensated by non-violations since the compatibility test is of non-compensatory nature (see as well Beach, Smith, Lundell, & Mitchell, 1988; Beach & Strom, 1989; Potter & Beach, 1994a, 1994b; van Zee, Paluchowski, & Beach, 1992). Second, Stevens (1998) hinted to Osborn's (1990) finding that information that has been 'used' during the screening process (what Stevens (1998) and Image Theory in general refers to as compatibility test) and deemed important by the job seeker then, was however unimportant when selecting the winning job opportunity. Stevens (1998) interpreted this research result as confirmation of van Zee et al.'s (1992) finding that information used during the compatibility test is 'consumed' in this screening process and, thus, does not play a role in the subsequent profitability test on the surviving alternatives.

The work of Thompson and Dahling (2010) is linked to vocational choices and values as well. The researchers were interested in how trajectory images were influenced by values images in the frame of vocational decisions. They identified four potential value images that determine a person's self-image: 'perceived social status', 'conformity to feminine role norms', 'conformity to masculine role norms', 'value for status at work'; further, they measured one trajectory image: 'career and leadership aspirations'. Thomas and Dahling (2010) found that 'value for status at work' was directly impacting

'career and leadership aspirations' whilst 'perceived social status' was only indirectly influencing the trajectory image through 'value for status at work'. Further, they could demonstrate a weak positive correlation of 'conformity to feminine role norms' and 'perceived social status' as well as a weak positive correlation of 'conformity to masculine role norms' and 'value for status at work'. As expected, they also found a moderately negative correlation of 'conformity to feminine role norms' and 'conformity to masculine role norms'. Thomas and Dahling (2010) concluded that Image Theory provided a promising decision framework were value images indeed influence respective trajectory images either directly or indirectly through other value images.

A third research project on vocational decision-making was conducted by Lee, Mitchell, Wise, and Fireman (1996). The researchers investigated the processes of employees, in their case nurses, resigning and leaving the organisation they work for. Lee et al. (1996) again confirmed already discussed findings of other research in "*... that factors others than affect prompt the leaving process, ..., and various mismatches among values, goals, and behavioral strategies are potent issues in the turnover process*" (Lee et al., 1996, p. 32).

Eventually, a fourth and last piece of work on the vocational application of Image Theory shall be touched on briefly. In a replica of Gilliland and Langdon's (1998) research on performance evaluation, Pesta, Kass and Dunegan (2005) researched appraisal behaviour and promotion decisions. They confirmed the application of the compatibility test for the promotion decisions if only one employee was considered for promotion. Participants, however, gave up the screening process when the researcher confronted them with a second employee as a contender for promotion. When employees were instructed to screen the alternatives, they returned to the application of the compatibility test. Pest et al. (2005) concluded that experimental conditions and instructions might drive screening behaviour of participants.

Brougham and Walsh (2007) tested Image Theory when asking the question why people retire. They surveyed 239 participants to evaluate conflict and facilitation of the potential achievement of 29 goals if they were to retire or continue working. Further, participants had to evaluate the probability of achieving these goals, and the respective goal importance. Eventually, their intent to retire was measured by them providing their

retirement time frame in 'years from now'. The researchers then performed various regressions on the variables: retirement intent on goal incompatibility; retirement intent on goal facilitation; and, retirement intent on a cost/benefit model. The results of which were compared to a corresponding incompatibility model. Brougham and Walsh (2007) found that the incompatibility model provided better or equal predictions than the facilitation or the cost/benefit model. They concluded from their results that indeed image compatibility plays a central role in individuals progress or adoption decisions regarding these individual's retirement intent.

Kuehn (2009) discusses the question 'why so few people chose to become an entrepreneur?' in the context of Image Theory. Based on the theory's feature that earlier experiences create decision frames and, thus, shape the constituents on which individuals build their assessments of decision alternatives, Kuehn (2009) develops three possible answers to the above question. First, he states that one might accept the relatively small numbers of entrepreneurs since the very basic value images or principles that frame decisions about career choices are created and shaped early in one's life even before adulthood is achieved; or as he puts it more bluntly "*... it seems to become harder to 'teach an old dog new tricks'*" (Kuehn, 2009, p. 104). The second answer he offers is a direct result of the first insight: based on the framework of Image Theory, if the number of entrepreneurs is to be increased, then education about the entrepreneurship needs to start early in a person's life to create the required predisposition permitting people to consider entrepreneurship as a career option. Eventually, the third option that Kuehn (2009) puts forward is linked to the question of how the framing of a decision situation can be affected. He introduces additional research (Slovic, Peters, Finucane, & MacGregor, 2005) that explains the influence of feelings and emotions on decision framing. With the related findings Kuehn (2009) potentially credits the little number of entrepreneurs to the "*negative affect ... associated with entrepreneurial 'themes', and thus related words and phrases ... [and therefore to] ... the larger socio-cultural 'conversation' and perceptions about entrepreneurship*" (Kuehn, 2009, p. 105).

As can be concluded from the previous description of Image Theory, one of its main elements is the compatibility test which is a defined protocol that describes the screening process reducing the number of decision alternatives presented to a decision-maker to a choice set holding a smaller number of alternatives. Beach et al. (1988)

describe it as the most important element of Image Theory's decision process since the compatibility test plays the role of the 'gate keeper' for the choice set. After all, only those alternatives that pass the compatibility test will be considered for implementation. This view is further nurtured when considering the research of Mintzberg (1975) who found that managerial decisions most times involve only one alternative; and the manager's decision task is reduced to the question whether or not to go with it. Not surprisingly, further research has been undertaken to evaluate the compatibility test's supporting assumptions and its applicability.

2.2.3 Research on Image Theory's Compatibility Test

Beach et al. (1988) conducted an experiment to test the applicability of Image Theory's compatibility test and to establish the simple and sufficient rule as described by equation (1). For their research they first interviewed 9 to 10 executives of three different companies to learn the principles (in the Image Theory meaning: beliefs, values, etc.) of that organisation. The researcher then fed a simulation system that used Image Theory's compatibility test as expert system with what they had learned about the firms in their interviews with the executives and, then developed up to 10 action plans that had to be evaluated for adoption by the companies' executives as well as by the simulation system. Beach and his colleagues (1988) found that the correlations between the simulation results, that is, the approval or rejection of a certain action plan, and those results obtained from the executives was as high as the correlations amongst the executives of the firm themselves. They concluded that the application of compatibility test is sufficiently valid even though their decision basis was not founded on a statistical process but rather on the Turing Test, developed by Turing (1950). This test states that a rule, in this case the protocol of the compatibility test, is descriptively sufficient provided an outside observer would be indifferent to use the rule of the executives or the rule of the simulation when asked to make a decision whether to adopt or reject a plan. The apparent lack of statistical foundation is of concern to the author. However, further research has shed more light on the applicability of the compatibility test.

Dunegan (1995), for instance, has tested the validity of the compatibility test in progress decisions. These are decisions for which an already existing plan is submitted to a

compatibility test based on the forecast of its outcome if further pursued. The research was based on a typical situation in which a progress decision might be required: the decision task to continue an existing project or to stop it. Dunegan (1995) confirmed the applicability of the compatibility test in progress decisions and demonstrated that decision-makers were more likely to continue an existing project (by providing more funding) when the perceived current and forecasted images of the project were compatible with the target images that ought to be achieved.

Dunegan, Dichon and Ashmos (1995) did also investigate the effect of low and high compatibility of existing projects on the decision-maker's deliberateness to provide further funding. The researchers found that when compatibility was high, decision-makers' other perceptions of the project had little influence on their decisions to provide more funding. Low compatibility however increased the importance of other perceptions of the project when deciding on the amount of additional funding. That is, money was not an issue when compatibility was high whilst low compatibility led to a more careful consideration to increase the funding of the project.

Richmond, Bissell and Beach (1998) undertook a field study to further investigate the compatibility test in progress decisions. For that purpose, they conducted two experiments during which participants in real life organisations had to compare the actual image (forecast) of supervisory behaviour with their desired image (goal). The researchers could provide evidence that compatibility of the participants' actual and desired images of supervisory behaviour generated higher satisfaction amongst participants and that hope for improvement further increased employees' satisfaction. Further, this research provided evidence that testing the compatibility test in progress decisions can be done in a field experiment and that simple research methods can be used in field studies since these provided the same results as more elaborated research methods.

Research into the question of what decision-makers do when all of the surviving decision alternatives become unavailable after the compatibility test, but not as a result of the latter, has been undertaken as well. The experiments of Potter and Beach (1994a) provided the answer to this question. The researchers demonstrated that if all decision alternatives of the choice set become unavailable, decision-makers prefer to start all

over again with new decision alternatives instead of revisiting those alternatives that have been dismissed by the compatibility test. If, however, no new alternatives become available and thus the initially incompatible ones must be reconsidered, decision-maker tend to do both, lower their rejection threshold and lower their weights of the considered attributes. Therefore, decision-makers compromise a little on both instead of changing one feature dramatically.

Potter and Beach (1994b) did also research the impact of paucity of available information and the effect of probability on the application of the compatibility test. The three experiments of the researchers allowed equally three findings: first, missing information is treated by the decision-maker as a violation of the attribute and thus adds to the compatibility score of the decision alternative in question; second, lack of information promotes rejection, the higher the information deficiency the higher the likelihood of rejection; and, third, low probability of a given attribute holding true for a decision alternative will lead to a violation of this attribute – this implies that probability is used in the compatibility test in an additive way and not in a multiplicative one as for the profitability test.

Benson and Beach (1996) investigated the effect of time constraints and of significance increase on the execution of the compatibility test by decision-makers. The research suggests that when decision tasks need to be addressed under time pressure, decision-maker tend to speed up in the execution of the compatibility test and are thus more prone to inconsistent rejection patterns. Unlike for choice decisions (Edland & Svenson, 1993), no evidence was found that decision-makers change their screening strategy during the compatibility test. When Benson & Beach (1996) increased the significance of the decision outcome, decision-makers were found to produce fewer inconsistent rejection patters, but to lower their rejection threshold as well and, therefore, generating a larger choice set.

Van Zee et al. (1992) conducted a series of experiments to learn how decision-makers use information on the decision alternatives of the choice set after the compatibility test had been completed. Van Zee and her colleagues found that decision-makers tend to underuse information provided early in the process. When decision-makers had to rate their choice set alternatives, that is, after screening, but prior to determining their final

choice and had further been given additional information after screening, the rating of the choice set alternatives were only based on the most recently provided information and not on pre-screening information. This led the researchers to assume that information provided for compatibility test purposes was 'used up' (Beach, 1998, p.24) by the screening and, thus, was not used in a potentially subsequent profitability test.

The research of Beach, Puto, Heckler and Marble (1996) on unit weighing versus differential weighing deserve to be mentioned here again, even though it has already been mentioned in the chapter Description of Image Theory. In further developing the initial Image Theory (Beach & Mitchell, 1987; Beach & Strom, 1989), Beach et al. (1996) confirmed that differential weighing of the attribute violations takes place during screening of the compatibility test and, therefore, that equation (1) required to be amended by adding the weights w_j .

Adoption decisions in Image Theory belong to the group of two staged multi-attribute decision procedures and the first step, the compatibility test, serves the same purpose as the Elimination of Dominated Alternatives process put forward by Prospect Theory (Kahneman & Tversky, 1979). Seidl and Traub (1998) compared the two procedures and showed that the compatibility test enjoys higher consistency rates (70%) than Prospect Theory's Elimination of Dominated Alternatives (15%). That is, that the compatibility test has proven to perform well as a model of the screening phase of a two-staged decision procedure. The researchers confirmed this with Selten's measure of predictive success (Selten, 1991) that was 4.5 times higher for compatibility test than for the Elimination of Dominated Alternatives.

Another research project on the compatibility test that should be mentioned in the context of this thesis is the work of Ordóñez, Benson and Beach (1999). Ordóñez and her colleagues (1999) conducted a series of experiments with the aim to further test the compatibility test with regards to instructions and accountability. The researchers found that instructions might influence the decision-maker to focus on 'bad' or 'good' decision alternatives. Further, it appears that accountability drives the decision-makers to become more stringent in the screening process by raising their rejection threshold. Generally, the findings supported that the application of Image Theory's screening process, the compatibility test, is implemented by screening out 'bad' alternatives and

not to screen in ‘good’ ones. This might also explain, why the calculation process contains violations of alternative attributes only and do not consider non-violations (Beach & Strom, 1989).

Eventually, the application of Image Theory’s compatibility test was also researched and confirmed in clinical applications. Falzer and Garman (2012) used Image Theory’s compatibility test to evaluate how clinical decisions were made to change the treatment of patients suffering from schizophrenia. They could demonstrate that, first, unequal weighting is applied instead of equally weighting the various decision criteria, therefore, confirming earlier research of Beach et al. (1996) and, second, that a rejection threshold and, consequently, the compatibility test was used when deciding on the future treatment of the patients.

Having described and reviewed literature providing clues and evidence to Image Theory’s real-life applications, more light needs to be shed on research that aims to create links between Image Theory and other theories and models as well as research that use Image Theory to develop new theory and concepts.

2.2.4 Linking Image Theory to other theories and models

Beach and Frederickson (1989) compared the elements of Image Theory to the financial auditing model developed by Waller and Felix (1984). The model of the latter two researchers postulates “*that an auditor reaches an opinion about the absence of material error in a set of financial statements through a series of revisions and modifications of his or her knowledge structure*” (Beach & Frederickson, 1989, p. 101). Obviously, the expression knowledge structure rings a bell when it comes to Image Theory. Consequently, Beach and Frederickson (1989) claim that this knowledge structure correspond to the images used by Image Theory. Further, the Waller and Felix model states that auditors have abstract schemata in mind when performing an audit. They categorise their work in ‘normal audits’ and ‘problem audits’. The audit itself is then conducted in 4 steps: First, auditors will decide to accept to perform an audit on a given customer or not. Second, they will collect information on the company to be audited, its industry and products. Third, the auditors will prepare and perform the audit itself and, fourth, eventually, form an opinion on the audit results. The decision rule

used in the financial audit is to compare the schemata available in the auditor's knowledge structure with the information and reality found during the relevant audit actions. Beach and Frederickson (1989) recognise the nature of this decision rule to be compatibility driven and non-compensatory. That is, violations of a relevant image of the auditor's knowledge structure cannot be compensated by other findings that appear to meet another auditor's image exceedingly well. Beach and Frederickson (1989) conclude their comparison by stating that the interpretation of the Waller and Felix (1984) financial auditing model with the help of image theory is rather different from the interpretation with the help of a classic utility theory. However, not surprisingly, the two researchers clearly favour the Image Theory interpretation of the Waller and Felix (1984) model. It has to be stated though that the very nature of financial audits is that of compatibility, rather than a compensatory one. Asare and Knechel (1995) further researched this topic based on the findings of Beach and Frederickson (1989) with real auditors and their customers. Except for the rejection threshold that Asare and Knechel (1995) found to be higher hinting on the auditors' real-life importance of not refusing a customer unnecessarily, their findings are comparable to those of Beach and Frederickson (1989).

O'Connor, Parsons and Liden (1992) developed a model that deals with support and resistance of individuals in organisations that decided to introduce new technologies to improve its effectiveness and efficiency. The researchers design their model based on the individual's usage of images as described by Image Theory. Their model has three main elements. First, a building block that they refer to as 'implementation process inputs', considers the planning and execution of strategies and steps required to implement the new technology. Further, the researchers combine the planned outcomes, that is, the goals (or trajectory images) of that improvement project with its anticipated outcomes or its forecasts under the second building block 'implementation process outputs'. Note the difference between planned and anticipated outcomes which provides the basis for that organisation's individuals' to either support or resist the introduction of the new technology. The third and last element of O'Connor et al.'s (1992) model is a control system referred to as 'facilitation and resistance control system' that allows objective as well as subjective comparisons of images based on current and required abilities, attitudes and other contextual information of the organisation.

O'Connor and his colleagues (1992) conclude that "*the power of images may be proactively utilized to assist in achieving desired results*" (O'Connor et al., 1992, p. 123).

Another research project that uses Image Theory to design intelligent agent systems was put forward by Schwartz & Te'eni (2001). The two researchers created an agent architecture for adaptive intelligent agent that use the concept of images and, in particular, Image Theory's two decision types, the adoption and the progress decision. Schwartz and Te'eni (2001) refer to this new architecture type as the 'imaginal agent architecture'. In the context of this architecture progress decisions play an important role in execution monitoring of the intelligent agent. Combined with the process of adoption decision and its implication of changing trajectory and, thus, action images, the new architecture offers a complete adaptive planning mechanism for the design of intelligent agents. Whilst the action and trajectory images materialise on the object-level in the software code, the 'Imaginal Agent Architecture' sees changing these images by progress and adoption decisions on the meta level. The researchers stress, as well, the capability of Image Theory to cover the non-action alternative of human beings when faced with a decision situation; the human feature of 'doing nothing' giving rise to their claim that imaginal intelligent agents might, thus, work more effectively.

Dunegan (2003) continued a stream of research that had been begun by Bissel and Beach (1996) as well as by Richmond, Bissell and Beach (1998). He researched the compatibility of the image that employees have of the ideal leader, who they imagined, and the image that they have of their current supervisor. Dunegan (2003) measured this image fit with a six-item questionnaire. He then compared the results of his leader-image compatibility measure with, first, data obtained from these employees for five variables expressing job satisfaction ('job satisfaction', 'intent to quit the job', 'role ambiguity', 'commitment to the organisation' and 'role conflict'), and, second, with data gathered by the Leader-Member Exchange questionnaire (Graen & Cashman, 1975; Dansereau, Graen, & Haga, 1975). Dunegan (2003) found that the items he used were a good measure to evaluate the leader-image compatibility. Further, he demonstrated that a high leader-image compatibility is positively correlated with high levels of 'job satisfaction' and 'commitment to the organisation', and negatively correlated with high levels of 'role ambiguity' and 'role conflict' as well as with increased levels for an employee's 'intention to quit the job'. Eventually, the leader-image compatibility results

were also significantly correlated with the data obtained by administering the Leader-Member Exchange questionnaire.

Additionally, Dunegan (2003) regressed the five vocational variables on both, the leader-image compatibility and the Leader-Member Exchange scores and could thus provide evidence that leader-image compatibility contributes to further explain the variance of the five dependent variables except for 'commitment to the organisation'.

Having discussed potential implications of Image Theory for the development of intelligent agents and the relation of leader-image compatibility and job satisfaction in general, the author endeavours now to touch on the potential of Image Theory to cope with business ethics. Morrell (2004) compared the possible application of rational choice theory (Zey, 1992) on one hand and Image Theory on the other when decision-makers are confronted with ethical dimensions that they have to evaluate. Rational choice theory, in the context of Morrell's (2004) paper, represents a meta theory regrouping all rational decision theories of which the core element is somehow utility maximisation. Morrell (2004) compares the two decision theories to three ethical systems: first, Utilitarianism that hails the goal of utility maximisation and is further described as being hedonic, calculus and consequentialist; second, Kantianism that is driven by categorical imperative and described as being reflexive and deontological, and, third, Virtue Ethics nurturing "*the cultivation of virtues and the pursuit of good life*" (Morrell, 2004, p. 245) and being dispositional and teleological. Morrell (2004) concludes that Image Theory has the capacity to deal with business ethics in all three ethical systems; that is, in distinction to the rational choice theory which is only useful in a utilitarian context.

Turino and Soetjipto (2012) researched the relationship between image compatibility and decision performance as well as escalation of commitment, a phenome extensively researched in behavioural decision-making (Garland, 1990; Ross & Staw, 1986, 1993; Teger, 1980; Bowen, 1987; Brockner, 1992; Desai & Chulkov, 2009) that describes an effect observed in decision-makers who stick to their initial decision even though rationality would recommend to rectify this decision. Turino and Soetjipto (2012) administered a questionnaire to 229 participants trading at the Indonesian stock exchange and holding respective portfolios during a bearish market period (from January 2008 to February 2009) and a bullish market period (from March 2009 to

February 2010). Their survey determined image compatibility based on Dunegan et al.'s (1995) approach operationalising the following variables: (1) closeness of actual performance of the portfolio and the trajectory image of the participant, (2) movement of the performance of the portfolio to the trajectory image, (3) likelihood that the portfolio performance achieves the intended target, and (4) extent to which the portfolio performance is with the participant's risk tolerance. Escalation of commitment was measured with a questionnaire developed by Staw (1976) and Brockner (1992), and performance was determined with the questionnaire developed by Lewellen, Lease and Schlarbaum (1977). Turino and Soetjipto (2012) demonstrated that image compatibility is a mediator for escalation of commitment in a bullish market only and that image compatibility is positively correlated to decision performance. Therefore, they propose to extend Image Theory to predict performance of a taken decision alternative.

Novicevic, Clayton and Williams (2011) compared Image Theory to Barnard's model of decision-making (Barnard, 1995), a model that was conceptualised by Barnard already in the 1930's but was only published post-hum in 1995. Novicevic and his colleagues (2011) found several commonalities as well as differences and, thus, defying a potential claim that Image Theory had developed out of Barnard's theory. They found three major similarities: first, the concept of value images that is of great importance in the context of Image Theory can also be found in Barnard's theory through the existence of "*socially established conditions ... [that] consist of beliefs, social conventions, and attitudes, ...*" (Novicevic et al., 2011, p. 431). The second commonality that the researchers have identified is the process of how possible decision alternatives are identified: in Image Theory it is desirable for an alternative to be aligned with previous goals. The same is valid in Barnard's theory; for an alternative to be desirable it has to meet as well certain standards appealing to the decision-maker. Eventually, a third finding of this research's comparison is the concept of decision framing. Both in Image Theory as well as in Barnard's theory prevail the view that the "*context in which decisions occur gives them meaning*" (Mitchell & Beach, 1990, p.10).

Interesting enough, the stages of Barnard's theory of decision making appear to be largely driven by intuition and non-conscious processes (Novicevic et al., 2011, pp. 421). The same appears to be valid for Image Theory as well. Therefore, the question arises, are these processes more prone to errors than if conducted thoughtfully and more

consciously? This leads the present discussion of relevant literature to the concept of temptation that will be introduced in a later chapter but requires now a review of its theoretical foundations.

2.3 Research on Temptation - the Affect Heuristic

The word temptation is obviously the noun to the verb 'to tempt'. The Oxford Advanced Learner's Dictionary (1995) explains 'to tempt' as "*to persuade or try to persuade [somebody] to do [something], [especially something] wrong or unwise*" (The Oxford Advanced Learner's Dictionary, 1995, p. 1175). This appears to be a 'spot-on' description of what the author tried to achieve with presenting tempting decision alternatives to the participants in his research project. As will be described in the chapter METHOD, in the context of the current research, accepting a temptation alternative could be considered as 'wrong' or 'unwise' since it does not meet the rejection threshold provided. The Oxford Advanced Learner's Dictionary (1995) continues to give a second definition of 'to tempt' which cues the reader in providing the key word for a respective literature search: "*to make [somebody] to feel a **desire** for [something]...*" (The Oxford Advanced Learner's Dictionary, 1995, p. 1175). Obviously, when discussing temptations, one needs to look into desires which, without providing further evidence, stem from affect.

Having just described and discussed Image Theory and related research, it seems obvious to approach affect from this angle and take the most important concept of that theory, images, as a starting point. Based on the brain research of Damasio and others, (Damasio, 1994; Damasio, Tranel & Damasio, 1990) Slovic, Finucane, Peters, & MacGregor (2007) state "*that thought is made largely from images, broadly construed to include sounds, smells, real or imagined visual impressions, ideas, and words. A lifetime of learning leads these images to become 'marked' by positive and negative feelings linked directly or indirectly to somatic or bodily states [hence somatic markers] ...*" (Slovic et al., 2007, p. 1335). Damasio et al. (1994) studied decision-making of patients with ventromedial frontal cortices damage. This condition leaves patients unable to 'generate' feelings and emotions albeit their cognitive capabilities in terms of logical and rational thinking as well as memory and intelligence do not suffer. In a series of other experiments, Bechara and Damasio (2005) could observe that this "*impairment*

degrades the speed of deliberation (e.g., choosing between two brands of cereal may take a patient a very long time because of endless reasoned analyses of the pros and cons of each brand), and also degrades the adequacy of the choice, i.e., patients may choose disadvantageously." (Bechara & Damasio, 2005, p. 339). This provides evidence that affect for one or any other decision alternative plays a significant role in decision-making, even to the extreme extent that - as for these patients - a proper decision-making becomes cumbersome or simple impossible without 'somatic markers' causing affect.

Other research on emotionally 'tagged' images and decision-making was conducted by Slovic et al. (1991), Peters and Slovic (1996), Mowrer (1960a, 1960b) and MacGregor, Slovic, Dreman and Berry (2000). These research projects confirmed that images are good predictors of participant's preferences.

The role of images in decision-making is expressed by Zajonc (1980, p. 154) as follows: "*We do not see 'a house': we see a handsome house, an ugly house or a pretentious house*". The effect of images with somatic markers in decision-making appears thus to be known for some time. Research on i.e. names (onomastic research) has unveiled that affectively unpleasant names lead to a perception of lower quality (Harari & McDavid, 1973; Erwin & Calev, 1984). Who would not rather be listening to John Denver singing a song than to a certain Henry J. Deutschendorfer jr.? Even though, the man behind these names is the same. Marketeers and the advertisement industry in general appear to master the impact of affect particularly well. All the short but useful slogans on i.e. food or other consumer goods packaging, such as 'lighter', '50% less calories', 'sales - 80% off', etc., have the one and only aim to trigger the affect heuristic in the consumer's brain: eating healthier is obviously desirable since one becomes more attractive and performant or lives longer; being granted a large discount makes us feel better and cleverer.

All these examples of 'affect at work' demonstrate that it requires a trigger for the affect heuristic to jump into action. The mechanism of this stimuli was researched by Zajonc (1968, 1980) and others, and later reviewed as well as meta-analysed by Bornstein (1989). Zajonc (1968) found that increased frequency of unreinforced exposure to a stimulus made the participants of his experiment to rate this stimulus more positively;

or as Bornstein (1989) put it "*familiarity leads to liking*" (Bornstein, 1989, p.265). Stang (1974) and Harrison (1977) found that more complex stimuli, inhomogeneous exposure frequencies and a delayed rating after exposure increased the positive rating response to the stimuli. In addition to these findings, Bornstein (1989) found that briefer exposure times favour the positive rating of a stimulus. A result that was later confirmed by Winkielman, Zajonc and Schwarz (1997). Further, Bornstein (1989) found support through his meta-analysis to add three other findings: first, incomplete stimulus recognition by participants led to an even amended positive rating effect compared to a brief, but recognisable stimulus exposure. Second, children do not react in the same way to stimuli exposure than adults; in fact, the effect of familiarity is inverted for children preferring new stimuli to known ones. Third, and in relation to the complexity of the stimuli, paintings, drawings and matrices are correlated with lower effect sizes than other auditory and visual stimuli¹. Bronstein (1989), in merging all findings, concluded that boredom appears to be the limiting factor for the stimuli-affect relationship which is also underpinned in the exposure frequency/affect size curve that levels off after 10-20 stimuli, after a relatively small number of exposures. Following Bornstein (1989), this implies in return that avoiding boredom increases the subject's affect for and triggered by that stimulus.

Once a stimulus has done its work and the affect has been 'generated', how does it then affect the decision-making process? Slovic et al. (2007) summarised three other elements that play an important role when it comes to the affect heuristic mechanism: evalability, proportion dominance and risk-benefit correlation.

Hsee (1996a; 1996b; 1998) has coined the expression evalability. Hsee (1998) asked participants in a first experiemnt to assess the price that they were prepared to pay for two music dictionaries: one (A) with 10,000 entries that is in impacable, like-new conditions and a second one (B) that is almost like new except for the torn cover and that holds 20,000 entries. Naturally, the average amount that participants were prepared to pay for dictionary B was much higher than what they assessed acceptable to pay for dictionary A, most likely due to the higher number of entries in dictionary B.

¹ Please note that Bornstein (1989) only reviewed research projects that tested auditory and visual stimuli-affect relations, not other stimuli natures such as olfactory and gustory ones.

However, when the perceived price for each dictionary was evaluated separately in a second experiment, that is, one group of participants assessed only dictionary A and a second group of participants only dictionary B, the average price that participants of the first group were prepared to pay for dictionary A was significantly higher than when evaluating both dictionaries at the same time (experiment 1). Hsee (1998) concluded that the number of entries is difficult to evaluate in the independent price assessment situation since the participants have difficulties in translating 10,000 or 20,000 entries into the notion of 'good' or 'bad'. The condition of the dictionaries is rather easily transferable to such a good/bad classification and, thus, becomes more important when only one dictionary is assessed by the participants at a time, hence, the higher average price for dictionary A in the second experiment. Hsee (1998) refers to effect as the evalubility principle that states "*the weight of a stimulus attribute in an evaluative judgement or choice is proportional to the ease or precision with which the value of that attribute ... can be mapped into an affective impression.*" (Slovic et al., 2007, p. 1340). This implies obviously that affect provides meaning to information, and that information on even important or most important criteria is not used by decision-makers unless they are able to map this criteria information into their affect frameworks.

The dominance of proportion effect observed in the affect heuristic is closely linked to the evalubility principle and has been researched as part of the psychological numbing effect by Baron (1997), Jenni and Loewenstein (1997), Fetherstonhaugh, Slovic, Johnson and Friedrich (1997), Friedrich, Barnes, Chapin, Dawson, Garst and Kerr (1999) and Hsee (1998). Latter for instance asked one group of participants (Group A) what they would be prepared to pay for ice cream A (see Figure 4, next page) and a second group (Group B) what they were happy to pay for ice cream B. Group A participants were prepared to pay in average \$1.66 whilst Group B had spent \$2.26 on ice cream B. The difference was significant ($t=2.47$, $p<.05$). Note, however, that in this separate assessment situation, Group B participants were happy to spend 60 cent more for 1 oz less ice cream. The results changed when the participants evaluated the two ice cream servings together. Then, the perceived price for ice cream A was \$1.86 whilst the price for ice cream B dropped sharply to \$1.56 ($t=4.31$, $p<.01$).

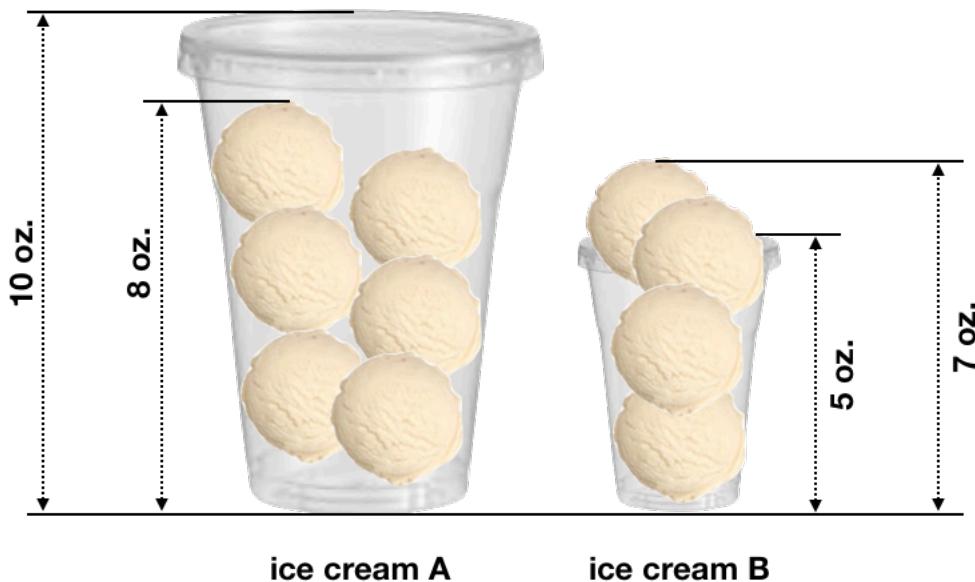


Figure 4:

Options in Hsee's 'ice cream experiment' (source: adapted from Hsee (1998))

It is important to underline the difference between evaluability and proportion dominance: whilst the evaluability principle deals with the question how good an attribute might be evaluated proportion dominance stresses the difference in reference point for that criteria. In Hsee's (1998) 'ice cream experiment', the reference point to determine the positive affect, and, thus, the participants' willingness to pay a certain price, is in the separate evaluation exercise relating to the size of the container. Only the juxtaposition of the two ice cream images enables the participant to reconsider his evaluation.

Obviously, being caught out by the affect heuristic when buying ice cream is not particular dramatic; implied risk is limited to pay eventually a little extra. However, Fischhoff, Slovic, Lichtenstein, Reid and Coombs (1978) discovered that for human beings, first, the perception of risk is closely connected to the degree of which the related activity or technology causes negative feelings, and, second, benefit and risk are negatively correlated. That is, the lower the benefit of an activity or technology, the higher the perceived risk and vice versa. Alhakami and Slovic (1994), as well as McDaniels, Axelrod, Cavanagh and Slovic (1997) confirmed these findings implying "...that people base their judgments of an activity or a technology not only on what they think about it but also on what they *feel* about it..." (Slovic et al., 2007, p. 1343).

Finucane, Alhakami, Slovic and Johnson (2000) further researched the relationship between risk and benefit. In a first study they tested the impact of time pressure on the deployment of the affect heuristic. They found that the less time is available to make a judgment the more negative grows the correlation between benefit and risk. That is, the less time is available, the stronger is the reliance on the affect heuristic; i.e. if someone holds a negative affect for 'fracking', then this someone would rate the risk higher and the benefit lower under time pressure. This confirmed earlier research regarding the influence of time pressure on the use of affect-based heuristics (Dijker & Koomen, 1996). Further, in a second study, Finucane et al. (2000) not only confirmed the negative correlated risk-benefit relationship, but also devised a causal model for it as shown in Figure 5.

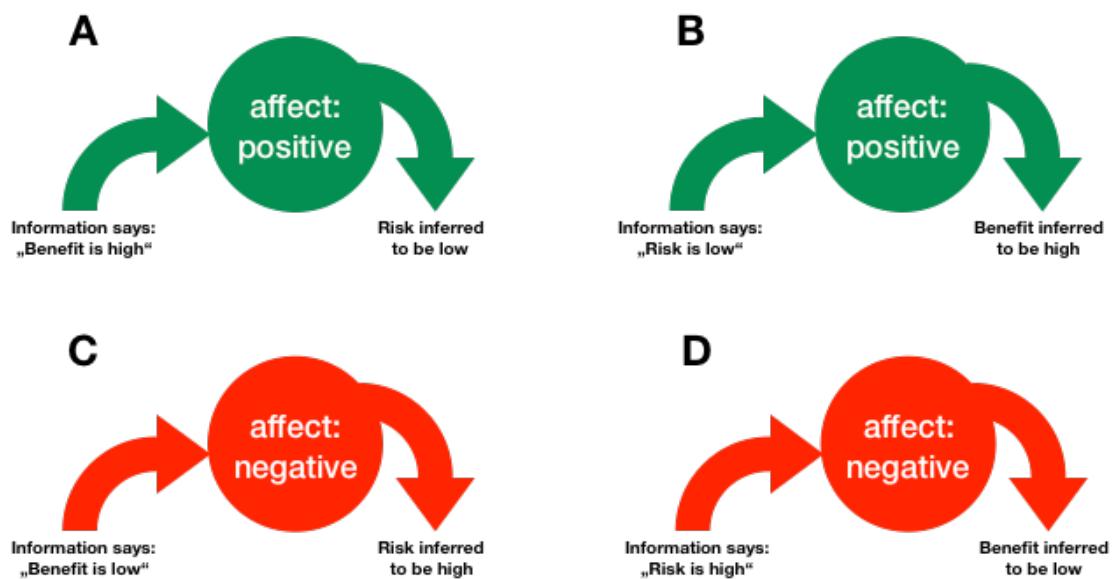


Figure 5:

Risk-benefit model of the affect heuristic (source: adapted from Finucane et al. (2000))

The model allows the researcher to make predictions of human perception of benefit (or risk) of an activity or technology when providing information on the related risk (or benefit). Looking at the mechanism D in the figure above: if an individual holds a negative affect with regards to parachuting and is presented with information on the potentially high risk of this activity, i.e. by providing the number of annual casualties, then this individual would perceive the benefits of parachuting as low.

In summarising the review of research on the affect heuristic, the following can be stated:

1. The concept of images as, for instance, described in Image Theory is also used as a basis for the understanding of the affect heuristic used in human decision-making. These images are 'tagged' with positive or negative affect, so called somatic markers, as a result of the individual's lifetime learning and experiences.
2. These images represent stimuli that might trigger the affect heuristic. The more familiar a stimulus, the more likeable it is. However, the effect caused by the stimulus diminishes, the more an individual becomes bored with the exposure to that stimulus.
3. The attributes of a decision alternative or in a judgment situation needs to be evaluable to individuals. That is, they need to be able to link it to their affect frameworks allowing them to identify the saliency of that attribute as being either 'good' or 'bad'. If evaliability of an attribute value is not possible, decision-makers cannot use it in their decision-making processes to evaluate the various alternatives.
4. Further, the proportion dominance effect is an important feature of the affect heuristic as well. It describes the observation that individuals might evaluate a feature differently depending on the reference point used for their evaluation. Even though the evaliability principle described earlier is closely linked to proportion dominance, the latter is a separate feature of the affect heuristic.
5. Eventually, the affect heuristic acts as a mediator for an individual's risk-benefit analysis. Risk appears to be negatively correlated with benefit. That is, for an individual, a high benefit activity that is 'tagged' with positive affect will be perceived as low risk and vice versa.

Overall, it can be stated that affect plays a vital role in human decision-making, and that decision performance suffers without the influence of affect. "*Although analysis is certainly important in some decision-making circumstances, reliance on affect and emotion is a quicker, easier, and more efficient way to navigate in a complex, uncertain, and sometimes dangerous world*" (Slovic et al., 2007, p. 1334). This implies that human decision-making relies on at least two distinct cognitive systems: an analytical one and a quick, emotional system that appears to inflict less burden on the decision-maker, and

that is closer to intuition or spontaneity. This takes this literature review to the next important domain: decision and process styles.

2.4 Decision and Process Styles

2.4.1 Decision Styles

Early research into decision-making style approached the topic on a cognitive level (Doktor & Hamilton, 1973; Mason & Mitroff, 1973; Coscarelli, Burk, & Cotter, 1995) describing decision-making styles as being determined by one's cognitive style. Following Doktor and Hamilton (1973; p. 885), cognitive style is defined as the "*self-consistent way of functioning that an individual exhibits across perceptual and intellectual activities*".

Further research (Arroba, 1977; Harren, 1979) identified three different decision-making styles: planning, intuitive and dependent. The individual's preference for one particular style would be determined by the level of personal responsibility assumed and by the level of rationality demonstrated (rational versus emotional).

Mitroff and Kilman (1975) explored decision-making styles based on the Myers-Briggs Type Indicator (Myers & McCaulley, 1985) and identified four cognitive styles as a combination of the Jungian dimensions for perception (sensing/intuition) and judgment (thinking/feeling). Nutt (1989) and his colleague Henderson (Henderson & Nutt, 1980) researched decision-styles of managers and how these relate to the perceived risk inherent in a decision. Other research (Johnson R. H., 1978; Mckenney & Keen, 1974) identified two dimensions that appeared to be important to cognitive style and decision-making respectively: information collection and information processing. Based on this two-dimensional approach Driver, Brousseau and Hunsaker (1990) identified five decision-making styles: decisive, hierarchic, flexible, integrative, and systemic.

Scott and Bruce (1995) defined decision-making style "*as the learned, habitual response pattern exhibited by an individual when confronted with a decision situation. It is not a personality trait, but a habit-based propensity to react in a certain way in a specific decision context*" (Scott & Bruce, 1995, p. 820). This underlines the contextual dependency of the observable decision-making style. Scott and Bruce (1995) created the

General Decision-Making Style (GDMS) inventory to determine the individual's decision-making style. Based on their initial evaluation of empirical findings of previous research and on their own testing of the GDMS (on four sample groups), they identified five decision-makings styles; based on empirical data: (1) rational decision-making style, (2) intuitive decision-making style, (3) dependent decision-making style, and (4) avoidant decision-making style. Through their own research, they discovered an additional decision-making style that they referred to as (5) spontaneous style.

Following Russ, McNeilly and Comer (1996) the rational style is "*deliberate, analytical, and logical. Rational decision-makers assess the long-term effects of their decisions and have a strong fact-based task orientation to decision-making*" (Russ et al., 1996, p. 5). The intuitive decision-making style is characterised by feelings and hunches, as well as by speed and error vulnerability. Decision-makers who rely on the dependent decision-making style are looking for advice and support from others. Avoidant decision-making is characterised by the decision-maker avoiding taking a decision, and, thus, might be deemed indecisive. Eventually, the spontaneous decision-making style is defined "*by a strong sense of immediacy and an interest in getting through the decision-making process as quickly as possible. Spontaneous decision-makers report that they make decisions on the spur of the moment, without a lot of reflection ... [and are] viewed as decisive or as impulsive*" (Russ et al., 1996, p. 5).

Leykin and DeRubeis (2010) choose the same approach as Scott and Bruce (1995) earlier. They reviewed the empirical data available through previous research and developed the Decision-Making Style Questionnaire (DSQ). Leykin and DeRubeis (2010) found that seven decision-making styles can be identified: (1) spontaneous, (2) dependent, (3) vigilant (referred to as rational by Scott and Bruce (1995)), (4) avoidant, (5) brooding (or regret), (6) intuitive and (7) anxious. Brooding or regret means that decision-makers think a lot about the consequences of their decisions, and thus take a long time to actually decide which alternative to pursue. This behaviour appears to be linked to the anxious decision style. Individuals demonstrating the latter style are simply afraid of taking decisions for various reasons, i.e. fear of taking the wrong decision, fear of putting people off, etc. .

Generally, speaking and in the light of what has been discussed so far, it appears logical to further research the links between the various decision styles or, putting it differently, the structure of decision styles.

2.4.2 Process styles - a framework for decision styles

Dewberry, Juanchich and Narendran (2013) claim that research on decision-making styles is missing an overall theoretical framework since it is a relatively young science (Appelt, Milch, Handgraaf, & Weber, 2011; Mohammed & Schwall, 2009). Therefore, they continue, *"research on decision styles tends to be fragmented, instruments designed to measure decisions styles focus on overlapping dimensions and omit dimensions measured by alternative tests..., and researchers find it necessary to use multiple instruments in order to measure decision styles comprehensively"* (Dewberry et al., 2013; p. 566).

2.4.2.1 Dual Processing Theories

Consequently, these researchers have proposed such framework that organises the seven dimensions introduced by Leykin and DeRubeis (2010). Dewberry et al. (2013) divide the decision styles in two broader categories: a cognitive process style category, and a regulatory process category that regulates the choice process of the decision-maker. Regulatory and cognitive styles are referred to as process styles to distinguish them from the decision styles described earlier.

The cognitive process style category contains two distinct systems: System 1 and System 2; two expressions originally coined by Stanovich (1999).

Dewberry et al. (2013) argue that the fast and intuitive System 1 with its reliance on error-prone heuristics, i.e. the affect heuristic, is conceptually close to the intuitive and spontaneous decision-makings styles. Intuition and spontaneity are thus similar and linked with each other. It appears that the spontaneous decision style is the high-speed version of the intuitive style.

Rationality, however, is the domain of System 2 which is conscious, systematic and analytic in its approach to decision-making. Therefore, the rational decision style is linked to System 2 thinking.

The idea of two separate systems, one analytic and effortful (System 2), the other intuitive and spontaneous (System 1), is not new in decision-making research. Epstein (1994, p. 710) claims: "*There is no dearth of evidence in everyday life that people apprehend reality in two fundamentally different ways, one variously labelled intuitive, automatic, natural, nonverbal, narrative and experimental, and the other analytical, verbal, and rational.*" Epstein and other researchers (Denes-Raj & Epstein, 1994; Epstein, 1991, 1994; Epstein, Pacini, Denes-Raj, & Heier, 1996) developed a dual processing theory that they called cognitive-experiential self-theory (CEST) that describes the experiential system (System 1) as working "*on an automatic, preconscious basis and ... [being] ... primarily non-verbal in nature*" (Hodgkinson, Langan-Fox, & Sadler-Smith, 2008, p. 9) whilst the rational system (System 2) "*operates at the conscious level and is analytical, verbal and relatively affect-free...*" (Hodgkinson et al., 2008, p.9). This implies that System 1 is 'emotionally driven' (Epstein, 1994, p. 715).

Sloman (1996) presented his 'two systems of reasoning'; an associative system, and a rule-based one (see as well Bargh, 1989; Smith & DeCoster, 1999). He described the first one as being "*able to divide perceptions into reasonable clusters on the basis of statistical ... regularities.*" (Sloman, 1996, p. 4). He continues to elaborate that "*the degree to which an association is operative is proportional to the similarity between the current stimulus and previously associated stimuli*" (Sloman, 1996, p. 4). Again, this sounds familiar to the image-based approaches of literature discussed in the subchapters Image Theory and Research on Temptation - the Affect Heuristic. Indeed, already James (1950) as quoted by Sloman (1996 p. 3) "*describes associative thought or 'empirical thinking' as 'trains of images suggested one by another'...*". In contrast to the associative system, productivity is one of the most important features of the rule-based system. That is, it is able to link or connect rules to generate a constantly growing number of options. The second characteristic of the rule-based system is that it is methodical describing its ability to transfer rules to newly arising facts or situations. If a given fact/situation has been deciphered based on a certain rule, this rule can potentially also be applied to decode other facts/situations.

In their article about intuition, Hodgkinson et al. (2008) provide a good overview on dual process theories reporting about "*an emerging consensus that a useful distinction can be made between two basic systems of information processing*" (Hodgkinson et al., 2008,

p. 8). Hodgkinson et al. (2008) compare the two systems in terms of their functionality and utility and conclude that System 1 is more adaptive than the rational System 2 since the former delivers assessments and affective responses based on past experiences. Hodgkinson et al.'s (2008) overview of the main dual processing theory streams is provided in Table 1.

	System 1	System 2
Cognitive-experiential self-theory <i>(Epstein (1994, 2000))</i>	Preconscious, automatic, effortless, rapid; minimally demanding of cognitive capacity; intimately associated with affect; holistic; associative; imagistic; experienced passively; self-evidently valid; long evolutionary history	Conscious; verbal; effortful; demanding of cognitive resources; affect-free; relatively slow; experienced as volitional; requiring evidence and logic to support beliefs; brief evolutionary history
Associative and Rule-based Processing <i>(Bargh, 1989; Sloman, 1996; Smith & DeCoster, 1999)</i>	Similarity and contiguity, personal experience Associationistic relations Reproductive Overall feature computation Automatic	Symbol manipulation, language, culture and formal systems Causal, logical and hierarchical relations Productive and systematic processing Abstraction of relevant features Strategic
Automatic and controlled social cognition <i>(Adolphs, 1999; Klein & Kihlstrom, 1998; Ochsner & Lieberman, 2001; Lieberman, Jarcho, & Satpute, 2004)</i>	Implicit, tacit or automatic self-processes that operate without effort, intention or awareness. Leads judgements based on accumulated experience without the explicit retrieval and evaluation of autobiographical evidence. Affective, slow to form, slow to change, relatively insensitive to one's thoughts about oneself and behaviour, and relatively insensitive to explicit feedback from others.	Effortful and intentional social cognition. Relies on symbolic representation and explicit autobiographical evidence, organized into propositions and processed serially in working memory and episodic memory. Called on to respond flexibly when habits and instincts are ill-equipped for the task.

Table 1:

Properties of System 1 and System 2 (source: Hodgkinson et al., 2008, p. 10)

Evans has undertaken extensive research in decision-making as well as in dual system theories (Evans, 1984, 1989, 2003, 2007a, 2007b, 2008, 2009, 2010, 2012, 2014; Evans & Over, 1996). He refers to System 1 as Type 1 and System 2 as Type 2 to avoid confusion with cognitive systems that operate in various regions of the human brain (Evans, 2014). Evans states that Type 1 (System 1) thinking, or, 'the old mind' as he refers to it as well (Evans, 2014), is a combination of "*an ancient learning system shared with other animals which allows associative and procedural learning to occur ... [and] ... basic emotions...*" (Evans, 2014, p. 131). In contrast, Type 2 (System 2), or respectively called 'the new mind', "*can seek to achieve goals by imagining the future, engaging in mental simulations, and consequential decision-making*" (Evans, 2014, p. 143). He further contrasts the two 'minds' by describing Type 1 to be output driven but able to cope with multiple tasks in parallel without using up the valuable brain's working memory. Type 2 is capable of developing a 'mental representations' (Evans, 2014, p. 139) of the future but, in return, draws heavily on the aforementioned working brain memory. Evans (2014) continues to elaborate that both 'minds' are typically synchronised to avoid contracting actions. However, in some instances they might be disconnected and in disharmony, i.e. if someone forgets that road works on his or her usual way to work cause traffic congestions, and, thus, he or she intends to use a different route, but uses the habitual way anyway. Stanovich (2004) describes the reason for such conflict that System 1 relies on evolutionary rationality whilst System 2 is based on individual rationality. Following him, the rationality difference provides the root cause for many biases in decision-making.

The 'Great Rationality Debate' (Stanovich, 2011) has produced many papers and research on dual system concepts and theories, a few of them have been described above describing System 1 as automatic, fast, intuitive, effortless, and System 2 as slow, controlled, complex and concentrated. Other theories did not find mention (Neisser, 1963; Piaget, 1926; Vygotsky, 1934/1987; Kahneman, 2011), and again other researchers found both systems to be strongly rooted in beliefs (Verschueren, Schaeken, & d'Ydewalle, 2005). Stanovich and West (2000) provide a very useful overview of some of those theories and their main elements shown in Table 2 (see next page).

Some neuroscientific research supports the dual-processing theories' approach: Lieberman and his colleagues (Lieberman, 2000; Lieberman et al., 2004) for instance

have performed an fMRI (functional magnetic resonance imaging) study. They refer to System 1 as 'X-system' and System 2 as 'C-system' and demonstrated that the "...*locus of the X-system ... is a network of neural structures consisting of the basal ganglia, ventro-medial prefrontal cortex (VMPC), nucleus accumbens, amygdala and lateral cortex...* [and that the X-system] ... *is located in neural substrates that are slow to form, slow to change and relatively insensitive to explicit feedback from others*" (Hodgkinson, Langan-Fox, & Sadler-Smith, 2008. p. 11).

Dual-Process Theories	System 1	System 2
Sloman (1996)	associative System	rule-based system
Evans (1984; 1989)	heuristic processing	analytical processing
Evans & Over (1996)	tacit thought processes	explicit thought processes
Reber (1993)	implicit cognition	explicit learning
Levinson (1995)	interactional intelligence	analytical intelligence
Epstein (1994)	experiential system	rational system
Pollock (1991)	quick and inflexible modules	intellection
Hammond (1996)	intuitive cognition	analytical cognition
Klein (1998)	recognition-primed decisions	rational choice strategy
Johnson-Laird (1983)	implicit inferences	explicit inferences
Shiffrin & Schneider (1977)	automatic processing	controlled processing
Posner & Snyder (1975)	automatic activation	conscious processing system
Properties	associative, holistic, automatic, relatively undemanding of cognitive capacity, relatively fast, acquisition by biology, exposure, and personal experience	rule-based, analytical, controlled, demanding of cognitive capacity, relatively slow, acquisition by cultural and formal tuition
Task Construal	highly contextualized, personalized, conversational, socialised	decontextualized, depersonalized, asocial
Type of intelligence	interactional	analytical
Indexed:	(conversational implicature)	(psychometric IQ)

Table 2:

Dual process theories and their properties (source: Stanovich & West, 2000, p. 659)

Based on dual-processing theory is the 'Risk-as-Feelings' hypothesis developed by Loewenstein and his colleagues (Loewenstein, Hsee, Weber, & Welch, 2001). This hypothesis claims that individuals faced with risk experience two reactions: on one side, they cognitively 'digest' or process the risk, on the other side, they feel related emotions that might already arise with minimum levels of cognitive activity. Whilst the cognitive process is driven by outcomes and probabilities, affect is linked to the liveliness of related

images, time proximity and other variables that do not appear to play a role in cognitive processes. For Loewenstein et al. (2001), this explains why, first, sometimes individuals "*experience fear reactions without even knowing what they are afraid of... [and, second,] ...a discrepancy between fear they experience in connection with a particular risk and their cognitive evaluation of the threat posed by that risk*" (Loewenstein et al., 2001, p. 280).

The role of fear in decision-taking leads back to the remaining decision styles discussed earlier but left uncategorised by the dual-processing theory approaches. Barlow (2000) sees fear in decision situations as closely related to decision anxiety.

2.4.2.2 Decision Anxiety and related decision styles

These remaining decision styles, avoidant, dependant, brooding (or regret), and anxious are put in the regulatory process category dealing with decision anxiety that plays a dominant role not only within the regulatory process category, but in decision-making in general. Anxiety might be caused by the expectation of uncertain, potentially detrimental outcomes of the decision that ought to be taken (Mohammed & Schwall, 2009). Barlow (2000, p. 1249) defines anxiety as "*perceived inability to predict, control, or obtain desired outcomes in certain upcoming personally salient situations or contexts*". Dewberry et al. (2013) field the appraisal theory (Lerner & Keltner, 2000, 2001; Lerner, Gonzalez, Small, & Fischoff, 2003; Lerner, Han, & Keltner, 2007) to explain the dominance of anxiety in the regulatory process category: "*specific emotions [i.e. fear and, thus, anxiety] are defined by a set of central dimensions which include perceived certainty, pleasantness, control, responsibility and attentional activity. For example, fear [or anxiety] is associated with low certainty, low pleasantness, medium attentional activity, high anticipated effort, low control, and medium responsibility*" (Dewberry et al., 2013, p. 567). Appraisal theory postulates that decision-makers who feel fear or anxiety at the time when a specific decision is to be taken, would expect to suffer the same emotions (fear or anxiety) as an outcome of their decision. Following Dewberry et al. (2013) and based of the appraisal theory approach, anxiety of the decision-maker might explain all other decision styles of the regulatory process category: obviously, if decision-makers are anxious, they might avoid taking any decision at all. Further, if anxious decision-makers don't want to take a decision, but taking a decision is

unavoidable, they might refer to others to gain support and help which would represent the dependent decision style. And eventually, since fear or anxiety seems to inflate the potential negative outcomes of a decision situation, the decision-maker might be prone to reflect more on negative than on positive consequences of the decision task, which would be referred to as brooding (or regret).

Anxiety, however, has another effect on decision-makers: if taking a decision is unavoidable for an anxious decision-maker, they might be prone to make an extra-effort or ‘go the extra mile’ to take the best decision possible. Even though the cost of that extra effort does not seem to be justified by the respective utility gained by the decision. This behaviour is referred to as maximisation and has been researched extensively (Schwartz, Monterosso, Lyubomirsky, White, & Lehman, 2002; Diab, Gillespie, & Highhouse, 2008; Spunt, Rassin, & Epstein, 2009; Dar-Nimrod, Rawn, Lehman, & Schwartz, 2009; Lai, 2010; Bin Rim, Turner, Betz, & Nygren, 2011). Further, the research of Purvis, Howell and Iyer (2011) have confirmed that anxiety and maximisation are associated.

2.4.2.3 *The Dewberry et al. (2013) model*

The final model of Dewberry et al. (2013) is shown in Figure 6 (see next page). Dewberry and his colleagues have developed a questionnaire that is based on 64 items taken of the GDMS and the DSQ as well as of items measuring a maximisation score (Schwartz et al., 2002) and items newly developed by the Dewberry research team. This is probably the most comprehensive inventory to identify an individual’s decision-making style. The Dewberry et al. (2013) approach will be further used in the context of this research project.)

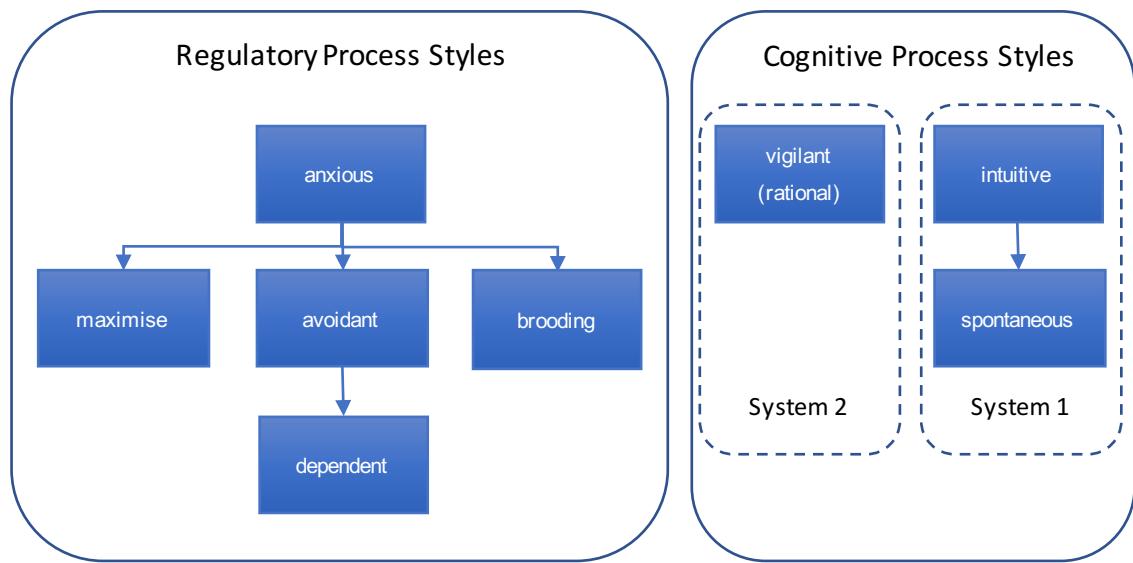


Figure 6:

The Dewberry et al. model (source: own, based on Dewberry et al., 2013, p. 570)

2.5 Summary

This literature review has first introduced Image Theory, a descriptive two-step decision theory before discussing in more detail research confirming the theory's applicability in everyday decision-making and its links into other theories.

Further, research on one of the corner stones of Image Theory, the compatibility test, was discussed extensively to unveil related findings. The compatibility test, the screening mechanism of Image Theory applied by the decision-maker to reduce the number of decision alternatives to a set of potential choices that appear to be the most promising to achieve a desired outcome, is characterised by the following framework:

1. The application of the compatibility test follows a simple rule that is described by equation (1) allowing to calculate an incompatibility score for each decision alternative;
2. Information used to screen the decision alternatives when applying the compatibility test is 'consumed' and thus not used in the second step of the decision process, the profitability test;
3. During the application of the compatibility test, the decision-maker considers only violations of pre-determined criteria. A violation of one criterion cannot be

compensated by the non-violation of another criterion. In this sense, the compatibility test is non-compensatory;

4. Criteria that are used during the compatibility test, are not equally important to the decision-maker. Importance differences amongst these criteria exist and are expressed by using an importance weight for each criterion when calculating the decision alternative's incompatibility score;
5. The compatibility test is used in both, progress and adoption decisions, and decision alternatives surviving the compatibility test form the choice set of decision-makers from which they select the one alternative that will be implemented;
6. The value of the rejection threshold, that is the level of incompatibility that a decision alternative must not drop under if it wants to become part of the choice set, as well as the values of the criterion importance weights appear to be vary depending on the decision frame work that the decision-maker finds himself in;
7. Compared to the profitability test, the compatibility test appears to be quicker and less effortful. Therefore, it appears to be driven by System 1 thinking opposed to the System 2 thinking that the profitability test seems to draw upon;

A second important element of Image Theory is - as the name suggests - the concept of images that determine the decision-maker's 'working frame' and, thus, amongst other factors form the basis for criteria and rejection threshold definition. In this context and based on the approach that images can trigger emotions and affect in a decision-maker, the concept and paradigms of the affect heuristic as well as related research were discussed. The affect heuristic can be described as follows:

8. Images might serve as stimuli that trigger the affect heuristic. The more familiar a stimulus the more likeable it becomes to the decision-maker. The familiarity-liability link is however countered by boredom that appears to reduce the images ability to trigger the affect heuristic;
9. Evaluability and proportion of dominance effect are important precursors for the affect heuristic to work;
10. Affect and emotions seem to influence the decision-maker's risk-benefit analysis. That is, a positive affect will make appear a perceived high benefit event or activity

look less risky and vice versa whilst a negative affect renders a perceived low benefit event or activity riskier (and vice versa),

Considering emotions and affect in the context of decision-making leads inevitably to the concepts of dual-processing theories of which some representatives have been described in the literature review whilst providing an overview of existing related theories. Research that seeks to tie together various decision styles on one side as well as the dual-processing theories and appraisal theory on the other, is the work of Dewberry et al. (2013). The researchers categorised eight decision styles identified through previous research into three process styles:

11. Two cognitive process styles that correspond to the System 1 and System 2 thinking of dual-processing styles, and
12. One regulatory style that contains those decision styles that are apparently linked to decision anxiety. Dewberry et al. (2013) field appraisal theory to tie those decision styles together in one process style.

The review of the literature leads to several questions that require further consideration. These questions and the derived hypothesis are subject of the next chapter.

3 HYPOTHESES

Based on the literature review of the last chapter, a number of questions arise that shall be developed in various hypothesis.

A first area of further research that the author has identified considers the finding (Beach & Strom, 1989; Ordóñez et al., 1999) that only violations determine whether or not an alternative will survive the compatibility screening. If only violations play a role during the compatibility test, then how decision-makers deal with alternatives that are incompatible with their images except for one, very important attribute for that the given alternative not only meets the attribute criterion but outperforms all other alternatives multiple times ('super attribute')? Will decision-makers be 'tempted' to let pass this alternative to the choice set despite its apparent failure to meet the rejection threshold? The affect heuristic might play a vital role in answering this question. Assumingly, if decision-makers consider an attribute of the alternatives as being more important than others, or, potentially, as even the most important attribute in that decision context, then they are almost certainly positively affected by how good this criterion is met by a decision alternative; otherwise they would not consider this attribute as very important. Articulated from a dual-processing theory point of view: will System 1 be able to 'trick' System 2 and 'sneak' the tempting alternative past it taking the hurdle of the compatibility test? Consequently, the first hypothesis that should be tested in the context of this research project reads as follows:

Hypothesis 1

"Participants are more prone to accept an alternative that is below their rejection thresholds but that is 'tempting' in a very important criterion, into the choice set than an alternative that does not offer this 'temptation'."

As will be detailed in the chapter METHOD, the falsification of the first hypothesis is somehow a 'stand-alone' exercise and the approach to test it is the only one based on an in-between subject experiment.

The subsequent hypotheses have all a common theme: Does a relationship exist between decision and process styles, demographic and other factors and the choice set variables that determine Image Theory's compatibility screening?

The author's latent structure expressing this relationship, sees statistically significant links between individuals' decision profiles, that is how they score in the eight decision styles, on one side, and the choice set variables (rejection threshold, number of alternatives in the choice set, and number of inconsistencies) on the other. Based on the work of Dewberry et al. (2013) the author's model claims that the eight decision styles as described earlier (rational, intuitive, spontaneous, anxious, avoidant, regret, dependent, and maximising) can be regrouped or categorised by the three overarching process styles: first, System 1 as the fast working, heuristic based but error prone intuitive processing system; second, System 2 as the analytical, heavy and effortful but distinctively separating human from animal capabilities, rational processing system; and, third, the regulatory processing system that deals with negative emotions, mostly decision anxiety potentially arising in the context of decision-making.

These three process styles influence an individual's rejection threshold, and thus the number of alternatives in the choice set as well as the number of inconsistencies as a by-product.

However, the salience of the decision process styles are not the only factors impacting the choice set variables' values. Factors that are linked to the decision context play naturally an important role, i.e. accountability of decision-makers for their decisions, time available to take the decision, demographic factors, emotions in general, alignment between the decision-maker's values, needs and principles, and perceived or real requirements forced on the decision-maker by third parties or the environmental context, etc. .

All these factors potentially impact the decision behaviour and, thus, the value of the choice set variables. Figure 7 (see next page) shows the author's model graphically.

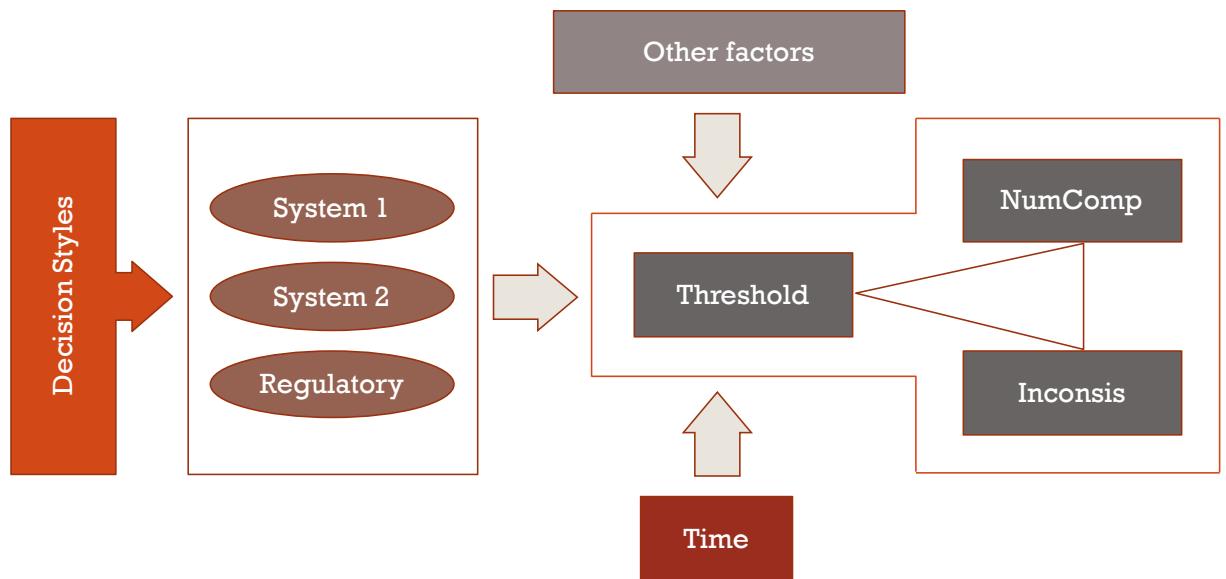


Figure 7:

The author's model of factors influencing Image Theory's compatibility screening

In the context of this thesis, not all factors can be considered. The author will focus on the role of the decision styles that manifest themselves through the process styles as well as the role of time.

Further, as 'Other factors', the author will consider the potential impact of the demographic factors, gender and age ('demographic factors'), as well as the criteria importance weights as assessed by the participants, and the alignment of these assessments with those importance weights provided by the author ('importance weight variables'). Clearly, these factors are not all 'Other factors' that potentially influence a human being's decision-making. Factors, such as, positive emotions or being distracted whilst reflecting on potential decision alternatives, could easily impact the decision behaviour and, thus, the decision-maker's choice set. These factors, however, are not known and their influence on this research project is blurred.

Obviously, the entire model as depicted in Figure 7 cannot be tested in 'one go'. This 'elephant needs to be sliced in digestible chunks'. A starting point is to look again at the work of Dewberry et al. (2013). As described earlier, Dewberry and his colleagues used initially 64 items to determine the eight decision styles (eight items for eight styles). The author's approach had to be limited to 40 items (five items per decision style) to do the same job. The reason for this was the chosen research method, the web survey, and

SurveyMonkey's limitation to a maximum of 50 questions when acquiring answers from its online panel. Therefore, the first step to test the author's model is to confirm the Dewberry et al. (2013) model with only five instead of eight items per decision style.

The related hypothesis reads as follows:

Hypothesis 2

"The Dewberry et al. (2013) model can be confirmed by using only 5 items in a questionnaire to identify a participant's decision style profile."

Hypothesis 2 requires a two-prong attack: first, the overall 40 items will have to be confirmed to load well enough into the eight decision styles, and, second, the structural model confirming the links between the eight decision styles and the three overarching process styles will have to be confirmed.

The subsequent step is to test the influence of the process styles, the factor 'time' and the two other variable groups, the 'demographic factors' and the 'importance weight variables' on the choice set variables. The respective hypothesis states the following:

Hypothesis 3

"There are significant links between the choice set variables and a decision-maker's process styles, demographic factor, 'importance weight variable' and 'time' to finish the survey."

Based on the assumption that hypothesis 2 and 3 cannot be falsified, then the question becomes: Can the choice set variables be predicted by these factors and variables? Consequently, the related hypothesis reads as follows:

Hypothesis 4

"The data collected with the survey will allow to predict with high reliability (80% of correct predictions) the values of an individual's choice set variables."

As will be described in the chapter *METHOD*, hypothesis 4 will be tested using classical statistical approaches: regression and discriminant analysis. The predictive capacities of those methods require the researcher however to know the fundamental nature of the relationship between the independent variables and the dependent one. Therefore, researchers need to decide whether they want to model i.e. a linear, log-linear or polynomial relationship between those variables. If, however, the nature of the model's relationships is unknown and these classic approaches fail, Garson (1998) recommends the application of neural networks provided that a sufficient number of data sets is available to train and test such network.

To increase the number of data sets available, the idea of predicting the choice set variables was abandoned in favour of predicting the outcome of the compatibility test, that is, forecasting if a specific decision alternative becomes a member of the choice set. By taking this approach, the number of data sets could be increased 9 times.

Based on the research of Collins and Clark (1993), who compared the performance of classical statistical approaches with the concept of neural networks, and who found that their neural networks generally made correct predictions in more than 80% of the cases, the author set the same predictive capability target for the neural network used in his research project. The related hypothesis eventually postulates then:

Hypothesis 5

"A neural network can predict with high reliability (>80% of correct predictions) whether or not an alternative (company) is accepted or rejected by a participant based on the data collected by the web survey."

For comparison reasons, the same 80% target has also been set for hypothesis 4.

The approach to use neural networks is in line with the author's earlier expressed assumption (see chapter Setting the scene) that the various decision and process styles interact like a neural network.

Further, and as described earlier in this chapter (see Figure 7 on page 57 and its description), other factors that are not known to the author and thus could not be considered in this research project, potentially influence decision-making. Whilst causal

impact of other factors than those described, remains speculative and provided an underlying impact pattern for those unknown other factors exists, then the prediction of choices can only be successful by selecting a methodology that allows to tolerate the unknown nature of these relationships; hence, the neural network approach is used (see as well Collins & Clark, 1993).

4 METHOD

This *METHOD* chapter describes the methodologies that have been used in the context of this research project to test the previously presented hypotheses. It includes a description of the author's epistemological position as well as ethical considerations important to this research project.

General approach and operationalisation will provide a bird's-eye-view of the approach taken to potentially falsify the hypotheses, and, thus, setting the scene for a more detailed elaboration on how the research was designed and conducted.

Based on the author's positivistic epistemological position (see next chapter), he wanted to avoid any interaction with the participants of his research project. Therefore, he decided to use online surveys to collect the required data. All used questionnaires as well as their general design principles and the usage of the respective online service providers, *SurveyMonkey* and *SurveyCircle*, are described in detail in the subchapter Research design.

Since the participants of *SurveyMonkey*'s web panel were paid to answer the respective questionnaires, particular attention was given to disqualify those participants that had more their own profit in mind than contributing to a research project when answering the questionnaires. To avoid using distorted or polluted data, three data cleaning protocols have been used and are described in the respective subchapter.

The subchapter Populations and samples provides insight in the two target populations of this research project as well as the samples taken thereof and the samples' respective demographics and how these developed in the light of the required data cleaning protocols.

Eventually, the last subchapter Statistical procedures and data analysis first describes important variables that have been calculated based on the data collected by the various surveys and that are important to all hypotheses testing, before continuing to lay down the respective methodology to test each of the hypothesis. It is in these chapters on

each hypothesis where the author introduces and explains the calculation of additional variables used to test a specific hypothesis.

4.1 Epistemological position of the author

For the purpose of this subchapter *Epistemological position of the author*, the author will adopt a first person singular narrative style to stress the individual and personal character of this topic.

If I look on my epistemological commitments and based on what I have learned during my DBA journey about my ontological commitment to objectivism (Rand, 1990), postmodernism (Kilduff & Mehra, 1997) can be ruled out as a sound epistemological position for me. Postmodernism is really far too subjectivist to suit my epistemological position. The Postmodernist claim that all knowledge is eventually the result of language games or the ‘linguistic turn’, is simply too far away from my perceived reality. If Berg (1989, p. 195 quoted in Johnson & Duberley, 2000) was true in writing “*In organisation and management science today it is not important whether a statement is true or false, but whether the fact or statement is accepted, saleable or valid for a larger audience*”, one could sell the boldest lies to anyone and it would be considered knowledge as long as the audience accepts it and the audience itself is large enough. Such a stance appears simply unacceptable and dangerous to me and, thus, I reject postmodernism on these grounds.

However, postmodernism shares with other epistemologies that are critical about positivism, their rejection of the positivistic claim that a theory-neutral language can be found. The argument developed by Kuhn (1970) in his conventionalist’s approach might – at first glance – be able to resolve this problem by linking the growth of knowledge to the paradigm agreed in a given community. However, with the underlying consensus theory of truth leading eventually to relativism, conventionalism is – to me – as unscientific as postmodernism. Thus, I have to reject conventionalism as well.

Critical Theory (Habermas, 1972) tries to resolve the problem with the theory-neutral language by claiming that scientific research has to achieve an ‘ideal speech situation’. But how can one be sure when, and if at all, such an ideal speech situation is achieved.

In the absence of a validity check against perceived reality and again based on a consensus theory of truth, Critical Theory leads as well to relativism and, for that very reason, has to be rejected. More importantly, Critical Theory is ideologically laden which adds to the grounds for its rejection. After all, science, in particular management research, should be free from any particular ideology. If not, researchers might be at risk to put themselves in an elevated position above their objects of research and pretending to hold superior knowledge.

When considering pragmatic-critical realism (Bhaskar, 1978; Sayer, 1981, 1992), I have to admit that this epistemology's test against reality rather appeals to me. In doing DBA studies, practicality and test in reality seem to gain particular importance. Hence, test against reality as benchmark for the validity of knowledge claims are attractive and most certainly marry well with my ontological objectivism. However, pragmatic-critical realism seems to lose itself in the 'abyss of causation' of particular events without being able to quantify or even measure this causal links. This is an unstable foundation for an epistemology that appeals to me. I therefore reject this epistemology as well.

Whilst I share some elements of this critique of the non-positivistic positions, i.e. I agree that there are issues with a theory-neutral language, which will have to lead to critical thinking but not to Critical Theory or for that purpose to any other of the previously mentioned epistemologies critical of positivism, I still believe that positivism is my epistemological 'home turf': my ontological commitments are defined by objectivist positions. I believe in the world of noumena as well as the world of phenomena in the Kantian meaning. I believe in a theory-neutral language although discursive contamination might be encountered. But it is the researcher's task to 'peel away' these layers of linguistic impurities to discover the truth. Further, for a knowledge claim to be true, it has to be tested against reality based on perceived sensory data. Any other epistemological approach appears to be an enormous 'wooden' construct to avoid by all means the obvious, natural, positivistic methodology, even if it requires sacrificing rationality, perceived reality and, eventually, humanity in the temple of relativism.

4.2 Ethical aspects

Considering the ethical aspects of the research will have to include the process to ensure the anonymity of the participants and the requirement for a non-compromising content of the decision situations and instructions of the questionnaire.

By taking the survey the participants must not be confronted with materials that violate their privacy. Participants have been allocated a participant number randomly without documenting which name is linked to what participant number. The participant number will establish the link between the individuals' decision style profiles and their respective survey answers.

Eventually, particular care has to be taken when designing the decision situations and the instructions. The author made sure that no participant might feel offended or discriminated by decision situations or the instructions how to answer correctly the survey. Therefore, the design of decision alternatives that are, for the purpose of the experiment, either compatible or incompatible with the respective rejection threshold of a participant was not based on differences in ethnics, age, gender, religion or cultural background. Further, the author has refrained from decision situations that might cause emotional stress for the participants. These considerations are obviously valid for all materials and information provided in written or visual form during the survey.

4.3 General approach and operationalisation

The five hypotheses can be split in three categories: first, testing to what extent the affect heuristic influences Image Theory's compatibility screening (hypothesis 1); second, researching the links between decision/process styles, various other factors and the elements of the compatibility test as well as these links' strengths and directions as well as their predictive capabilities (hypothesis 2 to 4); and, third, testing the predictive capability of the collected data to forecast a decision-maker's choice in the specific screening situation of this research project by using the methodology of neural networks (hypothesis 5).

4.3.1 The affect heuristic and the compatibility test

To research the potential impact of the affect heuristic on the compatibility test, the author required the following:

- a decision situation allowing the survey participants to perform a compatibility test;
- a set of decision options that differed in meeting respective criteria deemed more or less important;
- variables that documented the choice of options for each participant;
- decision options that represent potentially a temptation to the participant; and
- decision options that were identical to the temptation alternatives except for the salience in one, the most important criterion (twin alternative);

Since the research project was conducted as part of a DBA programme and thus focusing on business administration and contribution to management practice, the author designed the required decision situation in the context of a typical management decision: the participants assumed the role of a CEO of an investment company who wants to buy another company based on certain criteria that the potential acquisition targets would have to fulfil. The participant's task was to select companies that would be further investigated in the next step of the acquisition process. Simply put, the participant had to create a shortlist of companies.

Each participant was confronted with nine companies and had to decide which of these companies should become part of the shortlist. The author selected six criteria

('profit', 'price', 'investment', number of employees', 'debt' and 'industry'), their importance weights and respective desired target values that a company should meet to become part of the shortlist. The participant was bound to these criteria, their importance and target values when selecting a company for the shortlist since 'the CEO has agreed with his or her management team that a potential acquisition target should be evaluated based on these criteria, their provided importance weights and their respective target values'. In order to reflect the fact that the participant (the CEO) was bound to what the management team had decided in this respect, the author provided the respective values (criteria, their targets as well as their importance weight) to the participants and invited them to use these during their choice process.

Further, the author 'designed' eight companies for the survey by allocating values for each criterion to them. The participant's choices for or against these companies were not used to test hypothesis 1 but in later described analysis to determine the variables defining the compatibility test.

Additionally, two temptation alternatives (one for the criterion 'profit' and one for the criterion 'price'), were designed that failed to meet the target values of all criteria except for one of the two most important criteria ('profit' and 'price') for which they did not only achieve the desired value but outperformed all other companies by multiple times ('super attributes'). The author was conscious about his choice to take the 'profit' and 'price' criteria to design the temptations. Both criteria are of different nature in terms of recurrence of related benefits, and objectivity of their value determination.

Further, two twin alternatives were designed that were identical to the two temptation alternatives except for the super attributes ('profit' and 'price') for which the twin alternative met the respective criterion target value but only to the extent and in the value range that other presented companies met this criterion as well. That is, a twin alternative did not outperform other companies in this criterion.

The participants were then split in two experimental and two reference groups to test each of the two temptation alternatives. Each experimental group had to evaluate the eight companies and one temptation alternative, so in total nine companies, and had to decide which of those nine companies will become part of the short list (choice set). The reference groups were presented the eight companies and the respective twin

alternatives, and participants of this group had to decide which of those nine companies should make it on the shortlist.

The number of selected temptation alternatives of an experimental group was then compared to the number of selected twin alternatives of the respective reference group.

If the claim of Beach and Strom (1989) as well as of Ordóñez et al. (1999) is correct that only criteria violations determine whether or not an alternative will survive the compatibility screening, then there should be no differences being observed between the experimental and its respective reference group in terms of the number of selected temptation and twin alternatives respectively.

The main statistical method was the t-test.

4.3.2 Decision/process styles and the compatibility test

Researching the links between the participants' decision styles or decision profiles and the elements of their compatibility tests required the following:

- Questionnaire items that would determine the scores of the eight decision styles and thus a participant's decision profile;
- Variables that define and, thus, drive the compatibility test;

The author had selected *SurveyMonkey* as his service provider for two of the three web surveys. Since the author opted as well to purchase answers from *SurveyMonkey*'s web survey panel, the number of questions per survey was limited to 50. Ten of these 50 slots were already taken by the nine questions related to the screening process described in the previous chapter and one question that asked the participants to rank the six criteria following their importance to the participants themselves. This left a maximum of 40 questions to determine a participant's decision profile.

The starting point of the author's endeavour to research the links between decision styles and the compatibility test, is the work of Dewberry et al. (2013). Dewberry and his colleagues used, however, 64 questionnaire items to determine their participants eight decision styles. They relied on earlier research of Bruce and Scott (1995), Schwartz et al. (2002), and Leykin and DeRubeis (2010) as well as on other items that the researchers had developed themselves. Since the author of this thesis had only 40

questions to determine the scores of his participants' eight decision styles, he used the work of Bruce and Scott (1995), Schwartz et al. (2002) and Leykin and DeRubeis (2010). Five questions were selected from these research projects for each decision style based on the factor loadings that these items demonstrated in the respective research.

However, since 40 instead of 64 items were used by the author, he wanted to provide evidence that these 40 items are sufficient to confirm the result found by Dewberry et al. (2013). Therefore, the author performed first a number of Explorative and Confirmatory Factor Analysis to extract/confirm the eight decision styles and then calculated the respective scores of these eight decision styles. Further, the author extracted/confirmed the three process styles from the eight decision styles as well and undertook a series of regression analysis to investigate the links between the decision and process styles. Confirmation or falsification of the Dewberry et al. (2013) model was the subject of hypothesis 2.

After potentially confirming the work of Dewberry et al. (2013), the author needed to define the elements or variables that would document the results of the compatibility test. Those variables, referred to as choice set variables, are, first, the number of companies selected on the shortlist (choice set); second, the participant's rejection threshold that would determine whether or not a company would make it in the participant's choice set; and, third, the number of inconsistent choices; that is, companies that either had been selected in the participants' choice sets despite failing to meet their rejection threshold criteria or did not end up on the shortlist even though those companies met the threshold.

Additionally, some other variables were defined since they have been part of what the online service provider *SurveyMonkey* provides as standard data: these variables were the gender and age group of a participant (demographic variables) as well as the time it took the participant to complete the survey.

Since the author determined the criteria and their importance weights for a participant's screening process of selecting companies for the shortlist, he introduced the already mentioned question that would ask participants to rank the criteria based on their own preference. Besides providing a participant's criteria ranking, the answers to this question would also enable an assessment of how well any given participant was aligned

with the author's evaluation of criteria importance. The variables of the participants' criteria ranking and the variable expressing their alignment with the author's importance weights, created another set of variables referred to as the importance weight variables.

To test hypothesis 3, all of these variables were subject to descriptive statistics analysis, ANOVA, regression analysis and Structural Equation Modelling (SEM) to fully appreciate the links amongst them.

Eventually, and based on potential links between above mentioned variable sets, the author wanted to predict the choice set variables with the help of the other variable sets, in particular with assistance of the decision or process styles.

The author undertook respective regression analyses but was as well prepared to relax requirements to evaluate if a prediction of the choice set variables was at all possible using discriminant analysis as well.

4.3.3 Predicting choice

Testing the last hypothesis, hypothesis 5, implied trying to predict the choice of a participant regarding a specific company used in the context of this research project.

For the author to test this last hypothesis he needed to rearrange the collected data. Instead of using the data sets that were related to each participant, it became necessary to create data sets that collected data related to the selection or non-selection of a company in a choice set. A data set collected for one participant generated thus multiple data sets (nine or 14, depending on the used questionnaire) based on a participant's choice regarding a specific company. Thus, more than 6,600 data sets could be generated to create, train and test respective neural networks.

In addition to the already known and earlier described set of variables, each of the newly created data sets contained variables that provided information on whether or not the company to which the respective data set relates, meets the six criteria target values. The set of these six binary variables is referred to as compatibility variables.

The approach to test the hypothesis was, first, to generate neural networks relying on information of all variable sets, then to determine the influence of each variable set, and

eventually, generate and optimise neural networks that rely only on those variable sets having most impact on the networks task to correctly predict a participant's choice.

4.3.4 Recruiting participants

As already mentioned, (see page 61), the author conducted this research project by using various web surveys to avoid any interaction with the participants. He selected *SurveyMonkey* as the online service provider to design the required surveys and to administer two of the three surveys to *SurveyMonkey*'s web panel of participants related to the target population. The author pursued this approach since it enabled him to save time when collecting the required answers to his surveys and since it would allow him to select relevant participants being a member of the target population. He however recognises that issues might arise and have arisen concerning the quality of the data collected from a web panel, i.e. not reading instructions or questions thoroughly enough and, thus, answering the question not correctly, therefore, 'polluting' the data. These issues, however, have been addressed with appropriate data cleaning processes as described in the chapter Data cleaning. As mentioned earlier, only two of the three surveys have been conducted with the help of *SurveyMonkey*. The third one was still designed in *SurveyMonkey* but was put online via another online service provider, *SurveyCircle*, relying on a more academic audience to participate in the survey.

Three samples have been used in the context of this research project: first, the Base Sample which was drawn from the appropriate *SurveyMonkey* web panel: German decision-takers with internet access. Second, an additional sample, the Extension Sample, was drawn from the same population to test the temptation hypothesis (hypothesis 1) as well as specific characteristics of the neural networks generated to potentially falsify hypothesis 5. Eventually, a third sample, the Student Sample, was used to check the validity of the results found with the Base Sample. This was relevant with regard to two questions: first, how does the descriptive statistics of the two samples compare, and, second, how comparable are the results found for a non-student sample to a sample holding predominantly student members. The name Student Sample hints already on the predominant occupation of the sample members: 59 of the initially 99 participants of this sample stated to be students.

A questionnaire has been designed for each sample even though the Base Sample questionnaire provides the foundation for the Extension and Student Sample questionnaire. All questionnaires start with an introduction to the survey seeking consent of the participants to use the data generated by answering the survey questions. The Base and Student Sample questionnaire used 40 items to determine the participant's decision profile (Part I) before putting the participants in a number of specific decision situations in which, they assumed the role of a CEO selecting potential acquisition targets to extend the portfolio of companies owned by his or her investment company (Part II). The Extension Sample deviated from this questionnaire structure in that Part I was dropped in favour of an extended Part II. That is, no decision profile was generated for the members of the Extension Sample, but a larger choice of potential acquisition targets was presented to these participants, in particular, acquisition targets with a compatibility structure differing to those ones used for the Base and Student Samples.

4.4 Research design

4.4.1 General design principles

The questionnaires were designed and administered with the *SurveyMonkey* software. *SurveyMonkey* is a widespread online software application for market research and scientific web surveys administered on smart phones, notebooks and desk top computers. The web surveys for this research project consisted of one or two main part(s) as well as of an Administrative and Consent Part (ACP) at the beginning of the survey. The design of the entire web survey follows recommendations and research on web surveys provided in Tourangeau et al. (2013).

The survey language was German. Translations from English into German (decision style items) has been done by the researcher as well as the translation of the parts in German into English language. The three surveys are provided in German and English language in Appendix *Questionnaires*.

Participants of the Base and Extension Sample are members of the German online panel of *SurveyMonkey*. The participation of these members in the survey has been bought by the researcher from *SurveyMonkey*. This implies that *SurveyMonkey* will warrant to achieve the required sample size based on the chosen population. A more detailed description of Base and Extension Sample is provided in the chapter Populations and samples below (see page 91).

SurveyMonkey allows the researcher to select the gender, the age, the resident country and the participants' positions within their organisations.

The background colour of the survey is white. Further, the title of the survey is displayed in the 'title banner' on each page as well as the e-mail address of the researcher (only on the ACP page) in the 'subtitle banner'. All items/questions are numbered. Explanations and answers are displayed in smaller font sizes and of grey colour (in bold and red to highlight important information).

All questions had to be answered (mandatory questions). If the participant tried to skip a question, the message 'This question is mandatory" was shown in red font to the participant and navigation to the next page was impossible.

A percentage complete bar providing information on how many percent of the survey has been completed was displayed at the end of each page.

A 'Next'- and – where applicable – a 'Prev' (previous)-button allowed the participants to navigate from page to page. Participants were able to revisit pages for which they have already answered all the questions. The aim of this feature is to allow changing the answers to questions to increase data quality. On the last page, the 'End of survey' page, the 'Next'-button was replaced by a 'Done'-Button. Clicking this button completed the survey.

4.4.2 The Base Sample Questionnaire

The questionnaire designed to be administered to the participants of the Base Sample was the first questionnaire designed (see Appendix *Questionnaires* under the heading *Base & Student Sample Questionnaires* (original version in German language and English translation)).

A test of this questionnaire was carried out on two test samples with 50 participants each of the Base Population to identify the best way to operationalise the decision situation. Initially, the author wanted to present a list of decision alternatives (companies) and the participant were to select those alternatives that would make it to the 'short list'. However, the two tests revealed, that participants selected in many cases, only one company out of the presented list. Therefore, and after consulting again previous research on the application of Image Theory's compatibility test (Beach & Strom, 1989; Pesta, Kass, & Dunegan, 2005) and based on Klein's (1998) recognition-primed decision-making model, the researcher decided to change his approach and to present one decision alternative after the other asking participants if the respective company was to be part of their 'short lists' or not. As a consequence, the decision process appeared to be more realistic and the number of companies that were selected on the 'short list' rose respectively. Naturally, this triggers the question if changing the process was appropriate. After all, the participants that have only chosen one company following the initial process might well have done this purposely. However, the application of the second, one-after-the-other process by previous research and the experience of the researcher having observed various merger and acquisition processes

confirm the validity of this approach. It was still possible for a participant to select only one company.

The final Base Sample Questionnaire contained three parts: the ACP, a first part to determine the participants' decision styles scores and a second part that made the participants apply the compatibility test in a decision situation. All three parts are described in the following chapters. The last page of the questionnaire thanked the participants for their contribution and informed them that the survey is finished and completed.

4.4.2.1 Administrative and Consent Part

The ACP was the first page of the questionnaire and (1) provided limited background information on the research project, (2) informed and reassured the participants about the anonymity of survey, (3) provided an estimate of the time that completing the survey would take, and (4) sought consent of the participants to take part in the survey.

The first sentence explained that the survey is the centre piece of a research project on decision styles and decision processes. Further, the ACP informed the participants that it would take approximately 20 minutes to take the 50 questions of the survey. Additionally, the nature of these 50 questions was explained; 40 items to define the participant's decision style profile and 10 questions to select companies based on provided criteria on a merger and acquisition shortlist.

The ACP also encouraged the participants to answer the questions of the survey as they normally would do. That is, they should not be more rational, more intuitive or more spontaneous than they are normally, and they should not answer the questions how they think they ought to answer them, but in line with their real-life behaviour.

An important task of the ACP was to reassure the participants about the anonymity of their participation. No names, addresses, or other personal data was collected by the questionnaire or provided by *SurveyMonkey*.

Eventually, and having experienced participants that took the survey incredibly quickly during the two tests phases, the participants were encouraged to take their time to complete the survey and read instructions carefully.

An important role of the ACP was to seek consent of the participants to use the data collected by the survey for the author's research project and for subsequent academic, non-commercial research projects. The participants who wanted to provide consent were informed that they would do so by clicking on the 'Next'-button on the bottom of the page. All participants providing consent continued with the survey. All participants refusing consent were disqualified.

4.4.2.2 Part I: Determining Decision Styles

Part I of the Base Sample questionnaire was to determine the score of the participants in each of the eight decision styles. 40 questions (items) have been selected of previous research based on their level of factor loading in the respective decision style construct.

The 25 items (five per decision style) for the decision styles rational, intuitive, spontaneous, dependent and avoidant have been taken from Scott & Bruce (1995). All factor loadings except for one item (rational – *I plan my important decisions carefully*) have been known and range from .57 (intuitive – *When I make a decision, it is more important for me to feel the decision is right than to have a rational reason for it*) to .94 (avoidant – *I postpone decision making whenever possible*). The item for which no factor loading could be identified was accepted nevertheless for completeness reasons.

10 items to measure the decision styles regret and maximising have been taken from the research of Schwartz et al. (2002) with factor loadings ranging from .56 (regret – *Once I make a decision, I don't look back*²) to .81 (maximising – *When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program*).

Eventually, to measure the decision style anxious, 5 items were taken from the research of Leykin & DeRubeis (2010). Their respective factor loading ranged from .41 (*When making a decision, I am afraid that I might be wrong*) to .64 (*I feel as if I'm under tremendous time pressure when making decisions*)

They were displayed on five separate survey pages with eight items each; one item per decision style. The 40 items have been allocated by the author randomly to each page

² This item was reverse scored in the survey

using the MS Excel randomisation function. Columns ‘*Page*’ and ‘*Sequence*’ of the table in Appendix Decision alternatives and their characteristics provide information to which page and on that page, in what sequence each item has been allocated. The purpose of this process was to avoid a potential bias of the author that might occur when allocating the 40 questions to the pages of the questionnaire.

Further, the *SurveyMonkey* software has randomise the order of the items on each page when administering the questionnaire. That is, the sequence of items varied on each page from participant to participant. Again, this was done to avoid common method bias occurring when all participants answer the 40 questions in the same order. The five pages of Part I were however administrated in the same order (page 1 through to page 5) to the participants.

Each item was measured with a four-step Likert scale. A four-point Likert scale was chosen to avoid ‘regression to the mean’-effect (Kahneman, 2012). That is, that participants tend to select the middle point (neutral point) in a five-point Likert scale to avoid commitment for one or the other dimension. The four labels of each Likert scale are *disagree* (=1 point), *rather disagree* (=2 points), *rather agree* (=3 points) and *agree* (=4 points). The Likert scale was arranged horizontally to allow the eight items of each page to be displayed more compactly. The participant’s answer to each item on a page was confirmed by clicking a ‘Next’-Button and the participant was transferred automatically to the next page.

The Likert scale scores of the 40 items are captured for each participant in 40 variables. The related 40 variables and all other variables used for this research project are listed in Appendix List of used variables (see page XXXVIII).

4.4.2.3 Part II: Decision situations

The second part of survey put the participants in a specific decision situation. They assumed the role of the CEO of *Alpha Invest AG*, an imaginative investment company that sought to extend its portfolio of companies by acquiring another company. The CEO’s task was to select a number of companies presented by a Merger & Acquisition consultant to him or her and, thus, form a ‘short list’ of companies that ought to be investigated further in the next step. The acquisition target will have to have a turnover

of 50 M€ to 60 M€ and the consultant will not present companies that do not meet this requirement.

Further, the CEO agreed six criteria³ and their importance with his or her management team and respective values for each of the criteria that the target company should meet (target or To-Be-Met values). The CEO is however aware that potential companies might not meet all of these criteria. The agreed criteria as well as their importance to the CEO and his or her management team and the respective To-Be-Met values are shown in the following table.

Criterion	Importance	Value
Price:	very important (+++)	max. 30 M€
Profit:	very important (+++)	min. 6% EBIT
Debt:	important (++)	max. 20 M€
Employees:	important (++)	max. 400
Investment:	less important (+)	max. 15 M€
Industry:	less important (+)	same or neighbouring

Table 3:

Six criteria, their importance weights and target values of the Base Sample questionnaire

³ The author took six criteria based on the findings of Galotti (2007)

The price criterion is deemed very important by the CEO and the management team and the target company should be acquired for a maximum of 30 M€. Equally, the profit that the potential acquisition target should generate was very important to the entire team and it should be at least on a level of 6% EBIT or more. The criterion debt and number of employees had been rated both as important by the CEO and the management team and the selected target companies should ideally hold no more than 20 M€ in debt and employ not more than 400 staff respectively. Of least importance to the entire management team was the investment required by the target company after acquisition and the industry that this company is active in. The required investment should not be more than 15 M€ and the industry of the potential acquisition target should be the same as, or a neighbouring one to those in which, the companies already in the portfolio of the investment company are already active.

The task of the CEO (the participant) was to decide whether or not a specific company was to be put on his or her 'short list' of companies. To do so, the participant was faced with nine questions; one after the other. Each of them first provided him or her with a table containing the actual values for each of the six criteria achieved by the company subject of the respective question, as well as the To-Be-Met values and the importance weights for each criterion. This information was a repetition aiming to avoid unnecessary backward and forward movements within the survey and, thus, increasing the risk of terminating the survey before completing it. Basically, this approach was to ease the participant's decision task. The information was summarised in a respective table, again to ease the task (see Figure 8 next page).

Criterion (Importance)	To-Be-Met Value	Company F
Industry (+)	<i>same or neighbouring</i>	different
Profit (++ +)	<i>min. 6%</i>	4.6%
Employees. (++)	<i>max. 400</i>	383
Debt (++)	<i>max. 20 M€</i>	18 M€
Investment (+)	<i>max. 15 M€</i>	9 M€
Price (++ +)	<i>max. 30 M€</i>	36 M€

Figure 8:

Criteria table as displayed in the questionnaire for the decision task to short-list company F

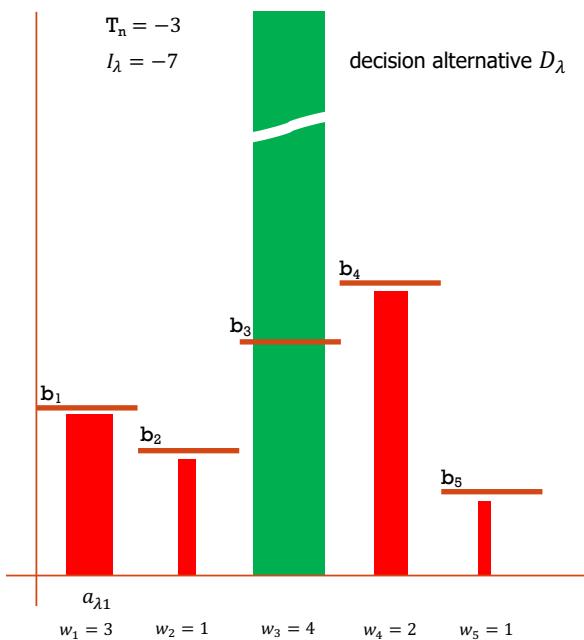
However, to avoid common method bias, the order of the criteria rows of each table was randomised. The participants had then to decide by answering a simple yes/no-question if they wanted that company on their shortlists or not.

To potentially falsify hypothesis 1, the author had to operationalise the concept of a temptation alternative and face an experimental subgroup of the Base Sample with the temptation whilst another subgroup, the reference subgroup, was confronted with an alternative identical to the tempting alternative except for the super attribute representing the temptation.

For the purpose of this research project, a temptation is defined as follows: Imagine a decision situation where the decision-maker will have to decide whether or not a decision alternative D_λ (see Figure 9 next page) will be allowed in the choice set. D_λ is a ‘temptation’ and has the following characteristics:

- All criteria (or attribute) values $a_{\lambda j}$ except one ($a_{\lambda \tau}$) fail to achieve the respective target values b_j
- The distance to a target value of the failed criteria is marginal, but obvious

- The one criterion that is acceptable is the most important one ($w_\tau > w_j$ for all $j \neq \tau$)
- D_λ achieves the highest value in the acceptable criterion compared to all other alternatives available and outperforms them by multiples ('super attribute': $a_{\lambda\tau} > x * a_{i\tau}$ for all $i \neq \lambda$)
- D_λ fails the compatibility test of decision-maker n ($T_n = -3, I_\lambda = -7$)

*Figure 9:**Example of a 'temptation'*

The design tools of *SurveyMonkey* allow to design questionnaire items with two different questions; Question A and Question B (A/B Question Item). Question A is administered to approximately 50% of the participants and Question B to the remaining participants. This allows to split any sample in two groups, an experimental group and a reference group. This technic was used to operationalise the temptation experiment.

The researcher provided the importance weight for each criterion to the participants. Two of the six criteria were deemed very important, the price and the profit criteria. Therefore, it was possible to create two temptation alternatives, one for each of the two most important criteria price and profit. Two A/B Question Items have been used to

create two times an experimental group and a reference group respectively. Please note as well, the different nature of the two most important criteria. Whilst the profit criterion holds a minimum to-be-met value and is of repetitive nature (a healthy company generates profit on an annual basis), price represents a maximum to-be-met criterion that is paid once when acquiring the company. At the same token, overachieving the profit criterion is an additional, repetitive gain whilst overachieving on the price criterion is a one-off, less-expense advantage.

Although the number of questions remained the same (in total 9), the number of different companies required in Part II of the Base Sample questionnaire rose by the two temptation alternatives from nine to eleven.

Based on equation (1) an incompatibility score I_i can be calculated for each of the eleven companies ($i = 1, 2, \dots, 11$). The importance weight, the to-be-met value and the actual company values for each criterion as well as the respective incompatibility score of each company are shown in Appendix *Decision alternatives and their characteristics* under the heading *Base & Student Sample Questionnaire*. When calculating the incompatibility score I_i , please note that v_{ij} of equation (1) is 0 if the attribute a_{ij} meets b_j and assumes the value -1 if the attribute a_{ij} does not meet b_j .

The design of the decision alternatives (companies) can be divided in three parts: first, a decision alternative was designed that meets the required values in all six criteria (company S). The main use of this company was during the application of a data sanity check that is described later. However, the selection or non-selection of company S was further used to calculate some of the variables that will be introduced later.

The second part of alternative design was to create the bulk of the decision alternatives. Companies C, G, H, J, K and F have been created by defining the values they take in the six criteria. The criteria values of each company have been chosen in order to generate a descending incompatibility score. That is, the incompatibility score of company C has been fixed to -2. The next company's score was decreased by 1 unit to -3 (Company G); the next one held the score -4 (Company H) and so on ($I_J = -5$, $I_K = -6$ and $I_F = -7$). This design allowed to calculate more easily the rejection threshold and number of inconsistencies of a participant.

The third and last part, was to create the temptation alternatives and their twin alternatives that differ from its twin in the ‘super attribute’ only. Particular care was taken, when selecting the criteria values for this group of companies. They ought to be in the same range as for the companies S to F to ensure that a potentially different selection behaviour for the temptation companies could only be attributable to the different score in the ‘super attribute’ and not to any other potential criteria differences. However, the incompatibility scores were defined in a way enabling the continuation of the descending order established by the incompatibility scores of companies C, G, H, J, K and F. Therefore, company E and R, the twins of the profit temptation experiment hold an incompatibility score of -8 and the incompatibility of companies D and T of the price temptation experiment was defined at -9.

As for the eight items on each of the five Part I pages to determine the participant’s decision style scores, the sequence of appearance of the nine questions (each on one survey page) related to the potential selection of one company has been randomised by selecting the appropriate options in the *SurveyMonkey* software.

With the 50th and last question of the survey, the participants were asked to provide their ranking of the six criteria. They should allocate a rank ranging from 1 to 6 to each of the criteria allocating 1 to the most important criterion and 6 to the least important criterion. The participants had as well the option to eliminate any criteria from the ranking by ticking a box that would declare the respective criteria as non-relevant. Please note that the participants could not vote for two criteria to be of equal importance, even though the author had ranked the six criteria being of pairwise equal importance. Latter was done on purpose to allow for two temptation experiments with the two most important criteria as the ‘super attribute’.

The design of Part II of the Base Sample questionnaire allowed first and foremost to the collect the following data and, thus, the scores for respective variables:

- A separator variable has been used for each of the two temptation experiments to separate the experimental groups from the reference groups. Both variables labelled GROUP_PRICE and GROUP_PROFIT could take the values 0 and 1 as well. The variable was 0 for a participant being part of the reference group and, thus, having not been confronted with a temptation alternative. It took the value 1, if the

participant being a member of the respective experimental group was faced with the profit or price temptation;

- Information on whether or not a participant had selected a respective company to become part of his or her shortlist. The respective variables have been labelled S, C, G, H, J, K and F representing the various companies. For the selection of companies E and R as well as for companies D and T, only one variable was defined for each pair of company: TEMP_PROFIT for the first pair and TEMP_PRICE for the latter. The values of these two variables had to be read in conjunction with GROUP_PROFIT or GROUP_PRICE respectively to identify which companies the participants did or did not select. All these variables could either take the value 0, if participants had not selected the respective company or 1 if they did select the company for their short lists.
- Last, but not least, a participant's individual ranking was recorded through the variables RANK_PRICE, RANK_PROFIT, RANK_DEBT, RANK_EMPLOYEE, RANK_INVEST and RANK_INDUSTRY. Each of these variables could take values ranging from 1 to 7 with 1 to 6 representing the rank allocated by the participant to the respective criterion and 7 identifying those criteria that the participant deemed non-relevant;

The various parts of the Base Sample questionnaire and the data that has been collected in each of these parts are shown in Figure 10 (see next page).

Apart from the above described variables that were directly downloaded as survey results from the *SurveyMonkey* website, a number of other variables have been calculated. These will be further explained in the chapter *Statistical procedures and data analysis*.



Figure 10:

Parts of and data collected with the Base Sample survey

4.4.3 The Student Sample questionnaire

The Student Sample questionnaire is largely identical to the one for the Base Sample. However, since the Student Sample was collected by publishing the related survey on *SurveyCircle*, a different online service provider, some additional questions had to be added to the Base Sample questionnaire.

These questions have been of pure demographical nature. When purchasing participants to complete a survey on *SurveyMonkey* important demographical information like gender and age were provided automatically when downloading the results from the *SurveyMonkey* website. Additionally, further information that frame the population can be preselected on *SurveyMonkey* when preparing the questionnaire for publishing. If the information either preselected or automatically provided by *SurveyMonkey* is required for a questionnaire published on *SurveyCircle* as well, then

the researcher has to ask for this information specifically by adding respective items to the questionnaire.

Therefore, the following questions and potential choices have been added to the Base Sample questionnaire:

51. Question:

“Are you male or female?”

Possible answers:

(1) Male / (2) Female

Variable: GENDER

52. Question:

“What is your age?”

Possible answers:

(1) Under 26 / (2) 26 to 35 / (3) 36 to 45 / (4) 46 to 55 / (5) 56 to 65 / (6) above 65

Variable: AGE_C

53. Question:

“Which of the following categories describes best your position in your organisation/company?”

Possible answers:

(1) owner or head of company / (2) upper management / (3) middle management / (4) experienced employee / (5) professional beginner / (6) student / (7) other

Variable: POSITION

These questions have been added to the Base Sample questionnaire as items number 51 to 53 forming together with the 50 Base Sample items the Student Sample questionnaire.

Please note that a different variable was defined for the participants' age groups since the age groups formed by SurveyMonkey could not be preselected and, thus, have not been known to the author when publishing the Student Sample questionnaire on SurveyCircle.

Further, it needs to be mentioned that the variable POSITION was not used for further statistical analysis. The purpose of the information on the participant's position in the

organisation or company was just to evaluate the nature of the sample underlying population and, thus, to get an indication on how comparable the Student Sample is to the Base Sample.

The various parts of the Student Sample questionnaire and the data that has been collected in each of these parts are shown in the figure below.



Figure 11:

Parts of and data collected with the Student Sample survey

4.4.4 The Extension Sample Questionnaire

The Extension Sample Questionnaire is probably most comparable to the Base Sample questionnaire. To further test hypothesis 5, a second questionnaire was administered to a second sample of the Base Population confronting the participants with decision situations only but more of them. The purpose was to collect data of the same population on additional decision situations, but with companies different to those that have been used to train the neural network that has been created to test hypothesis 5.

Compared to the Base Sample questionnaire, the questionnaire used to survey the Extension Sample did not make use of the first part dealing with the determination of the participants' decision styles. Instead the second part of the Base Sample questionnaire was extended and five additional companies (X, L, N, Y and P) with different compatibility structure were included. The name 'compatibility structure' refers to which of the six criteria are met by the companies and which ones are not. In total, 16 companies had been presented to the Extension Sample participants for selection on the short list in 14 questions. The experiments on price and profit temptation was kept, therefore, 16 companies in total. The characteristics of the 5 additional companies can be found in Appendix *Decision alternatives and their characteristics* under the header *Extension Sample Questionnaire (add on)*.

The last question of the Base Sample questionnaire asking the participant to rank the six decision criteria based on their own assessment was kept for data cleaning purposes only. The rankings were not used for further statistical processing.

The ACP and introduction of Part II of the Base Sample were kept the same for the Extension Sample questionnaire except for required changes as a result of deleting Part I and of increasing the number of decision situations in Part II.

The variables that have been created or used for this questionnaire are largely the same – as far as they are applicable – as the variables of the Base Sample questionnaire. Five additional variables have been created to cover the choices for the additional companies. The variables' names correspond to the name of the respective company: X, L, N, Y, and P.

The various parts of the Extension Sample questionnaire and the data that has been collected in each of these parts are shown in the following figure.

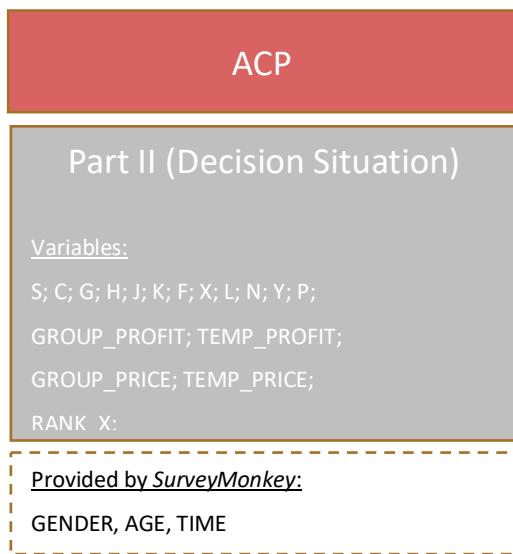


Figure 12:

Parts of and data collected with the Extension Sample survey

4.5 Data cleaning

When receiving the results of the first survey tests, it became obvious to the author that some participants (who were paid to attend the survey) appeared to spend extremely little time on completing the survey. One of them took as little as 1 minute and 24 seconds to answer all 50 questions. Even if one assumes that the members of *SurveyMonkey*'s web panel are very sophisticated and efficient to answer questionnaires, the time to take the survey of some of these participants casted sufficient doubt on the quality of the data that the researcher decided to introduce several sanity checks to clean the collected data from answer sets that did not follow instructions and, thus, are potentially useless or even distort the collected data and, therefore, the obtained results of the statistical analysis.

Three types of sanity checks have been performed on the data collected from *SurveyMonkey* as well as from *SurveyCircle* even though the detrimental behaviour was less observed for the latter in the Student Sample.

First, a cut-off time was defined and participants that took less time to take the survey than this cut-off time have been disqualified from the survey and their data was not used further. The cut-off time was determined by the author through several self-tests, tests with friends and taking into account that the participants know the *SurveyMonkey* software tool and are used to taking online surveys.

Based on this process, the following estimates to take the three parts of the surveys were generated for the Base and Student Sample participants:

- The estimated time to complete, that is, to read the ACP and click the 'Next'-button is 20 seconds.
- The first part of the survey was estimated to take the participants a minimum of 3 minutes to complete (4 to 5 seconds per item including one 'Next'-click per page).
- The minimum time to take the second part of the survey was estimated to be 1 minute and 40 seconds for a sophisticated participant. Included in this time are 30 seconds to read the instructions of Part II. Answering the simple yes/no questions was deemed to take no longer than 1 minute for all 9 questions. This equates to little less than 7 seconds per question to read and compare the criteria values of the company, read the question, tick the yes or no box and click on the 'Next' button. Included in the minimum time to take Part II are 10 seconds to answer question 50, the ranking of the criteria, that appears to be slightly more complex and thus time consuming.
- The last page of the survey was deemed to be completed within 5 seconds. Please note that the Student Sample had 3 more demographic questions to answer which however were estimated to be covered by the 5 seconds.

Therefore, the total minimum time, the cut-off time, for the Base and Student Sample participants to complete the survey was estimated to be 5 minutes and 5 seconds.

The Extension Sample participants had a shorter survey with only 15 questions. However, the ACP part was largely identical to the one of the Base or Student Sample questionnaire. Therefore, it was deemed to be completed by participant within 20 seconds as well. The introduction to the second part was nearly identical to the other Base and Student Sample questionnaire, therefore, 30 seconds were estimated to read the instructions. Considering and deciding on 14 companies for selection into the choice

set was estimated as for the Base or Student Sample with little less than 7 seconds per decision, thus, 1 minute and 35 seconds in total. Again, the question assessing the six criteria as well as the final page of the survey was identical to the Base or Student Sample and was thus estimated to take a participant no longer than 10 seconds in total to complete.

Therefore, the total minimum time, the cut-off time, for the Extension Sample participants to complete the survey was estimated to be 2 minutes and 40 seconds. The cut-off times calculation for all samples is summarised in Table 4 below.

Survey Part	Base & Student Sample	Extension Sample
ACP	20 sec	20 sec
Part I	180 sec	n/a
Part II (Introduction)	30 sec	30 sec
Part II (decisions)	60 sec	95 sec
Part II (ranking)	10 sec	10 sec
End	5 sec	5 sec
Total	5 min 5 sec	2 min 40 sec

Table 4:

Cut-off times used for data cleaning of the samples

The second sanity check was linked to the selection of company S into the choice set and to the selection of all companies in the choice set. Company S is the only option that meets all required criteria. Therefore, not putting company S on the short list clearly violates the instructions. The probability that someone did not follow the instructions appears to be high. The same can be assumed, if a participant has selected all companies. Therefore, participants that did not allow company S in their final choice set or have selected all companies to become part of their 'short list' were disqualified and data collected from these participants were not used further for the research project.

Eventually, a third sanity check was applied and is linked to the participants' assessment of the decision criteria. If participants deemed all criteria non-relevant, that is, all of their RANK_X⁴ scores are 7, then they were disqualified as well since a meaningful participation in the survey was not possible for those participants. The effect of these three sanity checks on the size of the three samples is described in the next chapter.

4.6 Populations and samples

The research was based on two populations and three samples. They will be described in the following chapters in terms of age and gender distribution

4.6.1 Base Population and Sample

The main population of this research project are German Heads of Company and other German decision takers, aged 18 to 65, with internet access (Base Population).

The commercial internet provider *SurveyMonkey* has been used to buy a Base Sample size of at least 1,300 participants from the Base Population. 1,369 participants have been administered the Base Sample questionnaire. 1,306 participants completed the questionnaire. This represents a finishing rate of 95.4%. Of the 1,306 participants 59.9% have been male and 40.1% have been female. The age distribution was as follow:

Age Group	Frequency	Percent
18 to 29	202	15.5%
30 to 44	698	53.4%
45 to 60	359	27.4%
Above 60	47	3.6%

Table 5:

Age distribution of the Base Sample before data cleansing procedures

⁴ X is a place holder for PRICE, PROFIT, DEBT, EMPLOYEES, INVEST or INDUSTRY

As described in the chapter *Data cleaning*, data sets of participants that completed the Base Sample questionnaire in less than 5 minutes and 5 seconds have been disqualified since it is assumed that they did not focus on answering the questions; rather they merely ‘clicked through’ the questionnaire to reach the end.

401 participants (31%) of the Base Sample have been disqualified by this first data cleaning step. By implementing the second and third data cleaning procedure, an additional 256 participants (19%) of the Base Sample have been disqualified.

Consequently, the number of data sets that survived the data cleaning process was 649 (50%) in the Base Sample.

After data cleaning, the median time of a Base Sample participant to answer the questionnaire was 9 minutes and 55 seconds and the mean time was 24 minutes and 19 seconds which is mainly due to a few very long answer times (one participant took as much as 23 hours and 22 minutes to finish the survey). Not considering the answers of participants that took more than one hour to complete the survey led to a mean time of 12 minutes and 35 seconds for the Base Sample.

377 (58.1%) of the remaining 649 participants of the Base Sample were male and 272 (41.9%) were female. The age distribution of the remaining participants can be taken from the table below.

Age Group	Frequency	Percent
18 to 29	88	13.6%
30 to 44	299	46.1%
45 to 60	229	35.3%
Above 60	33	5.1%

Table 6

Age distribution of the remaining 649 participants of the Base Sample

A second sample, the Extension Sample, was taken from the Base Population to be used to further research hypothesis 5.

4.6.2 The Extension Sample

The Extension Samples was drawn as well from the Base Population. In order for the Extension Sample to match the Base Sample in terms of gender distribution as close as possible, a 60% (male) – 40% (female) split was preselected in *SurveyMonkey* settings before purchasing the sample.

106 participants were administered the Extension Sample questionnaire by *SurveyMonkey*. 101 participants (95.3%) completed the survey, 60 (59.4%) of them were male and 41 (40.6%) were female. Thus, the envisaged gender distribution for the sample was achieved albeit before data cleaning. The initial age distribution can be taken from Table 7.

Age Group	Frequency	Percent
18 to 29	29	28.7%
30 to 44	39	38.6%
45 to 60	28	27.7%
Above 60	5	5.0%

Table 7:

Age distribution of the Extension Sample before data cleansing procedures

As described in the chapter *Data cleaning*, the cut-off time to complete the survey was estimated to be 2 minutes and 40 seconds. Applying the first data cleaning procedure to the Extension Sample disqualified 27 (26.7%) of the participants. The data sets of further 18 (17.8%) participants were rejected since they did not pass the second and third data cleaning procedure. Consequently, 56 (55.4%) participants remained and 35 (62.5%) of them were male and 21 (37.5) were female. Their age distribution is shown in Table 8 (see next page).

Age Group	Frequency	Percent
18 to 29	15	26.8%
30 to 44	20	35.7%
45 to 60	19	33.9%
Above 60	2	3.6%

*Table 8:**Age distribution of the remaining 56 participants of the Extension Sample*

After data cleaning, the median time of an Extension Sample participant to answer the questionnaire was 6 minutes and 18 seconds and the mean time was 7 minutes and 21 seconds.

4.6.3 The Student Population and Sample

For comparison reasons a second population (Student Population) has been included: the survey has been published on *SurveyCircle* for region 1 (Germany, Austria and Switzerland). For that purpose, the questionnaire was slightly modified to collect those demographic data that are included in the data provided by *SurveyMonkey* (the online software provider of which the answers of the first population have been purchased). These additional questions are about the gender, the age and the position in the participant's organization.

99 participants started the survey on *SurveyCircle* and 98 completed it. This represents a finishing rate of 98.9%. Of these 98 participants 41.8% have been male and 58.2% have been female. Their age distribution was as follows:

Age Group	Frequency	Percent
Under 26	58	59.2%
26 to 35	27	27.6%
36 to 45	8	8.2%
46 to 55	2	2.0%
56 to 65	3	3.1%

*Table 9:**Age distribution of the Student Sample before data cleansing procedures*

In the Student Sample, 34 (39.1%) of the remaining 87 participants were male and 53 (60.9%) were female.

The participants of the Student Sample were also asked to provide their position within their organization:

Position	Frequency	Percent
Owner/Head of Company	3	3.1%
Upper Management	2	2.1%
Middle Management	6	6.2%
Experienced Employee	17	17.5%
Professional Beginner	10	10.3%
Student	59	58.8%
Other	2	2.1%

*Table 10:**Positions held in their organisation by participants of the Student Sample*

Table 10 provides the reason why the authors refers to this sample as Student Sample: close to 59% of their members are students.

As for the other samples, the Student Sample was subject to the data cleaning procedures as well. The cut-off time led to the disqualification of 9 participants (9.2%) of the Student Sample. An additional 2 participants were disqualified based of the second and third data cleansing process leading to 11 disqualified participants in total (11.2%). Therefore, the data sets of 87 participants (89%) remained in the Student Sample and were used for further statistical analysis. The age distribution of the remaining 87 participants is shown in Table 11.

For the Student Sample, the median time to answer the questionnaire was 10 minutes and 55 seconds and the average time was 16 minutes and 20 seconds. Not considering the answers of participants that took more than one hour to complete the survey leads to an average time of 13 minutes and 31 seconds for the Student Sample. This is less than one minute longer than a participant of the Base Sample took in average to complete the survey.

Age Group	Frequency	Percent
Under 26	58	59.2%
26 to 35	27	27.6%
36 to 45	8	8.2%
46 to 55	2	2.0%
56 to 65	3	3.1%

Table 11:

Age distribution of the remaining 87 participants of the Student Sample

The reason why the participants of the Base Sample completed the questionnaire quicker than the participants of the Student Sample could either be found in the increased experience that the Base Sample participants hold when completing surveys (since they are paid for it and, thus, complete more questionnaires than the average

Student Sample participant), or could be traced back to statistical differences of both samples. However, the rather small difference between both samples is taken by the author as evidence that the data cleansing procedures appear to be effective.

4.6.4 Demographic variables and time variable

To allow collection of the data on age and time the following variables were created:

- AGE for the Base and Extension Sample: AGE could take the value 2 to 5 depending on the age of the participant (18 to 29 = 2; 30 to 44 = 3; 45 to 60 = 4; above 60 = 5).
- AGE_C for the Student Sample. AGE_C could take the values 1 to 5 depending on the age of the participant of this sample (under 26 = 1; 26 to 35 = 2; 36 to 45 = 3; 46 to 55 = 4; 56 to 65 = 5). Please note that the same values for AGE and AGE_C do not refer to the same age group.
- GENDER for all samples: GENDER took the value 1 for male participants and 2 for female participants.
- TIME for all samples: TIME is based on the time that a participant took to complete the survey in relation to the other participants of the same sample. TIME takes the value 1 for participants that are the quickest 25% participants (first quantile) of their sample to complete the survey. It becomes 2, 3 or 4 for participants allocated in the 2nd, 3rd or 4th quantile of that sample. Again, this implies that a participant that has been allocated a TIME value of 1 i.e. in the Base Sample is only comparable to a participant of the Student Sample with the same value to the extent that they belong to the quickest 25% of their sample. The same TIME value does not imply that they fall in the same time interval or took the same time to complete the survey.

4.7 Statistical procedures and data analysis

Two different software tools were used for statistical processing of the collected data: first, IBM SPSS (Field, 2013; Brosius, 2018; IBM, 1989-2017) was the main software that was used to test all hypothesis; second, the MPlus software (Muthén & Muthén, 1998-2017) was used in particular for confirmatory factor analysis as well as for structural equation modelling; both cannot be performed in IBM SPSS.

The standard settings were used in both software tools. Required deviations from this approach are described in the following subchapters describing the statistical processing of the data to test each of the five hypotheses.

The next subchapter describes the calculation of the choice set variables and the importance weight variables. Values for both variable sets were not gained directly from the questionnaires but required to be calculated based on the data collected by the surveys. These two data sets are of importance for testing all hypotheses. Therefore, a specific subchapter describing the calculation of both variable sets precedes the description of the statistical processing applied to test each hypothesis. The definition of other variables that are important to potentially falsify a specific hypothesis are described in the relevant subchapter dealing with the statistical processing of this hypothesis.

Further, the determination of the demographic variables as well as the calculation of TIME is laid out in the previous chapter (Demographic variables and time variable).

Eventually, the values of the decision and process styles variables were calculated by IBM SPSS in the context of the respective statistical data analysis. The method of their calculation is described in the respective subchapters. A list of all variables used for this research project is provided in Appendix List of used variables (see page XXXVIII).

The use of the various samples (Base, Student and Extension Sample) is described in the respective subchapters on hypothesis testing as well. The following table provides however a respective overview for simplicity reasons.

<i>Sample</i>	<i>Hypothesis 1</i>	<i>Hypothesis 2</i>	<i>Hypothesis 3</i>	<i>Hypothesis 4</i>	<i>Hypothesis 5</i>
Base	x	x	x	x	x
Student	x	x	x	x	x
Extension	x				x

Table 12:

Usage of the Base, Student and Extension Sample to test the five hypotheses

4.7.1 Important variables calculated from the participants' scores

Apart from the variables for which the scores were directly gained from the survey or were calculated as a result of a respective analysis, two variable sets required to be calculated from the data collected by the surveys. These two variable sets are the choice set variables and the importance weight variables. Their definition and calculation are provided in the following.

4.7.1.1 Choice Set Variables

Three variables have been identified to describe the process and outcome of the compatibility test, as a group of variables they will be referred to as choice set variables:

First, the number of alternatives in the choice set is of interest. That is, the number of the alternatives that have survived the compatibility test. In the context of this research, the number of alternatives in the choice set is the number of companies that have been selected to become part of the shortlist. The respective variable has been labelled NUMCOMP and can be calculated by the following trivial equation:

$$\text{NUMCOMP} = S + C + G + H + J + K + F + \text{TEMP_PROFIT} + \text{TEMP_PRICE} \quad (6)$$

The second variable that has influence on the choice set is the participant's rejection threshold that determines what alternatives are selected to become part of the choice set and which ones are rejected. The respective variable has been labelled THRESHOLD and can only be measured indirectly in the context of this research by looking at the alternatives in the choice set; that is, the number of companies selected by the participant. The rejection threshold is intimately linked with the third relevant choice set variable, the number of inconsistencies as a result of the application of the compatibility test (variable name: INCONSIS). An inconsistency is an alternative that either has been selected into the choice set even though it does not meet the rejection threshold, or it does but did not make it on the shortlist. An example shall shed further light on this dilemma.

One could identify the value for THRESHOLD as the incompatibility score of that company in the participant's choice set that has the lowest incompatibility score of a gapless sequence of incompatibility scores of a respective group of companies starting with the company holding the highest incompatibility score in the choice set. Looking at

participant 8's choice set in Table 13 might illustrate the process: participant 8 has selected company C, G and H in the choice set. The sequence of gapless incompatibility score starting with the highest score in the choice set is C, G, H since C holds the highest incompatibility score, -2, and G as well as H continue the incompatibility score sequence without gap ($G=-3$, $H=-4$). Participant 8's value for THRESHOLD would therefore be -4 since it is the lowest incompatibility score in a gapless sequence of incompatibility scores starting with the highest score in the choice set. Based on this approach, THRESHOLD would take the value -2 for participant 2 (see Table 13) since the next selected company is company H with an incompatibility score of -4. Therefore, a gap occurs in the sequence of incompatibility scores of participant 2's choice set companies.

<i>Company</i>	<i>C</i>	<i>G</i>	<i>H</i>	<i>J</i>	<i>K</i>	<i>F</i>
<i>Incompatibility Score</i>	-2	-3	-4	-5	-6	-7
<i>Participant 1 Choice</i> ⁵	1	0	0	1	0	0
<i>Participant 2 Choice</i>	1	0	1	0	0	0
<i>Participant 3 Choice</i>	1	1	0	1	1	0
<i>Participant 4 Choice</i>	0	0	0	0	0	0
<i>Participant 5 Choice</i>	1	0	0	1	0	0
<i>Participant 6 Choice</i>	0	0	0	1	0	1
<i>Participant 7 Choice</i>	0	1	1	1	0	0
<i>Participant 8 Choice</i>	1	1	1	0	0	0

Table 13:

Participants' choice sets containing various companies

Participant 5 (THRESHOLD = -2) has even a larger gap between company C and the next lower incompatibility score company which is company J. Based on the same protocol, the participant 3's score for THRESHOLD is -3. Based on this approach, inconsistencies are companies in the choice set holding a lower incompatibility score than THRESHOLD. The number of inconsistencies is 0 for participant 8, 1 (company H) for participant 2 as

⁵ 1 = yes, the company was selected in the participants choice set, 0 = no, the company was not selected

well as for participant 5 (company J), and 2 (companies J and K) for participant 3. However, taking a more precise look at participant 3's choice set unveils that this participant's number of inconsistencies might well be only one (company H) instead of 2, as previously determined, if only his or her incompatibility threshold is deemed to be -6 instead of -3. But then the problem becomes: how to determine THRESHOLD and INCONCIS for a participant?

The author has addressed this problem by taking the assumption that inconsistencies are not the aim of a participant. Therefore, the lowest number of inconsistencies shall be attributable to a participant. The allocation of the lowest INCONCIS value to a participant then also determines the value for THRESHOLD and, thus, the methodology to calculate it.

Looking again at Table 13: the number of inconsistencies for participant 1 can either be 2 (company G and H) when calculating THRESHOLD applying the gapless-incompatibility-score method as described above, or it can be 1 when adopting the second method (lowest-inconsistency-score method) to determine the value for THRESHOLD.

Applying the lowest-inconsistency-score rule, 1 shall become the value for participant 1's INCONCIS, and, thus, THRESHOLD takes the value -2. Based on the same logic, the value for INCONCIS/THRESHOLD would be 1/-6 for participant 3, 1/-2 for participant 5, 2/0 for participant 6 and 1/-5 for participant 7.

For participants 4 and 8, the INCONCIS/THRESHOLD values would be identical regardless which method was selected (for 4: 0/0 and for 8: 0/-4). In the case where both methods led to the same number of inconsistencies (i.e. participant 2), lowest-inconsistency-score method was chosen to determine the THRESHOLD value, since in such case it produces a higher THRESHOLD value than the gapless-incompatibility-score method.

To determine the values for THRESHOLD and INCONCIS, the participant's choice regarding all companies (incl. companies E, R, T and D) has been considered except for company S since it is the alternative that meets all criteria, holding therefore an incompatibility score of 0 and, thus, contributing nothing to this calculation. The selection of company S was used as a sanity check described in more detail in the chapter *Data cleaning*.

The choice set variables for the Extension Sample participants were calculated on the basis of the companies used in equation (6), even though the number of decision situations and, thus, the number of companies was larger for the Extension Sample than for the other two. To limit the calculation, the original companies were required to have comparable values for the choice set variables of the Extension Sample since their nature had to be the same when used as input of the neural network created to test hypothesis 5.

4.7.1.2 Importance Weight Variables

Apart from the three choice set variables described above, another set of variables has been determined from the data collected by the survey. All these variables are linked to the importance weights of the criteria and are thus collectively referred to as the importance weight variables.

The variables that collect a participant's importance ranking of the six criteria (RANK_PRICE, RANK_PROFIT, RANK_DEBT, RANK_EMPLOYEES, RANK_INVEST and RANK_INDUSTRY) have proved to be impractical for further statistical processing. In particular, if a participant deemed a certain criterion non-relevant, and, thus, allocated the value 7 to the specific variable, proved impractical for further statistical processing. Therefore, normalised variables ranging from 0 to 100% have been calculated. These variables have been labelled INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEES, INDIV_W_INVEST and INDIV_W_INDUSTRY respectively. The name is an abbreviation for **INDIVidual W**eight followed by the respective criterion name.

To calculate the values of these normalised variables an intermediate variable Y_x^6 was created that took the value 0 for all RANK_X⁷ variables holding the value 7. For each participant, the remaining values for RANK_X that held values different from 7 were organised in ascending order. Then, in a first step, the Y_x for the first criterion of that order took the value of the last RANK_X of the same order and vice versa. Second, the Y_x for the second criterion of that order took the value of the second-last RANK_X and vice versa, and, third, the third Y_x of that order took the value of the third-last RANK_X

⁶ X is a place holder for PRICE, PROFIT, DEBT, EMPLOYEES, INVEST or INDUSTRY

and vice versa. This protocol requires obviously six values in ascending order which implies that all six criteria have been ranked by the participants and, thus, are relevant to them. For such a participant, none of the RANK_X variables took the value 7. However, the protocol can easily be adapted for participants that have rated one or more criteria non-relevant. If the number of remaining RANK_X values, that is, RANK_X values that differ from 7, is 4 or 2, the protocol consists of two steps or one step instead of three steps. If the number of remaining RANK_X values is uneven for a given participant, then the X in Y_x and in RANK_X are identical for the middle value of the ascending order.

An example shall further clarify the protocol: a participant evaluates the importance of the six criteria as follows:

Criterion	Rank	Variable	Value
PROFIT	1	RANK_PROFIT	= 1
PRICE	2	RANK_PRICE	= 2
DEBT	3	RANK_DEBT	= 3
INVEST	4	RANK_INVEST	= 4
EMPLOYEES	5	RANK_EMPLOYEES	= 5
INDUSTRY	non-relevant	RANK_INDUSTRY	= 7

Table 14:

Example data to demonstrate the calculation of the intermediate variable Y_x

Following the above protocol, $Y_{INDUSTRY} = 0$ since RANK_INDUSTRY holds the value 7. The remaining values of respective variables are organised in ascending order which is identical to the ranking:

{RANK_PROFIT = 1; RANK_PRICE = 2; RANK_DEBT = 3; RANK_INVEST = 4; RANK_EMPLOYEES = 5}

Then, based on above protocol, $Y_{PROFIT} = 5$ and $Y_{EMPLOYEES} = 1$, $Y_{PRICE} = 4$ and $Y_{INVEST} = 2$, and, eventually, $Y_{DEBT} = 3$.

Having calculated all Y_X for a participant, the subsequent calculation of his or her INDIV_W_X scores is based on the equation:

$$INDIV_W_X = \frac{Y_X}{\sum_X Y_X} \quad (7)$$

For the above example $\sum_X Y_X = 15$, therefore the individual importance weight variables take the values shown in Table 15. Obviously, since the INDIV_W_X are normalised, the sum for any single participant of these variables equals 100%.

Variable	Value of Y_X	Calculation	Value of $INDIV_W_X$
<i>INDIV_W_PROFIT</i>	$Y_{PROFIT} = 5$	$\frac{5}{15}$	= .3333 (or 33.33%)
<i>INDIV_W_PRICE</i>	$Y_{PRICE} = 4$	$\frac{4}{15}$	= .2667 (or 26.67%)
<i>INDIV_W_DEBT</i>	$Y_{DEBT} = 3$	$\frac{3}{15}$	= .2000 (or 20.00%)
<i>INDIV_W_INVEST</i>	$Y_{INVEST} = 2$	$\frac{2}{15}$	= .1333 (or 13.33%)
<i>INDIV_W_EMPLOYEES</i>	$Y_{EMPLOYEES} = 1$	$\frac{1}{15}$	= .0667 (or 6.67%)
<i>INDIV_W_INDUSTRY</i>	$Y_{INDUSTRY} = 0$	$\frac{0}{15}$	= .0000 (or 0%)

Table 15:

Normalised individual importance weight values for the data of Table 14

Another variable belonging to the set of importance weight variables is a measure of how well a participant's overall assessment of the criteria importance aligns with the importance weights provided by the researcher. Knowing the alignment will enable the author to research links between this measure and other variable sets, i.e. the choice set variables, the decision style or process style variables described further below.

The alignment measure variable is referred to as IMPOR_WEIGHT_FIT and its calculation requires the participant's INDIV_W_X values as well as the importance weights provided

by the researcher. The questionnaire provides these importance weights by using words and symbols (see Table 3). However, a further intermediate variable \bar{Y}_X holding the values of the importance weights provided by the researcher, can easily be deducted from the used symbols by allocating one importance point for each '+'-symbol used to describe the importance of the respective criterion; i.e. the price criterion is marked with three '+'-symbols (+ + +) being one of the two most important criteria. The respective \bar{Y}_{PRICE} takes then the value 3. All other \bar{Y}_X can be calculated accordingly. Please note that these variables are constant for all participants.

<i>Variable</i>	<i>Profit</i>	<i>Price</i>	<i>Debt</i>	<i>Employees</i>	<i>Invest</i>	<i>Industry</i>
\bar{Y}_X	3	3	2	2	1	1
FXW_X	.25 (or 25.00%)	.25 (or 25.00%)	.1667 (or 16.67%)	.1667 (or 16.67%)	.0833 (or 8.33%)	.0833 (or 8.33%)

Table 16:

Values of the intermediate variables to calculate the alignment measure

With the help of the \bar{Y}_X values, normalised fixed importance weight variables FXW_X can be calculated that correspond to the $INDIV_W_X$ values for each participant. The abbreviation FXW stands for FiXed Weights since – as for \bar{Y}_X – all FXW_X are constant for all participants. Equation (7) is used for the calculation of the FXW_X values by replacing Y_X with \bar{Y}_X . The sum of all \bar{Y}_X equals 12. The obtained values for FXW_X as well as the respective \bar{Y}_X are shown in Table 16.

Eventually, both $INDIV_W_X$ and FXW_X are used to calculate a participant's alignment measure $IMPOR_WEIGHT_FIT$. A statistically proven concept has been used to calculate this measure: the square root of the squared error sum. The respective equation is shown below:

$$IMPOR_WEIGHT_FIT = \sqrt{\sum_x (FXW_X - INDIV_W_X)^2} \quad (8)$$

The smaller $IMPOR_WEIGHT_FIT$, the more aligned is the participant's criteria importance assessment with the one provided by the author.

Both, the choice set variables as well as importance weight variables, have been calculated before beginning the statistical analysis. However, these are not the only variables used in the analysis. Additional variables have been defined and will be presented in the following chapters, i.e. the process style variables and, first and foremost, the decision style variables that will be introduced and explained in the next chapter describing the approach to test hypothesis 1.

4.7.2 Statistical and data analysis to test hypothesis 1

Hypothesis 1 is linked to the temptation alternative and the question whether or not a temptation alternative will be allowed in the choice set even though it does not meet the rejection threshold.

All three samples were used to potentially falsify hypothesis 1. Of all samples, the following variables have been used:

- RANK_PROFIT and RANK_PRICE;
- TEMP_PROFIT and TEMP_PRICE, and
- GROUP_PROFIT and GROUP_PRICE;

When designing the questionnaire, the author defined that the criteria 'Profit' and 'Price' are to be considered as the most important criteria by the participants. Even though they are deemed to be of equal importance, the nature of both criteria differs greatly: whilst profit is (hopefully) a recurrent feature of a business, the price that ought to be paid for a business is a one-off payment. Other differences spring to mind as well: the generation of profit is documented following generally applicable rules, regulations and accounting laws and their correct application is subject to annual audits. Hence, the profit that a company generates appears to be a trustworthy and reliable number. The acquisition price for a company appears to be of 'softer' nature, calculated based on largely differing approaches and subject of lengthy discussions and arguments.

Based on these differently perceived business figures, the author designed two temptations, one for the 'Price' and one for the 'Profit' criterion. The nature of these temptation alternatives, company R ('Profit') and company T ('Price') as well as their non-tempting counterparts (companies E and D) is shown in Table 17 (see next page). Please note that the values for the temptation criteria of the non-temptation

alternatives is in the same range as for other companies (for other companies the price varied from 24 M€ to 39 M€ and their respective profit from 4.6% to 7.8%).

Criteria	Desired Values	Company E	Company R	Company D	Company T
Debt	max. 20 M€	23 M€	23 M€	24 M€	24 M€
Investment	max. 15 M€	18 M€	18 M€	19 M€	19 M€
Price	max. 30 M€	37 M€	37 M€	26 M€	7 M€
Employees	Max. 400	467	467	453	453
Industry	Same or neighbouring	neighbouring	neighbouring	different	different
Profit	min. 6%	6.9%	22.6%	4.8%	4.8%

Table 17:

Comparison of the two temptation alternatives with their non-tempting counterparts

With the help of questions 48 and 49 of the Base and Student Sample questionnaires or questions 8 and 9 of the Extension Sample questionnaire, an experimental and a reference group were formed for each temptation. The variables GROUP_PRICE and GROUP_PROFIT were used to separate the experimental from the reference groups. The allocation of a participant to a group has been performed randomly approximating very roughly a 50%/50% split of the respective sample. If GROUP_PRICE (GROUP_PROFIT) took the value 0, participants belonged to the reference group and were thus asked whether or not company D (company E) should become part of their shortlists. In contrast, if GROUP_PRICE (GROUP_PROFIT) became 1, then the participant was administered the temptation alternative company T (company R) and, therefore, became a member of the experimental group. Table 18 (see next page) shows how many participants have been allocated to which group.

The respective answer of the participants was recorded with the variables TEMP_PRICE and TEMP_PROFIT. For both variables, a value of 0 means that participants have not chosen the company offered to them to become part of their shortlists. Respectively, a value of 1 means the company became part of their choice sets. TEMP_PRICE and

GROUP_PRICE as well as TEMP_PROFIT and GROUP_PROFIT have to be interpreted together to identify whether or not the respective temptation has been selected.

For the Base Sample, the variables RANK_PRICE and RANK_PROFIT were used to potentially identify differences in the ranking of the two criteria in the respective experimental and reference group. 67.5% (67.7%) of the price (profit) temptation reference group and 64.4% (65.1%) of the price (profit) temptation experimental group ranked the criteria 'Price' on 1 or 2. Two ANOVAs were performed with this Base Sample data. The first one with RANK_PRICE as dependent variable and GROUP_PRICE as independent. The second ANOVA with RANK_PROFIT as dependent variable and GROUP_PROFIT as independent variable.

	<i>Base Sample</i>	<i>Student Sample</i>	<i>Extension Sample</i>
Temptation Price			
Experimental Group (GROUP_PRICE = 1)	323 (49.8%)	50 (57.5%)	26 (46.4%)
Reference Group (GROUP_PRICE = 0)	326 (50.2%)	37 (42.5%)	30 (53.6%)
	649	87	56
Temptation Profit			
Experimental Group (GROUP_PROFIT = 1)	294 (45.3%)	41 (47.1%)	32 (57.1%)
Reference Group (GROUP_PROFIT = 0)	355 (54.7%)	46 (52.9%)	24 (42.9%)
	649	87	56

Table 18:

Composition of the experimental and reference groups for all samples

Eventually, and for all samples, respective ANOVAs were performed with TEMP_PRICE (TEMP_PROFIT) as dependent variable and GROUP_PRICE (GROUP_PROFIT) as independent variable.

Results of the above described approach are provided in the subchapter Hypothesis 1.

4.7.3 Statistical and data analysis to test hypothesis 2

In addition to general descriptive and correlation analyses, the first step to test the latent structure described in chapter HYPOTHESES was to verify if the Dewberry et al. (2013) model applies. The verification was performed in three steps: first, factor analyses were conducted with the 40 decision style items used in the questionnaire to extract and confirm potentially eight decision styles. Second, with the factors extracted from this first analysis, a further factor analysis was performed to identify the overarching, potentially three process styles (SYSTEM1, SYSTEM2 and REGULATORY). Third, the structural model resulting of the first two analysis was verified with a Structural Equation Model (SEM) analysis.

For the first factor analysis, the data collected with the 40 decision style items was used. The related variables are ANXIOUS_X, AVOIDANT_X, DEPENDENT_X, MAXIMISING_X, REGRET_X, INTUITIVE_X, SPONTANEOUS_X, and RATIONAL_X. The 'X' in the names of these variables is a place holder and can take the values 1 to 5 since five items have been used for each decision style, and, thus, the respective questionnaires provided 5 values for each of the decision styles.

An Explorative Factor Analysis (EFA) using IBM SPSS and a Confirmatory Factor Analysis (CFA) using MPlus were performed. Schermelleh-Engel, Werner and Moosbrugger (2007, p.4) recommend using the Principle Component factor Analysis (PCA) as extraction method if a simple data reduction is required. The author followed this recommendation since the eight decision styles that should be extracted, are already known and have been confirmed in previous research. Therefore, the aim of the factor analysis is more of confirmatory than of explorative nature, but a CFA cannot be performed with IBM SPSS (Schermelleh-Engel et al., 2007, p. 2), therefore, an EFA was conducted. Further, the author has decided to use an orthogonal rotation approach (referred to as Equamax with Kaiser-normalisation in IBM SPSS) since he wanted to have the least possible correlation between the potentially eight decision styles (factors) without forcing no correlation at all. Two criteria are used to identify the various factors: first, the Kaiser-criteria (Schermelleh-Engel et al., 2007, p. 7) was used. That is, a factor is identified as such if its eigenvalue is above 1.0; and, second, a graphical identification with the help

of a scree plot (Schermelleh-Engel et al., 2007, p. 10). That is, factors are left to the 'kink' in the scree plot. The remainder of the analysis setting were default in IBM SPSS.

The following measures were used to evaluate the IBM SPSS outcomes:

- Kaiser-Mayer-Olkin (KMO) Value (Kaiser & Rice, 1974): the assessment criteria have been taken from Backhaus, Erichson, Plinke and Weiber (2011, p. 343):
 - KMO \geq .9 'marvellous'
 - KMO \geq .8 'meritorious'
 - KMO \geq .7 'middling'
 - KMO \geq .6 'mediocre'
 - KMO \geq .5 'miserable'
 - KMO \leq .5 'unacceptable'
- Significance following Bartlett (Dziuban & Shirkey, 1974) which is a χ^2 -test based on the usual probabilities (* $p<.05$; ** $p<.01$; *** $p<.001$); and
- no more than 50% of non-standardised residuals of the reproduced correlation matrix take an absolute value of more than .05 (Field, 2013, p. 700).

For the CFA with MPlus all default analysis settings have been used, except for the rotation method for which 'CF-EQUAMAX (ORTHOGONAL)' was used. The respective code for the MPlus input file is to be found in Appendix Syntax for the various analysis in MPlus.

The following measure have been used to evaluate the model fit of the MPlus results based on (Brown, 2015, p.74):

- the Root Mean Square Error of Approximation (RMSEA): its value should be equal to or smaller than .06 for 'good' model fit;
- the Comparative Fit Index (CFI): its value should be equal to or larger than .95 to have achieved 'good' model fit;
- the Tucker-Lewis-Index (TLI): a value of equal to or more than .95 is deemed as 'good' model fit; and
- the Standardised Root Mean Residual (SRMR) which should be equal to or lower than .08 for 'good' model fit.

In order to be able to investigate the relations of the various decision styles and, subsequently, to perform the second factor analysis that would potentially confirm the three overarching process styles, values were required to be calculated for the decision styles. Three possibilities have been considered by the author.

First, calculate the score of each decision style as average of the scores of the five items related to the respective decision style. This obviously treats all five items of the questionnaire the same way, as having equal weights. However, the factor loadings are then not considered at all, and included information will be lost. Therefore, and since the author did not want to lose this information, he decided against this approach and focused on the two other options. These were either, second, to calculate the decision style scores based on the factor loadings of all 40 questionnaire items for each style or, third, to use only the factor loadings of the five items per decision style and allocate the factors to the sum of these five items in a way that maximises the overall factor loading. Whilst the first approach of the latter two 'pollutes' the decision style scores by factor loadings of other style items, the second of the latter two ways runs the risk that the set of five items for a specific style, i.e. the anxious decision style, is allocated to a different decision style, i.e. to the avoidant decision style, if the factor loadings of these five items are very similar for those two styles which might potentially happen, if both decision styles are related. Since the author's intention was to have very distinct decision styles with as little correlation as possible and, thus, in line with the decision on the respective rotation method when selecting the IBM SPSS set up (in favour of the orthogonal and against the oblique method), the author used the third method to calculate the score of each decision style. Further, this approach would confirm the applicability of the 40 questionnaire items to identify the decision style profile in its entirety since it optimises the overall factor loading of these 40 items in the extracted factors.

The protocol to determine the score of each decision style (extracted factors) is based on an adapted version of the Vogel's approximation method (Reinfeld & Vogel, 1958) generally used to optimise transportation or cost allocation problems. The author selected the factor loadings of IBM SPSS EFA since this tool was the core statistical software used to test other hypotheses of this thesis as well. The six steps required to calculate the decision style scores were the following ones:

1. As discussed earlier, five items were selected for each of the eight decision styles. The first step was to sum the factor loadings of each of the eight sets of five items for all the extracted factors. An 8x8 matrix was generated providing the sums for each set of five items per factor (decision style).
2. For this (new) matrix, the difference between the highest and the second highest value was calculated per row and per column;
3. The largest of these differences was identified and, thus, the respective row or column was marked with a (*) and shall be further referred to as (*)-row or (*)-column;
4. The largest value (that is, the largest factor loading sum of a set of five items) of the (*)-row or (*)-column was allocated the respective decision style (factor);
5. The respective (*)-row and (*)-column were not further considered in the application of the protocol since the respective set of five items has just been allocated to a decision style (factor). The (*)-row and (*)-column were thus eliminated of the matrix; and
6. The process started again with step 2.

Once all factors had been allocated, the protocol stopped. The application of the protocol is documented step by step in the respective subchapter of the RESULTS chapter. The result of this process produced for each factor (decision style) a linear equation with five terms consisting of a respective coefficient each, that is, the factor loading of the item into this factor (decision style), and the five scores of the 'pack' of items allocated to this factor (decision style) by above process.

The next step was to investigate the relationship between the various decision styles. To do so, a series of eight regression analyses were performed for which each of the decision styles served as dependent variable and the remaining seven as independent variables. The selected settings in IBM SPSS were:

- the regression was performed listwise; that is, a predictor variable was included or excluded from the analysis based on their t-value based probability;

- the probability to include a predictor was .01 and to exclude a predictor was .05. Both values are lower than the IBM SPSS standard values. This analysis was thus focused on the main predictors; and
- generating a constant term was suppressed which, again, renders the predicting effect of the independent variables more obvious.

The corrected R² and the Durbin-Watson (Durbin & Watson, 1951; Backhaus, Erichson, Plinke, & Weiber, 2011, p.105) coefficient was used as quality measure of the regression. Further, a histogram was produced showing the frequency of the standardised residuals as well as a P-P plot (expected over observed cumulated probability).

The model that arose of the regression analyses was submitted to verification by a SEM analysis performed in MPlus.

The calculation of the decision style scores based on the above protocol enabled the second factor analysis to potentially determine the three overarching process styles. Again, two factor analysis have been performed, one in IBM SPSS for both, the Base and the Student Sample, and one in MPlus only for the Base Sample. The same settings have been used for in IBM SPSS as for the first factor analysis deemed to extract the eight decision styles out of the 40 items. For the MPlus analysis, the default settings have been used (rotation method was GeoMin and type of rotation was oblique) to check if results change when a different and oblique rotation method is used. However, the calculation of the values of the three process style variables SYSTEM1, SYSTEM2 and REGULATORY was performed for the Base and Student Sample by using IBM SPSS selecting the option to calculate Anderson-Rubin values (Anderson & Rubin, 1949) in the output setting. The advantage of the Anderson-Rubin approach is that the values calculated are not correlated (correlation is 0). Again, this decision is in line with the author's intention to have very distinct and 'non-polluted' values for the factors extracted by the analysis. The question then arises why Anderson-Rubin values have not been calculated for the 8 decision styles. The answer to that lies in the Dewberry et al. (2013) research that looked at the Pearson correlations of the decision styles. Since the correlations are '0' for Anderson-Rubin values, a comparison would not have been possible when Anderson-Rubin values had been calculated for the decision styles. Further, the Dewberry et al. (2013) model sees no or at least is silent on relations within the process styles. Therefore,

a calculation of the process styles based on the Anderson-Rubin approach makes sense. The Anderson-Rubin values have been calculated by IBM SPSS for both samples and were used for further analysis in the context of this research project.

The whole suite of analyses was applied to the data of the Base Sample. The Student Sample was used to cross-check results. Therefore, the linear equation determined with the Base Sample data was used to calculate the scores of the Student sample that were then used for further analyses. In the context of hypothesis 2, correlations of the decision styles were calculated based on these values. Further, the SEM analysis using MPlus and the second factor analysis using IBM SPSS to extract the three process styles were performed with this Student Sample decision style scores as well.

Results of the above described approach are provided in the subchapter Hypothesis 2.

4.7.4 Statistical and data analysis to test hypothesis 3

Having investigated the 'temptation hypothesis' and the Dewberry et al. (2013) model, the focus shifted then to the relationship between the choice set variables on one side and decision and process styles as well as time and demographic factors and importance weight variables on the other. The aim is to test the structure depicted in Figure 7.

The research on the links between above variables was conducted based on the following steps:

1. The Pearson correlations between the choice set variables, the decision and process styles as well as time and demographic factors, and importance weight variables were calculated;
2. For each of the choice set variables (dependent variables): number of companies (NUMCOMP), rejection threshold (THRESHOLD) and number of inconsistencies (INCONSIS), a series of ANOVAs (based on the IBM SPSS default settings) were performed:
 - a. a first ANOVA with the factors AGE, TIME, GENDER and the eight decision styles as covariant variables;
 - b. a second ANOVA, taking into account the results of the first one but replacing the eight decision styles by the three process styles variables

provided the first ANOVA was significant for the respective decision style(s) of that process style (i.e. if the first ANOVA was neither significant for TIME nor for RATIONAL, the second ANOVA did neither include TIME nor SYSTEM2);

3. Based on the results of the second step, a series of regressions per choice set variable were performed.
 - a. A first one with all significant variables of the first ANOVA and a second one with all relevant variables of the second ANOVA. If a constant term of the regression analyses proved not statistically relevant, another with the same variables was performed but supressing the constant term for that analysis;
 - b. Only then the importance weight variables were considered. They were included in the two regressions as per step 3.a. based on their correlations with the choice set variables. That is, an importance weight variable was only considered if their correlation with the choice set variables was significant at $p < .05$.
 - c. For the regressions with best corrected R^2 fit of step 3.a. and 3.b. and for each choice set variable, a regression supressing the constant term was performed.
 - d. For all regressions, the predicted values for the respective choice set variable was calculated by IBM SPSS. The predictive capability was calculated. That is, how many percent of the predicted values (rounded to integer) were equal to the observed values.
4. Considering all relevant information, the structural model of Figure 7 was revisited to allocate to the model actual variables enabling the final SEM analysis. The input syntax for the respective MPlus analyses can be found in Appendix Syntax for the various analysis in MPlus.

All analysis for this hypothesis was performed in IBM SPSS using the data of the Base Sample only except for the SEM analysis for which MPlus has been used and of which the results for the Base Sample have been verified with the second SEM analysis using the Student Sample data.

All regressions were performed listwise with step-by-step inclusion or exclusion of a predictor variable based on a $p < .05$ for inclusion and $p > .10$ for exclusion. These setting are relaxed compared to the regression analysis performed to test hypothesis 2. This relaxation was required since the significance of influence of some variables showed to be weaker than for the already known relations of hypothesis 2. The quality measures corrected R^2 and Durbin-Watson value have been used to evaluate the performance of the regressions as well.

Results of the above described approach are provided in the subchapter Hypothesis 3.

4.7.5 Statistical and data analysis to test hypothesis 4

Hypothesis 4 states that the values of the choice set variables can be predicted with a reliability of more than 80% using the data collected directly or derived from the questionnaire. It appears reasonable to test this hypothesis, in a first approach, with the regression analyses that have been performed on the Base Sample when researching hypothesis 3. The values predicted for the three dependent variables (number of alternatives in the choice set – NUMCOMP, rejection threshold value – THRESHOLD, and number of inconsistencies – INCONSIS) of each regression have been saved by IBM SPSS and were then compared with the observed values collected with the questionnaire or calculated respectively.

Then, and since the regressions were not capable of predicting the values of the dependent variables sufficiently well, the prediction range was enlarged. That is, a prediction was considered acceptable, if it was within ± 1 of the correct score. This prediction range enlargement was however only acceptable for NUMCOMP and THRESHOLD since the number of inconsistencies (INCONSIS) ranged only from 0 to 4 averaging 1.2 per participant. Thus, an enlargement of ± 1 was not meaningful for the number of inconsistencies.

Since the predictive power of the regressions were still not on the required level, a series of discriminant analyses were conducted on the Base Sample data. For the purpose of the discriminant analyses, the nature of the dependent variable has to be categorial, and, thus, the initial values of the choice set variables were regrouped in a number of groups. The more groups are generated by regrouping the initial values, the higher is

the predictive power of the discriminant analysis, since the range of values in one group is smaller compared to a small number of groups collecting more initial values in one group, and thus having a larger range of initial values in it.

The values of the choice set variables were therefore grouped in either two, three or four categorial variables for the number of companies in the choice set (NUMCOMP) and for the value of the rejection threshold (THRESHOLD). For the number of inconsistencies (INCONSIS), the creation of only two new categorial variables was necessary. Therefore, the values of INCONSIS were grouped in either two or three sets. The new categorical variables and the range of values they took for what value of the initial choice set variable are shown in Table 19 (see next page). Six discriminant analysis' have been performed for or all categorial variables of the choice set variables, except for INCONSIS, for which a seventh discriminant analysis has been performed for both categorial variables since the influence of the rational decision style became insignificant for the INCONSIS_GROUP2 discriminant analysis. Two of the six (seven) analysis were performed with all variables (either with all process or all decision styles) with a stepwise approach to find the potentially 'best' discriminant analysis.

<i>Choice Set variable</i>	<i>Categorical Variable</i>	<i>Value Categorical Variable</i>	<i>Value Respective Choice Set Variable</i>
<i>NUMCOMP</i>		1	1 or 2
	NUMCOMP_GROUP	2	3 or 4
		3	5 or 6
		4	7 or 8
		1	1, 2, 3 or 4
	NUMCOMP_GROUP2	2	5 or 6
		3	7 or 8
	NUMCOMP_GROUP3	1	1, 2, 3 or 4
		2	5, 6, 7 or 8
	<i>THRESHOLD</i>	1	0
		2	-1, -2 or -3
		3	-4, -5 or -6
		4	-7, -8 or -9
<i>INCONSID</i>		1	0
	THRESHOLD_GROUP2	2	-1, -2, -3 or -4
		3	-5, -6, -7, -8 or -9
	THRESHOLD_GROUP3	1	0, -1, -2, -3 or -4
		2	-5, -6, -7, -8 or -9
	<i>INCONSID</i>	1	0
		2	1 or 2
		3	3 or 4
	<i>INCONSID_GROUP2</i>	1	0 or 1
		2	2, 3 or 4

Table 19:

Creation of categorical variables collecting the values of the choice set variables

To enter an independent variable, its p-value had to be below .05 and to remove an independent variable from the analysis its p-value had to be higher than .10. Additionally, 4 (5) discriminant analysis were performed with those variables as predictors ('all-in' option in IBM SPSS) that have been shown significant by the respective regressions previously performed. What predictors were selected for which discriminant analysis is shown in Table 20 (see next page).

<i>Categorical Variable</i>	<i>Discriminant Analysis n°</i>	<i>Decision Styles Variables</i>	<i>Process Styles Variables</i>	<i>Demographic Factors</i>	<i>Importance Weight Variables</i>
<i>NUMCOMP_GROUP</i> <i>NUMCOMP_GROUP2</i> <i>NUMCOMP_GROUP3</i>	1	all	-	all	all
	2	-	all	all	all
	3	INTUITIVE DEPENDENT	-	-	-
	4	-	all	-	-
	5	INTUITIVE DEPENDENT	-	-	INDIV_W_PRICE
	6	-	all	-	INDIV_W_PRICE
<i>THRESHOLD_GROUP</i> <i>THRESHOLD_GROUP2</i> <i>THRESHOLD_GROUP3</i>	1	all	-	all	all
	2	-	all	all	all
	3	INTUITIVE RATIONAL	-	-	-
	4	-	all	-	-
	5	INTUITIVE RATIONAL	-	-	INDIV_W_PRICE
	6	-	all	-	INDIV_W_PRICE
<i>INCONSID_GROUP</i> <i>INCONSID_GROUP2</i>	1	all	-	all	all
	2	-	all	all	all
	3	SPONTANEOUS RATIONAL	-	-	-
	4	-	all	-	-
	5	SPONTANEOUS RATIONAL	-	-	INDIV_W_EMPLOYEE IMPOR_WEIGHT_FIT
	6	-	all	-	INDIV_W_EMPLOYEE IMPOR_WEIGHT_FIT
	7	SPONTANEOUS	-	-	INDIV_W_EMPLOYEE IMPOR_WEIGHT_FIT

Table 20:

Predictor variables⁷ for the discriminant analyses

⁷ TIME was predictor for each discriminant analysis

The following measures were used to evaluate the quality of the discriminant analysis (Backhaus, Erichson, Plinke, & Weiber, 2011, pp. 207):

- Eigen values for the first discriminant function, the higher the eigenvalue, the better separation of the groups of the dependent variable;
- Wilk Lambda's for the discriminant analysis. The lower Wilk Lambdas, the better separation of the groups of the dependent variable;
- The statistical significance of the χ^2 test for the discriminant analyses;
- The standardised canonical coefficients for each independent variable. The higher these coefficients for an independent variable, the higher is that variable's ability to separate the groups or categories of the dependent variable (in the case of two categories, these coefficients equal the Pearson correlation between the independent and the dependent variable);

The resulting non-standardised canonical coefficients and the constant term were used to construct the respective discriminant equation for each choice set variable.

Eventually, diagrams were created for the discriminant analyses with the highest prediction accuracy per choice set variable allowing to predict the probability of participants being in one of the formed groups based on their discriminant scores.

The Student Sample data has been used to test the predictive power of the diagrams. With the help of Microsoft Excel's 'TREND(...)' function, the probability to belong in either group 1 or 2 was calculated for each member of the Student Sample based on the totality of the Base Sample discriminant results and the Student Sample's participant discriminant score. The probability allowed to classify the Student Sample participants either in group 1 or 2, and, subsequently, to compare this classification with the observed group of that participant.

Results of the above described approach are provided in the subchapter Hypothesis 4.

4.7.6 Statistical and data analysis to test hypothesis 5

4.7.6.1 Neural networks in social science: concept and its limitations

As described briefly in the first chapter, neural networks mimic the nervous system of human beings. This chapter shall describe the methodology of neural networks used to address classification and prediction problems. For both, neural networks are an alternative to the classical approaches of multivariate linear analysis as well as structural equation models and expert systems (Garson, 1998). Following Garson "... *neural networks may outperform traditional statistical procedures where problems lack discernible structure, data are incomplete, and many competing inputs and constraints related in complex, nonlinear ways prevent formulation of structural equations, ...*" (Garson, 1998, p.1). The overview on neural networks that can be provided in this chapter is limited to multilayer perceptron networks used for this research project since this type of neural networks is most commonly used in social science research projects (Garson, 1998). For more detailed introduction, please refer to Garson (1998) from whose work this chapter is frequently drawing of.

Neural network approach

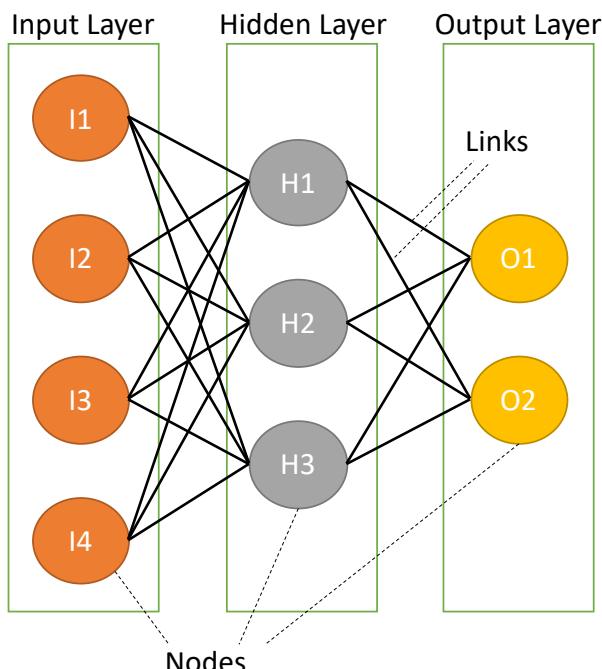


Figure 13

Example of a very simple neural network

How does a neural network work and of what elements does it exist? Figure 13 (see previous page) shows a very simple multilayer perceptron network which consists of an input layer with four input nodes (I1 to I4), an output layer with two output nodes (O1 & O2) and a hidden layer between the in- and output layers and with three hidden layer nodes (H1 to H3). All nodes of one layer are linked with all nodes of the previous and subsequent layer except for the input and output layer for which no previous layer or subsequent layer respectively exist.

The values of the independent variables are 'fed' into the network at the input nodes of the input layer. These values are then multiplied with the weights of each link connecting the input nodes with the nodes of the hidden layer.

The results of this mathematical operations are summed in the three hidden layer nodes. If the sum of the values received by one hidden layer node is greater than this hidden node's threshold, a signal (a value) is 'fired' to all output nodes where all the received values are summed up again representing the output value. If a sufficient number of input data is available, then the network can be 'trained' to calculate the correct output values based on a related set of input values. Since this 'training' process is an iterative process, it is also stated that the network is 'learning'. To allow the network to learn the required pattern to correctly predict the output value, the available data set that consists of the values of all considered independent variables (input values) and the observed values of the dependent variables (observed output values), is randomly regrouped in two or three subsets. The first subset is used to train the network and is, thus, referred to as the training data set.

During training, the input nodes take the values of the independent variables and the calculated output value is compared with the respective observed output value. The difference between the observed and the respective calculated output values is referred to as error and the aim is to train the network to minimise this error for all data sets presented to the network. Training in this context is achieved by modifying the weights of each link to adjust the calculated output values to the observed values.

The related algorithm is called backpropagation and has initially been developed by (Werbos, 1974). Werbos' idea was taken up by other researchers who developed their own backpropagation algorithms (Parker, 1982, 1985; LeCun, 1985, 1986; Rumelhart &

McClelland, 1986). The training data is generally presented to the network multiple times. When the entire training data set has been used once to train the network, then one epoch has passed. Therefore, during training, the network is typically confronted with many epochs of the training data set. Training is completed if the overall error is below an acceptable, predetermined value (stopping rule).

The training results are verified by a second set of data, the test data set (cross validation). Typically, the test data are presented to the network after each epoch and are used to verify the prediction or classification capability of the network. However, test data results will not lead to a modification of the network's weights.

Sometimes a third data set is used, the so called 'hold-out' data. As the name suggests, this data is kept out of training and testing the network but is used at the end of training and testing to measure the predictive capability of the network with data that has never been fed to the network.

The various elements of a neural network shall now be discussed briefly.

Input layer

As mentioned in the first chapter, neural networks consist of many nodes or perceptrons that are linked with each other and are comparable in function to the neurons of the nervous system of human beings. Depending on where and in what sequence those nodes are located in the network, they are regrouped in layers. One layer consists of at least one node but in general holds many more. The first layer is referred to as input layer. This is where the network is 'fed' with the values of the independent variables. Therefore, a neural network has at least as many nodes in the input layer as there are independent variables. If some of the independent variables are of ordinal or interval nature, the network designer might select to have one node for each value of such independent variable. (Schrodt, 1990) found that this approach improves results for the training data set but appears to slow down the training process as well.

Output and hidden layers

The input layer is linked to the second layer. This second layer is either - for very small networks - the output layer where the results of the network's calculation are presented,

or it can be a second layer that itself is connected to a third layer or to the output layer. Those layers that are between the input and output layer are referred to as hidden layers (see Figure 13). Whilst the absence of hidden layers might be acceptable for linear problems, more complex problems or problems that are at least perceived to be more complex might require one or even two hidden layers to be successfully addressed by the network (Garson, 1998, pp. 83). An important decision for the network designers is how many nodes does each hidden layer consist of. But in the absence of a general theory for determining the optimal number of hidden layers and the optimal number of nodes per hidden layer, a lot of the neural network modelling remains a trial and error approach (Garson, 1998, p.84). Whilst no precise rules exist and the network designer is free to decide on the number of hidden layers and the number of nodes per hidden layer, Garson states that networks with more than three hidden layers are not observed in research projects (Garson, 1998, p.84). Stanley (1988) and Ripley (1993) have suggested a rule of thumb to sum the number of input and output nodes, divide this sum by two and take the result as the initial number of hidden layer nodes. This approach seems to lack however any scientific validation and the fact that only the initial number of hidden layer nodes is determined hints again of the trial and error character of designing neural networks or as Garson reiterates: "*While as a rule of thumb it is better to err on the side of a larger number of hidden layer neurons, there is no substitute for trial-and-error experimentation with the optimal number.*" (Garson, 1998, p. 84).

Links between nodes

The links between the various nodes are represented by weights that the value, received from a node of the previous layer, is multiplied with, before the result of this multiplication is transmitted to the node of the receiving perceptron. Generally, all nodes of one layer are linked with all nodes of the subsequent layer. As for the signals of the human nervous system, the weights corresponding to a specific link can be of excitatory or inhibitory valence. Inhibitory weights are negative and thus reducing the total of the received values at the receiving node. Excitatory weights are positive therefore increasing this total.

Nodes

All nodes of a neural network have a summation function that sums the received values (that have been multiplied with the respective weights) except for the input layer nodes since those nodes take the values of the independent variables. Further, all nodes of a neural network have an activation function determining the threshold at which the node 'fires' a signal. Most networks are designed with a bias node for each layer. Bias nodes serve to provide the threshold to all nodes of a layer and thus avoid poor fit of the network when a larger or even only binary (0 and 1) input values are used. A bias node is linked with all nodes of a layer and 'fires' always the value 1 to these nodes. Bias nodes are however not used for output layers. For a more detailed description of bias nodes refer to Backhaus, Erichson, and Weiber (2013).

Activation functions

The purpose of the activation function is to transform the total of the incoming values at a node in an outgoing value provided a certain threshold value is achieved. There are several activation functions that are commonly used. A linear activation function "*is generally restricted to situations where output is continuous rather than categorical*" (Garson, 1998, p. 97). The sigmoid function and the hyperbolic tangent functions are similar. However, since the training time is shorter and due to its symmetric character (returning values between -1 and 1), the hyperbolic tangent function is recommended to be used as default (Garson, 1998, p. 98).

Training, test and hold out data

The application of neural networks requires a larger number of data sets. Garson (1998, p. 88) provides three rule of thumbs for the required number of data sets: first, a liberal rule following which, at least 10 times the number of input variables are required; second, a more conservative rule that considers 10 times the total of input and hidden layers as sufficient; and, third, a very conservative recommendation stating that at least 30 times as many data sets as links between the nodes are required.

Further, the entirety of the available data has to be regrouped in - at least - a training and a test data set, or potentially even in a third one, the hold-out data set. Garson (1998, p. 103) provides a rule of thumb that 80% of the available data should be used

for training purposes and the remainder of 20% for cross validation purposes (test and hold-out data). However, once one of above-mentioned rules to determine the required number of training data sets are met, the remainder of the data could be used for test and/or hold-out purposes.

Eventually, input data might be rescaled, either standardised or normalised, if the input data is of continuous nature. Garson (1998, p. 91) recommends normalising continuous input values to obtain better results.

Training

Training the network can occur in various approaches. IBM SPSS uses three different kind of training concepts that differ in the point in time when the weights of the network are modified (see IBM, 1989-2017, pp. 7):

- batch training: weights are only updated when the entire epoch is finished; that is, after all training data has been presented to the neural network. Batch training is the default set up in IBM SPSS;
- Online training: during online training, the weights of the neural network are modified after each input pattern. Online training seems to be preferable for a particular large number of data points without further specifying what 'large' in this context means; and
- Mini batch training: this approach is very similar to batch training. Instead of modifying the network's weights after confronting it with all training data, latter are packed in smaller size groups and the weights are indeed updated after feeding the network with each of those smaller data sets.

Advantages and Disadvantages when using neural networks

The author has selected some of the advantages put forward in the literature (Haykin, 1994, as referred to in Garson, 1998, p. 15):

- Neural networks are capable to handle non-linear problems;
- Probabilistic assumptions regarding the input and output values are not required;

- Networks are particularly flexible and can be retrained to fit new, potentially more recent data;
- Networks can handle dependencies amongst the input variables without knowing the nature of those relationships. These are considered or included in the modified weights of a neural network;
- Missing data and noise are tolerated by neural networks to a larger extent than by classical statistical approaches;
- A modular design can be implemented making it possible to exchange one or several modules or reuse these modules as a building block for other applications;

Besides these advantages, there appear to be limitations of the usage of neural networks in social science as well. Garson (1998, p. 16) states for instance that neural networks have difficulties in providing causal interpretations of the available data - a primary concern of social science researchers. The author of this thesis believes to have addressed this criticism by exploring the dependencies of his data by using appropriate classical approaches before venturing in the field of a neural network application.

A second limitation put forward by Garson (1998, p. 16) and shared by the author, is the 'trial-and-error' approach when designing the neural network and defining its parameters. Whilst this approach appears to be without alternative when developing the network, it nurtures a nagging doubt in researchers whether they found the optimal solution and how to reproduce this solution for a different problem.

4.7.6.2 Context of using neural networks in this thesis

To test the fifth and last hypothesis, a previously expressed thought was taken up again: it appears that the decision styles and the process styles relate to each other like a neural network. That is, the links between the various decision and process styles representing the knots of a neural network, are activated based on the requirements provided by the decision context (time, affect, accountability, etc.) or working frame. If this holds true, then a neural network could potentially predict the outcome of the compatibility test

for a specific decision alternative (company) based on the values of the following independent variables:

1. the demographic factors;
2. the time to take the survey;
3. the decision and/or process styles;
4. the importance weight variables;
5. the choice set variables;
6. the objective compatibility salience of each criteria for a decision alternative compared to the desired values of these criteria; and
7. information on whether or not the considered alternative is a temptation or not.

To allow the generation, training and testing of neural networks, the Base Sample data was used but required to be restructured since the research focus shifted, away from the relations between the decision or process styles and the choice set variables, towards the choice itself regarding a specific alternative. Further, two sets of new variables and an output variable were introduced. All networks created in the context of this thesis have been multilayer perceptron networks as recommended for prediction problems by Backhaus et al. (2013, p. 307).

The first set of newly introduced variables provided the neural network information on whether or not the considered alternative meets a criterion. Since six criteria are used, six variables are required. These variables are COMP_PRICE, COMP_PROFIT, COMP_DEBT, COMP_EMPLOYEE, COMP_INVEST, COMP_INDUSTRY and are referred to as the 'compatibility variables'. Each of these variables can take either the value '0', if the considered alternative does not violate the related criterion, or the value '1' if it does, and are thus of categorical nature.

The second set of additionally required variables simply tells the network whether or not the considered company represents a temptation or not. Since two different temptations were used, two categorical variables were required: TEMPTATION_PRICE and TEMPTATION_PROFIT. If the company is not a temptation, then both variables are

'0'; their respective value will however be '1', if the company is a tempting decision alternative.

Further, a variable CHOICE was created telling the neural network during its training whether or not the considered company has been allowed to a participant's choice set, and providing the 'verdict' of the neural network, that is to accept or reject a company, during the network's test phase and later application.

Since the participants of the Base Sample had to screen nine companies (including company S) when taking the questionnaire, the variable CHOICE had a value for each of the nine companies and for each participant. Therefore, 5,841 (=649 x 9) data sets were created consisting each of values for the above described variables. That is, one data set had a value for GENDER, AGE, TIME, AVOIDANT, ANXIOUS, REGRET, DEPENDENT, MAXIMISING, INTUITIVE, SPONTANEOUS, RATIONAL, SYSTEM1, SYSTEM2, REGULATORY, NUMCOMP, THRESHOLD, INCONIS, IMPOR_WEIGHT_FIT, INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_EMPLOYEE, INDIV_W_DEBT, INDIV_W_INVEST, INDIV_W_INDUSTRY, COMP_PRICE, COMP_PROFIT, COMP_DEBT, COMP_EMPLOYEE, COMP_INVEST, COMP_INDUSTRY, TEMPTATION_PRICE, TEMPTATION_PROFIT, and CHOICE.

For the first neural network all variables except the process styles were used, and for the second neural network all variables except the decision styles were used. This approach was based on the fact that the decision style variables and the process style variables contain in principle the same information. Therefore, and to avoid duplicity, a neural network was either designed with the eight decision styles or with the three process styles as covariates. This approach is in line with the author's approach to test the previous hypothesis.

The options chosen in IBM SPSS have been the default option except for the rescaling of the covariates, for which standardised has been chosen. Therefore, the value of CHOICE (0 or 1) represents the minimum and maximum of all covariates. Second, the partition has been chosen differently: IBM SPSS's default for the partition is to use 70% of the data sets for training and 30% for testing the network. Due to the sufficiently high number of data sets (5,481) compared to the number of nodes in the network (see next page), the researcher has chosen to use 50% of the data set for training, 30% for testing

and 20% as holdout to calculate the percentage of correct predictions. The important information on the IBM SPSS settings for the various layers is shown in Table 21 (page 131). Each of the neural networks was generated, trained and tested five times since the training of the network might end in a local minimum. That is, the resulting neural network might not be optimal. The generation of five networks was however only performed when the first generated network achieved at least 60% of correct predictions. In this case, the network was given a letter as well (A, B, C, ...) to identify the network.

The following measures have been selected as quality indication for the network: the respective ROC (Receiver Operating Characteristics) curves and the related AUC (Area Under Curve). The closer the AUC is to '1', the better is the predictive capability of the network. Further, the classification tables providing the cases that have been predicted correctly or incorrectly for the training, test and holdout sets were used as quality measure; in particular, the overall percentage of correct predictions.

After training and test of the first two neural networks, each set of variables was tested with its own neural network to gain knowledge about its capability to correctly predict CHOICE. Based on the gained information, the variables with more than 60% correct predictions were selected to generate, train and test a final neural network. Eventually, the final neural network existed of an input layer, two hidden layers and an output layer. Obviously, the input layer contained 16 input nodes (2 nodes for each categorical COMP_X variable and including the bias node of the input layer), the two hidden layers contained 9 and 7 nodes respectively (including a bias node for each hidden layer), and the output layer consisted of two nodes since CHOICE was a categorical variable as well.

The best performing neural network was further optimised by modifying the underlying IBM SPSS parameters. Table 21 (see next page) shows the base and the final setting. The major modifications to the base settings concerned the rescaling of the covariates. This has been changed from 'standardised' to 'normalised' as suggested by Garson (1998, p. 91). Further, and based on trial-and-error, a second hidden layer was introduced, and the activation function of the output layer was changed from 'softmax' to 'hyperbolic tangent' (which is recommended by Garson, 1998, p. 98 as default) which was the

activation function of the hidden layers as well. The change in the output layer function changed the error function as well from 'cross-entropy' to the 'sum of squares'.

Apart from these changes, the optimised networks were generated with a smaller initial sigma and lambda for the 'scaled conjugate gradient' algorithm to reduce probability for the error optimisation algorithm to end in a local minimum. Further, and based on trial-and-error, a larger interval off-set was used for the 'simulated annealing' optimisation.

Batch training was used for all networks.

		<i>Base setting</i>	<i>Final, optimised settings</i>
<i>Input Layer</i>	Rescaling Method for Covariates	Standardised	Normalised
<i>Hidden Layer(s)</i>	Number of Hidden Layers	1	2
	Activation Function	Hyperbolic tangent	Hyperbolic tangent
<i>Output Layer</i>	Dependent Variable	CHOICE	CHOICE
	Activation Function	Softmax	Hyperbolic tangent
	Error Function	Cross-entropy	Sum of squares

Table 21:

Base and optimised setting to generate neural networks with IBM SPSS

Please note that the best neural network has been generated using the Base Sample data. The next step was to verify the result with both the Student Sample and the Extension Sample. The Student Sample data resulted in 783 data sets for the neural network, and, accordingly, the Extension Sample generated 784 data sets. Out of these 784 data sets, 280 contained information on the newly introduced companies (companies X, L, N, Y, and P) and the remainder of 504 on the companies used in the questionnaire for the Student and Base Sample as well.

For the purpose of verification of the network with these two samples, a partition variable has been introduced that allowed separation of the training data from the test data and from the hold-out data.

The first test was performed with 6,624 data sets (=5,841+783) consisting of the Base and Student Sample. The Base Sample data was used to train and test the network. The

partition variable took the value '1' for the 4,088 (70%) data sets that were used to train the neural network and the value '0' for another 1,753 (30%) data sets that tested it. The partition variable took the value '-2' for the Student Sample. Again, five networks were generated.

The second test of the best network was performed with 6,625 (5,841+504+280) data sets consisting of the Base and Extension Sample data. The partition variable took the value '1' for the 4,441 (70%) data sets that were used to train the neural network and the value '0' for another 1,904 (30%) data sets that tested it. The values have been randomly allocated to the Base and Extension Sample data related to companies S, C, G, H, J, K, F, E, R, D and T.

A regrouping of the respective data of the Base and Extension Sample was possible since the samples were drawn from the same population. The partition variable took the value '-2' for the data sets of the Extension Sample (hold-out set) that contained observed CHOICE data for the new companies (companies X, L, N, Y, and P) for which the network had not been trained.

Five networks were generated, trained and tested to avoid again that the network is 'stuck' in a local minimum. Results of the above described approach are provided in the subchapter Hypothesis 5.

4.7.6.3 Limitations of IBM's SPSS neural network application

As mentioned in previous chapters, IBM's SPSS software has been used to design, train and test the neural networks. This choice was done for convenience since the same software tool was used to apply the classical statistical tools that served to test the other hypotheses of this thesis.

However, IBM SPSS has the following limitations which require to be mentioned:

- The sequence of presenting the training data to the network cannot be influenced by the researcher. This is, at first glance, not a disadvantage per se since this approach prevents researchers to introduce their own bias. However, there might be research projects that require the network to be trained with the training data set in a specific order;

- Further, IBM SPSS does not allow to create modular networks required for deep learning. Encapsulated neural networks of modular structure could be more promising for complex, non-linear problems;
- Eventually, IBM SPSS does not support a shared data base providing a collection of modular (sub-)structures designed by users and free for use of other users. Other, more open source software providers (i.e. MATLAB or TensorFlow) maintain such data bases which appear to be particular useful for the neural network design activity with its trial-and-error reliance as already stated by Garson (1998).

Overall and in hindsight, the author concludes that whilst IBM SPSS suffice to perform the task at hand, a more flexible tool to design, train and test the neural network concept would have been beneficial.

5 RESULTS

As the name suggests, the *RESULT* chapter details all relevant results of testing the five hypotheses. The five subchapters, one for each hypothesis, describes further analyses that have been conducted as a result of the first analyses. Depending on the analyses conducted, the hypothesis chapters have been divided in subchapters that describe respective results. Further and more detailed information of the various analyses can be found under the respective heading in the Appendices.

The following convention was used for reporting the respective level of statistical significance (unless otherwise indicated for the respective analysis):

<i>For a probability of...</i>	<i>... values were marked with...</i>
$p < .001$	***
$p < .01$	**
$p < .05$	*
$p < .10$	°
$p \geq .10$	+

Table 22:

Convention to report statistical significance

5.1 Hypothesis 1

As a reminder and to start the presentation of the results, hypothesis 1 reads as follows:

"Participants are more prone to accept an alternative that is below their rejection thresholds but that is 'tempting' in a very important criterion, into the choice set than an alternative that does not offer this 'temptation'."

5.1.1 Analysis regarding the 'Price' Temptation (company T)

The hypothesis was analysed with all three samples.

5.1.1.1 Base Sample

A first ANOVA that was performed for the Base Sample only with RANK_PRICE by GROUP_PRICE to identify any relevant differences between the reference group and the experimental group regarding their ranking of the 'Price' criterion. The ANOVA was non-significant ($F=.007$; $p<.94$).

326 (out of 649: 50.2%) participants were allocated in the experimental group, of which 257 (78.8%) rejected the temptation alternative. Only 69 (21.2%) put company T on their shortlist. 269 (83.3%) participants of the reference group rejected the non-tempting alternative (company D) whilst 54 (16.7%) allowed it into their choice set.

The respective ANOVA with the variables TEMP_PRICE by GROUP_PRICE was not significant ($F=2.089$; $p<.15$).

5.1.1.2 Student Sample

50 (57.5%) of the 87 participants of the Student Sample were allocated to the experimental group. The remaining 37 (46.5%) formed the reference group. In the experimental group, 10 (20%) selected the tempting alternative whilst 40 (80%) rejected it. Only 3 (8.1%) participants of the reference group selected the non-tempting alternative, the remaining 34 (91.9%) rejected it. A respective ANOVA was not significant ($F=2.376$; $p<.13$).

5.1.1.3 Extension Sample

Eventually, the 56 participants of the Extension Sample were split in an experimental and in a reference group as well. 26 (46.4%) can be found in the experimental group and the remaining 30 (53.6%) in the reference group. 5 (19.2%) participants of the experimental group were seduced to accept the temptation alternative in their choice set and 4 (13.3%) participants of the reference group accepted the non-tempting alternative. Therefore, 21 (80.8%) participants of the experimental group and 26 (86.7%) participants of the reference group rejected either the temptation or the non-temptation alternative respectively. A respective ANOVA was not significant ($F=.349$; $p<.56$).

The respective ANOVAs of all three samples were non-significant, consequently, hypothesis 1 has to be rejected for the 'Price' temptation.

5.1.2 Analysis regarding the 'Profit' Temptation (company R)

5.1.2.1 Base Sample

As for the 'Price' temptation, a respective ANOVA was performed for the Base Sample only, with the variables RANK_PROFIT and GROUP_PROFIT to verify, if differences in the ranking of the 'Profit' criteria exists between the experimental and the reference group. The ANOVA was not significant ($F=.251$; $p<.62$).

142 (48.3%) of the 294 participants in the experimental group allowed the 'Profit' temptation in their choice set. The remaining 152 (51.7%) rejected company R. For the reference group, a different picture presented itself: out of the 355 participants in this group, 287 (80.8%) rejected the non-tempting alternative company E which was, thus, selected by only 68 (19.2%) participants.

Following the respective ANOVA, the difference between the experimental and the reference group was highly significant ($F=68.836$; $p<.001$).

5.1.2.2 Student Sample

For the Student Sample, 41 participants were in the experimental group and 46 in the reference group. The majority of the experimental group (21; 51.2%) accepted the temptation alternative in their choice set; a remaining 20 (48.8%) participants did not.

In contrast, the majority of the reference group rejected the non-tempting alternative (39; 84.8%); only 7 let company E pass the compatibility test. The respective ANOVA was significant ($F=14.762$; $p<0.001$).

5.1.2.3 Extension Sample

The smallest sample of 56 participants was split in an experimental group of 32 (57.1%) participants and a reference group of 24 (42.9%) participants. The majority (22; 91.7%) of the reference group rejected the non-temptation alternative whilst only 2 selected company E. In contrast, 13 (40.6%) participants of the experimental group accepted the temptation and 19 (58.4%) rejected company R as well. The respective ANOVA was again significant ($F=8.084$; $p<0.01$) even though not to the level of the first two ANOVAs. The reason for this is to be found in the very small sample size of only 56 participants.

All ANOVAs performed with the data of three samples were found to be statistically significant. Therefore, hypothesis 1 cannot be falsified for the 'Profit' temptation.

5.1.2.4 Further analysis

This result obviously triggers further questions about those participants that accepted the profit temptation and those that did not. Are there any differences between these two groups of participants that can be found in the demographic factors, time to take the survey, importance weight variables and in the decision or process styles? To answer this question, the author performed a series of t-tests on the Base Sample comparing the values of the above-mentioned factors and variables of the two groups. That is, the group that has been faced with the temptation but rejected it (GROUP_PROFIT=1; TEMP_PROFIT=0) and the group that has been equally faced with the temptation but gave in to it (GROUP_PROFIT=1; TEMP_PROFIT=1). The results of these t-tests are shown in the table below (see next page).

<i>Factors and variables</i>	<i>t</i>	<i>p (2-tailed)</i>
GENDER	.113	.91
AGE	-.049	.96
AVOIDANT	-.395	.69
INTUITIVE⁸	-1.447	.15
RATIONAL	-.382	.70
SPONTANEOUS	-.828	.41
REGRET	-.339	.74
MAXIMISING	,158	.88
ANXIOUS	-.733	.46
DEPENDENT	.044	.97
REGULATORY	-.281	.78
SYSTEM1	-1.355	.18
SYSTEM2	-.432	.67
INDIV_W_PRICE	1.992	.05
INDIV_W_PROFIT	-1.721	.09
INDIV_W_DEBT	-.084	.93
INDIV_W_EMPLOYEES	1.829	.07
INDIV_W_INVESTMENT	-.221	.83
INDIV_W_INDUSTRY	-1.612	.11

Table 23:

t-test results comparing participants that have/have not selected the 'Profit' temptation

The demographic factors GENDER and AGE as well as TIME are not significantly different between the two groups. The same can be said for the decision and process styles. However, the decision style that is statistically most significant amongst the eight styles

⁸ Factors and variables with p<.20 have been highlighted in bold font.

is the intuitive style ($t=-1.447$; $p<.15$). Participants that have selected the 'Profit' temptation appear to have a slightly higher intuitive score (2.95 vs. 2.86) than those that rejected company R.

In line with this finding is the statistical relevance of System1 ($t=-1.355$; $p<.18$) which is only marginally higher than the intuitive style significance. Again, participants that have selected the temptation appear to be more active with System1 processing (.11 vs -.05).

Surprisingly, the importance weight factors between the two groups appear to be the most significantly different of the factors and variables considered. The highest and only statistically acceptable significance level is achieved by the important weight variable of the 'Price' criterion ($t=1.992$; $p<.05$), followed by the importance of 'Employees' ($t=1.829$; $p<.07$), 'Profit' ($t=-1.721$; $p<.09$) and 'Industry' ($t=-1.612$; $p<.11$). Participants that have selected the temptation appear to consider the criteria 'Price' (.216 vs .233) and 'Employees' (.103 vs .118) as slightly less important as well as the criteria 'Profit' (.238 vs .223) and 'Industry' (.119 vs .104) as slightly more important than those participants that have not selected the tempting alternative.

5.1.3 Discussion

A summary of the results of the respective ANOVAs is provided in the table below.

<i>ANOVAs Hypothesis 1</i>	<i>TEMP_PRICE by GROUP_PRICE</i>	<i>TEMP_PROFIT by GROUP_PROFIT</i>
<i>Base Sample</i>	F=2.089; p<.15	F=68.836; p<.001
<i>Student Sample</i>	F=2.376; p<.13	F=14.762; p<.001
<i>Extension Sample</i>	F=.349; p<.56	F=8.084; p<0.01

Table 24:

Results of six ANOVAs performed with the data of three samples

The results show clearly that an influence of temptations during the compatibility screening is present. All three ANOVAs for the 'Profit' temptation have been statistically significant, even for the rather small sample size of the Extension Sample (N=56). In contrast, ANOVAs of the 'Price' temptation have been non-significant. The difference might have various reasons.

First, and as already mentioned, a company's profit margin is difficult to debate; it is reliable information verified by an annual audit and is a recurring benefit of a company. The price for which a company can be bought is a softer information that is driven by different, sometimes opposing parameters. It can be calculated in different ways with differing results depending on the information considered or not considered during that calculation. Further, it is one single expenditure and, thus, the buyer benefits from a small price only once - at the time of the acquisition.

Second, and partially based on the first point, participants might have been more suspicious about the extremely low price of the 'Price' temptation than about the extremely high profitability levels of the 'Profit' temptation. A low price might be an indication that 'something is wrong' with the company and the seller wants to 'get rid of it by all means'. These thoughts create negative affect and increase the risk of buying such company since as long as potential buyers do not have enough information to determine the reason for such low price, they run the risk of buying a company that

might be confronted with serious operational, financial, legal or other type of problems. As described earlier (Finucane, Alhakami, Slovic, & Johnson, 2000), the perception of high risk combined with negative affect as mediator might lead to perceived low benefit if participants evaluate company T as a contender for their choice set. This might explain, why the level of acceptance was only marginally higher than those of the corresponding non-tempting alternative (company D).

On the other hand, the same mechanism might explain why the 'Profit' temptation has been selected into a participant's choice set. High profitability levels are highly desirable for the management of the company. When being responsible for leading a company, a lot is at stake: owners want to be paid dividends, high profits generate typically solid cash flows that ensure the survivability of the company; further, and more focused on the personal success of the responsible manager, profit warrants reputation and bonuses, higher profits even more so. Therefore, every manager perceives very high profitability levels as highly beneficial. With positive affect as mediator and the financial audit proven nature of profit, the 'Profit' temptation will be considered as low risk alternative and, thus, will end up on the shortlist even if the company's incompatibility score is heavily violating the decision-makers rejection threshold during the screening process.

The above described results suggest that in case of the acceptance of the 'Profit' temptation as well as the rejection of the 'Price' temptation, the affect heuristic can be observed at work. This claim is further supported by the, albeit not highly significant but still observable difference of System 1 processing activity in those participants that have selected the 'Profit' temptation compared to the ones that haven't. The difference appears to be driven by higher intuitive styles in the former participants compared to the latter ones. Further nurturing the affect heuristic might be the 'fertile ground' of differing judgement of criteria importance: the participants confronted with the 'Profit' temptation, and accepted it, deemed profit of higher and price of lower importance than those who were faced with it but rejected it.

As a consequence of these findings, hypothesis 1 cannot be rejected. The results provide evidence as well that in the context of the compatibility test, an alternative's overachievement in one 'super criterion' is compensating the failure of its other criteria

to meet the values desired by the decision-maker. Therefore, the compatibility test appears to be compensatory at least under the effect of the affect heuristic. These results thus contradict findings of earlier research (Beach & Strom, 1989; Ordoñez et al., 1999) that postulated that only criteria violations are relevant when the compatibility test is applied.

5.2 Hypothesis 2

The second hypothesis is:

"The Dewberry et al. (2013) model can be confirmed by using only 5 items in a questionnaire to identify a participant's decision style profile."

5.2.1 Factor analysis of the 40 questionnaire items

The minimum and maximum scores, the mean and the standard deviation of the 40 questionnaire items are shown in Appendix Descriptive statistics of the 40 questionnaire items.

Table 25 shows the eigenvalues and the squared rotated factor loadings for the eight factors, from the ninth component onward the eigenvalues drop below 1. Therefore, and following the Kaiser criterion, these components are not considered as factors.

<i>Component</i>	<i>Initial eigenvalues</i>			<i>After rotation sums of squared loadings</i>		
	total	% of variance	cumulative % variance	total	% of variance	cumulative % variance
1	9.062	22.656	22.656	3.910	9.775	9.775
2	4.083	10.209	32.865	3.404	8.510	18.285
3	3.107	7.768	40.633	2.879	7.198	25.483
4	1.677	4.192	44.824	2.852	7.130	32.613
5	1.458	3.645	48.469	2.849	7.122	39.735
6	1.310	3.275	51.744	2.424	6.060	45.795
7	1.105	2.762	54.506	2.290	5.724	51.519
8	1.067	2.668	57.174	2.262	5.655	57.174
9	.953	2.384	59.558			

Table 25:

Result of the first factor analysis extracting 8 factors of 40 decision style items

Based on the Kaiser criterion, eight factors were extracted. To complement the analysis a respective scree plot was generated as well. This however was more indecisive than the Kaiser criterion. As can be seen in Figure 14, the first 'kink' can be observed at the eigenvalue of component 4, a second and potentially third one, that are far less apparent, at the eigenvalues of component 7 and 9.

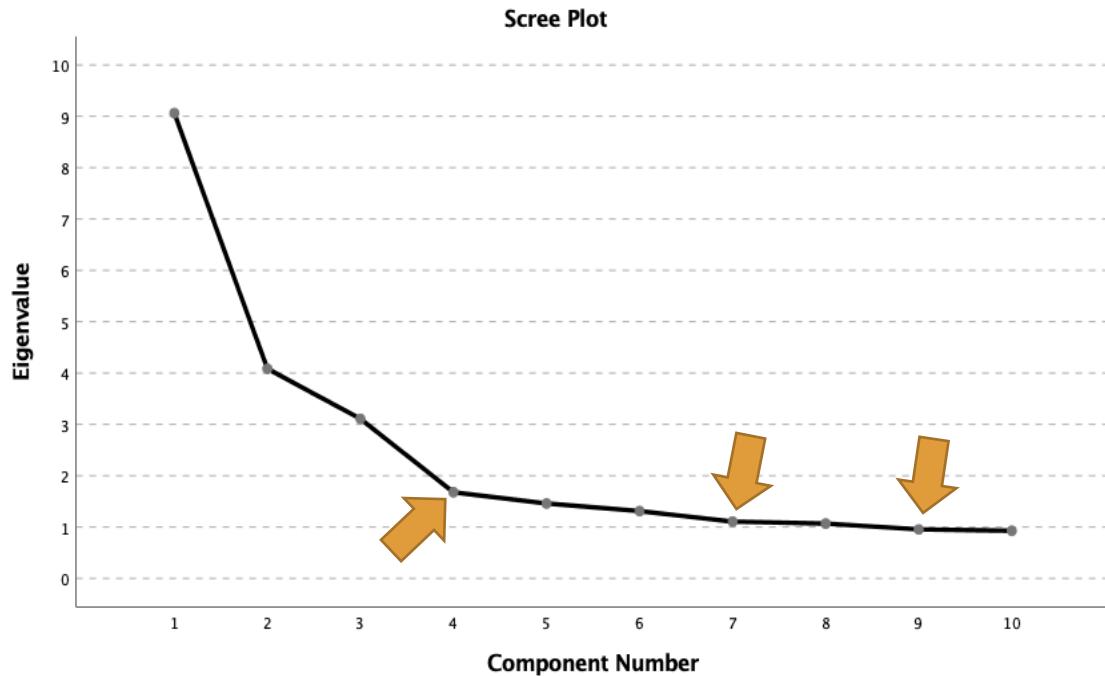


Figure 14:

Scree plot of first SPSS factor analysis extracting 8 factors of 40 questionnaire items.

Since the Kaiser criterion is a numerical one that by definition is less debatable than the scree plot criterion, the interpretation of the author shall follow the Kaiser criterion. Hence, the first factor analysis performed with IBM SPSS extracted eight factors as predicted. The analysis achieved the following quality measures as referred to earlier:

- The overall KMO Value was .911 which qualifies the suitability of the data set as 'marvelous';
- Bartlett significance was significant ($\chi^2 = 10,176.253$; $p < 0.001$);
- 21% non-redundant residuals with an absolute value higher than 0.05;
- 57% of the variance could be explained;

The CFA with MPlus extracted 8 factors as well and generated the following model fit parameters:

Model Fit Parameters	MPlus CFA	'Good' model fit benchmark (Brown, 2015, pp.74)
RMSEA	.041	<.060
CFI	.972	>.950
TLI	.955	>.950
SRMR	.026	<.080

Table 26:

Model fit parameters achieved by the MPlus CFA to confirm extraction decision styles

Based on the model fit parameters achieved as shown in Table 26, the CFA and, thus, the model fit was deemed 'very good'.

5.2.2 Determination of the decision styles by factor allocation

Having performed the EFA using IBM SPSS, factor loadings for each questionnaire item into each factor were available (see Appendix Factor loadings of the 40 questionnaire items into the 8 extracted components).

As per the protocol described earlier, the sums of each set of five questionnaire items were calculated and a respective matrix was generated (values in the inner frame of Figure 15). Further, the largest sums of each row and column ('Row Max' and 'Column Max') as well as the second largest sums of each row and column ('Row Max 2' and 'Column Max 2') have been identified. Eventually, the delta between the two sums was calculated for each row and column ('Delta Row' and 'Delta Column').

	Factors/Components								Row Max	Row Max 2	Delta Row
	1	2	3	4	5	6	7	8			
Items on Avoidant	3,365	0,089	-0,405	0,867	0,719	1,156	0,919	0,273	3,365	1,156	2,209
Items on Anxious	2,225	0,278	-0,612	1,443	1,088	1,401	1,13	1,168	2,225	1,443	0,782
Items on Regret	0,76	0,006	0,001	3,037	0,711	0,601	0,649	0,539	3,037	0,76	2,277
Items on Maximising	0,487	-0,024	-0,109	0,403	0,39	2,224	2,06	-0,15	2,224	2,06	0,164
Items on Dependent	0,606	0,275	0,113	0,714	3,229	0,567	0,527	0,41	3,229	0,714	2,515
Items on Intuitive	-0,107	3,294	0,159	-0,077	0,099	-0,197	0,146	-0,436	3,294	0,159	3,135
Items on Spontaneous	0,301	2,012	-0,76	0,328	0,035	0,232	0,671	-2,1	2,012	0,671	1,341
Items on Rational	-0,241	-0,097	3,283	0,154	0,361	-0,128	-0,209	0,385	3,283	0,385	2,898
Column Max	3,365	3,294	3,283	3,037	3,229	2,224	2,06	1,168			
Column Max 2	2,225	2,012	0,159	1,443	1,088	1,401	1,13	0,539			
Delta Column	1,14	1,282	3,124	1,594	2,141	0,823	0,93	0,629			

Figure 15:

Starting spreadsheet to allocate the sets of questionnaire items to the decision styles

Step 3 of the protocol calls now for the identification of the largest of all 'Delta Row' and 'Delta Column' values. This value can be found in row 'Items on Intuitive' (highlighted in blue and bold font in Figure 16).

	Factors/Components								Row Max	Row Max 2	Delta Row
	1	2	3	4	5	6	7	8			
	INTUITIVE										
Items on Avoidant	3,365	0,089	-0,405	0,867	0,719	1,156	0,919	0,273	3,365	1,156	2,209
Items on Anxious	2,225	0,278	-0,612	1,443	1,088	1,401	1,13	1,168	2,225	1,443	0,782
Items on Regret	0,76	0,006	0,001	3,037	0,711	0,601	0,649	0,539	3,037	0,76	2,277
Items on Maximising	0,487	-0,024	-0,109	0,403	0,39	2,224	2,06	-0,15	2,224	2,06	0,164
Items on Dependent	0,606	0,275	0,113	0,714	3,229	0,567	0,527	0,41	3,229	0,714	2,515
Items on Intuitive	-0,107	3,294	0,159	-0,077	0,099	-0,197	0,146	-0,436	3,294	0,159	3,135
Items on Spontaneous	0,301	2,012	-0,76	0,328	0,035	0,232	0,671	-2,1	2,012	0,671	1,341
Items on Rational	-0,241	-0,097	3,283	0,154	0,361	-0,128	-0,209	0,385	3,283	0,385	2,898
Column Max	3,365	3,294	3,283	3,037	3,229	2,224	2,06	1,168			Minimum Delta
Column Max 2	2,225	2,012	0,159	1,443	1,088	1,401	1,13	0,539			
Delta Column	1,14	1,282	3,124	1,594	2,141	0,823	0,93	0,629			Total factor loading:
									INTUITIVE	<==	3,294
											3,294

Figure 16:

First cycle of 'items-factor' allocation protocol

Then, the highest sum (in the inner frame of Figure 16) has to be identified. 3.294 is largest sum of factor loadings for the items on the intuitive decision style and can be found in the column of the second factor (highlighted in red in Figure 16). Therefore, this factor represents the intuitive decision style. The column of this factor and the row 'Items on Intuitive' are excluded from the next cycle of the 'item-factor' allocation protocol. Now, the second cycle starts. This process is repeated until all sets of items have been allocated to a factor. The respective result is shown in Figure 17.

	Factors/Decision Styles							
	1	2	3	4	5	6	7	8
	AVOIDANT	INTUITIVE	RATIONAL	REGRET	DEPENDENT	MAXIMISING	SPONTANEOUS	ANXIOUS
Items on Avoidant	3,365	0,089	-0,405	0,867	0,719	1,156	0,919	0,273
Items on Anxious	2,225	0,278	-0,612	1,443	1,088	1,401	1,13	1,168
Items on Regret	0,76	0,006	0,001	3,037	0,711	0,601	0,649	0,539
Items on Maximising	0,487	-0,024	-0,109	0,403	0,39	2,224	2,06	-0,15
Items on Dependent	0,606	0,275	0,113	0,714	3,229	0,567	0,527	0,41
Items on Intuitive	-0,107	3,294	0,159	-0,077	0,099	-0,197	0,146	-0,436
Items on Spontaneous	0,301	2,012	-0,76	0,328	0,035	0,232	0,671	-2,1
Items on Rational	-0,241	-0,097	3,283	0,154	0,361	-0,128	-0,209	0,385

Figure 17:

decision style/factor allocation after applying the 'item-factor' allocation protocol

The overall factor loading of all allocations is 20.282. As can be seen in above table, each set of items was allocated to the correct decision style. That is, items that are deemed to measure certain decision style are allocated to that decision style.

Based on this allocation of decision styles, the following equations can be determined to calculate the respective score of each decision style:

$$\text{AVOIDANT} = \frac{1}{3.365} (0.743av_1 + 0.605av_2 + 0.653av_3 + 0.720av_4 + 0.644av_5) \quad (9)$$

$$\text{INTUITIVE} = \frac{1}{3.294} (0.421in_1 + 0.757in_2 + 0.730in_3 + 0.752in_4 + 0.634in_5) \quad (10)$$

$$\text{RATIONAL} = \frac{1}{3.283} (0.660ra_1 + 0.654ra_2 + 0.698ra_3 + 0.626ra_4 + 0.645ra_5) \quad (11)$$

$$\text{SPONTANEOUS} = \frac{1}{0.671} (0.145sp_1 + 0.171sp_2 + 0.051sp_3 + 0.037sp_4 + 0.267sp_5) \quad (12)$$

$$\text{REGRET} = \frac{1}{3.037} (0.566re_1 + 0.490re_2 + 0.745re_3 + 0.778re_4 + 0.458re_5) \quad (13)$$

$$\text{MAXIMISING} = \frac{1}{2.224} (0.122ma_1 + 0.727ma_2 + 0.071ma_3 + 0.788ma_4 + 0.516ma_5) \quad (14)$$

$$\text{ANXIOUS} = \frac{1}{1.168} (0.106an_1 + 0.164an_2 + 0.195an_3 + 0.471an_4 + 0.232an) \quad (15)$$

$$\text{DEPENDENT} = \frac{1}{3.229} (0.533de_1 + 0.649de_2 + 0.735de_3 + 0.801de_4 + 0.511de_5) \quad (16)$$

Please note that the calculated values are normalised by dividing the respective sums by the sum of the factor loadings (coefficients before the brackets). The abbreviations av_i , in_i , ra_i , sp_i , re_i , ma_i , an_i , and de_i ($i = 1, \dots, 5$) stand for the variables of the five questionnaire items of each style and allow to write the above equations in more compact form than when using AVOIDANT_1, AVOIDANT_2, AVOIDANT_3, etc. ...

With the help of these five equations and the scores of the 40 questionnaire items, decision style scores for all participants of the Base Sample and the Student Sample were calculated.

5.2.3 Descriptive statistics and correlation analysis

For the Base and the Student Sample the following minimums, maximums, mean values and standard deviation were calculated. The results for both samples are shown in Table 27.

		Minimum Value	Maximum Value	Mean Value	Standard Deviation
Avoidant	Base	1.0	4.0	2.1	.7
	Student	1.0	3.8	2.3	.7
Anxious	Base	1.0	4.0	2.0	.7
	Student	1.0	3.8	2.3	.7
Dependent	Base	1.0	4.0	2.5	.6
	Student	1.2	4.0	2.9	.6
Regret	Base	1.0	4.0	2.3	.6
	Student	1.0	4.0	2.4	.7
Maximising	Base	1.0	3.9	2.2	.7
	Student	1.0	3.7	2.4	.6
Intuitive	Base	1.4	4.0	2.9	.5
	Student	1.4	4.0	2.7	.6
Spontaneous	Base	1.0	4.0	2.3	.6
	Student	1.0	3.5	2.0	.6
Rational	Base	1.6	4.0	3.2	.5
	Student	2.0	4.0	3.2	.4

Table 27:

Descriptive statistics for the decision styles of the Base and Student Sample

The respective histograms for the Base Sample data only are shown in Appendix Histograms for the Base Sample decision style scores.

When comparing the values of the two samples, it can be stated that the Student Samples variance for some of the decision styles, i.e. for the spontaneous style, are lower than for the Base Sample. This might well be an effect of the sample size. However, the mean values for both samples differ as well except for the rational style, for which both mean values are the same. The differences of the remaining mean values range from .1 for the regret style to .4 for the dependent style. If these differences are statistical relevant or not, was verified by performing respective t-tests to compare pairwise the decision style mean values for the Student and the Base Sample. The results of this analysis are shown in Table 28.

	Sample	Mean	t-Test Significance
Avoidant	Student	2.3	$t = 3.156, p < .01$
	Base	2.1	
Intuitive	Student	2.7	$t = -2.851, p < .01$
	Base	2.9	
Rational	Student	3.2	$t = .706, p < .49$
	Base	3.2	
Spontaneous	Student	2.0	$t = -4.551, p < .01$
	Base	2.3	
Regret	Student	2.4	$t = .718, p < .48$
	Base	2.3	
Maximising	Student	2.4	$t = 2.278, p < .05$
	Base	2.2	
Anxious	Student	2.3	$t = 2.570, p < .05$
	Base	2.0	
Dependent	Student	2.9	$t = 5.623, p < .01$
	Base	2.5	

Table 28:

t-test results for mean values of decision styles of the Base and Student Sample

The analysis shows that the Student Sample appears to be more avoidant, more maximising, more anxious, and more dependent but less intuitive and spontaneous than the Base Sample. Keeping the Dewberry et al. (2013) model in mind, the results could be interpreted for the Student Sample as having a higher regulatory process style score but a lower System 1 score than the Base Sample. Both differences could potentially be traced back to the age difference of both samples. The typical participant of the Student Sample was between 26 and 35 years old (leaning rather to the low end of this interval)

whilst the typical Base Sample participant was 30 to 44 years old (leaning towards the middle of the interval). If the regulatory process style and the cognitive process style System 1 depends on life-experience what has been suggested by the earlier discussion of the relevant literature, at least for the latter, then the difference in decisions styles appears to be reasonable.

The next step was to calculate the Pearson correlations, again for both samples. As a reminder, the Pearson correlation calculated by Dewberry et al. (2013) are shown in Table 29 as well. Cronbach's Alpha is annotated with a cross and shown diagonally in below table for all samples.

	Sample	AVOIDANT	ANXIOUS	DEPENDENT	REGRET	MAXIMISING	INTUITIVE	SPONTANEOUS	RATIONAL
S = Student B = Base D = Dewberry ** p<0,01 * p<0,05 + Cronbach's Alpha	S	.86+							
AVOIDANT	B	.86+							
	D	.90+							
ANXIOUS	S	.70**	.88+						
	B	.68**	.85+						
	D	.77**	.81+						
DEPENDENT	S	.52**	.57**	.84+					
	B	.42**	.47**	.75+					
	D	.56**	.60**	.89+					
REGRET	S	.68**	.53**	.35**	.78+				
	B	.50**	.54**	.46**	.73+				
	D	.68**	.85**	.58**	.81+				
MAXIMISING	S	.47**	.51**	.37**	.37**	.50+			
	B	.52**	.49**	.32**	.37**	.64+			
	D	.51**	.51**	.35**	.53**	.57+			
INTUITIVE	S	-.12	-.23*	-.08	-.23*	-.13	.81+		
	B	.02	.04	.09*	.02	-.01	.74+		
	D	-.11*	-.16**	-.13*	-.14*	.01	.82+		
SPONTANEOUS	S	-.27*	-.32**	-.23*	-.13	-.14	.51**	.77+	
	B	.19**	.12**	.02	.11**	.14**	.48**	.71+	
	D	.13*	.08	-.03	.07	.10	.41**	.83+	
RATIONAL	S	.03	.15	.28**	.12	.02	-.34**	-.46**	.63+
	B	-.17**	-.13**	.12**	.05	-.09*	-.06	-.34**	.72+
	D	-.06	-.06	.13*	.10	-.03	.19**	-.19**	.91+

Table 29:

Correlations of the decision styles of Base/Student Sample and the Dewberry research

Considering first the Cronbach Alphas of the three samples, it can be stated that they are roughly in the same range except maybe for the rational style for which the items of the Dewberry et al. (2013) research achieve a substantially higher score than for the

Base and Student Samples of the present research project. On average, the Dewberry et al. (2013) Cronbach Alphas (mean value is .82) are slightly higher than those for the Student Sample (.76) and the Base Sample (.75). The reason might be that Dewberry et al. (2013) used eight items per decision style whilst the author used only five items per style.

When turning to the correlations themselves, it can be observed that for those decision styles that Dewberry et al. (2013) regrouped under the regulatory process style (anxious, avoidant, regret, dependent, and maximising), correlations are very comparable in size, direction and statistical significance (all $p < .01$). Generally, Dewberry et al. (2013) appear to have found slightly stronger effects.

The Base Sample findings for the intuitive style seem to lack statistical significance except for the correlation between intuitive and dependent for which an effect opposite to the Dewberry et al. (2013) findings have been detected. For the Student Sample, the results seem to largely confirm the Dewberry et al. (2013) findings in terms of effect direction and size.

The Dewberry et al. (2013) correlations found for the spontaneous decision style appear to lack statistical significance (only the correlation between spontaneous and avoidant, and spontaneous and intuitive are significant). In contrast, the Base Sample findings are of high statistical significance but contradict the correlations found with the Student Sample data, in particular for the intuitive style correlations with avoidant and anxious. Potentially, this might be linked to the poor factor loadings achieved for the spontaneous decision style. However, and most importantly, whilst the correlation of the two System 1 decision styles, intuitive and spontaneous, and the other decision styles miss significance and clarity, the size and direction of the correlation between spontaneous and intuitive are very comparable for all samples.

For the correlation of the rational decision style and the other styles, one can find a similar indecisive picture as for the System 1 decision styles and the remaining styles. Two exceptions to this impression exist: first, the correlation of the rational and the dependent decision style is in direction and partially in size very comparable for all samples; and, second, the negative correlation between the rational and the spontaneous style was confirmed by the data of all three samples. An obvious

contradiction between the Dewberry et al. (2013) finding and the result of the Student Sample exists for the correlation between the rational and the intuitive decision style whilst the evaluation of the Base Sample did not find a significant relation at all.

However, in summarising the results of the Base and Student Samples on one side and the Dewberry et al. (2013) findings on the other, it can be stated that a high degree of confirmation has been achieved. This is in particular valid when considering the in-between correlations of those groups of decision styles that have been formed by Dewberry et al. (2013) and are referred to as System 1 (intuitive and spontaneous), System 2 (rational) and Regulatory (anxious, avoidant, regret, dependent, and maximising).

5.2.4 Regression path modelling and SEM analysis

The next step was to generate a path model using sequential regression analysis. A series of eight regressions were performed with IBM SPSS with the data of the Base Sample only.

	x ANXIOUS	x AVOIDANT	x REGRET	x SPONTANEOUS	x MAXIMISING	x DEPENDENT	x INTUITIVE	x RATIONAL
ANXIOUS =	-	.45	.28	-	.15	.23	-	-.13
AVOIDANT =	.46	-	.19	.12	.22	-	-	-
REGRET =	.24	.17	-	.10	-	.24	-	.25
SPONTANEOUS =	-	.13	-	-	.11	-	.87	-.12
MAXIMISING =	.26	.34	-	.15	-	-	-	.24
DEPENDENT =	.18	.13	.21	-	-	-	.15	.33
INTUITIVE =	-	-	-	.51	-	.11	-	.38
RATIONAL =	-.14	-	.23	-.13	.09	.33	.61	-

p<.001 for all values

Table 30:

Coefficients of the eight sequential regression analysis of eight decision styles

Every decision style was used once as dependent variables and the remaining seven decision styles as predictors.

The regression coefficients of these regressions are shown in Table 30 (see previous page). The respective histograms and P-P plots are shown in Appendix Histograms of standardised residuals & P-P plots for decision style regressions .

The missing values in above table state that the respective decision style has been excluded from the regression by IBM SPSS based on the t-test significance criteria ($p>.05$.). Achieved model fit was very good as can be seen from the corrected R^2 and the Durbin-Watson values (latter should be 2.0 for perfect fit) shown in Table 31 below.

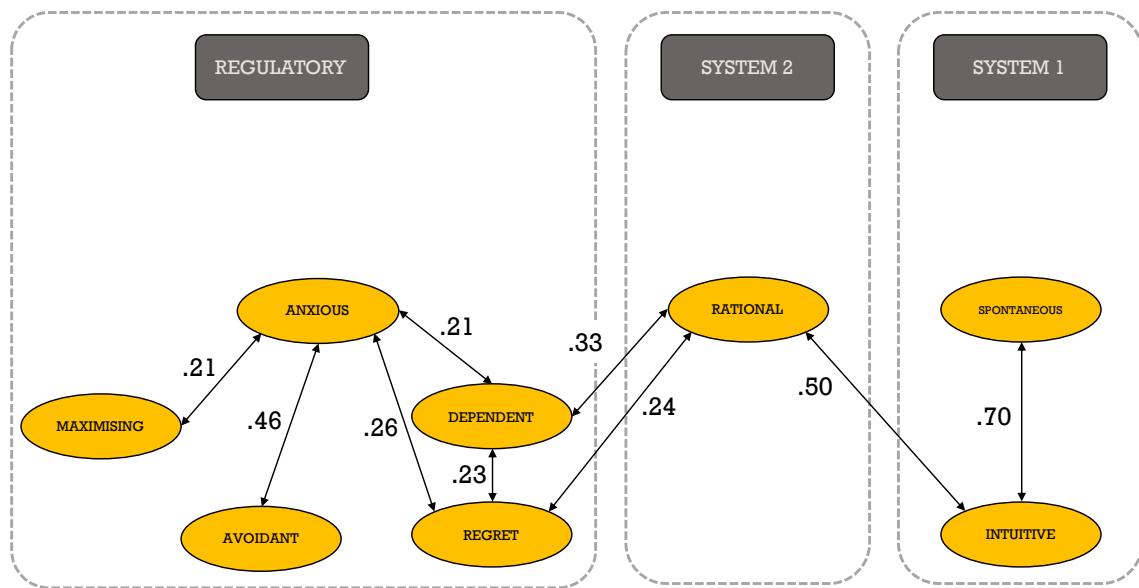
Dependent variable	Correct. R^2	F-value	Durbin-Watson
ANXIOUS	.95	2,549.984**	1.98
AVOIDANT	.95	3,330.488**	1.97
REGRET	.96	3,082.397**	1.97
SPONTANEOUS	.96	3,793.452**	1.98
MAXIMISING	.94	2,319.747**	1.96
DEPENDENT	.97	3,560.825**	1.94
INTUITIVE	.98	8,649.298**	1.94
RATIONAL	.96	2,792.422**	1.90

** $p<.01$

Table 31:

Quality measures (R^2 , Durbin-Watson) of the regressions on the decision styles

A pairwise comparison of the coefficients in Table 30 reveals, that these have the same direction and roughly the same size. Therefore, the author considered these

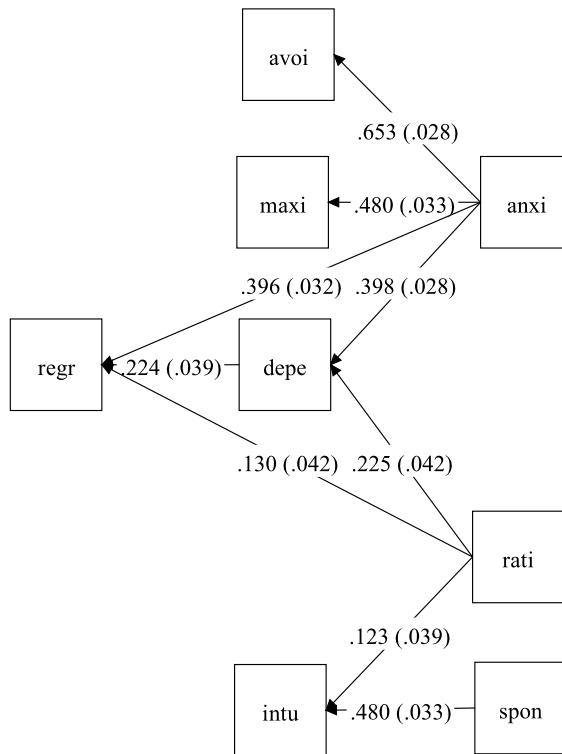


*Figure 18:
The path model of the decision style regressions*

effects as reciprocal and, thus, calculate the average for each pair. The result is shown in Figure 18 that also represents a graphical depict of the sequential path analysis. This compares already well to the Dewberry et al. (2013) model with some differences.

A last verification of this structure was performed in MPlus based on a SEM analysis of the structure in Figure 18. The result (the regressions coefficients and their standard errors as well as the model fit parameters) for the Base Sample and the Student Sample is shown in Figure 19 (see next page).

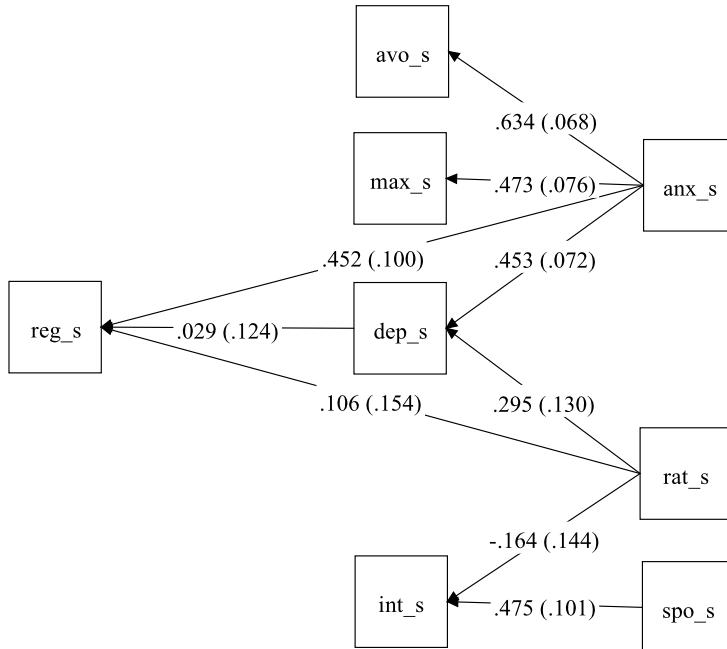
Base Sample



AVOIDANT	= avoi
MAXIMISING	= maxi
DEPENDENT	= depe
REGRET	= regr
INTUITIVE	= intu
ANXIOUS	= anxi
RATIONAL	= rati
SPONTANEOUS	= spon

Model fit parameters:
 RMSEA: 0.09 (<0.06*)
 CFI: 0.97 (>0.95*)
 TLI: 0.91 (>0.95*)
 SRMR: 0.04 (<0.08*)
 $\chi^2 = 57.758$; p<0.01
 * Brown (2015, pp.74)

Student Sample



AVOIDANT	= avo_s
MAXIMISING	= max_s
DEPENDENT	= dep_s
REGRET	= reg_s
INTUITIVE	= int_s
ANXIOUS	= anx_s
RATIONAL	= rat_s
SPONTANEOUS	= spo_s

Model fit parameters:
 RMSEA: 0.05 (<0.06*)
 CFI: 0.99 (>0.95*)
 TLI: 0.97 (>0.95*)
 SRMR: 0.03 (<0.08*)
 $\chi^2 = 12.351$; p<0.27
 * Brown (2015, pp.74)

Figure 19:

Non-standardised coefficients (and their standard error) for the MPlus SEM analysis

Both models demonstrate acceptable (Base Sample) to very good (Student Sample) fit. The Student Sample results suffer however from insufficient significance which the author explains with the very small sample size ($N=87$). Further, the regression coefficients show high similarity except for the ones between the regret and the dependent styles that differ in size and the ones between the intuition and rational styles that are of opposite direction.

Whilst these results are rather promising, the relationship between the eight decision styles and the three process styles has, however, not been investigated yet. This was the next step.

5.2.5 Factor analysis of the decision styles

The last step to test hypothesis 2 is to perform an EFA on the eight decision styles to extract potentially the three process styles and calculate the participants' values for these process styles that will be used for further processing.

The first factor analysis was performed with IBM SPSS, on both, the Base and the Student Sample. Respective factor loadings are shown in Table 32 (see next page). Three factors have been extracted for both samples, and, thus, confirmed the grouping of the decision styles as proposed by Dewberry et al. (2013).

Please note however that for the Student Sample the Kaiser criterion extracted only two factors and the respective scree plot was consistent with this finding. Subsequently, the settings in IBM SPSS have been changed for the Student Sample and the extraction of three factors has been forced.

	Sample	REGULATORY	SYSTEM 1	SYSTEM 2
AVOIDANT	Base	.83	.03	-.19
	Student	.78	-.02	.28
ANXIOUS	Base	.85	.03	-.09
	Student	.82	-.15	.31
DEPENDENT	Base	.67	.13	.41
	Student	.51	.09	.73
REGRET	Base	.75	.08	.19
	Student	.71	-.19	.02
MAXIMISING	Base	.70	-.04	-.17
	Student	.73	-.07	.02
INTUITIVE	Base	-.02	.91	.10
	Student	-.15	.90	.06
SPONTANEOUS	Base	.13	.77	-.39
	Student	-.11	.74	-.37
RATIONAL	Base	-.07	-.13	.89
	Student	-.17	-.50	.71

Table 32:

Factor loadings of the eight decision styles into the process styles

The three-dimensional depict of the decision styles in the space generated by the three process styles axis, and the respective scree plot of the factor analysis for the Base Sample underlines these findings graphically (see Figure 20).

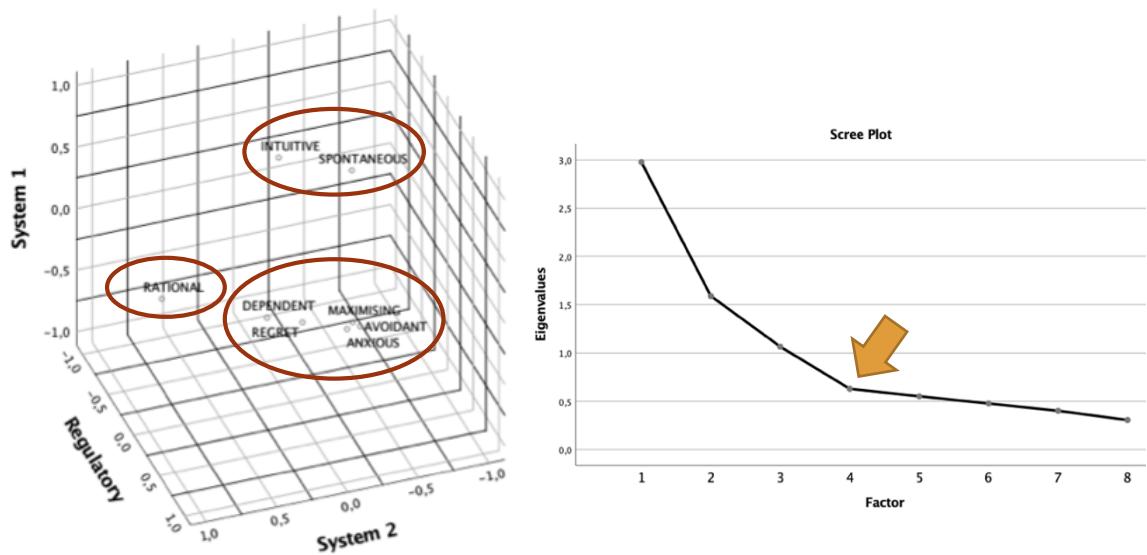


Figure 20:

3D depict of the decision styles and scree plot (IBM SPSS EFA for the Base Sample)

A protocol to allocate the factors was not used since the decision style loadings have been bluntly obvious except for the dependent decision style that loads higher into SYSTEM2 (.73) than into REGULATORY (.51) for the Student Sample. This, however, might be linked to the small sample size ($N=87$) but confirms the decision styles structure identified earlier (see *Figure 18 & Figure 19*) as well.

The suitability of the data set was deemed 'middling' for both samples based on the overall KMO value (Base Sample: .74; Student Sample: .76). The Bartlett test was highly significant (Base Sample: $\chi^2 = 1,464.533$; $p<0.001$; Student Sample: $\chi^2 = 225.690$; $p<0.001$) for both samples and 64% non-redundant residuals took a value above .05 for the Base Sample (60% for the Student Sample) which appears to be very high, and, thus, disadvantageous, but on the other side as much as 70% of the variation could be explained for the Base Sample (71% for the Student Sample). Overall, this is deemed acceptable.

The corresponding analysis in MPlus with an oblique GeoMin rotation that was only performed for the Base Sample confirmed the findings of the IBM SPSS analysis. Three

factors were extracted, and the decision styles were loading into the same process styles as for the respective IBM SPSS analysis. Model fit was almost perfect ($\text{RMSEA} = .03$; $\text{CFI} = 0.99$; $\text{TLI} = 0.99$; $\text{SRMR} = 0.01$).

5.2.6 Discussion

The eight decision styles could be extracted from the data collected by the questionnaire for both, the Base and the Student Sample. The respective model had very good fit.

The comparison of the Pearson correlations of the two samples used in this thesis with the correlations calculated of Dewberry et al. (2013) largely confirmed the findings of latter. In particular, the findings for the regulatory process styles, anxious, avoidant, dependent, regret, and depending, were virtually identical to those of the Dewberry et al. (2013) research. Further, the results for the correlation between the intuitive and the spontaneous styles as well as the rational style as 'stand-alone' style could be confirmed as well.

There have however been some differences to the Dewberry et al. (2013) model as well:

- the dependent and intuitive styles were weakly negatively correlated in the Dewberry et al. (2013) study whilst this research project found a weak positive correlation for the Base Sample data. The Student Sample results, albeit statistically not as relevant, confirm however the findings of the Dewberry et al. (2013) research for the intuitive style correlations;
- the findings for the Base Sample on the spontaneous decision styles correlations with the others were in line with the results of the Dewberry et al. (2013) study (in particular when considering the respective statistical significance) but in contradiction to the Student Sample findings except for the correlation between the spontaneous and the intuitive style;
- for the rational decision style, the findings for the Base Sample matched very well the results found by Dewberry and his colleagues except for the correlation between rational and intuitive that Dewberry et al. (2013) found to be positively correlated whilst the findings of the analysis of the Base Sample and in particular the Student Sample Data unveiled a negative correlation. The results for the latter sample was

in line with the two others if only the statistically significant correlations are considered;

The subsequent SEM unveiled similar but not an identical picture of the relations amongst the decision styles. The findings of the present research suggest amending the Dewberry et al. (2013) model as follows:

- the dependent style is not necessarily subordinated to the avoidant style;
- there are important links between the dependent and the regret style;
- relations exist that 'cross the border' between the regulatory and the System 2 process styles (between dependent and rational as well as between regret and rational), and between System 2 and System 1 process styles (between intuitive and rational). These findings put the rational System 2 in the core of this structure influencing the two other process styles;

Whilst the influence of System 2 on the two other process styles makes sense, the non-existing links of the SEM between System 1 and the Regulatory process style comes as a surprise since System 1 seems to be driven by emotions and, thus, should impact decision anxiety represented by the regulatory style. Respective links are only postulated when considering the Pearson correlations but do not 'shine through' on the SEM.

Eventually, the three process style factors were extracted from the decision style scores determined by the 40 questionnaire items. These decision styles loaded well in the three process factors as predicted by Dewberry et al. (2013). The variables of these three factors were thus labelled REGULATORY, SYSTEM1 and SYSTEM2. The related Anderson-Rubin values for the Base and Student Sample were calculated for further processing. The analysis was confirmed with a respective MPlus EFA using a different, oblique rotation method.

When looking at the results of the analysis so far and offering a further interpretation of the (smaller) differences between the present and the Dewberry et al. (2013) research, the various decision styles could well be linked to each other, in particular within a given process style, but change the strength and direction of their interaction based on the context of the decision situation and the decision-maker's 'working images'. The

decision styles and their interaction could be interpreted like a neural network where the decisions styles represent the nodes of the network and the links between them are activated as required based on contextual information and/or the 'working images'. This neural network approach will be developed further later in this thesis (see hypothesis 5).

In concluding the discussion on the results to test hypothesis 2, it can be stated that hypothesis 2 cannot be falsified based on the presented findings.

5.3 Hypothesis 3

As for all result subchapters, the hypothesis shall be repeated to set the scene for the subsequent presentation and discussion of related results:

"There are significant links between the choice set variables and a decision-maker's process styles, demographic factors, 'importance weight variables' and time to finish the survey."

5.3.1 Descriptive statistics for all the newly introduced variables

The first subchapter will present the descriptive statistics of the variables that have not been used yet or that have been calculated by prior processes and analyses. The variables relevant for hypothesis 3 are the choice set variables (NUMCOMP, THRESHOLD, INCONSID), the demographic variables (AGE and GENDER), the variable TIME, and the importance weight variables (IMPOR_WEIGHT_FIT, INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEES, INDIV_W_INVESTMENT, and INDIV_W_INDUSTRY) as well as the Anderson-Rubin values for the process style variables (REGULATORY, SYSTEM1, and SYSTEM2). Please note that the latter ones are normalised and standardised which implies that their mean values equal '0' and their standard deviation is '1'; they are nevertheless included in the presentation. Descriptive statistics for the decision style variables have already been presented at the beginning of the result subchapter for hypothesis 2 (see Table 27, p. 148).

Table 33 (see next page) shows the minimum, maximum and mean values as well as the standard deviation of the above-mentioned variables for the Base and Student Samples.

Variables	Sample	Min. Value	Max. Value	Mean Value	Standard Deviation
NUMCOMP	Base	1	8	4.1	1.5
	Student	1	6	3.0	1.2
THRESHOLD	Base	-9	0	-3.3	2.5
	Student	-9	0	-3.0	1.3
INCONSIS	Base	0	4	1.2	1.0
	Student	0	3	1.1	.9
REGULATORY	Base	-2.3	3.1	0.0	1.0
	Student	-2.2	2.5	0.0	1.0
SYSTEM1	Base	-3.0	2.9	0.0	1.0
	Student	-2.2	2.3	0.0	1.0
SYSTEM2	Base	-3.6	3.4	0.0	1.0
	Student	-2.4	2.8	0.0	1.0
AGE / AGE_C	Base	2	5	3.3	.8
	Student	1	5	1.6	1.0
GENDER	Base	1	2	1.4	.5
	Student	1	2	1.6	.5
TIME	Base	1	4	2.5	1.1
	Student	1	4	2.5	1.1
IMPOR_WEIGHT_FIT	Base	.063	.928	.192	.079
	Student	.060	.520	.177	.083
INDIV_W_PRICE	Base	.000	.546	.225	.072
	Student	.000	.450	.247	.057
INDIV_W_PROFIT	Base	.000	.455	.226	.069
	Student	.000	.550	.253	.073
INDIV_W_DEBT	Base	.000	1.000	.170	.076
	Student	.000	.450	.155	.068
INDIV_W_EMPLOYEES	Base	.000	.400	.109	.069
	Student	.000	.240	.086	.051
INDIV_W_INVESTMENT	Base	.000	.400	.160	.070
	Student	.000	.330	.161	.062
INDIV_W_INDUSTRY	Base	.000	.333	.111	.081
	Student	.000	.290	.098	.076

Table 33:

Descriptive statistics for variables relevant to hypothesis 3 (statistically relevant differences are shown in bold)

A respective t-test has been performed on the mean values for each of the three choice set variables between the Base and the Student Sample to verify the statistical significance of the differences. Only the t-test for the number of companies selected in the choice set became significant ($T=-6.762$; $p<.01$) stating that the Student Sample participants selected less companies than the participants of the Base Sample.

Further, and as stated earlier, the participants were in average much younger and 'more female' than the participants of the Base Sample as can be determined from the mean values of the variables collecting the age group of the participants (AGE, AGE-C) and the gender variable (GENDER). The variable TIME is obviously identical for both samples due to the way its values have been calculated (quantiles). The mean value differences between the two samples for the importance weight variables have been checked with respective t-tests as well. Three tests were significant: the participants' weights for price ($T=-2.735$; $p<.01$), for profit ($T=-3.231$; $p<.01$) and for employees ($T=3.690$; $p<.01$).

Appendix Histograms for the choice set and process style variables shows the histograms for the choice set variables and the process style variables of the Base Sample only.

5.3.2 Correlation analysis

The next step is to analyse the correlation of all variables.

Table 34 on the next page shows all correlations between the variables and their statistical significance. For the correlation analysis, the decision style variables have been considered as well. The subsequent analysis will focus on the statistically significant correlations.

All decision styles are positively correlated with the number of selected companies except for the rational and the maximising style. These relationships are also reflected in the positive correlations of the number of selected companies (NUMCOMP) with the process styles.

The rejections threshold is negatively (THRESHOLD) correlated with almost all decision styles except for avoidant, spontaneous and maximising. This is in line with the findings for NUMCOMP; the negative nature of this correlations is caused by the fact, that THRESHOLD is negative as well. This implies that the effect is for both choice set variables the same. That is, a higher value for these decision styles is linked to a lower rejection threshold and, thus, to higher number of alternatives in the choice set. Again, the correlation of THRESHOLD with the decision styles is also reflected in the process styles. The number of inconsistencies (INCONSIS) however is negatively correlated with the rational style and positively with the spontaneous style. This makes sense, since a more thoughtful, analytical behaviour should produce less inconsistencies than a quick, spontaneous selection of the decision alternatives. The correlations in-between the choice set variables is as expected as well: first, a higher number of selected companies increases the risk of inconsistent choices, therefore, NUMCOMP and INCONSIS are positively correlated. Second, the number of companies is negatively correlated with the rejection threshold. That is, the lower the value for THRESHOLD, the more companies are selected in the choice set. The correlation between these two variables is also the strongest of all correlations in the analysis.

		INCONCIS	TIME	GENDER	AGE
* p<.05;					
** p<.01;					
Insignificant values in light grey font colour					
NUMCOMP	AVOIDANT	INTUITIVE	RATIONAL	SPIONTANEOUS	MAXIMISING
.086*	.153**	.060	.125**	.134**	.015
THRESHOLD	REGRET				
-.077	-.134**	-.113**	-.069	-.107**	-.029
INCONCIS	DEPENDENT				
.048	.067	.128**	.145**	.065	.035
TIME	SYSTEM 1				
-.038	-.095*	.127**	-.167**	-.088*	.008
GENDER	REGULATORY				
.067	.136**	-.074	.002	.01	-.045
AGE	DEPENDENT				
-.086*	-.012	.053	-.041	-.119**	-.153***
IMPOR_WEIGHT_FIT	SYSTEM 2				
.040	.148**	-.002	.110**	.046	.028
INDIV_W_PRICE	NUMCOMP				
-.024	-.108**	-.043	-.093*	-.050	-.003
INDIV_W_PROFIT	THRESHOLD				
-.030	-.036	.001	-.020	-.057	.004
INDIV_W_DEBT	INCONSIS				
-.013	-.016	.052	-.022	.002	-.013
INDIV_W_EMPLOYEE	TIME				
.113**	.031	-.015	.018	.076	.005
INDIV_W_INVEST	GENDER				
-.019	.015	.020	.040	.033	.000
INDIV_W_INDUSTRY	AGE				
-.021	.101*	-.017	.070	-.002	.008

Table 34: Pearson correlations between various variables of the research project

TIME is positively correlated with the rational decision style and negatively correlated with the two System 1 decision styles, intuitive and spontaneous, as well as with the regret decision style. All these correlations make sense: on the one side, the more time participants took to answer the questionnaire, the higher the likelihood that they have thought through their selections carefully; and, on the other side, the more intuitively or spontaneously they selected the companies the less time they required to complete the survey. A possible explanation can also be provided for the regret decision style's negative correlation with TIME. Decision-makers who feels regret about the consequences of their decisions might as well want to leave those decisions behind them as quickly as possible. Therefore, the higher the salience of the regret decision style in decision-makers, the quicker they might want to take the survey. Please note however, that the effect size of this relationship is small and that the respective process style, the regulatory style, is not correlated with TIME. This implies that the regret effect is only 'active' on its link into System 2 which explains the lower correlation of latter compared to the rational style alone. The regret effect is potentially damping the effect of the rational style.

Looking at these 'cross-process-style' effects, it might well be stated that the rational style is 'damping' as well the System 1 correlation (as can be seen at the lower correlation of System 1 compared to the combination of spontaneous and intuitive correlations with TIME) through its link to the intuitive decision style. This might be taken as evidence that the monitoring role that System 2 plays on System 1. Eventually, TIME is negatively correlated with the number of companies in the choice set and the number of inconsistencies. Both are not evident at first glance. However, if participants took less time to finish the questionnaire, they apparently were more prone to reject companies than to accept them into their choice sets. If this holds valid, it is also true that the number of inconsistencies is lower for participants that took less time to finish the survey. Logically, and as can be determined from the correlation of THRESHOLD and TIME, the less time participants took to complete the questionnaire the higher was their rejection thresholds and, thus, the less companies made it onto their shortlists.

The demographic variables GENDER and AGE play no role for the determination of the choice set variables; respective correlations do not exist. However, there are some correlations to the decision and process styles that should be discussed briefly: Based

on the Base Sample data, female participants appear to be more intuitive and more anxious when taking decisions. Further, the older participants are, the less decision anxiety they feel. This can be determined through the regulatory style's and the respective decisions styles' correlation with AGE and the reason for it is most likely to be found in life-time experience of older participants. The age group of the participants is also positively correlated with TIME. This implies, the older the participants the longer they took to complete the survey. Eventually, the gender of a participant is negatively correlated to the age. That is, the older a participant the higher the likelihood that the participant is male. In combination with the nature of the underlying population of which the sample has been drawn (German deciders with internet access), and assuming that older managers are in higher positions, this might imply that women in Germany still have not the same probability to achieve the higher manager ranks than men.

All importance weight variables are correlated with the number of inconsistencies except the individual importance weight of the debt criteria which is positively correlated with AGE implying that older participants assessed debt as more important than younger participants. The rejection threshold and the number of companies are only correlated with the individual importance weight for the criterion price and with the measure of how well the criteria importance ranking of a participant marries with the criteria importance weights provided by the researcher (IMPOR_WEIGHT_FIT). That is, the number of companies in the choice set is larger when the participant-researcher consensus on criteria importance weights and the participant's ranking of the price criterion is lower. For the rejection threshold the opposite is the case: the lower the participant-researcher consensus and the lower the participant's ranking of the price criterion is, the lower is the participant's rejection threshold. The same two importance weight variables are as well correlated with TIME. The longer it took the participant to complete the questionnaire the more consensus existed for the criteria rankings between the participant and the author and the more important became the price criterion.

When it comes to the correlations of the decision and process styles with the importance weight variables, the following could be observed: IMPOR_WEIGHT_FIT and the System 1 process style as well as the two related decision styles, intuitive and spontaneous, are positively correlated. This implies that the more System 1 is active,

that is, the more participants act intuitively or spontaneously, the less compatible are their assessments of the criteria importance with the criteria ranking provided by the researcher. This makes sense; System 1 is more prone to errors because of its quick and heuristic based cognitive processing approach.

The opposite, negative correlations, can be observed between the same decision styles, their respective process style, and the individual importance weight of the price criterion. That is, the higher participants deem the importance of the price for which a company can be bought, the less intuitive and spontaneous they are. An interpretation of this correlation appears to be difficult. Potentially, when price is an important criterion, the non-analytical, quick decision skills are inhibited to avoid errors.

Eventually, two other correlation effects need to be mentioned: first, a higher ranking of the number of employees criterion seems to come with higher decision anxiety, most likely caused by images of people being laid off. Second, it appears to be more intuitive to venture into different industries; thus, a correlation exists between the intuitive decision style and the participant's importance weight for the industry criterion.

5.3.3 ANOVA

Having discussed the correlations of the various variables, an analysis of variance appears to be appropriate to further investigate their relationships. The results of the six performed ANOVAs are shown in Table 35.

	Dependent Variables ->	NUMCOMP	THRESHOLD	INCONSIS	
	**p<.01; *p<.05; °p<.10 insignificant values in light grey font colour	F =	F =	F =	F =
Factors	GENDER	.065	-	.084	-
	AGE	.382	-	.577	-
	TIME	2.619*	2.769*	2.943*	2.774*
	TIME*AGE	1.505	-	.675	-
	TIME*GENDER	.393	-	.046	-
	GENDER*AGE	.499	-	.595	-
	TIME*GENDER*AGE	.391	-	.218	-
Covariants	AVOIDANT	.054	-	.903	-
	ANXIOUS	1.458	-	.797	-
	DEPENDENT	3.251°	-	.776	-
	REGRET	1.096	-	.205	-
	MAXIMISING	2.549	-	.785	-
	INTUITIVE	4.125*	-	5.583*	-
	SPONTANEOUS	3.284°	-	.708	-
	RATIONAL	4.357*	-	11.308**	-
	REGULATORY	-	8.903**	-	6.495**
	SYSTEM1	-	17.232**	-	10.126**
	SYSTEM2	-	7.577**	-	12.937**
					5.253*

Table 35:

ANOVA results for choice set variables and other variables

The ANOVAs largely confirmed the findings of the correlation analysis. Even though the relations of the decision styles and the choice set variables became less significant, the findings for the process styles and for TIME are identical to the correlation analysis. One combined effect of gender and age group for the number of inconsistencies could be identified. When interpreting this finding in conjunction with the result of the correlation analysis, one could claim that older male participants that took longer to complete the questionnaire produced less inconsistencies than younger participants, female participants or participants that finished the survey earlier. The reason for this effect might be found in what was previously stated: older men appear to hold more senior positions than female of comparable age. Since Merger and Acquisition decisions are typically taken on highest company levels, these older male managers might have more experience in this kind of decisions either because they have been in such a decision situation already or they have observed it first-hand. Therefore, their additional experience potentially provides them with an advantage in the decision situations of the survey.

5.3.4 Regression analyses

Regression analyses were performed to investigate the path model introduced earlier. Five regressions were performed for each choice set variable.

First, two regressions were performed using the decision styles or the process styles, TIME, and the demographic factors as predictors for each of choice set variables.

Then, based on the statistically significant correlations between the respective choice set variable and the importance weight variables, latter have been included in the regression analyses. This led to further two regressions for each choice set variable: one with the decision styles, TIME, demographic factors and for the respective choice set variable significant importance weight variables, and a second one with the process styles, TIME, demographic factors and, again, for the respective choice set variable significant importance weight variables.

For the decision style regressions for THRESHOLD as dependent variables, the constant term became insignificant. The regression was therefore repeated whilst suppressing the constant term.

Eventually and since the corrected R^2 values for those two regressions performed for THRESHOLD were higher than for the other regressions with constant term, the author performed a fifth regression for each choice set variable suppressing the constant term for those earlier regressions for which the constant term was not insignificant and that had the best corrected R^2 value.

A summary of all 15 regressions performed is provided in Table 36 on the next page. A summary page of each regression is provided in Appendix Summary pages for the 15 regression analyses.

Regression n°:	NUMCOMP					THRESHOLD					INCONSIS				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
predictor variables as input for the regression:															
Corrected R ²	.054	.067	.084	.094	.091	.657	.050	.663	.069	.569	.040	.033	.065	.059	.611
Durbin-Watson	1.981	1.950	2.005	2.009	1.858	1.918	1.941	1.930	1.956	1.872	1.904	1.944	1.945	1.962	
F-value	13.436	12.725	15.773	14.441	493.477	414.957	9.566	320.360	10.662	172.698	10.023	8.833	9.967	9.119	204.466
p-value	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01	p<.01
constant term	non-standardised	2.665***	4.556***	3.614**	5.284**	-	-	-3.868***	-	-4.896***	-	1.671**	1.549**	1.261**	-
TIME	standardized	-.142**	-.140**	-.120**	-.119**	.292**	.174**	.104**	.132*	.086*	.259*	.131**	.136**	.108**	-.110*
	non-standardized	-.191**	-.189**	-.162**	-.161**	.467**	.262**	.230**	.199*	.190*	.291**	.121**	.126**	-.117**	-.123**
SYSTEM 1	standardized	-	.156**	-	.138**	.101**	-	-.119**	-	-.103**	-.114**	-	.096*	-	.073*
	non-standardized	-	.234**	-	.207**	.140**	-	-.294**	-	-.255**	-.471**	-	.099*	-	.075*
SYSTEM 2	standardized	-	.114**	-	.102**	.035*	-	-.144**	-	-.134**	.080**	-	.078*	-	.082*
	non-standardized	-	.172**	-	.154**	.152**	-	-.354**	-	-.329**	.328**	-	.081*	-	.085*
REGULATORY	standardized	-	.106**	-	.103*	.050**	-	-.093*	-	-.090*	.068**	-	-	-	-
	non-standardized	-	.159**	-	.155**	.218**	-	-.229*	-	-.222*	.281**	-	-	-	-
INTUITIVE	standardized	.129**	-	.113**	-	-	-.442**	-	-.523**	-	-	-	-	-	-
	non-standardized	.382**	-	.334*	-	-	-.618**	-	-.731**	-	-	-	-	-	-
SPONTANEOUS	standardized	-	-	-	-	-	-	-	-	-	.096*	-	.079*	-	.483**
	non-standardized	-	-	-	-	-	-	-	-	-	.176*	-	.144*	-	.326**
RATIONAL	standardized	-	-	-	-	-	-	-.531**	-	-.654**	-	-.079°	-	-.085**	-
	non-standardized	-	-	-	-	-	-	-.685**	-	-.844**	-	-.172°	-	-.186**	-
DEPENDENT	standardized	.122**	-	.114**	-	-	-	-	-	-	-	-	-	-	-
	non-standardized	.315**	-	.196**	-	-	-	-	-	-	-	-	-	-	-
IMPOR_WEIGHT_FIT	standardized	-	-	-	-	-	-	-	-	-	-	-	.149**	.148**	.305**
	non-standardized	-	-	-	-	-	-	-	-	-	-	-	1.935**	1.910**	2.363**
INDIV_W_PRICE	standardized	-	-	-.177**	-.169**	.618**	-	-	.256**	.146**	.507**	-	-	-	-
	non-standardized	-	-	-.3711**	-.3533**	11.415**	-	-	4.458**	5.019**	.8850**	-	-	-	-
INDIV_W_EMPLOYEE	standardized	-	-	-	-	-	-	-	-	-	-	-	.078*	.078*	.125**
	non-standardized	-	-	-	-	-	-	-	-	-	-	-	1.157*	1.162*	1.563**
% correct predictions		27%	27%	29%	29%	20%	18%	17%	20%	18%	39%	40%	40%	40%	38%

Table 36:

Results of regressions analyses for the choice set variables as dependent variables

As observation the following can be stated:

- The corrected R² for each of the regressions with constant terms are below .10 which indicated poor model fit. However, the regressions without constant term are - as expected - far higher and range from .57 to .79. Please note that the corrected R² for a regression with and without constant term cannot be compared.
- The Durbin-Watson values demonstrate all good to very good model fit ranging from 1.872 to 2.005.
- The regressions are all statistically significant ($p < .01$). The large sample size ($N=649$) of the Base Sample appears to play an important role.
- The regression coefficients are all of high significance ($p < .01$ or $p < .05$) except for four values that seem to be less significant ($p < .10$) but have been kept in the regression due to a higher corrected R² achieved.
- The findings of the decision style ANOVAs and the correlation analysis can be confirmed for the process styles.
- Only four of the eight decision styles are significant: these are the intuitive, the spontaneous, the rational, and the dependent decision style.
- Only three of the seven importance weight variables are significant: these are the participant-researcher consensus measure (IMPOR_WEIGHT_FIT), and the participant's importance weight assessments for the criteria price (INDIV_W_PRICE) and number of employees (INDIV_W_EMPLOYEES).
- Based on the histograms of non-standardised residuals and the P-P plots of the expected and observed cumulated probabilities, the fit for the regressions of THRESHOLD and INCONCIS have been of poorer quality than the regression for NUMCOMP.
- The predictive power of the regressions was low and achieved about 29% of correct predictions for the number of companies selected in the choice set, 20% for the rejection threshold and about 40% for the number of inconsistencies.

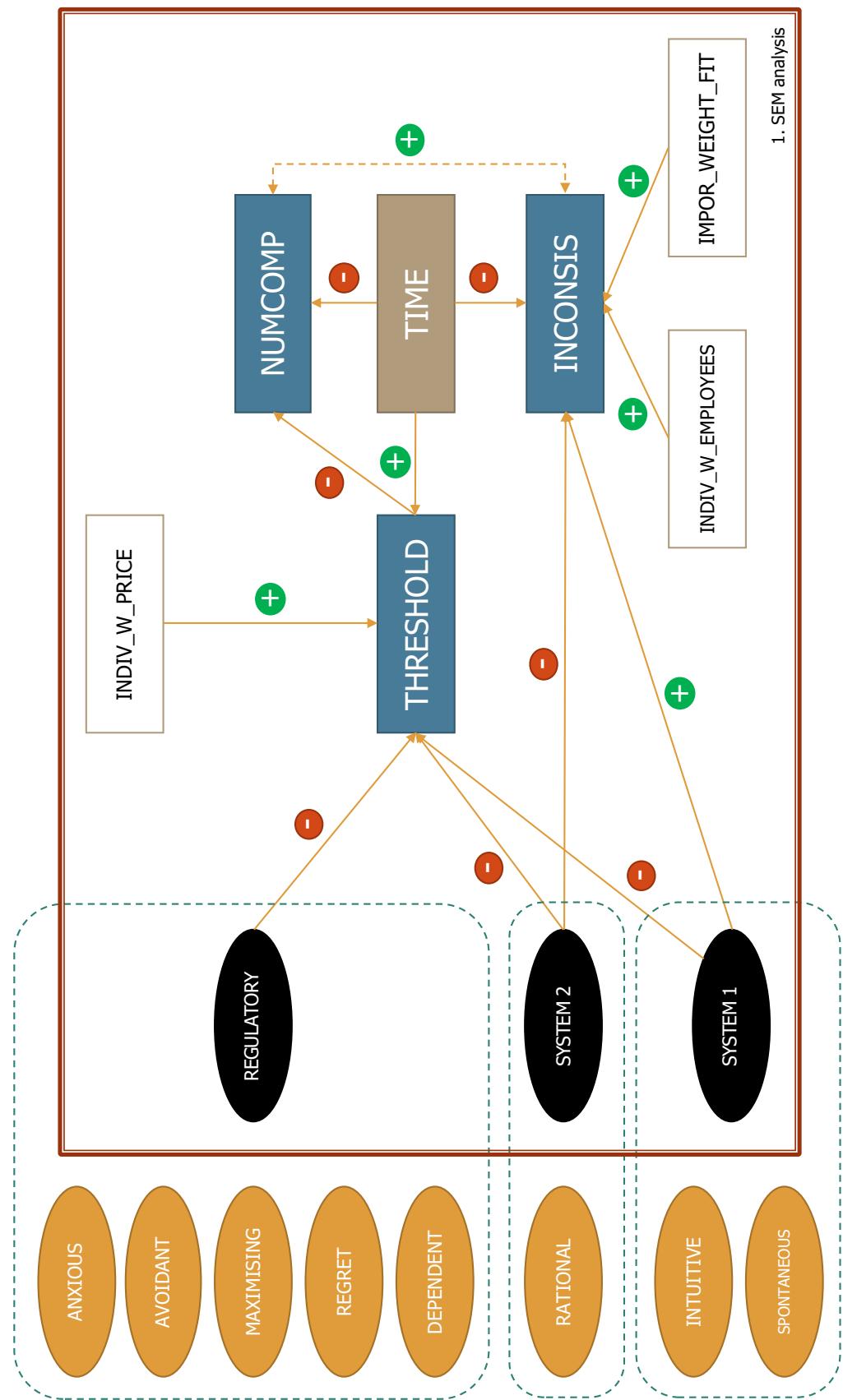
Based on these findings, the structural model of Figure 7 (see page 57) was revised taking into account the analyses performed so far in this research project. The result is shown in Figure 21 (see page 176). The coefficients have been omitted, only the direction of the respective effect is provided (positive or negative).

The left-hand side of Figure 21 has been determined when testing hypothesis 2 and is fundamentally confirming the findings of Dewberry et al. (2013). The negative influence of the process styles on the rejection threshold and other influences on the choice set variables by the factor TIME and the remaining importance weight variables are based on the findings of the respective regressions. The link between the number of companies selected and the number of inconsistencies stems from the correlation analysis and, thus, represents a reciprocal effect.

The model postulates that some of the effects discovered by the regression analyses are working through other variables. It is, for instance, assumed that the impact of the process style variables on the number of companies in the choice set 'flows' through the rejection threshold (THRESHOLD). This appears to be logical since the rejection threshold is existing before even a first company has been selected. TIME plays a central role in the decision process impacting independently all three choice set variables.

The influence of the participant-researcher consensus measure on the number of inconsistencies appears to be obvious as well. Somehow surprising is the influence of INDIV_W_PRICE on THRESHOLD as well as INDIV_W_EMPLOYEES on INCONIS respectively. Potentially, the latter can be explained by the 'fear' of laying off people that might influence the number of inconsistencies; the former might be driven by the reluctance to spend substantial amounts of money to buy a company.

The structural model was used as basis for the following SEM analysis.

*Figure 21:*

Structural model of decision styles' influences on Compatibility Test variables

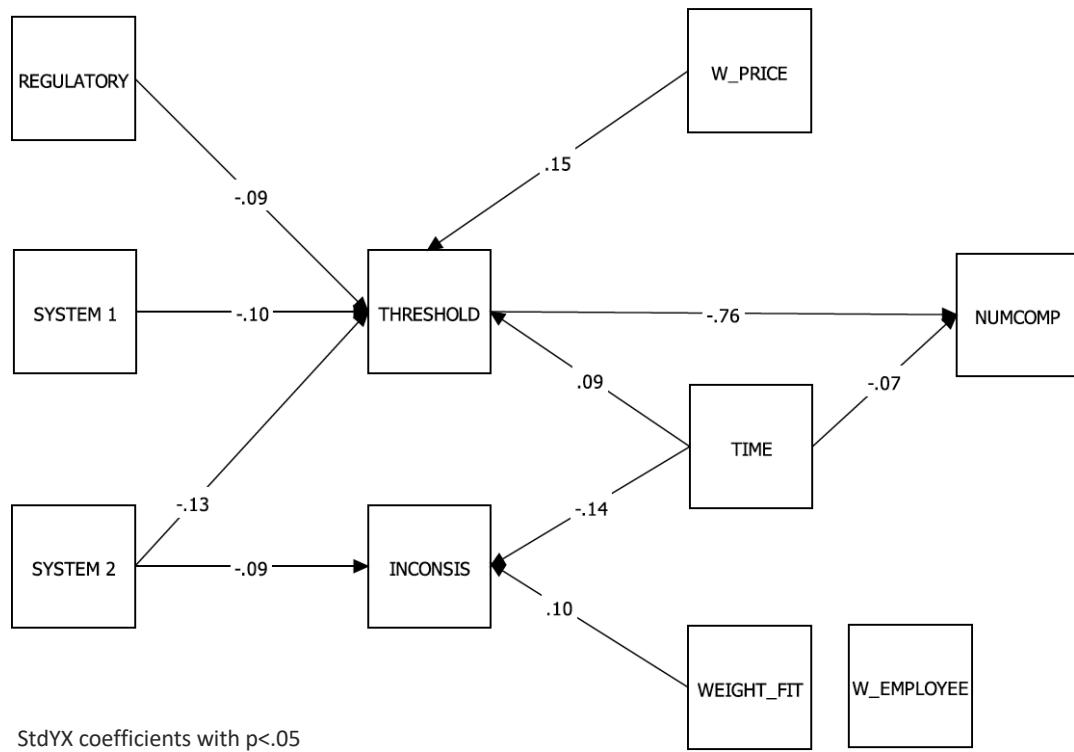
5.3.5 SEM analysis

So far, it has been demonstrated that eight factors can be extracted from the 40 questionnaire items designed to identify the participants' decision styles (decision profile). Subsequently, and for each participant, these decision styles have been calculated using the factor loadings of the five items selected from previous research to identify the respective decision style. Then, another three factors, the process styles, have been extracted from the calculated scores for the eight decision styles. A correlation analysis and a series of ANOVAs and regressions have identified relations between these three process styles and the choice set variables which appear to be influenced by other factors as well. Some of them were the importance weight variables, TIME and potentially some other factors outside the control of the experimental set-up. Based on the knowledge gained about the relationships between these variables, a coarse structure (see Figure 21, see previous page) was designed based on an even broader concept introduced in the hypothesis chapter (Figure 7, p. 57).

The last step is now to verify this structure with the help of a SEM analysis using MPlus. The starting point for the first structural model that was tested, were the three process styles (see the double-lined frame in Figure 21).

The structural path model of this SEM analysis for the Base Sample is shown in Figure 22. Paths with a statistical significance of $p>.15$ as well as effects with a size of smaller than .05 have been omitted. The variable names of INDIV_W_PRICE, INDIV_W_EMPLOYEES and IMPOR_WEIGHT_FIT have been abbreviated for ease of presentation.

As can be seen, the individual importance weight for the number of employees criterion has no link to the number of inconsistencies anymore since the respective coefficient became insignificant ($p>.46$). The coefficient indicating a link between SYSTEM1 and the number of inconsistencies has become insignificant as well ($p>.55$) and was very weak ($b_{SYSTEM1}<.05$). The remainder of the coefficients are in size and direction in line with the regression analyses.

*Figure 22:*

Structural model of the first MPlus SEM analysis on the Base Sample data

The respective standardised (StdYX⁹) coefficients, their p-values as well as the respective R² of the underlying regressions are summarised for this first SEM in Table 37, see next page). The covariance between INCONCIS and NUMCOMP took a standardised value (StdYX) of .637 (.618, non-standardised). The achieved model fit was very good with a significant χ^2 -test ($\chi^2 = 21.681; p < .0271$), a RMSEA of .04, a CFI of .99, a TLI of .98, and a SRMR of .04.

⁹ $b_{\text{StdYX}} = b * \text{Standard Deviation}(x) / \text{Standard Deviation}(y)$; (Muthén & Muthén, 1998-2017, p. 799)

Dependent Variable	R ²	THRESHOLD	REGULATORY	SYSTEM 1	SYSTEM 2	TIME	IMPOR_WEIGHT_FIT	INDIV_W_PRICE	INDIV_W_EMPLOYEES
THRESHOLD	.077	StdYX	-	-.092	-.104	-.134	.085	-	.146
		p<	-	.016	.007	.001	.028	-	.001
INCONSIS	.042	StdYX	-	-	.018	-.085	-.138	.096	-
		p<	-	-	.554	.005	.001	.003	-
NUMCOMP	.591	StdYX	-.785	-	-	-	-0.70	-	-
		p<	.001	-	-	-	.006	-	-

Table 37:

Standardised coefficients of the first SEM analysis on the Base Sample data

After this promising result, the author's next step was to perform an SEM analysis on the Base Sample data starting from the data of the eight decision styles, extract the process styles as latent variables and apply the rest of the structural model. The difference to the approach so far is that the calculation of the process style values was not based on the Anderson-Rubin approach but a result of respective regressions with Kaiser normalisation. The rotation method was again EQUAMAX (ORTHOGONAL). MPlus provided a warning when performing this SEM analysis. The text of that warning is shown in Appendix Syntax for the various analysis in MPlus. The problem involved the variable spontaneous for which the residual variance became (slightly) negative. Therefore, an R² for that variable was not calculated and respective regression values have to be considered with care. The calculation however terminated normally and for the rest of the variables no issues have been reported. Model fit was again very good with a highly significant χ^2 -test ($\chi^2 = 121.358$; p<.001), a RMSEA of .04, a CFI of .98, a TLI of .96, and a SRMR of .05.

The results (the StdYX coefficients) of this second SEM analysis are shown in Table 38a &b and in Figure 23 (see next page). In the latter, coefficients between the process styles and the decision styles (left-hand side of the diagram) that are below a strength of .40, have been omitted. This cut-off value was .05 for the coefficients between the process styles, the importance weight variables, time and the choice set variables (right-hand side of the diagram) and thus lower, since the effects have been weaker than those between decision and process styles.

Dependent		R ²	THRESHOLD	REGULATORY	SYSTEM 1		TIME	IMPOR_WEIGHT	INDIV_W_PRICE	INDIV_W_EMPL
Variable	THRESHOLD				SYSTEM 2	TIME				
THRESHOLD	.093	StdYX	-	-.120	-.092	-.191	.087	-	.151	-
		p<	-	.006	.116	.001	.025	-	.001	-
INCONSIS	.046	StdYX	-	-	.009	-.119	-.139	.096	-	.022
		p<	-	-	.769	.007	.001	.001	-	.491
NUMCOMP	.586	StdYX	-.755	-	-	-	-.71	-	-	-
		p<	.001	-	-	-	.006	-	-	-

Table 38a

Dependent		RATIONAL	INTUITIVE	SPONTANE	DEPENDEN	REGRET	ANXIOUS	MAXIMISIN	AVOIDANT
Variable	R ²	.382	.217	undef.	.439	.475	.696	.363	.679
REGULATORY	StdYX	-.034	.017	.076	.607	.669	.823	.586	.789
	p<	.0378	.533	.039	.001	.001	.001	.001	.001
SYSTEM 1	StdYX	-.104	.465	1.047	.061	.109	.006	.048	.040
	p<	.015	.002	.002	.204	.004	.859	.204	.299
SYSTEM 2	StdYX	.608	.024	-.375	.259	.122	-.136	-.134	-.230
	p<	.001	.448	.001	.001	.054	.036	.025	.001

Table 38b:

Standardised coefficients of the second SEM analysis on the Base Sample data

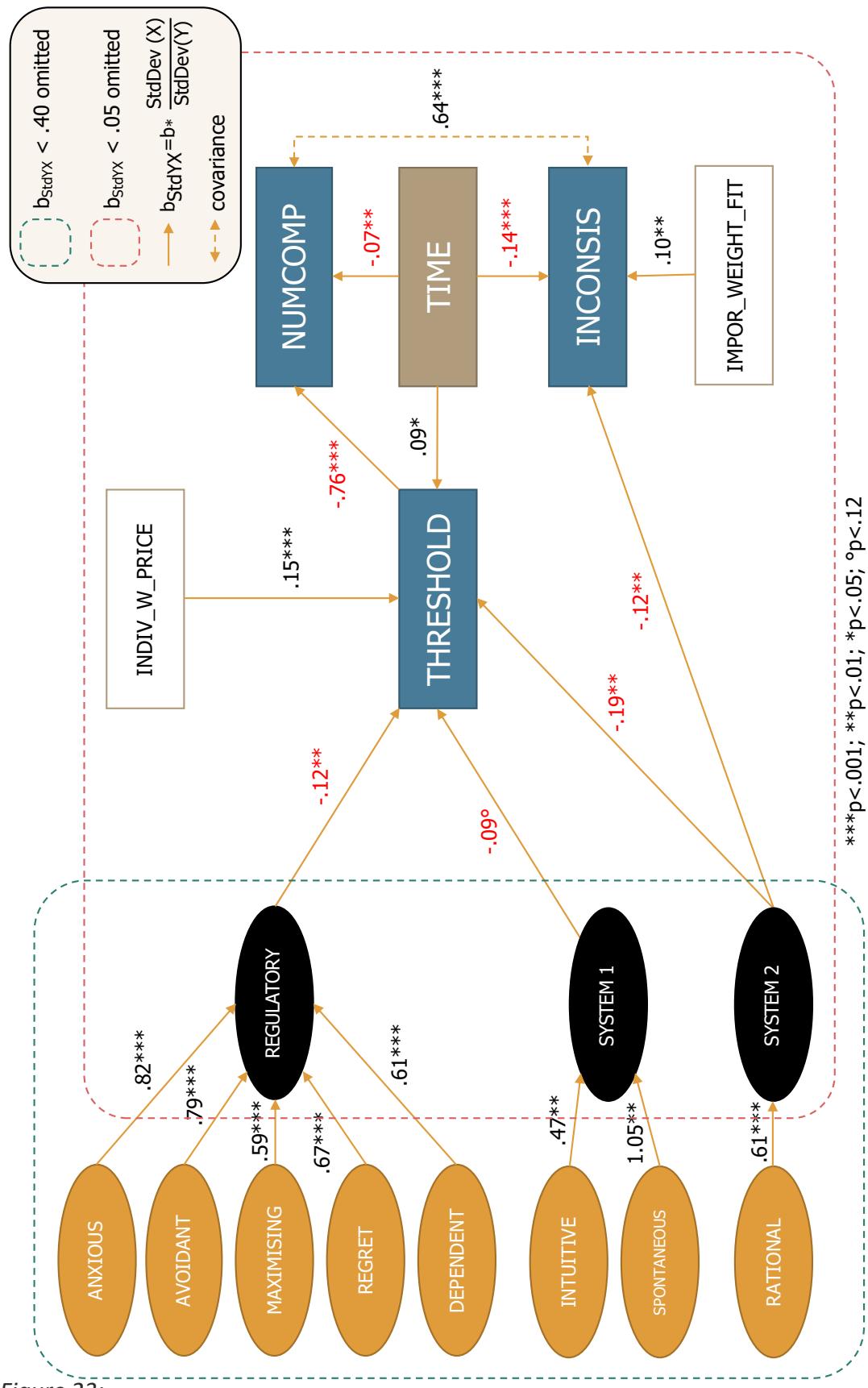


Figure 23:

StdYX coefficients of the second SEM analysis (Base Sample) for the full structural model

Further, the statistical significance of the coefficients between THRESHOLD and SYSTEM1 was the only one of the shown coefficients that was not below .05 (its value is $p < .12$). It was nevertheless kept in the result diagram since it was significant for the first SEM analysis. In contrast to the coefficient of INDIV_W_EMPLOYEES which was insignificant for both SEM analysis and, thus, is not shown in Figure 23.

The last step was to verify these findings with a third SEM on the Student Sample data. The respective MPlus SEM analysis did however not converge and no viable results were generated. Even an above default number of iterations (increase from 500 to 10,000) did not make the model converge for the Student Sample. The respective MPlus message stated that a residual value became negative, and that issues existed with variable SPONTANEOUS. Further, the χ^2 -statistic for model fit became negative.

Since the model could not be made converging which is most likely due to the small sample size ($N=87$ for the Student Sample), the author went one step back in his series of analyses and tested the 'right-hand side' model of Figure 23 with the Student Sample data. That is, the decision style variables were excluded from the SEM analysis and the starting point were the process style values calculated in the course of one of the former IBM SPSS factor analyses. Basically, the same syntax as for the first SEM analysis on the Base Sample was used to perform this fourth SEM analysis on the Student Sample.

This time the calculation of the estimates terminated normally. Some of the model fit parameters suggested a good fit of the model. The χ^2 -test of model fit was still significant ($\chi^2 = 19.858$; $p < .05$), the CFI was .95, and the SRMR took a value of .07. In contrast, the TLI was only .89 and the RMSEA was calculated with .10. Overall, the model fit was still deemed acceptable and the low performance of some model fit parameters appear again to be linked to the small sample size of Student Sample.

Figure 24 shows a graphical depict of the structural model achieved with the Student Sample data.

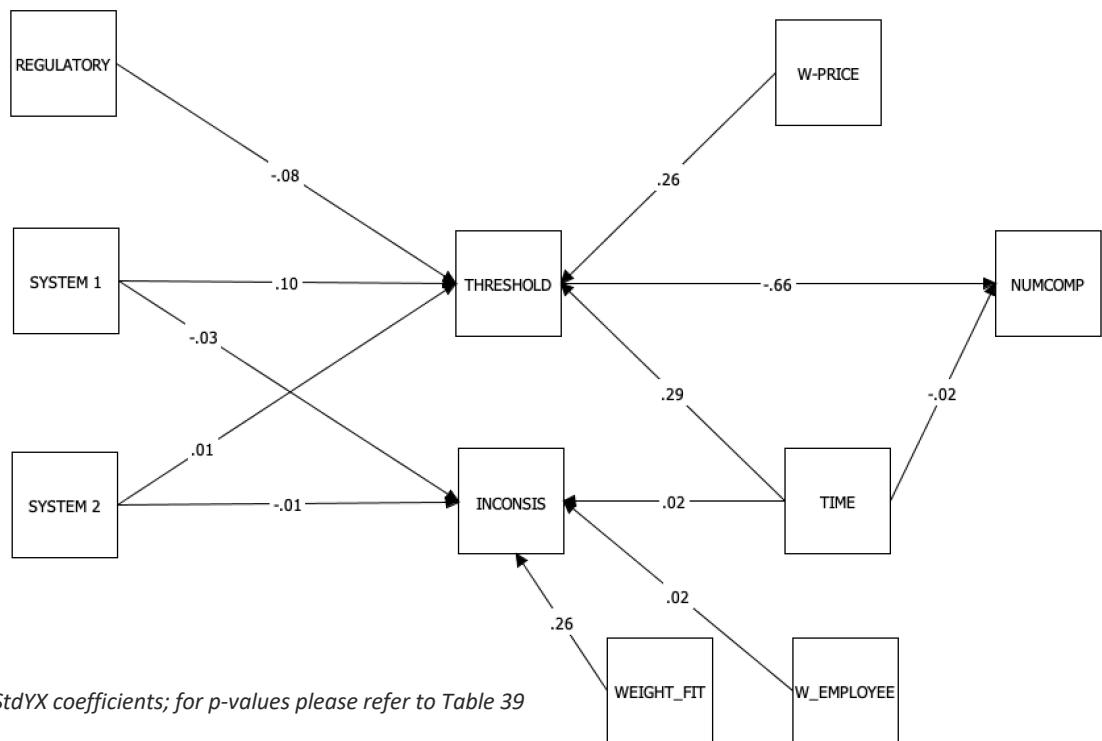


Figure 24:

Structural model of the first MPlus SEM analysis on the Student Sample data

The small sample size that appears to be responsible for the degradation of model fit, left its ‘track’ as well on the statistical significance of the calculated StdYX coefficients that are shown in Table 39 (see next page).

The covariance between NUMCOMP and INCONCIS was .842 ($p < .001$) for the Student Sample.

Dependent Variable	R ²	THRESHOLD	REGULATORY	SYSTEM 1	SYSTEM 2	TIME	IMPOR_WEIGHT_FIT	INDIV_W_PRICE	INDIV_W_EMPLOYEES
THRESHOLD	.139	StdYX	-	-.078	.105	.015	.292	-	.262
		p<	-	.444	.301	.882	.003	-	.009
INCONSIS	.061	StdYX	-	-	-.030	-.005	.019	.259	-
		p<	-	-	.606	.927	.858	.001	-
NUMCOMP	.437	StdYX	-.655	-	-	-	-.022	-	-
		p<	.001	-	-	-	.782	-	-

Table 39:

Results of the first SEM analysis on the Student Sample data

5.3.6 Discussion

In the context of testing hypothesis 3, the author has first performed a correlation analysis to unveil basic relations between the choice set variables and the other variables either directly collected via the questionnaire responses or derived from those. The correlation analysis unveiled some findings that are not subject to this research project and, thus, will not be considered further.

The next step and in preparation of the path analysis, a series of ANOVAs and regression analyses were performed with the choice set variables as dependent variables and the remaining variables as predictors.

5.3.6.1 Influence of demographic factors and time

The results showed that no impact of the demographic factors, age and gender, exists. Further, time to finish the survey appears to play a central role in the context of Image Theory's compatibility test since evidence of a respective influence on all three choice set variables was found.

5.3.6.2 Impact of decision and process styles

Further, the influence of all three process styles on the choice set variables was detected with statistical significance except for the regulatory process style or decision anxiety not having any relevant influence on the number of inconsistencies produced by the decision-maker. Even though the activities of the process styles are determined by the activities of all related decision styles, they appear to be mainly driven by four decision styles only: intuitive, spontaneous, rational and dependent.

5.3.6.3 Decision/process styles and number of alternatives in the choice set

First, the intuitive and dependent styles appear to impact the number of alternatives in the choice set; that is, the number of companies selected on the shortlist by a participant. The effects of both predictors are however weak but of the same strength and direction. This implies that a decision-maker scoring high in intuitive and dependent is likely to select a higher number of companies than someone with a lower score in these two decision styles. This appears reasonable since intuition is a feature of System 1 that is emotional, effortless and quick. A decision-maker who is intuitive might not want to

think too much about the reasons to reject a certain alternative, in particular, in the context of a screening process of which the outcome is not the one and only winning alternative that ought to be implemented, but a choice set that will be evaluated and processed further.

The activity of the dependent style might drive the influence of both process styles, of the regulatory style or decision anxiety, and of System 2. Decision-makers might be subject to anxiety because they fear to make an error when selecting a respective company. They might choose a company that is not in line with the requirements provided by the researcher or make an error of different nature. It is known from the analyses to test hypothesis 2 that the dependent style is linked with System 2 as well. Therefore, the influence of System 2 on the number of companies selected might be explained, at least partially, by the activity of the dependent style. A possible explanation might be that decision-makers rely on the requirements provided by the researcher; therefore, a sort of dependency might be created. They then have to consider, evaluate and conclude whether or not to put the respective company on their shortlists. Evaluation, consideration and thoughtful conclusions are the domain of System 2, hence, the impact of System 2 on the number of companies selected. Potentially, it could even be stated that the application of requirements that are not self-generated by the decision-maker but provided to or imposed on him or her by another party (i.e. by a researcher), must be burdened with System 2 processing since the decision-maker will have to understand the requirements, 'digest' and make meaning of them which can only be done by putting System 2 at work.

5.3.6.4 Decision/process styles and the rejection threshold

Second, the rational and intuitive styles are linked to the rejection threshold. Both decision styles' influence on the rejection threshold appears to be stronger than the influence of intuitive and dependent style on the number of selected companies. Further, both decision styles hold negative regression coefficients. That is, the more rational and intuitive decision-makers are, the lower are their rejection thresholds. This implies that the effect of rational and the intuitive styles on the rejection threshold leads to the same result as the effect of both styles on the number of companies on the shortlist. That is, the more salient these decision styles are in a decision-maker, the

higher the number of companies in that decision-maker's choice set. Keeping in mind the strong link between dependent and rational, the result for the rejection threshold is in line with and, thus, confirms the findings for the number of companies selected. Therefore, the chain of reasoning is the same.

5.3.6.5 Decision/process styles and inconsistent choices

Third, the impact of System 1 and 2 on the number of inconsistencies is determined by the decision styles spontaneous and rational. Both effects are very weak and of opposing direction: whilst a decision-maker with a high spontaneous score is prone to have more inconsistencies, the more rational decision-maker is set to have less. Considering the nature of System 1 and 2, this appears to be logical. Again, System 1 with its fast but frugal nature is more error prone than the cumbersome but analytical System 2.

5.3.6.6 Influence of importance weight and their alignment with third party requirements

Apart from the influence of the decision or process styles on the choice set variables, three of the importance weight variables also appeared to be significant: these are the participant-researcher consensus measure (IMPOR_WEIGHT_FIT) and the two individual criteria weights for price (INDIV_W_PRICE) and for the number of employees (INDIV_W_EMPLOYEES).

5.3.6.7 Importance of price and its impact on the number of selected companies and the rejection threshold

The individual price weight is negatively and strongly impacting the number of companies in the choice set. That is, the more important participants considered the acquisition price of a company, the less companies they have selected. This relationship comes as a surprise since there does not appear to exist a simple explanation for it. However, if decision-makers consider the price of a company as very important, they potentially do not want to spend a lot of money in the M&A process. Therefore, acting intuitively and unconsciously, they will select less companies than others. In combination with the already unveiled link between the intuitive style and the number of companies, this explanation might make sense.

The observed connection between the rejection threshold and the individual price weight confirms this finding: the more relevant the price is to decision-makers, the higher are their rejection thresholds, and, thus, the less companies they allow in their choice sets.

5.3.6.8 Importance weights and inconsistent choices

The two remaining significant importance weight variables IMPOR_WEIGHT_FIT and INDIV_W_EMPLOYEES are connected to the number of inconsistencies. The importance weight fit measure providing information on how well the participants' importance weights align with the requirements provided by the researcher, has a comparably high positively correlated impact on the number of inconsistencies. This appears to be logical: the more participants disagree with the researcher's assessment of the importance weights, the higher their scores of IMPOR_WEIGHT_FIT become, and, thus, the more prone they are to inconsistencies. The to the number of inconsistencies equally positively correlated coefficient of the individual importance weight for the criterion 'number of employees', is only half the strength of IMPOR_WEIGHT_FIT but of the same direction. This means that the higher participants evaluate the importance of the number of employees, the more inconsistencies can be found in their decision-making. There does not seem to be an explanation readily available. However, the significance of this relation was further investigated by the last series of analyses, the SEM analysis.

5.3.6.9 Structural Equation Modelling (SEM)

Four SEM analyses, two for the Base Sample and two for the Student Sample, have been conducted. The first SEM analysis (with the Base Sample data) and the last SEM analysis (with the Student Sample data) focused on the relations between the choice set variables and the process styles, TIME, and the importance weight variables.

Both SEM analyses confirmed the findings of the previous regressions with two exceptions. First, the influence of System 1 on the number of inconsistencies became non-significant, noting that the related significance was already at bordering level for one of the related regressions (INCONSIS regression n°4; standardised $b=.73$; $p<.063$).

Second, the individual importance weight for the criteria 'number of employees' became insignificant as well even though the same previous regression showed an acceptable significance level for this variable (standardised $b = .078$; $p < .042$).

For the last SEM analysis on the Student Sample, the significance suffered in general, but the resulting model fit parameters achieved satisfactory fit albeit not being on the level of the respective Base Sample SEM analysis.

These SEM analyses 'sharpened' the model. The second Base Sample SEM analysis eventually established the link from the choice set variables to the decision styles via the process styles that were calculated in this analysis as latent variables. The results confirmed on one side the findings of the regressions and the first and fourth SEM analysis, and on the other side again the Dewberry et al. (2013) model seeing the decision styles strongly linked to the process styles.

However, there are two facets that cast a little shadow on the findings: first, the third SEM analysis conducted with the Student Sample data did not converge since 'issues' with the values of the spontaneous style had been detected by MPlus. In retrospect, it can be confirmed that these issues exist as well for the second SEM analysis (on the Base Sample data) but were overcome by the large size of the Base Sample. The author believes that the issues with the spontaneous style stem from the poor factor loadings achieved by the respective questionnaire items that loaded better in the intuitive style than in the spontaneous style. The close links between the two styles underlined already by Dewberry et al. (2013, p. 567) might contribute further to the 'issues' found by MPlus. Therefore, and since the two styles represent the System 1 process styles, these problems might well explain the poor statistical significance of the System 1 impact on the rejection threshold and the number of inconsistencies.

Overall, however, it can be stated that hypothesis 3 is not falsified and, thus, cannot be rejected.

5.4 Hypothesis 4

Hypothesis 4 reads as follows...

"The data collected with the survey will allow to predict with high reliability (80% of correct predictions) the values of an individual's choice set variables."

The predictive capability of the regressions (see page 173, Table 36, last row) have been poor and ranged for the Base Sample data from 20% to 29% correct predictions for NUMCOMP, from 17% to 20% for THRESHOLD and from 38% to 40% for INCONSID. The enlargement of the prediction range (observed values ± 1) led obviously to an increase in predictive capability of the regressions: 40% to 53% of correct predictions for NUMCOMP and 29% to 32% for THRESHOLD. The prediction range relaxation was not performed for INCONSID since the mean value was (only) 1.2 and, thus, the prediction range relaxation would have been meaningless when a predicted value considered correct that was more than 80% off the mean.

Since the results of the regression analyses were poor and in order to improve predictive capabilities, the author formed value groups for each choice set variable, creating thus categorical variables that would allow the application of discriminant analysis. The results of the in total 52 discriminant analyses on the Base Sample for the entirety of the three choice set variables are provided in the next three subchapters.

Table 40 to Table 47 show the results of the discriminant analysis for each choice set variables.

5.4.1 Discriminant analyses for NUMCOMP

NUMCOMP_GROUP						
Discriminat Analysis n°: independent variables as input for the discriminant analysis:		1	2	3	4	5
Decision Styles ^a						
Demographic Factors ^b						
IMPOR_WEIGHT_FIT ^c						
all individual weights ^c						
Process Styles ^d						
Demographic Factors ^b						
IMPOR_WEIGHT_FIT ^c						
all individual weights ^c						
TIME, INTUITIVE, DEPENDENT						
TIME, PROCESS STYLES ^c						
TIME, INTUITIVE, DEPENDENT, INDIV_W_PRICE						
INDIV_W_PRICE						
Eigen Value ^e	.105	.109	.068	.090	.098	.116
Wilks Lambda ^f	.890**	.899**	.931**	.910	.902**	.884**
Chi square value	75.152	75.469	45.864	60.844	66.083	79.487
p-value	p<.001	p<.001	p<.001	p<.001	p<.001	p<.001
method	stepwise ^h	stepwise ^h	all-in	all-in	all-in	all-in
TIME	standardized canonical ^e	.487	.446	- .584	- .516	.445
	max. correlation w/ function ⁱ	.519/1	.509/1	.742/2	.758/2	.540/1
	equality of group means ^g	.971**	.971**	.971**	.971**	.971**
SYSTEM 1	standardized canonical ^e	-	- .507	-	.620	-
	max. correlation w/ function ⁱ	-	.677/3	-	.662/1	-
	equality of group means ^g	-	.961**	-	.961**	-
SYSTEM 2	standardized canonical ^e	-	- .417	-	.522	-
	max. correlation w/ function ⁱ	-	.726/2	-	.722/2	-
	equality of group means ^g	-	.979**	-	.979**	-
REGULATORY	standardized canonical ^e	-	-	-	.279	-
	max. correlation w/ function ⁱ	-	-	-	.283/1	-
	equality of group means ^g	-	-	-	.993+	-
INTUITIVE	standardized canonical ^e	- .526	-	.652	-	- .486
	max. correlation w/ function ⁱ	.739/3	-	.718/1	-	- .579/1
	equality of group means ^g	.966**	-	.966**	-	.966**
ANXIOUS	standardized canonical ^e	-	-	-	-	-
	max. correlation w/ function ⁱ	-	-	-	-	-
	equality of group means ^g	-	-	-	-	-
RATIONAL	standardized canonical ^e	- .403	-	-	-	-
	max. correlation w/ function ⁱ	.750/2	-	-	-	-
	equality of group means ^g	.982**	-	-	-	-
DEPENDENT	standardized canonical ^e	-	-	.380	-	- .285
	max. correlation w/ function ⁱ	-	-	- .705/3	-	.568/2
	equality of group means ^g	-	-	.986*	-	.986*
INDIV_W_PRICE	standardized canonical ^e	.523	.510	-	-	.572
	max. correlation w/ function ⁱ	.625/1	.619/1	-	-	.665/1
	equality of group means ^g	.957**	.957**	-	-	.957**
	% correct predictions	31%	27%	27%	30%	29%
						28%

**p<0.01; *p<0.05; ^not significant

^a AVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL^b GENDER, AGE, TIME^c INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^d REGULATORY, SYSTEM 1, SYSTEM 2^e for first function^f for function 1 through 2 or 3 respectively^g Wilks' Lambda with Chi-Square probability^h for stepwise method: to enter variable p<.05; to remove variable p>.10ⁱ taken from the SPSS output structure matrix

Table 40

Results for the discriminant analyses for the categorical variable NUMCOMP_GROUP

NUMCOMP_GROUP2						
Discriminant Analysis n°:		1	2	3	4	5
independent variables as input for the discriminant analysis:		Decision Styles ^a IMPOR_WEIGHT_FIT	Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	Process Styles ^d Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	TIME, INTUITIVE, DEPENDENT	TIME, Process Styles ^c TIME, INTUITIVE, DEPENDENT, INDIV_W_PRICE
**p<0.01; *p<0.05; +not significant						
Eigen Value ^e	.115	.108	.066	.089	.095	.114
Wilks Lambda ^f	.883**	.893**	.935**	.913**	.907**	.887**
Chi square value	80.262	73.214	43.308	58.747	63.076	76.936
p-value	p<.001	p<.001	p<.001	p<.001	p<.001	p<.001
method	stepwise ^g	stepwise ^h	all-in	all-in	all-in	all-in
TIME	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.454 -.491/1 .971**	.456 .516/1 .971**	-.605 .753/2 .971**	-.527 .748/2 .971**	.462 .556/1 .971**
SYSTEM 1	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.495 -.584/1 .964**	- - -	.607 .650/1 .964**	- - .
SYSTEM 2	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.427 .716/2 .979**	- - -	.532 .735/2 .979**	- - .
REGULATORY	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- .274 .279/1	- - .	.234 .243/1 .993+
INTUITIVE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.504 .541/1 .967**	- - -	.647 .713/1 .967**	- - -	-.480 .630/2 .967**
ANXIOUS	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.302 .278/2 .991*	- - -	- - -	- - -	- - -
RATIONAL	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.447 .605/2 .983**	- - -	- - -	- - -	- - -
DEPENDENT	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	.354 .429/2 .989*	- - -	-.264 .475/2 .989*
INDIV_W_PRICE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.490 -.583/1 .958**	.506 .617/1 .958**	- - -	.573 .667/1 .958**	-.488 -.597/1 .958**
% correct predictions		50%	50%	46%	49%	49%
						52%

^a**p<0.01; *p<0.05; +not significant^b AVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL^c GENDER, AGE, TIME^d INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^e REGULATORY, SYSTEM 1, SYSTEM 2^f for first function^g for function 1 through 2 or 3 respectively^h Wilks' Lambda with Chi-Square probabilityⁱ for stepwise method: to enter variable p<.05; to remove variable p>.10^j taken from the SPSS output structure matrix

Table 41:

Results for the discriminant analyses for the categorical variable NUMCOMP_GROUP2

NUMCOMP_GROUP3						
Discriminat Analysis n°:		1	2	3	4	5
independent variables as input for the discriminant analysis:		Decision Styles ^a Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	Process Styles ^d Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	TIME, INTUITIVE, DEPENDENT	TIME, Process Styles ^c	TIME, INTUITIVE, DEPENDENT, INDIV_W_PRICE
p<0.01; *p<0.05; +not significant		Eigen Value ^e Wilks Lambda ^f Chi square value p-value method	.070 .934 43.891 p<.001 stepwise ^h	.072 .933** 44.777 p<.001 stepwise ^h	.043 .959** 26.900 p<.001 all-in	.051 .952** 31.978 p<.001 all-in
TIME	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.505 .605 .975**	.479 .599 .975**	-.733 -.778 .975**	-.669 -.712 .975**	.495 .595 .975**
SYSTEM 1	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.414 -.539 .980**	- - -	.563 .640 .980**	- - .980**
SYSTEM 2	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	.352 .276 .996*	- - .996*
REGULATORY	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	.245 .268 .996*	- - .996*
INTUITIVE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.389 -.485 .984**	- - -	.545 .623 .984**	- - -	-.368 -.476 .984**
ANXIOUS	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	- - -	- - -
RATIONAL	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	- - -	- - -
DEPENDENT	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	.274 .328 .995*	- - -	-.187 -.250 .995*
INDIV_W_PRICE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.669 .756 .961**	.656 .748 .961**	- - -	- - -	.651 .743 .961**
	% correct predictions	61%	60%	58%	58%	61%
						62%

^a **p<0.01; *p<0.05; +not significant^b AVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL^c GENDER, AGE, TIME^d INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^e REGULATORY, SYSTEM 1, SYSTEM 2^f for first function^g for function 1 through 2 or 3 respectively^h Wilks' Lambda with Chi-Square probabilityⁱ for stepwise method: to enter variable p<.05; to remove variable p>.10^j taken from the SPSS output structure matrix

Table 42:

Results for the discriminant analyses for the categorical variable NUMCOMP_GROUP3

The prediction accuracy for the NUMCOMP group variables ranged from 27% to 31% for NUMCOMP_GROUP, from 48% to 52% for NUMCOMP_GROUP2 and from 58% to 62% for NUMCOMP_GROUP3. The highest predictive power (62% of correct predictions) was achieved by the discriminant analysis n°6 on NUMCOMP_GROUP3 (see Table 42) as

dependent variable and TIME, SYSTEM1, SYSTEM2 and INDIV_W_PRICE as predictors. The discriminant function for this analysis was:

$$DS_{NC} = -3.016 + .431 * TIME + 8.651 * INDIV_W_PRICE - \\ -.190 * REGULATORY - .400 * SYSTEM1 - .246 * SYSTEM2 \quad (17)$$

Based on equation (17), a discriminant score has been calculated for each participant. The probability that participants belong either in group 1 (NUMCOMP_GROUP3 = 1), that is, they select up to 4 companies in their choice sets, or in group 2 (NUMCOMP_GROUP3 = 2) which implies the participants allow more than 4 companies on their 'shortlists', displayed over the individuals' discriminant scores resulted in the diagram below.

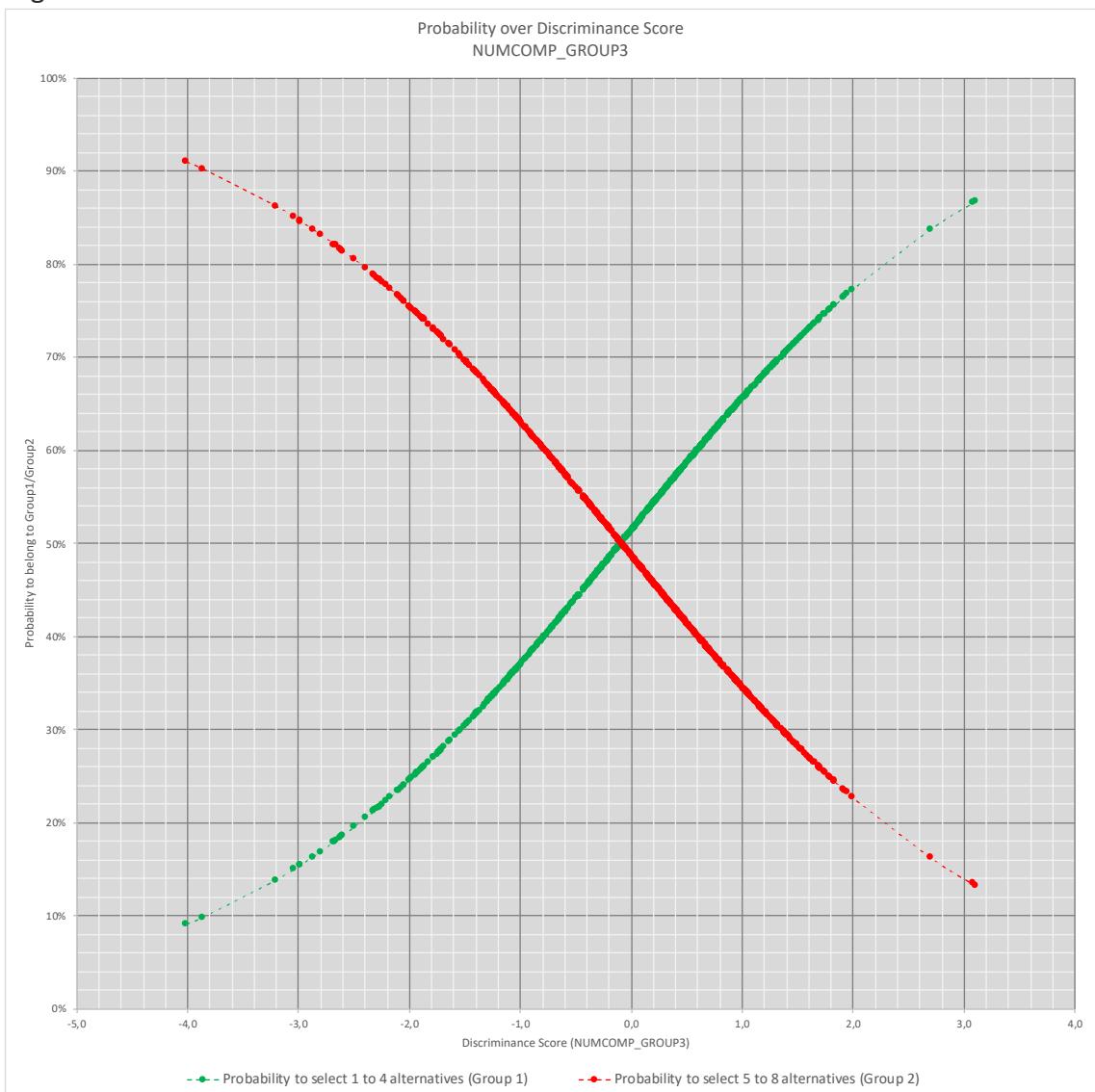


Figure 25:

Probability for a participant to select at least five or less companies

Figure 25 can be used to determine the probability of a decision-maker to select at least five companies or less in the context of the questionnaire task. All it requires, is the input variables TIME, INDIV_W_PRICE, SYSTEM 1, SYSTEM 2, and REGULATORY that will allow the calculation of the decision-maker's discriminant score. This score can then be used to determine the decision-makers probability to select at least five or less companies with the help of the above diagram.

Then, the data of the Student Sample was used to test the predictive capability of the discriminant function for NUMCOMP with the highest predictive capability for the Base Sample data. A discriminant value has been calculated for each participant of the Student Sample. Then, using Microsoft Excel's 'TREND' function with the Student Sample discriminant scores and the Base Sample data as reference, a probability was calculated for each member of the Student Sample. Based on this probability the Student Sample participants were allocated either in group 1 (NUMCOMP_GROUP3 = 1) or group 2 (NUMCOMP_GROUP3 = 2).

Based on the described procedure, 39 (45%) participants of the 'Student Group' have been allocated correctly and 48 (55%) incorrectly.

5.4.2 Discriminant analyses for THRESHOLD

		THRESHOLD_GROUP					
Discriminat Analysis n°:		1	2	3	4	5	6
independent variables as input for the discriminant analysis:		Decision Styles ^a Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	Decision Styles ^a Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	TIME, INTUITIVE, RATIONAL	TIME, Process Styles ^c	TIME, INTUITIVE, RATIONAL, INDIV_W_PRICE	TIME, Process Styles ^c , INDIV_W_PRICE
p<0.01; *p<0.05; +not significant		Eigen Value ^e .824 Chi square value 124.733 p-value p<.001 method stepwise ^h	.161 .826** 122.555 p<.001 stepwise ^h	.160 .921** 53.063 p<.001 all-in	.067 .895** 71.690 p<.001 all-in	.097 .867** 91.950 p<.001 all-in	.128 .844** 109.273 p<.001 all-in
TIME	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.363 .464/1 .965**	.352 .456/1 .965**	.685 .680/1 .965**	.541 .595/1 .965**	.410 .600/3 .965**	.356 .456/1 .965**
SYSTEM 1	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.442 -.522/1 .958**	- - -	.625 .718/3 .958**	- - -	.454 .529/1 .958**
SYSTEM 2	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.153 .694/2 .980**	- .970/2 .980**	.262 .970/2 .980**	- - -	.187 .891/2 .980**
REGULATORY	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.346 .464/3 .980**	- - -	.460 .634/3 .980**	- - -	.356 .430/3 .980**
INTUITIVE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	.659 .878/2 .970**	- - -	-.431 -.488/1 .970**	- - -
ANXIOUS	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.331 .643/3 .976**	- - -	- - -	- - -	- - -	- - -
REGRET	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.331 .643/3 .976**	- - -	- - -	- - -	- - -	- - -
RATIONAL	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.306 .676/2 .983*	- - -	.375 .731/3 .983*	- - -	-.228 .877/2 .983*	- - -
SPONTANEOUS	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	-.475 -.481/1 .960**	- - -	- - -	- - -	- - -	- - -
IMPOR_WEIGHT_FIT	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	- - -	- - -	- - -
INDIV_W_PRICE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.624 .668/1 .926**	.627 .687/1 .926**	- - -	- - -	.710 .784/1 .926**	.630 .704/1 .926**
INDIV_W_EMPLOYEE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	- - -	- - -	- - -
INDIV_W_PROFIT	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.237 .614/2 .979**	.196 .659/2 .978**	- - -	- - -	- - -	- - -
% correct predictions		41%	40%	34%	35%	40%	39%

*p<0.05; **p<0.01; +not significant

^aAVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL

^b GENDER, AGE, TIME

^c INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY

^d REGULATORY, SYSTEM 1, SYSTEM 2

^efor first function

^f for function 1 through 2 or 3 respectively

^g Wilks' Lambda with Chi-Square probability

^h for stepwise method: to enter variable p<.05; to remove variable p>.10

ⁱ taken from the SPSS output structure matrix

Table 43:

Results for the discriminant analyses for the categorical variable THRESHOLD_GROUP

THRESHOLD_GROUP2							
Discriminant Analysis n°: independent variables as input for the discriminant analysis:		1	2	3	4	5	
Decision Styles ^a	Decision Styles ^a						
Demographic Factors ^b	Demographic Factors ^b						
IMPOR_WEIGHT_FIT	IMPOR_WEIGHT_FIT						
all individual weights ^c	all individual weights ^c						
Process Styles ^d	Process Styles ^d						
Demographic Factors ^b	Demographic Factors ^b						
IMPOR_WEIGHT_FIT	IMPOR_WEIGHT_FIT						
all individual weights ^c	all individual weights ^c						
TIME, INTUITIVE, RATIONAL	TIME, INTUITIVE, RATIONAL						
TIME, Process Styles ^e	TIME, Process Styles ^e						
TIME, INTUITIVE, RATIONAL, INDIV_W_PRICE	TIME, INTUITIVE, RATIONAL, INDIV_W_PRICE						
INDIV_W_PRICE	INDIV_W_PRICE						
6	6						
Eigen Value ^e	.093	.094	.040	.056	.070	.086	
Wilks Lambda ^f	.898**	.890**	.949**	.932**	.920**	.906**	
Chi square value	69.312	74.703	34.099	45.328	53.409	63.501	
p-value	p<.001	p<.001	p<.001	p<.001	p<.001	p<.001	
method	stepwise ^g	stepwise ^h	all-in	all-in	all-in	all-in	
TIME	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	-.386 -.473/1 .980**	.357 .469/1 .980**	-.641 -.626/1 .980**	-.521 -.580/1 .980**	.444 .513/1 .980**	
SYSTEM 1	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.409 -.519/1 .975**	- - -	.620 .674/1 .975**	- - .975**	
SYSTEM 2	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	-.101 .825/2 .981**	- - -	.338 .955/2 .981**	- .973/2 .981**	
REGULATORY	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- .434/1 .989*	.426 - -	.344 .352/1 .989*	
INTUITIVE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- .643/1 .984**	- - -	- -.412 .984**	- - -	
ANXIOUS	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	- - -	- - -	
REGRET	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	- - -	- - -	- - -	- - -	
RATIONAL	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.283 .913/2 .984**	- - -	.511 .865/2 .984**	- - -	-.282 .916/2 .984**	- - -
SPONTANEOUS	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.524 .534/1 .973**	- - -	- - -	- - -	- - -	- - -
IMPOR_WEIGHT_FIT	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.641 .694/1 .957**	- - -	- - -	- - -	- - -	- - -
INDIV_W_PRICE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	.602 .655/1 .960**	- - -	- - -	.670 .763/1 .960**	-.599 -.695/1 .960**
INDIV_W_EMPLOYEE	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	.289 -.379/2 .990*	- - -	- - -	- - -	- - -	- - -
INDIV_W_PROFIT	standardized canonical ^e max. correlation w/ function ⁱ equality of group means ^g	- - -	.475 .507/2 .975**	- - -	- - -	- - -	- - -
% correct predictions	49%	49%	42%	45%	45%	47%	

^a*p<0.01; *p<0.05; ^not significant^bGENDER, AGE, TIME^cINDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^dREGULATORY, SYSTEM 1, SYSTEM 2^efor first function^ffor function 1 through 2 or 3 respectively^gWilks' Lambda with Chi-Square probability^hfor stepwise method: to enter variable p<.05; to remove variable p>.10ⁱtaken from the SPSS output structure matrix

Table 44:

Results for the discriminant analyses for the categorical variable THRESHOLD_GROUP2

THRESHOLD_GROUP3						
	1	2	3	4	5	6
Discriminat Analysis n°: independent variables as input for the discriminant analysis:	Decision Styles ^a IMPOR_WEIGHT_FIT all individual weights ^c	Decision Styles ^d Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	TIME, INTUITIVE, RATIONAL	TIME, Process Styles ^c	TIME, INTUITIVE, RATIONAL, INDIV_W_PRICE	TIME, Process Styles ^c , INDIV_W_PRICE
**p<0.01; *p<0.05; +not significant	.073	.075	.040	.051	.065	.075
Eigen Value ^e Wilks Lambda ^f Chi square value p-value method	.932** 45.222 p<.001 stepwise ^h	.930** 46.868 p<.001 stepwise ^h	.962** 25.189 p<.001 all-in	.951** 32.341 p<.001 all-in	.939** 40.533 p<.001 all-in	.930** 46.868 p<.001 stepwise ^h
TIME	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	-.350 -.425 .987**	-.323 -.417 .987**	-.603 -.574 .987**	-.467 -.505 .987**	.399 .450 .987**
SYSTEM 1	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	.431 .521 .980**	- -.631 .980**	.584 -.431 -.431	- -.521 .980**
SYSTEM 2	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	.391 .371 .990*	- -.450 .990*	.511 -.371 -.390	- -.371 .990*
REGULATORY	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	.330 .339 .991*	- -.411 .991*	.404 -.339 -.330	- -.339 .991*
INTUITIVE	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	.416 .470 .984**	- -.635 .984**	.628 -.441 -.497	- -.441 -.497	- -.497 -.497
ANXIOUS	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	- -.635 -.984**	- -.445 -.992*	- -.420 -.349	- -.420 -.349
REGRET	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	.330 .394 .989**	- -.635 -.989**	- -.445 -.992*	- -.420 -.349	- -.420 -.349
RATIONAL	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	.379 .329 .992*	- -.645 -.992*	.575 -.445 -.992*	- -.420 -.349	- -.420 -.349
SPONTANEOUS	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	- -.645 -.992*	- -.445 -.992*	- -.420 -.349	- -.420 -.349
IMPOR_WEIGHT_FIT	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	- -.645 -.992*	- -.445 -.992*	- -.420 -.349	- -.420 -.349
INDIV_W_PRICE	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	-.587 -.684 .967**	-.571 -.672 .967**	- -.629 -.724	- -.629 -.724	- -.571 -.672
INDIV_W_EMPLOYEE	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	- -.645 -.967**	- -.445 -.967**	- -.420 -.349	- -.420 -.349
INDIV_W_PROFIT	standardized canonical ^g max. correlation w/ function ⁱ equality of group means ^g	- - -	- -.645 -.967**	- -.445 -.967**	- -.420 -.349	- -.420 -.349
% correct predictions		66%	65%	58%	62%	64%
65%						

^a*p<0.01; *p<0.05; +not significant^b AVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL^c GENDER, AGE, TIME^d INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^e REGULATORY, SYSTEM 1, SYSTEM 2^f for first function^g for function 1 through 2 or 3 respectively^h Wilks' Lambda with Chi-Square probabilityⁱ for stepwise method: to enter variable p<.05; to remove variable p>.10^j taken from the SPSS output structure matrix

Table 45:

Results for the discriminant analyses for the categorical variable THRESHOLD_GROUP3

Prediction accuracy for the THRESHOLD group variables ranged from 34% to 41% for THRESHOLD_GROUP, from 42% to 49% for THRESHOLD_GROUP2 and from 58% to 66% for THRESHOLD_GROUP3. The highest prediction capability (66% of correct predictions) was achieved by the discriminant analysis n°1 on THRESHOLD_GROUP3 as dependent variable and TIME, INTUITIVE, REGRET, RATIONAL and INDIV_W_PRICE as predictors. As for the diagram for NUMCOMP_GROUP3, Figure 26 (see next page) provides a diagram that allows to predict the probability of a participant having a rejection threshold of equal to or higher than -4 or lower than -4 based on the participant's discriminant score that was calculated based on following equation:

$$\begin{aligned} DS_{TH} = & -3.537 - .316 * TIME - 8.341 * INDIV_W_PRICE + \\ & + .537 * REGRET + .826 * INTUITIVE + .807 * RATIONAL \end{aligned} \quad (18)$$

Based on the already above described procedure (see page 195), 64 (74%) participants of the Student Sample have been allocated correctly and 23 (26%) incorrectly.

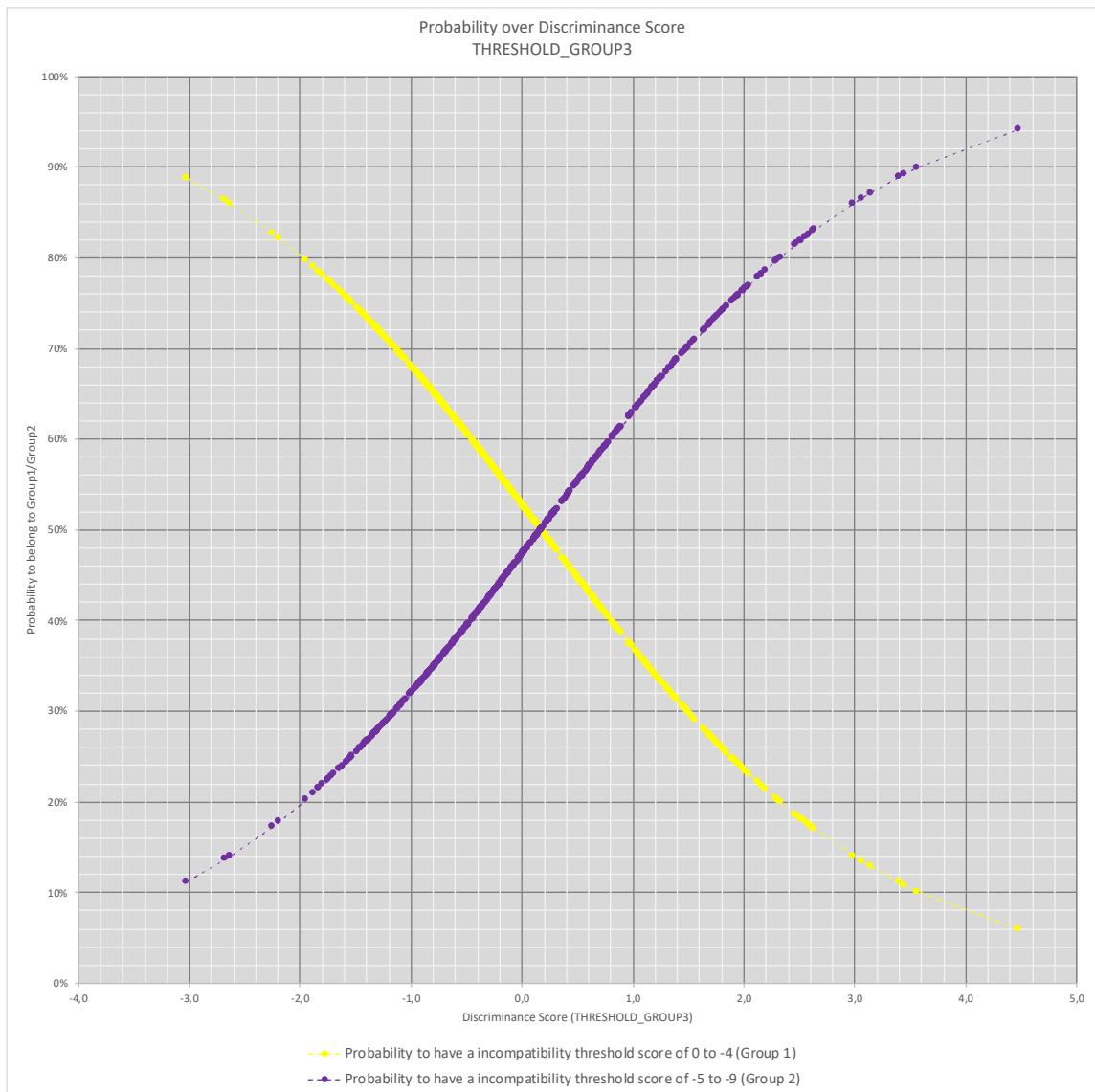


Figure 26:

Probability of a participant having a rejection threshold of minimum -4 or less

5.4.3 Discriminant analyses for INCONIS

INCONIS_GROUP							
Discriminat Analysis n°:		1	2	3	4	5	6
	independent variables as input for the discriminant analysis:	Decision Styles ^a Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	Process Styles ^d Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	TIME, SPONTANEOUS, RATIONAL	TIME, SYSTEM 1, SYSTEM 2	TIME, SPONTANEOUS, RATIONAL, INDIV_W_EMPLOYEE, IMPOR_WEIGHT_FIT	TIME, SYSTEM 1, SYSTEM 2, INDIV_W_EMPLOYEE, IMPOR_WEIGHT_FIT
p<0.01; *p<0.05; +not significant	Eigen Value ^e Wilks Lambda ^f Chi square value p-value method	.044 .947 35.226 p<.001 stepwise ^h	.042 .953** 31.360 p<.001 stepwise ^h	.039 .959** 27.339 p<.001 all-in	.033 .960** 26.147 p<.001 all-in	.060 .938** 40.933 p<.002 all-in	.054 .941** 39.078 p<.001 all-in
TIME	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	- - -	- -.623/1 .985**	.497 .626/1 .985**	.563 .676/1 .985**	-.360 -.504/1 .985**	-.396 -.527/1 .985**
SYSTEM 1	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	- - -	.475 .683/2 .983**	- -.759/2 .983**	-.540 -.759/2 .983**	- -.706/2 .983**	-.354 -.706/2 .983**
SYSTEM 2	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	- - -	-.500 .733/2 .987*	- -.623/2 .987**	.518 .623/2 .987**	- -.657/2 .987**	-.420 .657/2 .987**
INTUITIVE	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	.152 .850/2 .988*	- - -	- -.549 .978**	- -.549 .978**	- -.447 .727/2 .978**	- -.447 .727/2 .978**
SPONTANEOUS	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	- - -	- -.676/1 .981**	-.418 -.676/1 .981**	- -.560/1 .981**	.303 .560/1 .981**	.497 .618/1 .981**
RATIONAL	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	-.688 -.684/1 .978**	- -.743/1 .978**	.549 .743/1 .978**	- -.727/2 .978**	-.447 .727/2 .978**	- -.447 .727/2 .978**
IMPOR_WEIGHT_FIT	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	.692 .701/1 .978**	.678 .728/1 .978**	- -.599/1 -.978**	- -.599/1 -.978**	.559 .641/1 .978**	.583 .665/1 .978**
INDIV_W_EMPLOYEE	standardized canonical ⁱ max. correlation w/ function ^j equality of group means ^g	- - -	- -.248/2 -.996 ^k	- -.248/2 -.996 ^k	- -.248/2 -.996 ^k	.230 .256/1 .996 ^k	.250 .394/2 .996 ^k
	% correct predictions	36%	36%	33%	35%	35%	36%

^ap<0.01; *p<0.05; +not significant^bAVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL^cGENDER, AGE, TIME^dINDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^eREGULATORY, SYSTEM 1, SYSTEM 2^ffor first function^gfor function 1 through 2 or 3 respectively^hWilks' Lambda with Chi-Square probabilityⁱfor stepwise method: to enter variable p<.05; to remove variable p>.10^jtaken from the SPSS output structure matrix

Table 46:

Results for the discriminant analyses for the categorical variable INCONIS_GROUP

Prediction accuracy for the INCONIS group variables ranged from 33% to 36% for INCONIS_GROUP and from 52% to 62% for INCONIS_GROUP2. The highest prediction capability (62% of correct predictions) was achieved by the discriminant analysis n°7 on INCONIS_GROUP2 as dependent variable and TIME, SPONTANEOUS, IMPOR_WEIGHT_FIT and INDIV_W_EMPLOYEE as predictors.

INCONSI_GROUP2									
Discriminat Analysis n°: independent variables as input for the discriminant analysis:		1	2	3	4	5	6		
		Decision Styles ^a IMPOR_WEIGHT_FIT all individual weights ^c	Demographic Factors ^b IMPOR_WEIGHT_FIT all individual weights ^c	Process Styles ^d IMPOR_WEIGHT_FIT all individual weights ^c	TIME, SPONTANEOUS, RATIONAL	TIME, SYSTEM 1, SYSTEM 2	TIME, SPONTANEOUS, RATIONAL, INDIV_W_EMPLOYEE, IMPOR_WEIGHT_FIT	TIME, SYSTEM 1, SYSTEM 2, INDIV_W_EMPLOYEE, IMPOR_WEIGHT_FIT	TIME, SPONTANEOUS, INDIV_W_EMPLOYEE, IMPOR_WEIGHT_FIT
		.062	.062	.037	.034	.069	.065	.067	.067
	Eigen Value ^e								
	Wilks Lambda ^f	.941**	.941**	.964**	.967**	.936**	.939**	.937**	.937**
	Chi square value	39.005	39.005	23.517	21.671	42.928	40.822	42.057	42.057
	p-value	p<.001	p<.001	p<.001	p<.001	p<.001	p<.001	p<.001	p<.001
	method	stepwise ^h	stepwise ^h	all-in	all-in	all-in	all-in	all-in	all-in
TIME	standardized canonical ⁱ	-.632	-.632	.803	.859	-.550	-.584	-.567	-.567
	max. correlation w/ function ^j	-.681	-.681	.882	.920	-.648	-.665	-.655	-.655
	equality of group means ^g	.972**	.972**	.972**	.972**	.972**	.972**	.972**	.972**
SYSTEM 1	standardized canonical ⁱ	-	-	-	-.364	-	.176	-	-
	max. correlation w/ function ^j	-	-	-	-.474	-	.343	-	-
	equality of group means ^g	-	-	-	.992*	-	.992*	-	-
SYSTEM 2	standardized canonical ⁱ	-	-	-	.160	-	-.134	-	-
	max. correlation w/ function ^j	-	-	-	.234	-	-.169	-	-
	equality of group means ^g	-	-	-	.998*	-	.998*	-	-
INTUITIVE	standardized canonical ⁱ	-	-	-	-	-	-	-	-
	max. correlation w/ function ^j	-	-	-	-	-	-	-	-
	equality of group means ^g	-	-	-	-	-	-	-	-
SPONTANEOUS	standardized canonical ⁱ	-	-	-.388	-	.224	-	.279	.279
	max. correlation w/ function ^j	-	-	-.569	-	.418	-	.423	.423
	equality of group means ^g	-	-	.988**	-	.988**	-	.988**	.988**
RATIONAL	standardized canonical ⁱ	-	-	.176	-	-.157	-	-	-
	max. correlation w/ function ^j	-	-	.400	-	-.294	-	-	-
	equality of group means ^g	-	-	.994*	-	.994*	-	-	-
IMPOR_WEIGHT_FIT	standardized canonical ⁱ	.629	.629	-	-	.582	.594	.581	.581
	max. correlation w/ function ^j	.656	.656	-	-	.624	.640	.631	.631
	equality of group means ^g	.974**	.974**	-	-	.974**	.974**	.974**	.974**
INDIV_W_EMPLOYEE	standardized canonical ⁱ	.398	.398	-	-	.376	.386	.381	.381
	max. correlation w/ function ^j	.394	.394	-	-	.375	.385	.379	.379
	equality of group means ^g	.990*	.990*	-	-	.990*	.990*	.990*	.990*
	% correct predictions	61%	61%	56%	58%	61%	62%	62%	62%

^a**p<0.01; *p<0.05; 'not significant^b AVOIDANT, ANXIOUS, REGRET, MAXIMISING, DEPENDENT, INTUITIVE, SPONTANEOUS, RATIONAL^c GENDER, AGE, TIME^d INDIV_W_PRICE, INDIV_W_PROFIT, INDIV_W_DEBT, INDIV_W_EMPLOYEE, INDIV_W_INVEST, INDIV_W_INDUSTRY^e REGULATORY, SYSTEM 1, SYSTEM 2^f for first function^g for function 1 through 2 or 3 respectively^h Wilks' Lambda with Chi-Square probabilityⁱ for stepwise method: to enter variable p<.05; to remove variable p>.10^j taken from the SPSS output structure matrix

Table 47:

Results for the discriminant analyses for the categorical variable INCONSI_GROUP2

The diagram shown in Figure 27 (see next page) allows to predict the probability of participants producing no or max. 1 inconsistency or more than 1 inconsistencies based on their discriminant scores which was determined with the following equation:

$$DS_{IC} = -1.892 - .516 * TIME + 5.513 * INDIV_W_EMPLOYEE + \\ + 7.412 * IMPOR_WEIGHT_FIT + .497 * SPONTANEOUS \quad (19)$$

For INCONSI, the best discriminant function had the capability to predict 62% of the INCONSI_GROUP2 values correctly. 47 (54%) of the participants of the Student Sample were allocated correctly and 40 (46%) incorrectly.

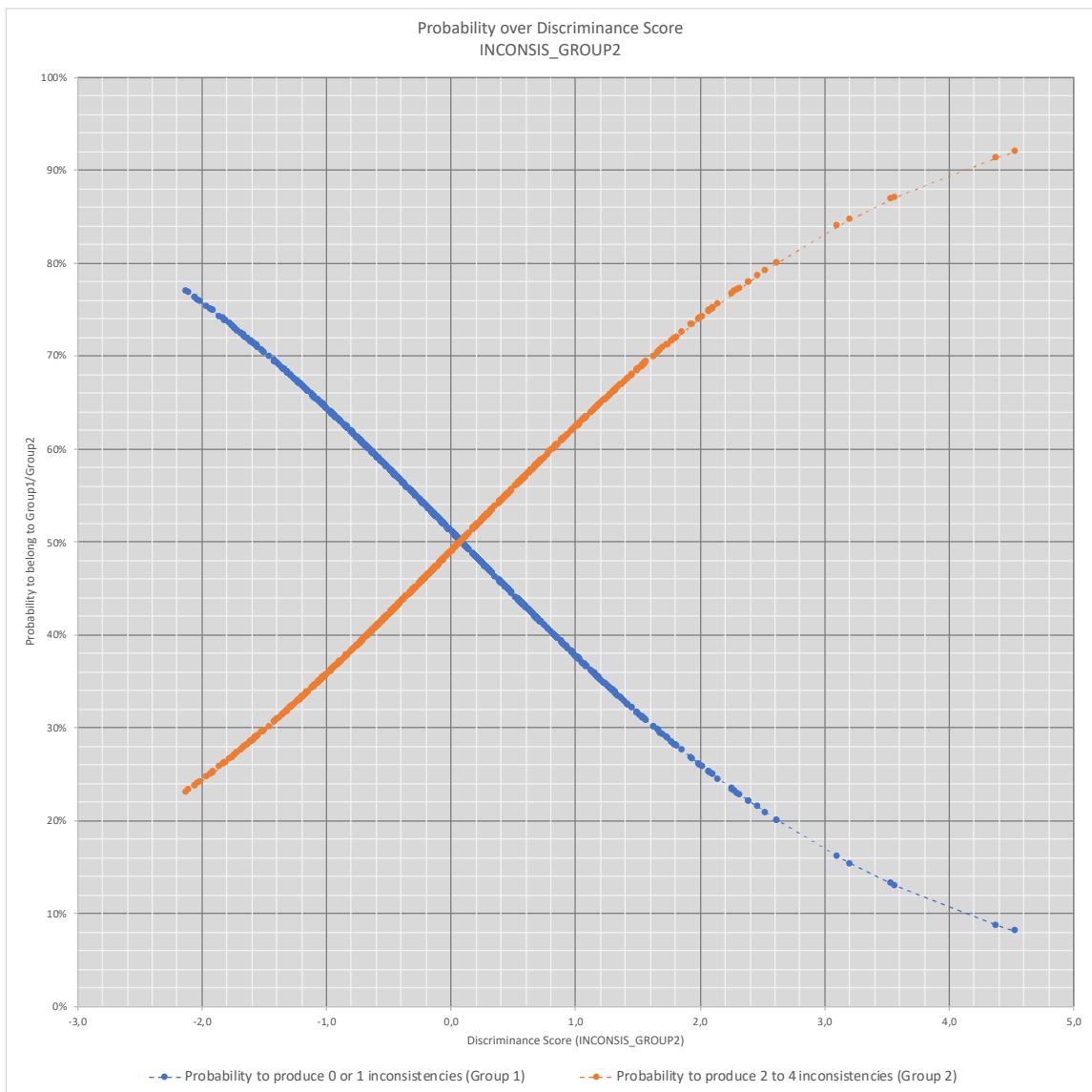


Figure 27:

Probability of a participant generating a maximum of 1 or more than 1 inconsistency

5.4.4 Discussion

The regressions analysis used when researching hypothesis 3 demonstrated to have only poor predictive capability to forecast the score for the number of alternatives in a participant's choice set, a participant's rejection threshold and the number of inconsistencies that a participant produces when performing Image Theory's compatibility test.

The regressions for the rejection threshold demonstrated the poorest fit to predict the respective variable (THRESHOLD). Only a maximum of 20% of the predictions were correct. The predictions of the regressions regarding the number of alternatives in the choice set (NUMCOMP) were better but are – with a maximum of 29% correct predictions – still way below expectations. Eventually, the best results could be achieved with the regressions for the number of inconsistencies (INCONSIS). 40% of the predictions were correct for the third regression for this choice set variable; the best performance of all regressions, but still below the level required for the hypothesis to be valid. It appears that there are too many other factors that decisively impact the choice set variables but that are neither known to the researcher nor controlled by the experimental set-up.

As a consequence, the definition of the term 'correct prediction' was relaxed for the number of companies in the choice set (NUMCOMP) and the rejection threshold (THRESHOLD). That is, predictions that produced a value of ± 1 of the respective observed value were considered acceptable. This relaxation increased the percentage of 'correct' predictions to 31% for NUMCOMP and 53% for THRESHOLD respectively. The relaxation was not performed for the number of inconsistencies since the range of the INCONSIS scores was only half of the range of the scores of the other two variables.

The results of the relaxation were again better, but insufficient to not reject the hypothesis.

The researcher then decided to investigate if a correct prediction could be performed successfully, if the participants were categorised in various groups based on their scores for the three variables. A set of respective categorial variables were created to be used as dependent variable for a series of discriminant analysis.

The maximum predictive capability of the tested discriminant analysis was 66% for the categorial variable THRESHOLD_GROUP3 separating the participants in two groups, those with a rejection threshold of minimum -4 (Group 1) and those with a threshold of at least -5 (Group 2);

The highest percentage of correct predictions was 62% for both, NUMCOMP_GROUP3 and INCONCIS_GROUP2. Both variables divided the sample in two groups as well: for NUMCOMP, the first group selecting a maximum of 4 companies, and the second group choosing a minimum of 5 companies to form the shortlist. The first group of INCONCIS_GROUP2 contained the participants that suffered a maximum of 1 inconsistency when performing the compatibility test. The second and last group of this categorial variable regrouped participants that produced at least 2 inconsistencies.

The best performing discriminant analyses for each choice set variable were used to produce a chart each allowing to determine the probability of participants being members of the respective group 1 or 2 based on their discriminant scores.

All the discriminant analyses 'suffered' from very low eigenvalues and, thus, very high Wilk Lambdas. Both an indication that the groups generated by the creation of the categorical variables do not separate sufficiently. That is, their centroids (in the case of a two-group discriminant analysis the centroid equates to the mean value of the respective group) have not been sufficiently distinguishable. Looking at the canonical coefficients of the respective discriminant analyses, the involved importance weight variables seem to possess greater discriminating capability ($b_{INDIV_W_PRICE}^{NC} = 8.651$; $b_{INDIV_W_PRICE}^{TH} = 8.341$; $b_{IMPOR_WEIGHT_FIT}^{IC} = 7.412$; $b_{INDIV_W_EMPLOYEE}^{IC} = 5.513$) than the decision styles which appear to be more relevant than the process styles. Statistical relevance of the latter was only observed for the best NUMCOMP discriminant analysis. It was however this discriminant analysis that performed the worst when looking at the results of the verifications of the best discriminant analyses with the Student Sample data.

TIME was relevant for all discriminant analyses. A fact that does not come as a surprise since TIME demonstrated already to be of central importance when performing compatibility screening (see the results subchapter for hypothesis 3, page 162).

It appears though that there are too many other, unknown factors that influence the choice set variables and, thus, a prediction, even based on relaxed acceptability criteria, is not possible; neither with a regression nor with a discriminant analysis.

Since the best overall predictive capability of a regression or a discriminant analysis was 66%, hypothesis 4 has to be rejected and is considered falsified as a result of this analysis.

5.5 Hypothesis 5

The last hypothesis of this research project differs from the previous ones since it relates to the question whether or not participants will allow a specific company in their choice sets. It reads:

"A neural network can predict with high reliability (>80% of correct predictions) whether or not an alternative (company) is accepted or rejected by a participant based on the data collected by the web survey."

The first step to potentially falsify this hypothesis is to gain knowledge, first, about the predictive capability of a neural network with all variables, and, then, about the predictive strength of the various sets of variables that have been used so far or that have been specifically created for the test of hypothesis 5.

5.5.1 Neural networks with all variables

5.5.1.1 Neural Networks with all variables but the process styles

The first set of neural networks was generated using all variables except the process style variables, SYSTEM1, SYSTEM2 and REGULATORY.

The best neural network using all variables except the process styles, is the fourth one (see Table 48 next page) generated providing for the training, test and holdout sets correct predictions averaging above 80%. It will be referred to as Neural Network A.

Neural Network A's AUC of .891 indicates that for i.e. a randomly chosen acceptance choice regarding a specific company (CHOICE = 1), the probability for that company being classified as an acceptance by the network is 89.1% higher than for its classification as a rejection. The AUC is thus a measure of a neural network's capability to correctly separate acceptance from rejection choices.

Neural networks, all variables but process styles

<i>Neural Network</i>		1	2	3	4 (A)	5	\emptyset		
<i>AUC</i>		.879	.864	.883	.891	.885	.880		
<i>Training</i>	<i>Observed</i>	0	84.4%	81.9%	90.4%	88.6%	83.7%	85.8%	
		1	73.0%	75.4%	69.2%	74.1%	77.6%	73.9%	
<i>Testing</i>		\emptyset	79.1%	79.0%	81.0%	82.0%	80.9%	80.4%	
		0	85.4%	80.7%	85.5%	88.9%	83.1%	84.7%	
		1	72.1%	73.6%	69.9%	71.8%	76.0%	72.7%	
<i>Holdout</i>		\emptyset	79.5%	77.4%	78.3%	81.3%	79.9%	79.3%	
		0	84.2%	79.4%	87.8%	88.1%	84.6%	84.8%	
		1	76.4%	75.6%	69.7%	72.3%	75.8%	74.0%	
		\emptyset	80.8%	77.7%	79.2%	80.8%	80.8%	79.9%	
\emptyset		79.8%	78.0%	79.5%	81.4%	80.5%	79.9%		

Table 48:

Correct predictions of five neural networks with all variables but the process styles

For the Neural Network A, the ROC and the whisker-box plot is shown in below figure.

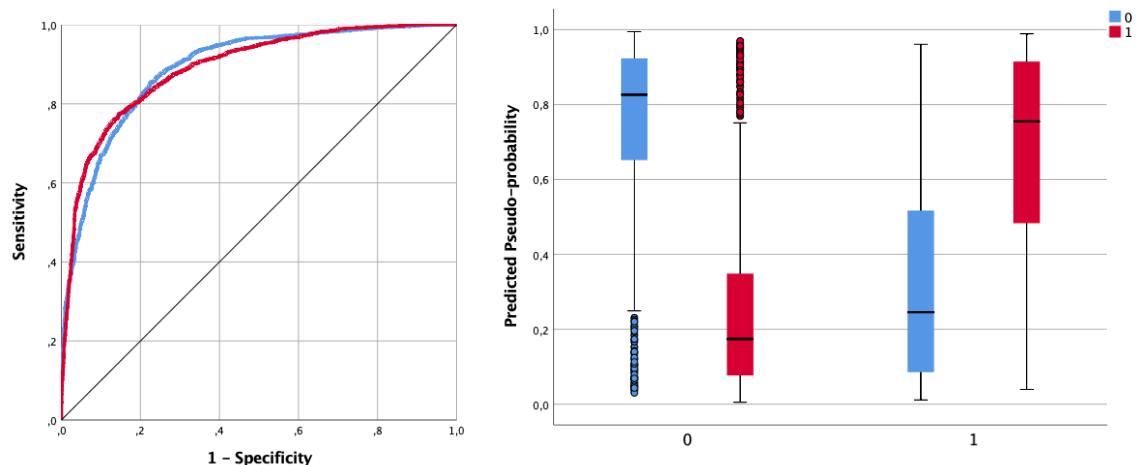


Figure 28:

ROC diagram and whisker-box plot for the training & test sets of Neural Network A

The ROC diagram shows the sensitivity of a choice over its value '1-specificity'. In the case of the neural networks of this thesis, sensitivity means the relative probability that the network predicts an acceptance of a company, when an acceptance is actually observed. It is therefore also referred to as the true positive rate (O'Connell & Myers, 2002, p. 136). Specificity is the relative probability that the network predicts a rejection when a rejection is actually observed. Thus, it is referred to as true negative rate (O'Connell & Myers, 2002, p. 136). '1-specificity' is then the relative probability that a rejection is predicted but an acceptance observed (false positive rate). The red line in the above diagram shows the ROC curve for the case CHOICE = 1 (observed values) and the blue line the case CHOICE = 0 respectively.

ROC curves allow to define cut-off points. That is, in the case reflected by the diagram of Figure 28, if the author wants to achieve a probability to predict 90% of acceptance choices (CHOICE = 1) correctly, then he will have to accept that the model is only capable of predicting 63% (=100% - 37%) of the rejection choices (CHOICE = 0) correctly. The point where both curves cross, indicate that both probabilities are approximately the same (approx. 80%). Further, and since the two curves are well away from the shown diagonal, the predictive capability of the network is better than 'guessing' which is represented by precisely that diagonal. The farther away the curves are from the diagonal, the better is their predictive capability. The same is expressed by the already mentioned quality measure AUC.

The whisker-box plot on the right side of Figure 28, shows four box plots; two for the case of CHOICE taking the value 0, and two for it being 1. Both box plot pairs are symmetrical to a line parallel to the x-axis, intersecting the y-axis at .5. The first box plot (from the left) shows the cases that have been predicted as rejections and for which rejections have been observed (CHOICE = 0). The box plot indicates that 75% of these values are at or above a value of predicted pseudo-probability of approx. .65 (with the exception of some out-layers). The median is at approx. .83.

The second box shows the misclassified cases for observed CHOICE = 0. That is, they have been predicted as acceptances, but were observed as rejections. 75% of these cases had a predicted pseudo-probability of .35 or lower. Their median is approx. .17. If

it was important to capture more correct rejection choices, the cut-off point could be lowered from .5 to .35; thus, capturing more of the misclassified choices.

The third box plot provides information on misclassified cases for the observed acceptances. That is, the network predicted a rejection, but an acceptance was observed. 75% of the misclassified cases have a predicted pseudo-probability of approx. .53 or less. Their respective median value is approx. .24. The last box plot describes the correctly predicted cases for CHOICE = 1, that is, for observed acceptances that have been predicted as acceptance. 75% hold a pseudo-probability of .57 or higher and their median is .76.

Neural Network A is already close to an acceptable level.

5.5.1.2 Neural Networks with all variables but the decision styles

The next step is to exchange the decision styles with the process styles and evaluate the resulting network. The process was the same: five networks have been generated. The respective results are shown in Table 49.

Neural networks, all variables but decision styles

<i>Neural Network</i>		1	2	3	4	5(B)	\emptyset		
<i>AUC</i>		.885	.873	.898	.896	.901	.891		
<i>Training</i>	<i>Observed</i>	0	84.2%	86.1%	87.0%	83.9%	84.5%	85.1%	
		1	75.2%	72.2%	75.2%	75.9%	78.2%	75.3%	
<i>Testing</i>		\emptyset	80.1%	79.6%	81.6%	80.3%	81.6%	80.6%	
		0	83.4%	84.2%	85.6%	87.4%	85.0%	85.1%	
		1	76.3%	73.0%	74.2%	75.2%	75.8%	74.9%	
		\emptyset	80.3%	79.1%	80.5%	81.8%	80.8%	80.5%	
		0	83.1%	85.3%	86.7%	85.8%	84.0%	85.0%	
		1	75.6%	72.4%	74.4%	75.7%	78.0%	75.2%	
<i>Holdout</i>		\emptyset	79.6%	79.8%	81.1%	81.2%	81.3%	80.6%	
		\emptyset	80.0%	79.5%	81.1%	81.1%	81.2%	80.6%	

Table 49:

Correct predictions of five neural networks with all variables but the decision styles

The best network in this sequence of five is the fifth one achieving an AUC of .901 and 81.2% of correct predictions. This neural network (Neural Network B) achieves very similar performance measures as Neural Network A. Whilst the latter is slightly better in its predictions (81.4% compared to 81.2% of Neural Network B), the former achieves the better AUC value (.901 compared to .891 of Neural Network A). Overall, both, Neural Network A and B, appear to be of equal quality and performance.

However, when comparing the respective values of Table 48 and Table 49, the correct predictions for the acceptance case (CHOICE = 1) are higher for Neural Network B than for Neural Network A. This can also be determined when looking at the respective whisker-box plots shown in Figure 29 (together with the ROC diagram).

For the two box plots on the right side of Figure 29 the median as well as the 75% lines, that is, the upper (blue box) and lower (red box) end of the boxes, are more separated for the box plots of Neural Network B than for those of the Neural Network A. This implies that Neural Network B is more capable to predict an acceptance case correctly. In this respective,

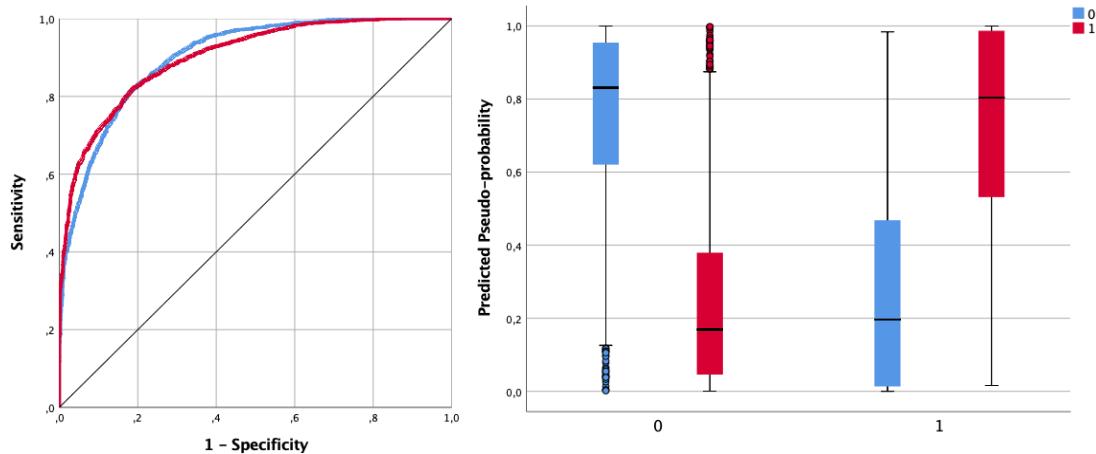


Figure 29:

ROC diagram and whisker-box plot for the training & test sets of Neural Network B

Neural Network B appears to be better than Neural Network A despite very comparable AUCs and percent correct prediction values.

5.5.2 Neural network of the various variable sets

The question then becomes what the predictive capabilities of the various variable sets are. To investigate this question, a neural network has been designed, trained and tested for each set of variables. For those sets of variables that have not been above 60% of correct predictions, only one network was generated. In contrary and like for the neural networks with all variables, for those variable sets achieving more than 60% correct predictions, five neural networks have been generated. Table 50 shows first the variables sets that fail to achieve the 60% threshold.

Neural networks of variable sets with low predictive capability

<i>Set of Variables</i>		<i>GENDER, AGE, TIME</i>	<i>Decision Styles</i>	<i>Process Styles</i>	<i>Temptation Variables</i>	<i>Importance Weight Variables</i>	
<i>AUC</i>		.520	.542	.542	.529	.531	
<i>Training</i>	<i>Observed</i>	0	100.0%	99.5%	90.4%	94.9%	
		1	0.0%	0.1%	12.7%	5.4%	
		∅	55.3%	54.8%	54.7%	53.6%	
<i>Testing</i>		0	100.0%	99.2%	91.6%	95.7%	
		1	0.0%	0.8%	11.3%	6.1%	
		∅	53.9%	55.6%	55.3%	55.3%	
<i>Holdout</i>		0	100.0%	99.7%	91.5%	95.3%	
		1	0.0%	0.2%	10.7%	4.0%	
		∅	54.0%	51.9%	55.7%	55.3%	
		∅	54.4%	54.1%	55.2%	54.7%	
		∅	54.4%	54.1%	55.2%	55.1%	

Table 50:

Correct predictions of neural networks generated with low predictive variable sets

As can be determined from above table, the neural network based on GENDER, TIME, and AGE is always predicting a rejection, therefore achieving little more than 50% of correct predictions. The same can be said of the network based on the decision styles; the network's capacity to predict CHOICE correctly, is the worst amongst the networks considered. However, the other variable sets are only doing marginally better. The

temptation variables' network is getting closer to the 55% mark and the importance weight variables' network and the one generated with the process styles eventually achieve a level of above 55% which are the best value of those variable sets not crossing the threshold of 60% correct predictions. Surprisingly the process styles achieve a slightly better prediction capability than the decision styles which indicates that the decision styles interaction reflected in the process styles might play a more important role. This might explain as well, why the network with all variables was slightly superior when including the process styles (Neural Network B) instead of the decision styles (Neural Network A).

There are two remaining variable sets that appear to drive prediction power of the Neural Network A and B: the set of compatibility variables and the choice set variables. The results of five networks for the compatibility variables are shown in Table 51.

Neural networks, only compatibility variables

<i>Neural Network</i>		1	2	3	4(C)	5	\emptyset		
<i>AUC</i>		.779	.775	.782	.783	.780	.780		
<i>Training</i>	<i>Observed</i>	0	85.3%	85.3%	86.3%	75.4%	85.4%	83,5%	
		1	57.8%	55.6%	56.2%	68.1%	56.6%	58,9%	
		\emptyset	72.7%	72.0%	72.7%	72.0%	72.4%	72,4%	
<i>Testing</i>		0	86.6%	87.0%	86.4%	75.3%	84.8%	84,0%	
		1	53.2%	59.2%	55.5%	68.9%	55.1%	58,4%	
		\emptyset	71.4%	74.3%	72.0%	72.4%	71.0%	72,2%	
<i>Holdout</i>		0	86.5%	86.1%	84.4%	75.2%	86.0%	83,6%	
		1	58.3%	54.5%	58.9%	67.6%	54.7%	58,8%	
		\emptyset	74.1%	71.4%	73.1%	71.9%	72.0%	72,5%	
\emptyset		72.7%	72.6%	72.6%	72.1%	71.8%	72.4%		

Table 51:

Correct predictions of five neural networks relying on the compatibility variables only

It is certainly not surprising that the compatibility variables play a major role in predicting whether or not a participant would reject or accept a company. After all, the more compatible an alternative is, the more reasonable it is to accept it.

The above table shows that the capability of these neural networks to predict a positive choice is poor; not even 59% of observed acceptance choices are predicted correctly. This percentage is driven by Neural Network C, the best network of this series, that is capable of predicting approx. 68% of the observed acceptance choices correctly. This picture is confirmed by looking at the respective whisker-box plot of Neural Network C (Figure 30). The two box plots for the observed acceptance choice suffer from a large overlap, explaining the network's problem to conclude on an acceptance choice.

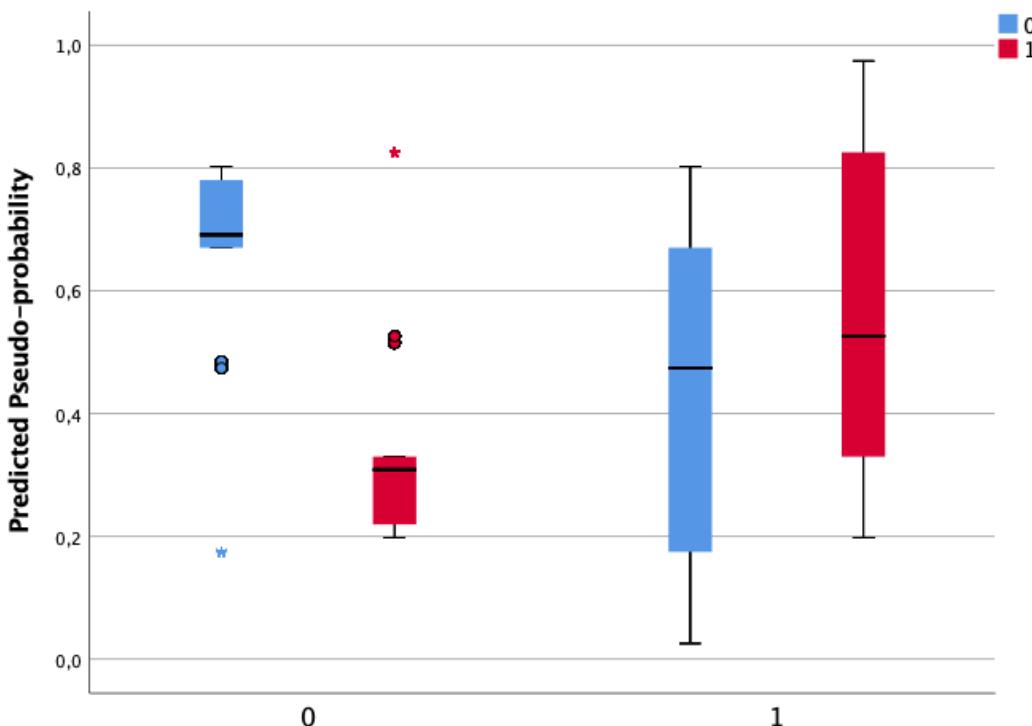


Figure 30:

Whisker-box plot of Neural Network C

The networks generated with the help of the compatibility variables appear to provide a large portion of the predictive capability of the Neural Network A and B. It seems as if they reflect the reasonable and logical input based on how well a company fits the desired values of the defined criteria. But looking at the higher correct predictions achieved by the Neural Network A and B, there appears to be another set of information

that is required; unless the (very poor) predictive capabilities of the already discussed sets of variables together are responsible for that increase in correct predictions achieved by Neural Network A and B.

The results for the last remaining set of variables, the choice set variables, are shown in Table 52.

Neural networks, only choice set variables

<i>Neural Network</i>		1	2	3	4	5(D)	\emptyset		
<i>AUC</i>		.684	.686	.685	.682	.678	.683		
<i>Training</i>	<i>Observed</i>	0	77.3%	75.5%	78.3%	76.3%	76.6%	76.8%	
		1	49.5%	49.8%	47.9%	49.2%	48.6%	49.0%	
		\emptyset	64.7%	63.9%	64.7%	63.9%	64.0%	64.2%	
<i>Testing</i>		0	77.4%	76.6%	78.2%	76.3%	75.3%	76.8%	
		1	45.6%	52.3%	46.4%	49.7%	49.9%	48.8%	
		\emptyset	62.9%	65.1%	63.6%	64.5%	63.8%	64.0%	
<i>Holdout</i>		0	78.4%	77.8%	77.9%	76.3%	76.2%	77.3%	
		1	47.7%	46.2%	46.0%	52.0%	53.9%	49.2%	
		\emptyset	64.5%	64.0%	62.9%	65.1%	65.8%	64.5%	
\emptyset		64.0%	64.3%	63.7%	64.5%	64.5%	64.2%		

Table 52:

Correct predictions of five neural networks relying on the choice set variables only

Even though the percent of correct predictions is not as high as for the compatibility variables, the pictures is very comparable: the networks based on the choice set variables have equally a week predictive capability of the observed acceptance choices.

The choice set variables provide information on the decision-maker and not on the decision alternatives: how many alternatives are typically selected in such situation, what are the decision-makers' rejection thresholds and how prone to errors are they? This is obviously important information for the network to correctly predict each decision-maker's choice.

Since the nature of the information provided by the compatibility variables and the choice set variables is very different and in order to have the most parsimonious model possible, the question becomes how a network performs that relies on these two sets of variables only.

5.5.3 Neural Network based on compatibility and choice set variables

Five neural networks have been generated, trained and tested, using only the two sets of variables that have proven to hold the best predictive capability to forecast a rejection or an acceptance choice for a specific company. The results of these five networks are shown in Table 53.

Neural networks, with choice set variables and compatibility variables

<i>Neural Network</i>		1	2	3(E)	4	5	\emptyset		
<i>AUC</i>		.903	.911	.919	.915	.907	.911		
<i>Training</i>	<i>Observed</i>	0	86.9%	86.5%	89.6%	87.5%	85.0%	87.1%	
		1	80.2%	77.9%	80.9%	78.3%	79.5%	79.4%	
<i>Testing</i>		\emptyset	83.8%	82.6%	85.6%	83.4%	82.5%	83.6%	
		0	86.3%	86.4%	87.3%	86.4%	83.4%	86.0%	
		1	77.1%	77.8%	79.6%	78.6%	82.9%	79.2%	
		\emptyset	82.2%	82.4%	83.8%	82.8%	83.2%	82.9%	
		0	86.5%	87.9%	87.6%	86.9%	82.9%	86.4%	
<i>Holdout</i>		1	78.1%	71.9%	81.7%	82.0%	80.5%	78.8%	
		\emptyset	82.9%	80.9%	85.0%	84.6%	81.8%	83.0%	
		\emptyset	83.0%	82.0%	84.8%	83.6%	82.5%	83.2%	

Table 53:

Correct predictions of five neural networks using the compatibility and choice set variables

The results show that a combination of the choice set variables and the compatibility variables lead to neural networks with the best predictive capability and, thus, with the highest percentage of correct predictions of in average 83.2%. The best performing network, Neural Network E, achieves close to 85% of correct predictions. More

importantly, even the predictions of the acceptance choices are above 80% except for the testing set.

Having received the above results, the next and final step in the author's endeavour to generate the best possible neural network was to apply optimisations to the IBM SPSS settings. The earlier described optimisations (see Table 21, page 130) were mostly arbitrary and, thus, on a 'trial-and-error' basis. However, as can be seen from the results shown in Table 54, the percentage of correct predictions could be further enhanced.

***Optimised neural networks,
with choice set variables and compatibility variables***

<i>Neural Network</i>		1	2	3	4(E ⁺)	5	Ø		
<i>AUC</i>		.948	.920	.930	.951	.947	.939		
<i>Training</i>	<i>Observed</i>	0	90.6%	91.4%	91.0%	90.9%	90.4%	90.9%	
		1	82.8%	79.8%	79.2%	82.5%	81.6%	81.2%	
<i>Testing</i>		Ø	87.2%	86.1%	85.5%	87.1%	86.5%	86.5%	
		0	90.1%	92.0%	89.7%	89.3%	91.1%	90.4%	
		1	82.1%	76.4%	78.3%	81.3%	82.1%	80.0%	
<i>Holdout</i>		Ø	86.5%	84.9%	84.6%	85.8%	86.8%	85.7%	
		0	90.3%	92.7%	89.9%	91.3%	89.4%	90.7%	
		1	79.5%	75.7%	80.9%	82.7%	81.5%	80.1%	
		Ø	85.3%	85.0%	85.9%	87.3%	85.8%	85.9%	
		Ø	86.3%	85.3%	85.3%	86.7%	86.4%	86.0%	

Table 54:

Predictions of optimised networks using the compatibility and choice set variables

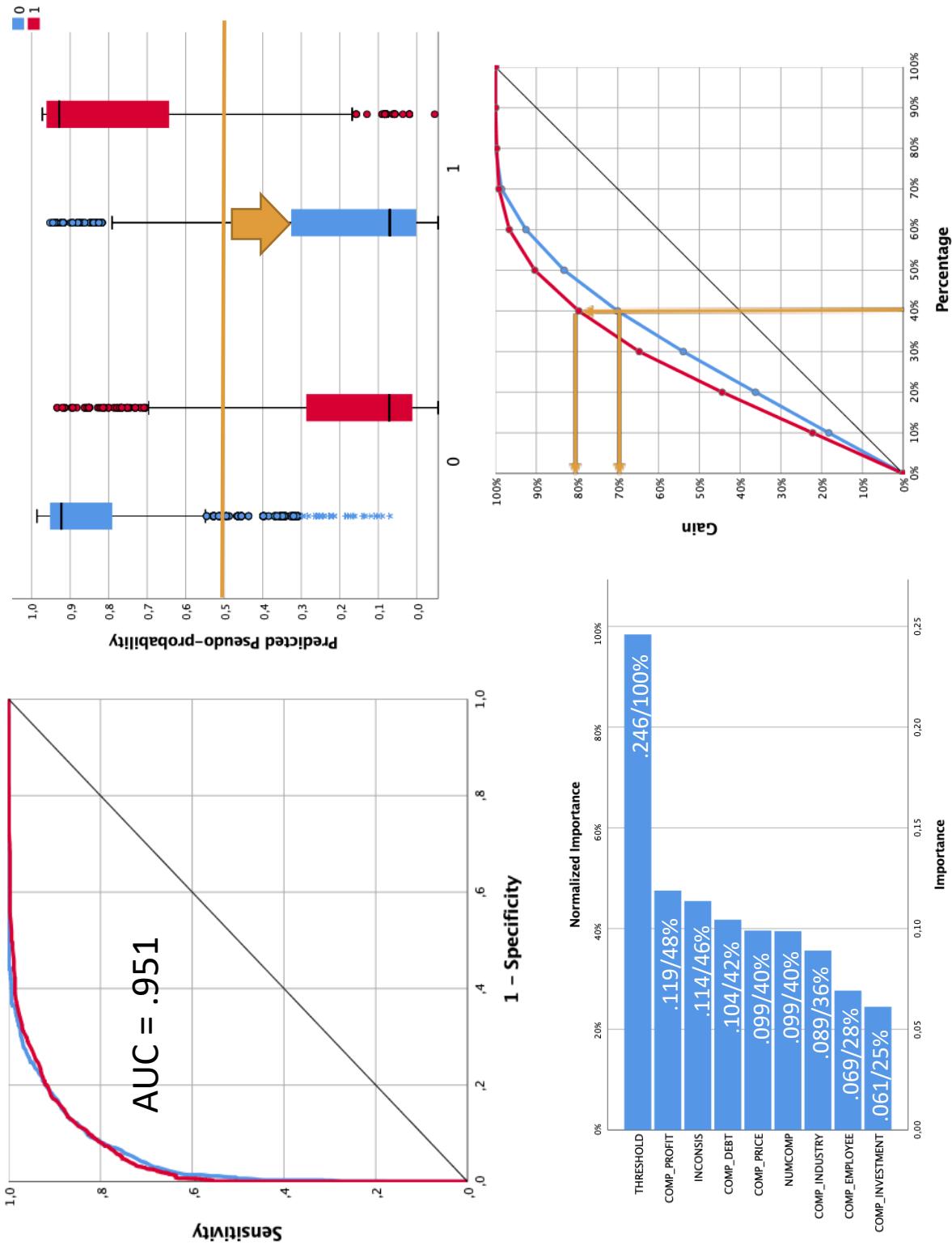
The optimisation led to an increase in correct predictions of approx. 3%. The improvement is however stronger in the rejection choices which are for the optimised networks all above 90% for all three sets (training, test and hold-out), whilst an improvement can also be observed for the acceptance choices, it is only of about half the strength than for the rejections. The best optimised neural network, Neural Network E⁺, achieves correct percentages that are all solidly above 80%, with the correct rejection predictions of around 90% and correct acceptance predictions of approx. 82%. The AUC

value of the Neural Network E⁺ achieves a value of .951 which implies that for any randomly selected acceptance (or rejection) choice, the probability of the network to predict this acceptance (rejection) choice correctly is in excess of 95%. Figure 31 (next page) shows the relevant diagrams and charts for the Neural Network E⁺. The ROC diagram underlines the improvement of predictive capability compared to the first neural networks generated with all variables.

The whisker-box plots show a clear separation of for both, rejection (CHOICE = 0) and acceptance (CHOICE = 1) choices. To further improve the predictions for acceptance choices and to balance both choice types, the cut-off point could be moved from .50 to approx. .32 predicted pseudo probability allowing to capture more correct acceptance choices (whisker-box plot on the right) without increasing too much the false rejection choices (whisker-box plot second from left). Keeping in mind that the neural network is stronger in predicting rejections this manipulation seems appropriate.

The importance chart (see bottom left side in Figure 31) underlines the importance of the rejection threshold (THRESHOLD) contributing double as much to the predictions of the neural network than the next important variable COMP_PROFIT, the compatibility information for the profit criterion. Apart from that dominating position of the rejection threshold, the remainder of the variables are staggered nicely, losing 2% to 4% of importance from the variable for the compatibility of the profit criterion to the one of the investment criterion. The two remaining choice set variables blend in nicely in that order.

The gain chart on the bottom right side of Figure 31 provides information on how many cases of acceptance and rejection choices are captured when sorting all choice data based on their respective predicted pseudo-probability (rejection or acceptance). For instance, looking at the predicted pseudo-probability for acceptance (rejection) and sorting all from the network obtained choice data based on this pseudo-probability, 80% (70%) of the acceptance (rejection) cases were captured when looking at the top 40% of that sorted list (see orange coloured arrows).

*Figure 31:**Various diagrams and charts for Neural Network E⁺*

Neural Network E⁺ is the network with the strongest predictive capability for the Base Sample data. The question became then how the network performs when fed with the Student and Extension Sample data.

5.5.4 Verification with the Extension and Student Sample data

For verification purposes, the Student Sample data was used as hold-out set when generating five neural networks with the settings for the Neural Network E⁺. The training and test sets were again taken from the Base Sample. The results for the five networks are shown in Table 55. The difference between the Base and the Student Sample is a different population. The same procedure was applied to the data of the Extension Sample. That is, the Extension Sample data was used as hold-out set and the Base Sample data was taken to train and test the five networks generated. The difference between the two sample is that the Extension Sample data introduced decision alternatives (companies) that the network was not trained or tested with. The respective results are shown in Table 55 and Table 56

Optimised neural networks, with choice set variables and compatibility variables, Student Sample data as hold-out set

<i>Neural Network</i>		1	2	3	4	5	\emptyset	
<i>AUC</i>		.936	.932	.939	.942	.933	.936	
<i>Training</i>	<i>Observed</i>	0	90.3%	92.7%	90.6%	90.8%	89.9%	90.9%
		1	80.3%	77.2%	80.4%	81.5%	81.0%	80.1%
		\emptyset	85.7%	85.6%	85.9%	86.5%	85.8%	85.9%
<i>Testing</i>	<i>Observed</i>	0	89.7%	92.0%	90.2%	89.4%	89.9%	90.2%
		1	80.7%	78.2%	81.6%	82.9%	82.0%	81.1%
		\emptyset	85.7%	86.0%	86.4%	86.5%	86.4%	86.2%
<i>Holdout</i>	<i>Observed</i>	0	93.8%	96.4%	94.5%	93.8%	95.2%	94.7%
		1	80.5%	76.2%	80.5%	81.1%	79.1%	79.5%
		\emptyset	90.3%	92.7%	90.6%	90.8%	89.9%	90.9%
\emptyset			88.0%	87.5%	88.4%	88.3%	88.1%	88.1%

Table 55:

Predictions of optimised neural networks using the Student Sample data as hold-out set

As can be seen from Table 55, the results for the Student Sample are very similar to the results achieved with the Base Sample. This implies that the networks have been able to predict the observed choice results for the Student Sample participants with the same reliability as for the Base Sample participants. The networks appear to perform even stronger in predicting the rejections of the Student Sample (approx. 95% of correct predictions) than of the Base Sample (approx. 91% correct predictions).

Optimised neural networks, with choice set variables and compatibility variables, Extension Sample data as hold-out set

<i>Neural Network</i>		1	2	3	4	5	\emptyset		
<i>AUC</i>		.936	.927	.900	.950	.934	.929		
<i>Training</i>	<i>Observed</i>	0	90.3%	89.9%	90.7%	91.8%	89.3%	90.4%	
		1	80.8%	79.3%	78.7%	80.9%	80.5%	80.0%	
<i>Testing</i>		\emptyset	86.0%	85.1%	85.2%	86.8%	85.3%	85.7%	
		0	90.2%	89.3%	91.0%	91.5%	88.9%	90.2%	
		1	82.3%	79.6%	79.6%	82.2%	81.9%	81.1%	
<i>Holdout</i>		\emptyset	86.8%	85.1%	86.0%	87.4%	85.9%	86.2%	
		0	79.0%	60.1%	73.4%	78.3%	65.7%	71.3%	
		1	59.1%	75.9%	62.8%	59.9%	76.6%	66.9%	
		\emptyset	69.3%	67.9%	68.2%	69.3%	71.1%	69.2%	
\emptyset		80.7%	79.4%	79.8%	81.2%	80.8%	80.4%		

Table 56:

Predictions of optimised networks using the Extension Sample data as hold-out set

For the test with the Extension Sample (see Table 56), the picture is very different. Having achieved a high 91% for the Base Sample data, the average correct predictions of rejection choices fall for the Extension Sample to approx. 71%. A similar tendency can be observed for the correct predictions of acceptance choices. Achieving 81% for the Base Sample, the correct acceptance predictions drop to an all low average of 67%. Note however that the drop of the acceptance predictions (-14%) is not as severe as for the rejection predictions (-20%). Further, the best correct predictions of the Extension Sample choice data are not achieved by the assumingly best neural network, that is with

the highest AUC or the highest correct predictions during test and training (network 4). Eventually, a high percentage of correct predictions of acceptance choices seem to coincident with a particular low percentage of correct rejection predictions (network 2 and 5).

5.5.5 Discussion

When including all variables, the fit of the neural network was already close to satisfactory, but to amend the model further additional analyses have been performed. They unveiled that a large number of variables do not contribute to the quality (in terms of correct predictions) of the model. Neither the demographic variables, gender and age, nor the importance weight variables and the information whether or not a company represented a temptation, play a role in determining a participant's choice regarding a specific company.

Further, the time to complete the survey does not contribute directly to the capability of a neural network aiming to correctly predict the acceptance or rejection of a specific company. This appears to be surprising since an influence of TIME on all choice set variables could be evidenced in previous analyses. However, TIME is influencing the choice set variables and, thus, might indirectly influence the predictions of the neural networks through the choice set variables. The same seems to be the case for the decision and process styles: neither the decision styles nor the process styles showed to have an important direct influence on the predictive capability of the network. However, as could be witnessed in previous analyses, there appears to be a link between the process styles and the choice set variables. Therefore, and similar to the influence of TIME, the effect of the decision styles might develop through the process styles into the choice set variables as well.

The requirement of having the most parsimonious model possible led eventually to the removal of those variables that did not contribute significantly to the predictive capability of the neural networks. Two sets of variables remained: the six categorial compatibility variables that provided information if the respective company met the desired criteria or not, and the choice set variables, that is the number of companies in the choice set, the participant's rejection threshold and the number of inconsistencies.

The latter set feeds the neural networks with information on the decision-makers themselves; individual information that is impacted by the process and thus the decision styles as well as by TIME and some of the importance weight variables.

A series of neural networks were designed that only relied on these two sets of independent variables to predict a participant's rejection or acceptance choices. The best of these networks, Neural Network E, demonstrated better fit than the first networks with all variables included. It predicted the holdout sample with 85% accuracy (AUC was .92) whilst the best initial neural network was at 81% (AUC = .90). Obviously, the variables or at least some of them that have been eliminated from the analysis, did not only contribute nothing to the performance of the network but reduced its capability to predict the choices correctly.

Neural Network E could be further amended by fine tuning the architecture and training settings of IBM SPSS and, eventually, achieved an optimum of 87% with an AUC of .95 (Neural Network E⁺). Further, the order of importance of the independent variables unveiled that the variable THRESHOLD had greatest predictive power with approximately double as much importance (.246) than the next variable COMP_PROFIT (.119). The importance of the remainder of the variables is nicely cascaded losing .005 to .010 in importance.

It appears to be logical that the participant's rejection threshold plays the most important role when performing the compatibility test since this measure is central when allowing a decision alternative in the choice set. Even though the order of importance of the criteria compatibility scores is not fully in line with the participants' ranking, the big picture is represented in the design (see Figure 32, see next page).

Potentially, and with a growing number of data sets to train and test the network, the order of importance of the criteria compatibilities will potentially align closer to the ranking of the participants or the one provided by the author, or a mix of both.

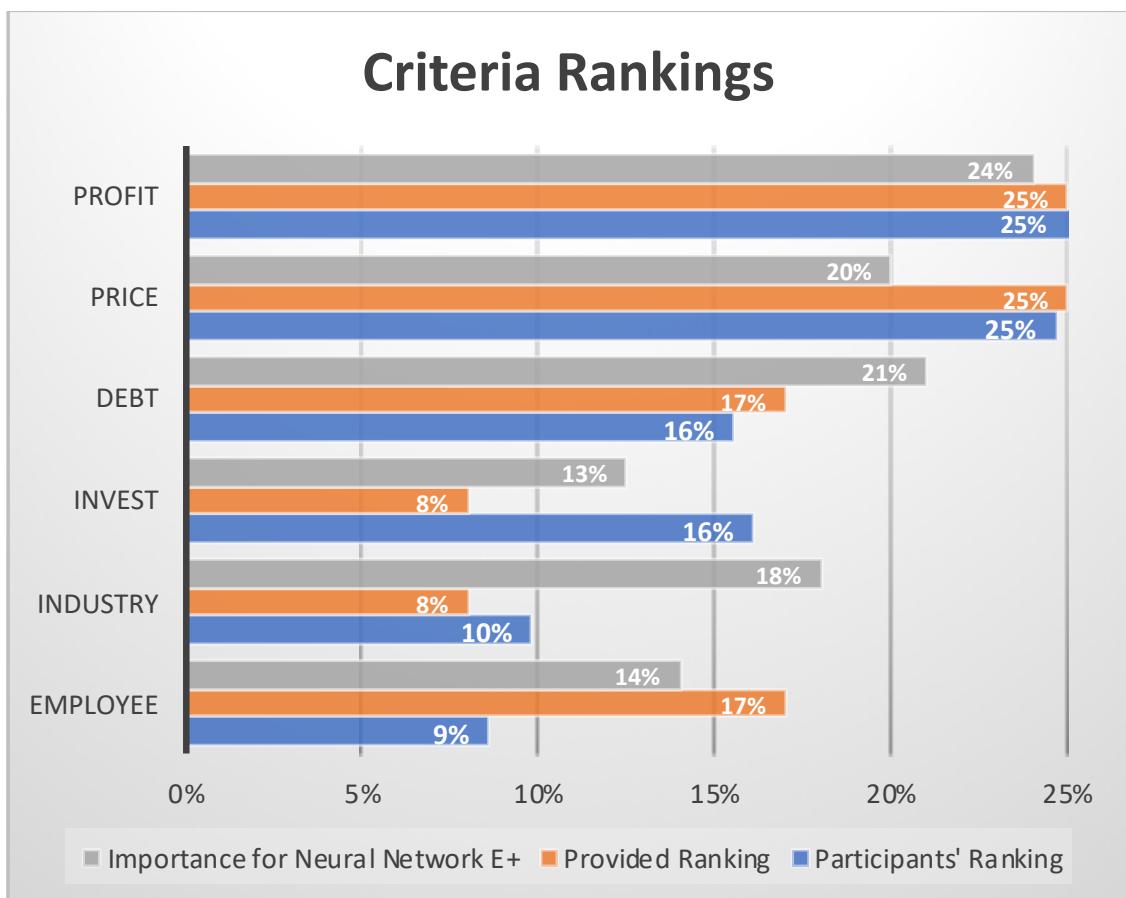


Figure 32:

Criteria importance for the author, for the participants, and for Neural Network E⁺

The number of inconsistencies as third important variable, albeit very close to the second placed compatibility profit variable, doesn't seem to be surprising since the knowledge about inconsistencies appears to be advantageous to correctly predict a participant's choice.

The strong contribution of the compatibility variables makes perfectly sense since they represent the 'hard facts' related to the company in focus. However, the influence of the choice set variables, in particular THRESHOLD and INCONSIS, is also logical since they contribute the 'soft facts' about the participant's screening behaviour. Latter appear to adjust the 'brutal reality' of the compatibility scores.

Based on the relationships discovered and discussed earlier between the choice set variables and the decision and process style, it could be stated that the choice set

variables ‘absorbed’ the nature and decision profile of the participant and, thus, shape the perception of the compatibility facts.

Looking at the findings of the performed analyses, hypothesis 5 cannot be rejected and is considered not falsified as a result of this analysis. The information gathered with the questionnaire allows to predict with high reliability (>80%) whether or not a specific company is accepted or rejected by participants to become part of their choice sets.

The verification with the Student Sample data allows to hypothesis that this finding can be transferred to other populations than the one of which the Base Sample has been drawn of.

Further, the best performing neural network, Neural Network E⁺, is even capable to predict choices related to companies for which it was neither trained for nor tested with (Extension Sample data), even though its predictive capabilities drop significantly to more mediocre levels (69% of correct predictions).

6 GENERAL DISCUSSION

The aim of this research project was to revisit the application of Image Theory's compatibility test and verify various hypotheses linked to three areas of research questions:

1. How is Image Theory's compatibility test influenced by tempting decision alternatives?
2. How does the decision style profiles of decision-makers influence the elements of the compatibility test, that is, their rejection thresholds, the number of alternatives surviving their compatibility screenings and the number of their inconsistent choices? If the assumed influence exists, is it possible to predict the elements of compatibility test with sufficient reliability?
3. Is it possible to reliably predict the choice of a decision-maker with regards to a specific decision alternative based on the concept of neural networks?

These research questions have been translated in five hypotheses that were tested with the help of three online surveys using three samples (Base Sample, Student Sample and Extension Sample) and two populations (German decision takers with internet access; German spoken social science research friendly members of *SurveyCircle*).

The subsequent general discussion will summarise related results and identify their limitations. Further, the contribution to scientific knowledge as well as their implications for management practice will be described and the potential for future research unveiled.

6.1 Compatibility Screening in the presence of temptations

The central concept of Image Theory is the compatibility test, a screening process that enables the decision-maker to reduce the number of decision alternatives and thus form a choice set of which the winning alternative that ought to be implemented, is selected. The discussion of relevant literature determined what drives this screening process. Basically, decision-makers compare the desired values of criteria that are important to

them, with their salience in the decision alternatives available. For each decision alternative an incompatibility score is thus calculated which expresses how well an alternative meets the expectations of the decision-maker by comparing its incompatibility score to the decision-maker's rejection threshold. The rejection threshold represents the expectation of the decision-maker with regards to what features a potentially winning alternative should provide. If a decision alternative fails to meet the decision-maker's rejection threshold, it is rejected and, therefore, not further considered for implementation. If, however, the decision alternative meets the rejection threshold, it will become part of the decision-maker's choice set collecting those alternatives perceived to be promising to maximise subjective utility. The calculation of the incompatibility score is driven on one side by criteria weights reflecting the importance of these criteria to the decision-maker, and, on the other side, by a binary variable describing if the target value is of a specific criterion is met or not. More importantly, research of Beach and Strom (1989) as well as of Ordóñez et al. (1999) claim that only criteria violations are relevant when performing the compatibility test. This implies, that in performing the compatibility test, the decision-maker appears rather to screen out decision alternatives that do not meet the rejection threshold than to select those ones that meet criteria expectations. The compatibility test is thus non-compensatory which implies that a decision alternative cannot cure the failure of criteria violation by overachieving the targets for other criteria. Transferring this logic to the world of dual process theory, would classify the application of the compatibility test as a System 2 activity: analytical, rule-based and rational. System 2 is however always subject to be 'tricked' by the fast, heuristic-based and spontaneous System 1 which appears to be prone to errors resulting in inconsistent choices. The question then becomes: when does System 1 get involved in the application of the compatibility test? Can System 1 'trick' System 2? These questions combined with the findings of previous research that achieving or over-achieving a desired criterion value does not contribute to the screening process led the author to above first research question: can a tempting decision alternative trigger System 1 to sneak a rationally failing alternative past System 2? What constitutes a temptation and what mechanism would the intervention of System 1 rely on?

The theoretical foundations for a potential System 1 intervention are based on the affect heuristic, in particular, the mediating role of affect in the perception of benefit-risk relations as described by Finucane et al. (2000).

The author operationalised the concept of a temptation being a decision alternative that fails to meet the target values for all but one criterion and, thus, does not meet the decision-maker's rejection threshold. The one criterion that is met, is not only the most important criterion to the decision-maker but overachieves the respective target value of that criterion compared to competing alternatives by multiple times creating thus a 'super attribute' that should seduce decision-makers to accept the temptation into their choice sets even though it does not meet the requirement of the respective rejection threshold.

The researcher made the participants of his survey select companies for an M&A process based on six criteria. He designed temptation alternatives for the two most important criteria 'Profit' and (acquisition) 'Price'. Further, two twin alternatives were designed for which the criteria salience was identical to these temptations except for the 'super attribute'. In an in-between experimental design, the experimental groups of three samples stemming from two populations where faced with the temptations, the reference group had to decide on the respective, non-tempting twin alternative becoming part of the choice set or not.

The results are twofold: on one side, no evidence was found that the 'Price' temptation triggered the affect heuristic since the results for all three samples were statistically non-significant; on the other side, the seductive power of the 'Profit' temptation was highly significant. The affect heuristic made a significant number of participants of all samples to accept the 'Profit' temptation in their choice sets.

The reasons for the two temptations performing differently might be of various nature.

First, a company's profit margin is difficult to debate; it is reliable information verified by an annual audit and is a recurring benefit of a company. The price for which a company can be bought is highly subjective and sometimes inflated by emotions of the selling or even buying party. Therefore, it is a 'softer' information that is driven by different, sometimes opposing parameters. It can be calculated in different ways with

differing results depending on the information considered during that calculation. Further, it is one single expenditure and, thus, the buyer benefits from a lower price only once, that is, at the time of the acquisition.

Second, and partially based on the first point, participants might have been more suspicious about the extremely low price of the 'Price' temptation than about the extremely high profitability levels of the 'Profit' temptation. A low price might be an indication that 'something is wrong' with the company and the seller wants to 'get rid of it by all means'. These thoughts create negative affect and increase the perceived risk of buying such company since as long as potential buyers do not have enough information to determine the reason for such a low price, they run the risk of buying a company that might be confronted with serious operational, financial, legal or other type of problems. As described by Finucane et al. (2000), the perception of high risk combined with negative affect as mediator might lead to perceived low benefit if participants evaluate the 'Price' temptation as a contender for their choice sets.

On the other hand, the same mechanism might explain why the 'Profit' temptation has been selected into a participant's choice set: high profitability levels are highly desirable for the management of the company. When being responsible for leading a company, a lot is at stake: owners want to be paid dividends, high profits generate typically solid cash flows that ensure the survivability of the company; further, and more focused on the personal success of the responsible manager, profit warrants reputation and bonuses, higher profits even more so. Therefore, every manager is trained to perceive high profitability levels as highly beneficial. With positive affect as mediator and the financial audit proven nature of profit, the 'Profit' temptation will be considered as low risk alternative and, thus, will end up on the shortlist even if the company's incompatibility score is clearly violating the decision-maker's rejection threshold.

The author suggests therefore that in the case of the acceptance of the 'Profit' temptation and in the case of the rejection of the 'Price' temptation, the affect heuristic can be observed at work despite the fact that no evidence has been found in the latter case.

This claim is further supported by the, albeit not highly significant but still observable difference of System 1 processing activity. The difference appears to be driven by higher

intuitive styles of the participants that have selected the 'Profit' temptation compared to the ones that were faced with it but have not chosen it.

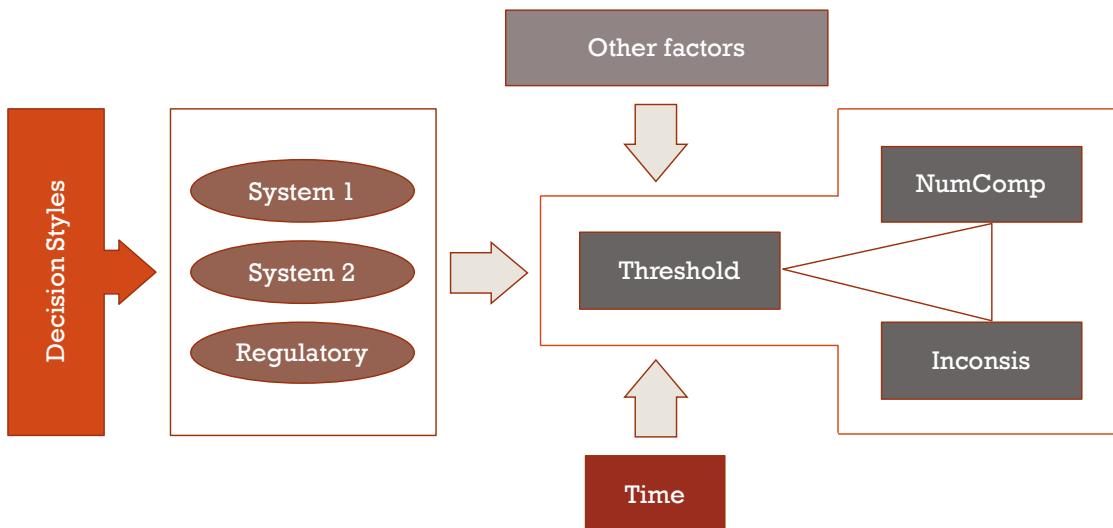
In concluding and based on these findings, the author suggests complementing the statement of previous research (Beach & Strom, 1989; Ordóñez et al., 1999):

Image Theory's compatibility test rather screens out those alternatives that fail to meet the decision-maker's rejection threshold but remains vulnerable for the System-1-driven affect heuristics that might lead to inconsistent choice behaviour.

6.2 How decision and process styles influence compatibility screening

The second research area of this thesis is its centre piece and investigates the links and their potential predictive capability, between the participant's decision style profile and the parameters of the compatibility test, referred to as choice set variables in this research project; that is, the rejection threshold, the number of alternatives in the choice set, and the number of inconsistent choices. Inconsistencies are decision alternatives that either made it in the choice set and shouldn't have done so based on their apparent failure to meet the rejection threshold or did not make it in the choice set even though they met the rejection threshold's requirement.

The author designed a structural model of relationships that should be tested in the context of this research project (see figure next page).

*Figure 33:*

The author's structural model regarding the influences on the choice set variables

This model is partially based on previous research of Dewberry et al. (2013) that categorised eight decision styles (rational, intuitive, spontaneous, dependent, regret, avoidant, anxious, maximising) in two cognitive process styles, System 1 (being spontaneous, intuitive, quick but error prone) and System 2 (being rational, effortful and analytical), as well as in one regulatory process style dealing predominantly with decision anxiety.

The author's model saw the activation of these three process styles being driven by the strength of the salience of the eight underlying decision styles. Further, the author believed that the three process styles and other factors, i.e. the criteria importance weights, as well as the time to perform the compatibility test, impact the three choice set variables mentioned above.

The verification of the structural model shown in Figure 33 led to the formulation of three hypothesis dealing, first, with the verification of the Dewberry et al. (2013) model, second, with the investigation of the links between the choice set variables and the decision styles as well as with the other factors, and, eventually, third, with testing the capabilities of these potential links when used to predict the values of the choice set variables.

6.2.1 Confirmation of the Dewberry model

The first hypothesis dealt with the confirmation of the Dewberry et al. (2013) structural model. Based on the limitation of the online service provider *SurveyMonkey* that allows only 50 questions per survey if the answers to that survey are provided by *SurveyMonkey*'s respective online panel of potential participants, and keeping in mind that the participants would have to perform the compatibility test and, therefore, be confronted with a number of decision alternatives, the author could only use five questionnaire items per decision style (40 questionnaire items in total) to determine a participant's decision style profile. Since Dewberry and his colleagues used more items to identify the eight decision styles, the applicability of their structural model had to be verified for this research project. The author therefore selected 40 required items (5 per decision style) from previous research projects based on their factor loadings achieved during these projects.

As for the Dewberry et al. (2013) model, the respective statistical analysis allowed the extraction of the eight decision styles from the data collected by these 40 questionnaire items. Further and in particular, Dewberry's regrouping of the eight decision styles in the two cognitive process styles (System 1: intuitive and spontaneous style, and System 2: rational style) and the regulatory style (anxious, avoidant, dependent, maximising and regret styles) could be confirmed as well. The decision styles loaded well in the three process styles as predicted by Dewberry et al. (2013).

Nevertheless, statistical analysis of the data showed some differences to the Dewberry et al. (2013) model as well.

First, the dependent style is not necessarily subordinated to the avoidant style but appears to maintain non-negligible links to the regret style as well. Both seems to make sense: the dependent decision style might also be triggered by requirements that are provided to the decision-maker by another party, i.e. requirements or decision criteria determined in a team or by supervisors. In such cases, decision-makers might be bound by and rely on those requirements without feeling the necessity to avoid any related decision but might feel regret in the case the requirements provided do not match their 'working images'. That is, the decision-maker's decision framework does not align with the one provided by the team or the supervisor.

Second, the rational decision style appears to play a much more central role amongst the decision styles than determined by Dewberry and his colleagues. Even though the rational style is a 'stand-alone' style in the sense being the one and only decision style allocated to System 2, it appears to nurture links to the regret and the dependent styles of the regulatory process style as well as to the intuitive style of System 1. Again, all of these relations do not lack a certain logic: if one extends the definition of the dependent style as not being only driven by avoidance but by commitment as well, as described earlier, the influence of the rational style on the dependent style as well as on the regret style can be explained: 'Digesting' requirements provided by an outside party to the decision-makers require them to think and reflect on those, and eventually 'translate' the requirements into their decision framework ('working images') enabling them the application of those requirements during the decision process. It appears obvious that this 'digesting' or 'translation' is an effort-full and analytical process that triggers System 2 processing and, thus, the rational decision style. More specifically, an existing mismatch between the 'outside' requirements and the decision-maker's 'working images' causes potentially brooding that is evidence of the regret style at work.

However, the present research unveiled some contradicting and, thus, inconclusive findings with regards to the intuitive and spontaneous styles. In some instances, the results for one of the two samples confirmed the Dewberry research but contradicted the results found for another sample. All of these inconsistencies were related to the System 1 styles, intuitive and spontaneous. The author sees the reason for these inconsistencies in the poor factor loadings of the questionnaire items deemed to load well in the spontaneous style. Since the spontaneous style items loaded even better in the intuitive style, the separation of both styles appears to suffer tremendously.

6.2.2 Researching the drivers of the choice set variables

Having unveiled the relationships amongst the decision styles and their categorisation into three process styles, the next hypothesis formulated could then focus on how the decision and/or process styles as well as the criteria importance weights, demographic factors and time to perform the compatibility test, influence the three choice set variables.

This hypothesis that claimed that the choice set variables are impacted by the considered variables was tested with a series of ANOVAs and regression analyses which very quickly and consistently clarified that no impact of the demographic factors, age and gender, existed.

The time to perform the compatibility test, expressed through the time to take the survey, had a statistically significant influence on all three choice set variables: the more time participants spent to take the survey, the smaller was the number of inconsistencies, the smaller was the number of alternatives in their choice sets, and, thus, the higher was their rejection thresholds (keeping in mind that the valence of the rejection threshold is negative). The finding that a longer time to take the survey decreases the number of inconsistencies is not surprising since more time to think about a decision alternative appears to come hand in hand with a rational, effortful but less error-prone System 2 activity. However, and even though the finding for the number of alternatives in the choice set and the rejection threshold are in itself consistent, they appear to be in contradiction with the finding (that will be presented later) of the rational decision style driving a higher number of alternatives in the choice set, and, thus, a lower rejection threshold. This apparent mismatch could potentially be explained if one assumes that those participants that take more time to take the survey are leaving the context of the compatibility test. If so, they were assessing the alternatives with the profitability test, Image Theory's protocol that aims to find the winning alternative amongst the choice set alternatives; the alternative that would maximise subjective utility. It appears then to be logical that a higher System 2 activity will lead to a smaller number of alternatives and a higher rejection threshold since the application of the profitability test aims to find one and only one winning alternative. This interpretation is further nurtured by the assumption that the compatibility test is potentially not

sharply separated from the profitability test, and that applying the former might seamlessly merge in the application of the latter.

Further, the influence of all three process styles on the choice set variables was detected with statistical significance except for the regulatory process style or decision anxiety which was found not to have any relevant influence on the number of inconsistent choices produced by the decision-maker. Even though the activities of the process styles are determined by the activities of all related decision styles, they appear to be driven by four decision styles only: intuitive, spontaneous, dependent, and rational.

Apart from the influence of the decision or process styles on the choice set variables, two of the importance weight variables also appeared to be significant: these are the participant-researcher consensus measure providing information on how well the criteria importance assessment of the participant aligned with the one provided by the researcher, and the individual importance weight for the 'Price' criterion.

6.2.2.1 Factors influencing the number of alternatives in the choice set

The intuitive and dependent styles seem to drive the activity of all three process styles impacting the number of alternatives in the choice set. The effects of both styles are however weak but of the same strength and direction. This implies that a decision-maker with high intuitive and dependent scores is likely to select a higher number of alternatives than someone with lower scores in these two decision styles. This appears reasonable since intuition is a feature of System 1 that is emotional, effortless and quick. A decision-maker who is intuitive might not want to think too much about the reasons to reject a certain alternative, in particular, in the context of a screening process of which the outcome is not the one and only winning alternative that ought to be implemented but a choice set that will be evaluated and processed further.

The activity of the dependent style appears to drive the influence of the regulatory style and of System 2. Decision-makers might be subject to anxiety because they fear to make an error when selecting a respective company. They might choose a company that is not in line with the requirements provided by the researcher or make an error of other nature.

As discussed earlier, the dependent style is as well linked to the rational style and thus, to System 2. Therefore, the influence of System 2 on the number of companies selected might as well be explained, at least partially, by the activity of the dependent style. The underlying mechanism could be the one described earlier: decision-makers rely on the requirements provided by the researcher and dependency might thus be created. They then have to consider, evaluate and conclude whether or not to put the respective company on their shortlists. Evaluation, consideration and thoughtful conclusions are the domain of System 2, hence, the impact of System 2 on the number of companies selected.

Further, the individual price importance weight is negatively but strongly impacting the number of companies in the choice set. That is, the more important participants considered the acquisition price of a company, the less companies they selected. This relationship comes as a surprise since there does not appear to exist a simple explanation for it. However, if decision-makers consider the price of a company as very important, they potentially do not want to spend a lot of money in the merger and acquisition process. Therefore, acting intuitively and unconsciously, they will select less companies than others. In combination with the already unveiled link between System 1 and the number of companies, this explanation appears to make sense.

6.2.2.2 Factors influencing the rejection threshold

The rational and intuitive styles are linked to the rejection threshold by activating all three process styles. Both decision styles' influence on the rejection threshold appears to be stronger than the influence of intuitive and dependent style on the number of selected companies. The more rational and intuitive decision-makers are, the lower are their rejection thresholds (again keeping the negative valence of this variable in mind). This implies that the effect of rational and the intuitive styles on the rejection threshold leads to the same result as the effect of the intuitive and the dependent style on the number of companies on the shortlist. That is, the more salient these decision styles are in a decision-maker, the higher the number of companies in that decision-maker's choice set. Keeping in mind the link between dependent and rational, the result for the rejection threshold is in line with, and thus confirms, the findings for the number of companies selected. Therefore, the chain of reasoning appears to be the same.

The observed connection between the rejection threshold and an individual's importance weight for the 'Price' criterion is the same as the influence of the latter on the number of alternatives in the choice set: the more relevant the price is to decision-makers, the higher are their rejection thresholds, and, thus, the less companies they allow in their choice sets.

The findings for the rejection threshold and the number of alternatives in the choice set are firmly linked. This appears to be logical since the rejection threshold drives the potential selection of a company in the choice set, and therefore is the determining factor for the number of companies selected.

6.2.2.3 Factors influencing inconsistent choices

Eventually, the impact of System 1 and 2 on the number of inconsistencies is determined by the decision styles spontaneous and rational. Both effects are very weak and of opposing nature: whilst a decision-maker with a high spontaneous score is prone to have more inconsistencies, the more rational decision-maker is set to have less inconsistencies. Considering the nature of System 1 and 2, this appears to be logical. Again, System 1 with its fast but frugal nature is more error prone than the cumbersome but analytical System 2.

The importance weight fit measure providing information on how well the participants' importance weights align with the requirements provided by the researcher, has a comparatively high positively correlated impact on the number of inconsistencies. This appears to be reasonable as well: the more participants disagree with the researcher's assessment of the importance weights, the higher their scores of the alignment measure becomes, and, thus, the more prone they potentially are to inconsistencies. It seems that a participant's disapproval of the researcher provided criteria values enables a stronger System 1 activity sneaking inconsistent choices past the analytical skills of System 2.

6.2.2.4 Structural Equation Modelling (SEM)

A series of SEM analyses was performed to confirm the author's overall structural model.

The result is shown in the figure below.

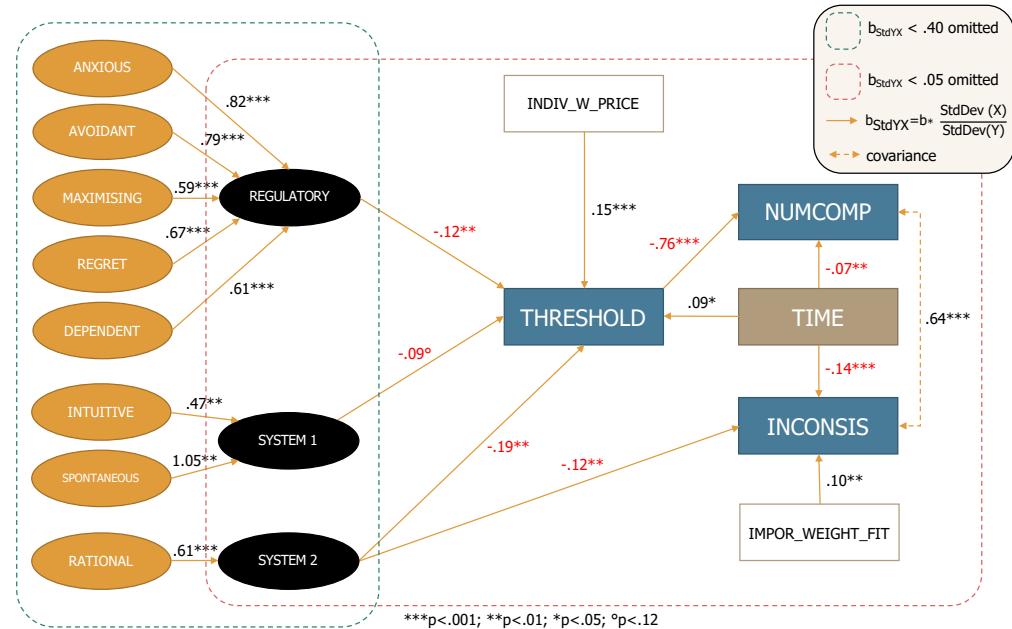


Figure 34:

Confirmed structural model of how decision styles influence choice set variables

These SEM analyses 'sharpened' the model unveiled by the ANOVAs and the regression analyses. The results confirmed on one side largely the findings of the regressions, and on the other side again the Dewberry et al. (2013) model seeing the decision styles strongly linked to the process styles.

The already mentioned 'issues' with the spontaneous and the intuitive styles became apparent again. One of the SEM analysis did not converge due to problems with the values of the spontaneous style. Besides the poor factor loadings of the spontaneous style items, the close links between the two styles underlined already by Dewberry et al. (2013, p. 567), might well contribute to these 'issues' as well. Therefore, and since the two styles represent the System 1 process styles, these problems might well explain the comparably poor statistical significance of the System 1 impact on the rejection threshold and the number of inconsistencies.

6.2.3 Predicting the choice set variables

The regressions analysis used when researching the links between the choice set variables and the decision/process styles as well as other factors demonstrated to have only poor predictive capability to forecast the score for the choice set variables. Correct predictions for all three variables were well below 50%. The lowest number of correct values, only 20%, were achieved when predicting the rejection thresholds of the participants. The best predictive capabilities with 40% of correct values, could be stated for their number of inconsistencies.

Even a relaxation of the definition what constitutes a correct prediction, did only marginally increase the level of correct values to 53% in the best case of the rejection threshold predictions.

Eventually, the requirement for a correct prediction was further relaxed to test the hypothesis: The initial values of each choice set variable were regrouped thus creating sets of respective categorial variables that were then used as dependent variable for a series of discriminant analysis.

But even this approach did not lead to a satisfactory result with regards to correctly predicting categorical variables related to the values of the choice set variables. A maximum of 66% correct predictions of the categorical variable was achieved - far away from being in line with the requirement of the hypothesis (80%) and, thus, satisfactory.

The best performing discriminant analyses for each choice set variable were however used to produce charts allowing to determine the probability of participants being members of the respective group of a categorical variable based on their discriminant scores. This allowed at least to produce a tendency of what might be a participant's choice set variable values.

It appears though that there are too many other, unknown and uncontrolled factors that influence the choice set variables and, thus, their prediction. Further, the influences of the process/decision styles as well as of the other factors on the choice set variables appear to be too weak. Therefore, it was not possible to achieve acceptable prediction levels even when applying relaxed acceptability criteria; neither with a regression nor with a discriminant analysis.

When looking at the results of the analysis so far, a further interpretation of the interaction of decision/process styles and the choice set variables can be fielded: the various decision styles could well be linked to each other, in particular within a given process style, but change the strength and direction of their interaction based on the context of the decision situation and the decision-maker's 'working images'. The decision styles and their interaction could be interpreted as a neural network where the decisions styles represent the nodes of the network and the links between them are activated as required based on contextual information and/or the individual's 'working images'. This neural network approach was the driving concept to test the capability of the collected data to predict whether a specific decision alternative is accepted or rejected in a decision-maker's choice set.

6.3 Predicting acceptance and rejection of a decision alternative

The last area of research that the author investigated was the possibility to predict whether or not a specific decision alternative (in the case of this research project a specific company) will be accepted or rejected by a decision-maker. Taking up the idea of the previous paragraph and considering that the relationship between the various variables is almost certainly of non-linear nature, a series of neural networks was generated, trained and tested to identify their capabilities to correctly predict an acceptance or rejection choice of a participant. For the purpose of this analysis, the data collected by the various questionnaires had to be restructured, focussing on a participant's individual choice per company considered for that participant's choice set.

When including all available variables, the fit of the neural network was already very close to satisfactory (80% correct predictions). In order to amend the model further additional analyses were performed. They unveiled that a large number of variables did not contribute to the quality (in terms of correct predictions) of the model.

Neither the demographic variables, gender and age, nor the importance weight variables and the information whether or not a company represented a temptation, played a role in a participant's choice to reject or accept a specific company.

Further, the time to complete the survey did not contribute directly to the predictive capability of the neural networks. This appears to be surprising since an influence of the time variable on all choice set variables could be witnessed in previous analyses. However, since the time to complete the survey is influencing the choice set variables, it might indirectly influence the predictions of the neural networks through these choice set variables.

The same seems to be the case for the decision and process styles: neither the decision styles nor the process styles demonstrated to have an important direct influence on the predictive capability of the networks. However, as could be shown in previous analyses, there appears to be a link between the process styles and the choice set variables. Therefore, and as for the variable TIME, the effect of the decision styles might develop through the process styles into the choice set variables as well.

The requirement of having the most parsimonious model possible led eventually to the removal of those variables that did not significantly contribute to the predictive capability of the neural networks.

Two sets of variables remained: the six categorial compatibility variables that provided information if the respective company met the desired criteria, and the choice set variables, that is the number of companies in the choice set, the participant's rejection threshold and the number of inconsistencies. Whilst the categorical compatibility variables provide objective information, the choice set variables feed the neural networks with information on the decision-makers themselves; individual information that is impacted by the process and thus the decision styles and by the time required to complete the survey, as well as by other factors beyond the control of the research design.

A series of neural networks were designed that only relied on these two sets of independent variables to predict a participant's rejection or acceptance choice. The best of these networks, Neural Network E, demonstrated better fit than the first networks with all available variables included. This implies that at least some of the variables that have been eliminated from the analysis, did not only contribute nothing to the performance of the network but hampered its capability to predict the choices correctly.

Neural Network E could be further amended by fine tuning the architecture and training settings of IBM SPSS and, eventually, achieved an optimum of 87% of correct predictions with an AUC of .95 (Neural Network E⁺).

Further, the rejection threshold was most important for the neural network's predictive capability holding double as much weight than the compatibility of the company's profit with the requirement for that criterion provided by the researcher. It appears to be reasonable that the participant's rejection threshold plays the most important role when performing the compatibility test since this measure is central for allowing a decision alternative into the choice set.

Based on the relationships discussed earlier between the choice set variables and the decision and process style variables, it could be stated that the choice set variables absorb the decision profile of participants and, thus, shape their perceptions of the very objective criteria compatibilities.

The verification of these findings with the Student and the Extension Sample confirmed them in the case of the former sample (88% correct predictions) whilst a significant drop of correct predictions could be observed for the latter. However, the best performing neural network, Neural Network E⁺, was still capable to predict correctly 69% of choices related to companies for which it was neither trained for nor tested with.

6.4 Contribution to knowledge and management practice

6.4.1 Contribution to knowledge

The author sees four basic contributions of his work to knowledge: first, Beach and Strom (1989) as well as Ordóñez et al. (1999) claim that when applying the compatibility test, the screening process of Image Theory, to reduce the number of decision alternatives, and thus to form the choice set, decision takers only consider criteria that fail to meet a desired value. That is, only criteria violations are considered when decision-makers apply the compatibility test. Therefore, failing alternatives are screened out rather than good alternatives selected. This implies that criteria that are met do not contribute to decision-makers' selection processes to form their choice sets; in particular, criteria which overachieve their respective desired target value, cannot compensate for a criterion that has not been met by this alternative. The results of this research project prove the claim of above researchers as being untenable. Affect seems to allow an alternative in the choice set that outperforms all other alternatives in one criterion that appears to be of utmost important to the decision-maker despite its failure to meet all other criteria values. The 'super attribute' of this alternative appears to compensate for the failing to meet the other criteria values.

Second, the current research confirms the validity of the Dewberry et al. (2013) model by using only five instead of eight questionnaire items to determine one's decision styles. That is, the results of Dewberry et al. (2013) have largely been confirmed by using a reduced number of questions. This implies that future research might rely on this smaller set of questions providing a more parsimonious approach.

Third, even though Galotti et al. (2007) and Galotti (2007) have researched potential links between Image Theory and decision styles, the author's research appears to be the first research ever that found evidence of links between one's decision styles and quantitative elements of Image Theory's compatibility test; at least the author has not found any related evidence that these links have been researched when reviewing the relevant body of literature.

Fourth, the present research provides evidence that neural networks can be used to mimic a decision-makers choice behaviour for a specific decision alternative. Neural

networks are typically known to perform very well (even better than human beings) when tasked to visually identify objects, signs, writing, etc. . The author's research provides evidence that neural networks can predict a decision-maker's choice based, first, on a set of compatibility variables expressing how well an alternative meets the desired criteria values, and, second and more importantly, on the elements of the compatibility test, the choice set variables. Introducing the latter set of variables allows to correctly predict inconsistent, and thus, for an outside party, irrational choices of the decision-maker as well, and not only rationally correct choices (which typically is the domain of normative decision theories).

6.4.2 Contribution to management practice

The author offers two contributions for management practice of which the first one is twofold:

First, a very specific application of the findings related to researching hypothesis 5 can be imagined: a consultancy company specialised in M&A activities and, therefore, in finding acquisition targets for potential buyers, could use the Base Sample questionnaire to select companies to be proposed for acquisition to that potential buyer. The decision-maker(s) of the company intending to buy another company had only to answer the Base Sample questionnaire, thus, providing the first part (the values of subjective set of variables) of the required input data for the neural network created and optimised in the context of this research project.

The second part of required input is defined by the target company's achievements of the six criteria. The neural network will then predict whether or not this target company will be most likely accepted or rejected by the decision-maker(s) of the acquiring company.

Obviously, if the Base Sample questionnaire is amended in a way to cover all possible combinations of companies achieving and missing the selected criteria, an even better performing neural network could be generated, trained and tested. Second, and based on the above, very specific first application, the underlying approach can be extended to a more general principle covering potentially any managerial decision situation: with the findings and the approach of this research project, it is possible to devise expert

systems based on a neural network approach requiring two sets of input data: the choice set variables and the compatibility information of the considered decision alternative.

The compatibility variables provide the very objective facts regarding the salience of the criteria in the considered decision alternative. The choice set variables contribute subjective information on the decision-makers themselves including their decision style profiles, the time they spent on evaluating decision alternatives and, more importantly, their subject matter expertise.

Currently, expert systems are often based on a combination of neural networks and a set of rules extracted from domain experts by the means of structured interviews. This approach aims to define objectively correct decision rules but neglect those experts' 'stomach feelings' that they are - at least sometimes - not capable to express themselves but that are based on those experts holding years if not decades of experience in their field of expertise. Further, and since taking questionnaires, such as, the one designed for this research project is far quicker than conducting structured interviews and can be taken anytime and anywhere, the probability of having a larger number of experts contributing to the type of expert systems proposed in this research project appears to be higher than for at least partially rule based systems. Therefore, the knowledge and experience of potentially thousands of experts could manifest itself in the proposed neural network approach being potentially a valuable support for managers tasked to lead their companies through difficult times.

The second, albeit minor implication for management practice of the findings of this research project becomes obvious when considering the main driver for management actions: it is the stakeholders' expectations that largely determine management behaviour to be comprehensibly rational aiming to act in the best interest of the company. Behaviour that appears suspicious implying that a manager acts selfishly and puts personal interest before the requirements of the company, might lead to tension and distrust between management and supervisory entities of the company, and have contributed repeatedly to damage the role and reputation of the management profession. Examples might be easily thought of: the CEO who uses the company aircraft to travel to holiday destinations, managers that are rewarded with high bonuses whilst other employees had to be laid off. Such management behaviour might be perceived as

being insensitive or 'cold blooded' but might not necessarily be a conscious act of the manager. In such case and since management is under constant public scrutiny, it is important for managers to have routines in place allowing them to reflect and reconsider their own behaviour. Therefore, knowing about the vulnerability of the decision process or elements thereof, i.e. the compatibility test, with regards to the affect heuristic might be advantageous for the manager in a decision situation. Confronted with a set of potential decision alternatives and based on decision-makers' preferences for certain criteria, they might reflect on their decision behaviours by asking themselves the question whether the preferences for given alternatives stem from a logical and rational reasoning, i.e. based on the alternatives meeting objectively agreed target values, or from a bias caused by the decision-makers' affect for a particular criterion strongly salient in those decision alternatives. Therefore, and in this sense, the author recommends to managers but as well to institutions and organisations trusted with management education and training to introduce compulsory courses discussing the effects of heuristic and biases in managerial decision-making.

6.5 Limitations of the research and potential future research

The first limitation of the seven identified by the author in the context of his research project, is related to fielding the previously mentioned idea of institutions and organisations providing management training on the effects of biases and heuristics on managerial decision-making: the present research project has considered the effects of the affect heuristic only despite an apparent claim that other heuristics, i.e. the availability heuristic, the representative heuristic, etc. (see Bazerman & Moore, 2013, p. 58), assumingly impact the performance of the compatibility test as well. Researching these impacts will have to be left to future research.

A second limitation is the research's focus on only one particular decision situation. One could imagine that modifying the decision framework and, thus, the 'working images' could alter the links between the participants' decision style profiles and the choice set variables or the affect heuristic's intervention.

Obviously, the underlying samples and populations represent another, the third limitation of the research. Even though the findings could be observed for two rather

different samples, the Base and the Student Sample, it would be rewarding for future research projects to test the effects of heuristics and biases and the links between decision style profiles and the elements of the compatibility test by using different populations.

The fourth limitation is linked to the 'issues' encountered with the System 1 styles intuitive and spontaneous. Both styles are closely linked, and the questionnaire items of the intuitive style loaded equally well in the spontaneous style and vice versa. This potentially caused the statistically weak impact of System 1 on the rejection threshold during the SEM analysis. The author's recommendation for future research is to test different questionnaire items that potentially allow a better separation of the two styles.

As mentioned in the introductory chapter of this thesis, decision-making is a complex task and subject to many, unknown and sometimes even undetectable factors. The fifth limitation of this research is its inability to identify and control all possible factors that might have influenced the participants when taking the survey. Some participants might have been stressed and under time pressure, others might have been sad or excited. All these factors and potentially others have not been controlled by the research design even though they might have an impact on participants answering the survey. Due to the relatively large sample size of the Base Sample, the author would like to believe that the effects of some of those factors have been of opposing nature and, therefore, cancelled each other out. But since no evidence can be presented for such compensatory behaviour being the case, it remains speculation. The suggestion for potential future research would be to control or avoid those factors in a more laboratory environment and set up.

The regulatory process style deals predominantly with anxiety and thus with negative emotions. But not only negative emotions, such as, anxiety or fear are potentially impacting human decision-making. Excitement or more generally happiness are almost certainly influencing the process of taking a decision as well. The Dewberry et al. (2013) model does not cater for any positive emotions and the author did not include the effect of these emotions on decision-making in his research project which represents the sixth limitation of his work. Future research, however, could first supplement Dewberry et al.'s (2013) model by introducing a regulatory process style regrouping decision styles

rooted in positive emotions before researching the links and impacts of those decision styles on the compatibility test.

The seventh and last limitation of this research that deserves being mentioned, is linked to the selected decision criteria: first, the design of the decision alternatives, the companies, did not cover all possible combinations of missing and fulfilling the desired values of the six selected criteria. This shortcoming unfolds its detrimental effect in particular during the training of the neural networks since the network could not learn all possible alternatives and, thus, how the participants would react to them. Second, neither the impact of having more or less than six decision criteria, nor the influence of having criteria that differ from those six have been researched.

Eventually, the author wants to conclude this report on his research project on providing his view on the three main thrusts for future research that hopefully might arise out of his work and the related findings.

First, researching the impact of other biases and heuristics than the affect heuristic appears to be very beneficial in the light of its impact on managerial training.

Second, researching the effects of decision styles representing positive emotions and thus complementing the Dewberry et al. (2013) model appears to be promising and constitutes the foundation for investigating those decision styles' impact on the elements of Image Theory's compatibility test, the choice set variables.

Eventually, third, and most likely the most practical and exciting path of future research appears to be the investigation of the potential application of expert systems that are based on the approach put forward by the author: a neural network that relies on two sets of input data: a first one capturing the objective fit of a decision alternative when compared to the desired values of relevant decision criteria, and, a second set providing the subjective nature of compatibility tests performed in the relevant decision situation by experts in the required field of expertise. This second set of variables allows the neural network to take full benefit of the experience of the experts even for knowledge that they are either not aware of or simply regard as irrelevant. This second set of variables embraces much more than can be observed.

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8 APPENDICES

8.1 List of used variables

<i>Name</i>	<i>Description</i>	<i>Type</i>	<i>Values</i>
<i>AGE</i>	Age group of the Base & Extension Sample participants	ordinal	2 to 5: 2 = 18 – 29 3 = 30 – 44 4 = 45 – 60 5 = Above 60
<i>AGE_S</i>	Age group of the Student Group participants	ordinal	1 to 5: 1 = under 26 2 = 26 – 35 3 = 36 – 45 4 = 46 – 55 5 = 56 – 65 6 = Above 65
<i>ANXIOUS</i>	Calculated score for the anxious decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>ANXIOUS_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the anxious decision style (see Appendix 40 <i>items</i> <i>to determine the decision styles</i>).	ordinal	1 = low 4 = high
<i>AVOIDANT</i>	Calculated score for the avoidant decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>AVOIDANT_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the avoidant decision style (see Appendix 40 <i>items to determine the</i> <i>decision styles</i>).	ordinal	1 = low 4 = high

Name	Description	Type	Values
<i>CHOICE</i>	Information whether or not a given company has been allowed through to the choice set by the participant	ordinal	0 = company rejected 1 = company selected
<i>COMP_DEBT</i>	Information whether or not a given company meets the debt criteria	ordinal	0 = criteria met 1 = criteria failed
<i>COMP_EMPLOYEES</i>	Information whether or not a given company meets the employee criteria	ordinal	0 = criteria met 1 = criteria failed
<i>COMP_INDUSTRY</i>	Information whether or not a given company meets the industry criteria	ordinal	0 = criteria met 1 = criteria failed
<i>COMP_INVEST</i>	Information whether or not a given company meets the invest criteria	ordinal	0 = criteria met 1 = criteria failed
<i>COMP_PRICE</i>	Information whether or not a given company meets the price criteria	ordinal	0 = criteria met 1 = criteria failed
<i>COMP_PROFIT</i>	Information whether or not a given company meets the profit criteria	ordinal	0 = criteria met 1 = criteria failed
<i>DEPENDENT</i>	Calculated score for the dependent decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>DEPENDENT_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the dependent decision style (see Appendix 40 items to determine the decision styles).	ordinal	1 = low 4 = high
<i>FXW_DEBT</i>	Importance weight provided by the researcher for the debt criterion	const.	Ranking, constant value: FXW_DEBT = 2

Name	Description	Type	Values
<i>FXW_EMPLOYEES</i>	Importance weight provided by the researcher for the employee criterion	const.	Ranking, constant value: <i>FXW_EMPLOYEE</i> ES = 2
<i>FXW_INDUSTRY</i>	Importance weight provided by the researcher for the industry criterion	const.	Ranking, constant value: <i>FXW_INDUSTRY</i> = 3
<i>FXW_INVEST</i>	Importance weight provided by the researcher for the invest criterion	const.	Ranking, constant value: <i>FXW_INVEST</i> = 3
<i>FXW_PRICE</i>	Importance weight provided by the researcher for the price criterion	ordinal	Ranking, constant value: <i>FXW_PRICE</i> = 1
<i>FXW_PROFIT</i>	Importance weight provided by the researcher for the profit criterion	ordinal	Ranking, constant value: <i>FXW_PROFIT</i> = 1
<i>GENDER</i>	Information on the gender of each participant	ordinal	1 = male 2 = female
<i>GROUP_PRICE</i>	Information on whether or not the participant was faced with the price temptation alternative (Company T)	ordinal	0 = Company D offered 1 = Company T offered
<i>GROUP_PROFIT</i>	Information on whether or not the participant was faced with the profit temptation alternative (Company R)	ordinal	0 = Company E offered 1 = Company R offered
<i>ID</i>	Identification number of the Base Sample participants	ordinal	1 to 649
<i>ID_E</i>	Identification number of the Extension Sample participants	ordinal	1 to 56
<i>ID_S</i>	Identification number of the Student Sample participants	ordinal	1 to 87
<i>IMPOR_WEIGHT_FIT</i>	Alignment measure providing information on how well a	metric	see Table 33, page 163

Name	Description	Type	Values
	participant's overall assessment of the decision criteria aligns with the importance weights provided by the researcher.		
<i>INCONSIS</i>	Calculated number of inconsistencies	metric	see Table 33, page 163
<i>INCONSIS_GROUP</i>	Categorical variable that divided the respective sample in three groups based on the values of INCONSIS	categorical	1, 2 or 3 see Table 19, page 118
<i>INCONSIS_GROUP2</i>	Categorical variable that divided the respective sample in three groups based on the values of INCONSIS	categorical	1 or 2 see Table 19, page 118
<i>INDIV_W_DEBT</i>	A participant's normalised importance weight for the criterion debt	ordinal	see Table 33, page 163
<i>INDIV_W_EMPLOYEES</i>	A participant's normalised importance weight for the criterion number of employees	ordinal	see Table 33, page 163
<i>INDIV_W_INDUSTRY</i>	A participant's normalised importance weight for the criterion industry	ordinal	see Table 33, page 163
<i>INDIV_W_INVEST</i>	A participant's normalised importance weight for the criterion invest	ordinal	see Table 33, page 163
<i>INDIV_W_PRICE</i>	A participant's normalised importance weight for the criterion price	ordinal	see Table 33, page 163
<i>INDIV_W_PROFIT</i>	A participant's normalised importance weight for the criterion profit	ordinal	see Table 33, page 163
<i>INTUITIVE</i>	Calculated score for the intuitive decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>INTUITIVE_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the intuitive	ordinal	1 = low 4 = high

Name	Description	Type	Values
decision style (see Appendix 40 items to determine the decision styles).			
<i>MAXIMISING</i>	Calculated score for the maximising decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>MAXIMISING_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the maximising decision style (see Appendix 40 items to determine the decision styles).	ordinal	1 = low 4 = high
<i>NUMCOMP</i>	Number of companies in a participant's choice set	metric	see Table 33, page 163
<i>NUMCOMP_GROUP</i>	Categorical variable that divided the respective sample in four groups based on the values of NUMCOMP	categorical	1, 2, 3 or 4 see Table 19, page 118
<i>NUMCOMP_GROUP2</i>	Categorical variable that divided the respective sample in three groups based on the values of NUMCOMP	categorical	1, 2 or 3 see Table 19, page 118
<i>NUMCOMP_GROUP3</i>	Categorical variable that divided the respective sample in two groups based on the values of NUMCOMP	categorical	1 or 2 see Table 19, page 118
<i>POSITION</i>	Provides information on the position of a participant in his or her organisation or company. The scores of this variable was however not used for further statistical analysis.	ordinal	Integer, 1 to 7 1 = Owner/ Head of Company 2 = Upper Management 3 = Middle Management 4 = Experienced Employee 5 = Professional Beginner 6 = Student 7 = Other

Name	Description	Type	Values
<i>RANK_PRICE</i>	Rank allocated by a participant to the criterion price	ordinal	Ranking: 1 = high importance, 6 = low importance, 7 = not relevant
<i>RANK_PROFIT</i>	Rank allocated by a participant to the criterion profit	ordinal	Ranking: 1 = high importance, 6 = low importance, 7 = not relevant
<i>RATIONAL</i>	Calculated score for the rational decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>RATIONAL_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the rational decision style (see Appendix 40 items to determine the decision styles).	ordinal	1 = low 4 = high
<i>REGRET</i>	Calculated score for the regret decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>REGRET_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the regret decision style (see Appendix 40 items to determine the decision styles).	ordinal	1 = low 4 = high
<i>REGULATORY</i>	Score for the regulatory process style. The score for each participant has been calculated by the SPSS confirmatory factor analysis. The following decision styles load in this factor:	metric	see Table 33, page 163

Name	Description	Type	Values
	ANXIOUS, REGRET, MAXIMISING, DEPENDENT		
<i>SPONTANEOUS</i>	Calculated score for the spontaneous decision style based on the factor loading of the 5 items related to that style.	metric	see Table 27, page 148
<i>SPONTANEOUS_X</i>	X can range from 1 to 5. These five variables collect the answers to the five questions related to the spontaneous decision style (see Appendix 40 items to determine the decision styles).	ordinal	1 = low 4 = high
<i>SYSTEM1</i>	Score for the system 1 process style. The score for each participant has been calculated by the SPSS confirmatory factor analysis. The following decision styles load in this factor: SPONTANEOUS, INTUITIVE	metric	see Table 33, page 163
<i>SYSTEM2</i>	Score for the system 2 process style. The score for each participant has been calculated by the SPSS confirmatory factor analysis. The following decision style loads in this factor: RATIONAL	metric	see Table 33, page 163
<i>TEMP_PRICE</i>	Information whether or not the presented company (either company T or D) has been selected	ordinal	0 = alternative rejected 1 = alternative accepted
<i>TEMP_PROFIT</i>	Information whether or not the presented company (either company R or E) has been selected	ordinal	0 = alternative rejected 1 = alternative accepted
<i>TEMPTATION_PRICE</i>	Information whether or not a company is the temptation price alternative	ordinal	0 = no temptation

Name	Description	Type	Values
			1 = temptation price
<i>TEMPTATION_PROFIT</i>	Information whether or not a company is the temptation profit alternative	ordinal	0 = no temptation 1 = temptation profit
<i>THRESHOLD</i>	The value of a participant's incompatibility threshold	metric	see Table 33, page 163
<i>THRESHOLD_GROUP</i>	Categorical variable that divided the respective sample in four groups based on the values of THRESHOLD	categorical	1, 2, 3 or 4 see Table 19, page 118
<i>THRESHOLD_GROUP2</i>	Categorical variable that divided the respective sample in three groups based on the values of THRESHOLD	categorical	1, 2 or 3 see Table 19, page 118
<i>THRESHOLD_GROUP3</i>	Categorical variable that divided the respective sample in two groups based on the values of THRESHOLD	categorical	1 or 2 see Table 19, page 118
<i>TIME</i>	Information on the time that a participant required to finish the questionnaire. The score for each participant is the quartile number that his or her time to take the survey falls under in his or her sample. Therefore, the score is specific for the respective sample.	ordinal	The participant belongs to... 1 = the fastest 25% 2 = the second fastest 25% 3 = the second slowest 25% 4 = the slowest 25% ...to take the survey
<i>X</i>	Place holder in variable names representing either the number of the item of a decision style (see above) or the name of the six criteria		1 to 5 for the decision style items, or PRICE, PROFIT, DEBT, EMOLOYEES, INVEST or INDUSTRY for

Name	Description	Type	Values
			variable names linked the six criteria
Y_x	Intermediate variable created to calculate the individual importance weights for each criterion	metric	Integer, 0 to 6
\bar{Y}_x	Intermediate variable created to calculate the importance weights for each criterion as provided by the author	metric	Integer, 0 to 6

8.2 Questionnaires

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8.2.1 Base & Student Sample Questionnaire (German original & English translation)

Page 1 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Fragen zur Umfrage?
Senden Sie eine E-Mail an
alexander.muller@student.shu.ac.uk

WICHTIGE HINWEISE (Bitte lesen!):

Die Umfrage ist das Kernstück einer wissenschaftlichen Studie zur Untersuchung von Verbindungen zwischen Entscheidungsprofilen und -prozessen.

Die Umfrage sollte nicht mehr als 20 min Ihrer Zeit in Anspruch nehmen und besteht aus insgesamt 50 Fragen zu zwei Bereichen:

- 40 Fragen dienen zur Feststellung Ihres Entscheidungsprofils. Hierzu werden Sie aufgefordert zu beurteilen, ob eine Aussage bezogen auf ein bestimmtes Entscheidungsverhalten auf Sie zutrifft oder nicht.
- Ihre Aufgabe bei weiteren 10 Fragen ist es, aus einer Liste von Unternehmen potentielle Übernahmekandidaten auszusuchen, die Ihres Erachtens sechs Kriterien ausreichend genug erfüllen.

Alle Antworten sollten Ihr TATSÄCHLICHES Entscheidungsverhalten widerspiegeln und NICHT ein von Ihnen beabsichtigtes oder erwünschtes!

Seien Sie also nicht rationaler, nicht spontaner und nicht intuitiver als Sie dies in einer Entscheidungssituation sind!

Die Teilnahme an dieser Umfrage ist vollkommen anonym.

Wenn Sie auf die unten gezeigte Schaltfläche 'Weiter' klicken, stimmen Sie der Nutzung und Verarbeitung der mit dieser Umfrage erhobenen, anonymen Daten im Rahmen der oben genannten wissenschaftlichen Studie oder anderer, nicht-kommerzieller, wissenschaftlicher Projekte ausdrücklich zu.

Bitte LASSEN SIE SICH ZEIT bei der Beantwortung der Fragen!

Vielen Dank für Ihre Teilnahme!

Page 1 [English translation]

[Header 1]¹⁰ Decision Profiles and Processes [print version][°]

[Header 2][°] Questions regarding the survey?

[Header 2][°] Send an e-mail to

[Header 2][°] alexander.muller@student.shu.ac.uk

IMPORTANT REMARKS (please read!)

This survey is the centre piece of a scientific study investigating the relations between decisions profiles and processes.

The survey should not take more than 20 minutes of your time and consists of 50 questions related to two areas:

- 40 questions serve to identify your decision profile. To do so, you will be asked to evaluate if a given statement describes your behaviour in a decision situation or not.
- For further 10 questions, your task is to select from a list of companies, potential acquisition targets that meet sufficiently well six criteria.

All answers should reflect your TRUE decision behaviour and NOT a desired or intended behaviour.

Don't be more rational, more spontaneous or more intuitive than you are in a decision situation.

The participation in this survey is entirely anonymous.

If you click the 'Next' button below, you expressively agree that the anonymous data collected with this questionnaire, can be used and processed for the purpose of this study or any other non-commercial, scientific study.

Please TAKE YOUR TIME when answering the questions!

Thank you very much for your participation!

¹⁰ Expressions marked with a circle were not shown in the original version of the questionnaire

Page 2 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Fragen zur Bestimmung des Entscheidungsprofils

Treffen folgende Aussagen auf Sie zu ?

* 1. Ich verschiebe Entscheidungen wenn immer möglich.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 2. Normalerweise treffe ich Entscheidungen, die sich richtig anfühlen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 3. Ich überprüfe meine Informationsquellen, um sicherzustellen, dass ich über die richtigen Fakten verfüge, bevor ich eine Entscheidung treffe.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 4. Ich treffe Entscheidungen oft impulsiv.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 5. Wenn ich darüber nachdenke, wie mein Leben läuft, bereue ich oft Gelegenheiten, die ich verpasst habe.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 6. Wenn ich TV schaue, surfe ich Kanäle, indem ich oft von einem zum nächsten Sender schalte; sogar wenn ich ein bestimmtes Programm gerne ansehen möchte.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 7. Wenn ich Entscheidungen treffe, fürchte ich falsch zu liegen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 8. Ich mag es, wenn mich jemand in die richtige Richtung lenkt, wenn ich mit wichtigen Entscheidungen konfrontiert bin.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page 2¹¹ [English translation]

[Header 1]^{*} Decision Profiles and Processes [print version]^{*}

[Header 2]^{*} Questions to determine the decision profile

Do you agree with the following statements?

***121. I postpone decision making whenever possible**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***2. I generally make decisions that feel right to me**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***3. I double-check my information sources to be sure I have the right facts before making decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***4. I often make impulsive decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***5. When I think about how I'm doing in life, I often assess opportunities I have passed up**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***6. When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***7. When making a decision, I am afraid that I might be wrong**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***8. I like to have someone to steer me in the right direction when I am faced with important decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

¹¹ the sequence of items was randomised when administering the survey online; the sequence of pages 2 to 6 was however the same for each participant.

¹² an asterix in front of an item means that answering the item was mandatory; participants could move forward to the next page without answering all mandatory items.

Page 3 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Fragen zur Bestimmung des Entscheidungsprofils

Treffen folgende Aussagen auf Sie zu ?

* 9. Ich zögere oft, wenn wichtige Entscheidungen anstehen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 10. Wenn ich Entscheidungen treffe, neige ich dazu, mich auf meine Intuition zu verlassen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 11. Ich plane meine wichtigen Entscheidungen sorgsam.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 12. Ich treffe oft Entscheidungen aufgrund einer momentanen Eingebung.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 13. Sobald ich eine Entscheidung getroffen habe, schaue ich nicht zurück.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 14. Beim Einkaufen ist es für mich schwierig, Kleidung zu finden, die ich wirklich toll finde.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 15. Ich bekomme Panik, wenn ich daran denke, dass meine Entscheidung falsch sein könnte.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 16. Ich treffe selten wichtige Entscheidungen, ohne andere Leute um Rat zu fragen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page 3¹³ [English translation]

[Header 1]^{*} Decision Profiles and Processes [print version]^{*}

[Header 2]^{*} Questions to determine the decision profile

Do you agree with the following statements?

***9. I often procrastinate when it comes to making important decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***10. When I make decisions, I tend to rely on my intuition**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***11. I plan my important decisions carefully**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***12. I often make decisions on the spur of the moment**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***13. Once I make a decision, I don't look back¹⁴**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***14. When shopping, I have a hard time finding clothing that I really love**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***15. I panic when I think that my decision might be wrong**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***16. I rarely make important decisions without consulting other people**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

¹³ the sequence of items was randomised when administering the survey online; the sequence of pages 2 to 6 was however the same for each participant.

¹⁴ This item was reverse scored.

Page 4 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Fragen zur Bestimmung des Entscheidungsprofils

Treffen folgende Aussagen auf Sie zu ?

* 17. Ich schiebe viele Entscheidungen auf, weil mir bei dem Gedanken an diese unwohl ist.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 18. Beim Treffen von Entscheidungen verlasse ich mich auf meinen Instinkt.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 19. Wenn ich Entscheidungen treffe, betrachte ich verschiedene, auf ein bestimmtes Ziel bezogene Alternativen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 20. Ich treffe Entscheidungen schnell.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 21. Wann immer ich eine Entscheidung getroffen habe, versuche ich Informationen zu erhalten, wie andere Alternativen sich entwickelt haben.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 22. Wenn ich im Auto Radio höre, wechsle ich oft den Sender, um zu hören ob auf einem anderen etwas besseres läuft; sogar wenn ich mit dem was ich aktuell höre, mehr oder weniger zufrieden bin.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 23. Ich fühle mich sehr ängstlich, wenn ich eine Entscheidung treffen muss.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 24. Wenn ich die Unterstützung von Anderen habe, ist es einfacher für mich wichtige Entscheidungen zu treffen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page 4¹⁵ [English translation]

[Header 1]^{*} Decision Profiles and Processes [print version]^{*}

[Header 2]^{*} Questions to determine the decision profile

Do you agree with the following statements?

***17. I put off making many decisions because thinking about them makes me uneasy**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***18. When making decisions, I rely upon my instincts**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***19. When making a decision, I consider various options in terms of a specific goal**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***20. I make quick decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***21. Whenever I make a choice, I try to get information about how the other alternatives turned out**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***22. When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***23. I feel very anxious when I need to make a decision**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***24. If I have the support of others, it is easier for me to make important decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

¹⁵ the sequence of items was randomised when administering the survey online; the sequence of pages 2 to 6 was however the same for each participant.

Page 5 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Fragen zur Bestimmung des
Entscheidungsprofils

Treffen folgende Aussagen auf Sie zu ?

* 25. Ich vermeide es, Entscheidungen zu treffen, bis ich den nötigen Druck verspüre.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 26. Wenn ich eine Entscheidung treffe, vertraue ich auf meine Gefühle.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 27. Meine Entscheidungsfindung benötigt sorgsames Nachdenken.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 28. Wenn ich Entscheidungen treffe, tue ich, was sich momentan am natürlichsten anfühlt.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 29. Wenn ich eine Entscheidung treffe, bin ich neugierig was passiert wäre, wenn ich anders entschieden hätte.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 30. Ich finde es oft schwierig, ein Geschenk für einen Freund/eine Freundin zu kaufen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 31. Ich kann nicht normal denken, wenn ich eine Entscheidung in Eile treffen muss.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 32. Ich nutze die Ratschläge anderer Leute, um meine wichtigen Entscheidungen zu treffen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page 5¹⁶ [English translation]

[Header 1]^{*} Decision Profiles and Processes [print version]^{*}

[Header 2]^{*} Questions to determine the decision profile

Do you agree with the following statements?

***25. I avoid making important decisions until the pressure is on**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***26. When I make a decision, I trust my inner feelings and reactions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***27. My decision making requires careful thought**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***28. When making decisions, I do what seems natural at the moment**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***29. Whenever I make a choice, I'm curious about what would have happened if I had chosen differently**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***30. I often find it difficult to shop for a gift for a friend**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***31. I can't think straight if I have to make decisions in a hurry**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***32. I use the advice of other people in making my important decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

¹⁶ the sequence of items was randomised when administering the survey online; the sequence of pages 2 to 6 was however the same for each participant.

Page 6 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)			
Fragen zur Bestimmung des Entscheidungsprofils			

Treffen folgende Aussagen auf Sie zu ?

* 33. Normalerweise treffe ich wichtige Entscheidungen in letzter Minute.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 34. Wenn ich eine Entscheidung treffe, ist es für mich wichtiger, dass sich die Entscheidung richtig anfühlt als rationale Gründe zu haben, die dafür sprechen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 35. Meine Entscheidungsfindung folgt einer logischen und systematischen Methode.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 36. Normalerweise treffe ich Blitzentscheidungen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 37. Wenn ich eine Entscheidung treffe und sich diese als gut herausstellt, fühle ich dennoch, ein wenig versagt zu haben, wenn ich herausfinde, dass sich eine andere Entscheidung als besser herausgestellt hat.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 38. Filme auszuleihen, ist wirklich schwierig. Ich zaudere immer mit mir, den Besten auszusuchen.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 39. Ich fühle mich, als ob ich unter enormen Zeitdruck stünde, wenn ich Entscheidungen treffe.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

* 40. Ich brauche oft Hilfe von anderen Leuten, wenn ich wichtige Entscheidungen treffe.

trifft nicht zu	trifft eher nicht zu	trifft eher zu	trifft zu
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Page 6¹⁷ [English translation]

[Header 1]^{*} Decision Profiles and Processes [print version]^{*}

[Header 2]^{*} Questions to determine the decision profile

Do you agree with the following statements?

***33. I generally make important decisions at the last minute**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***34. When I make a decision, it is more important for me to feel the decision is right than to have a rational reason for it**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***35. I make decisions in a logical and systematic way**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***36. I generally make snap decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***37. If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***38. Renting videos is really difficult. I'm always struggling to pick the best one**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***39. I feel as if I'm under tremendous time pressure when making decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

***40. I often need the assistance of other people when making important decisions**

[Likert scale: 'disagree'; 'rather disagree'; 'rather agree'; 'agree']

¹⁷ the sequence of items was randomised when administering the survey online; the sequence of pages 2 to 6 was however the same for each participant.

Page 7 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten - Anleitung

Versetzen Sie sich nun in folgende Situation:

Sie sind der Vorstand des Private Equity Unternehmens *Alpha Invest AG* und beabsichtigen, Ihr Portfolio von Unternehmen zu erweitern und ein weiteres Unternehmen hinzuzukaufen.

Das Zielunternehmen dieser Transaktion muss einen Umsatz von 50 bis 60 Mio€ vorweisen können. Der von Ihnen vor einigen Wochen beauftragte M&A Berater wird Ihnen keine Unternehmen zum Kauf vorschlagen, die außerhalb dieser Bandbreite liegen.

Zudem haben Sie mit Ihrem Management-Team weitere Kriterien, die das Zielunternehmen erfüllen muss, deren Wichtigkeit bzw. Gewichtung vereinbart und anschließend diese Information Ihrem Berater mitgeteilt.

Ihnen ist bewusst, dass potentielle Übernahmekandidaten nicht alle Kriterien gleich gut erfüllen können.

Das Zielunternehmen soll ...

1. für einen **Kaufpreis von höchstens 30 Mio€** gekauft werden (**sehr wichtig: + + +**).
2. einen **Gewinn (EBIT) von mind. 6%** des Umsatzes erwirtschaften (**sehr wichtig: + + +**).
3. zum Zeitpunkt der Übernahme **höchstens 20 Mio€ zinstragende Verbindlichkeiten** besitzen (**wichtig: + +**).
4. **höchstens 400 Mitarbeiter** beschäftigen (**wichtig: + +**).
5. **höchstens 15 Mio€ Investitionen** benötigen (**weniger wichtig: +**).
6. in **der gleichen oder einer angrenzenden Branche** tätig sein wie das aktuelle Portfolio (**weniger wichtig: +**).

Ihr M&A Berater hat Ihnen nun eine Auswahl von zehn Unternehmen vorgelegt, für die er die Ist-Werte der sechs Kriterien zusammengestellt hat und die er für geeignet hält ('Longlist').

Ihre Aufgabe ist es nun, eine Liste von potentiellen Übernahmekandidaten ('Shortlist') zu erstellen.

Vergleichen Sie hierzu für jedes Unternehmen die Ist-Werte mit den Soll-Werten der einzelnen Kriterien und entscheiden Sie dann ob das Unternehmen auf Ihre 'Shortlist' aufgenommen werden soll oder nicht.

Zum Abgleich der Ist- und Soll-Werte pro Unternehmen, wird eine Tabelle mit den Kriterien, deren Wichtigkeit/Gewichtung und deren Sollwerte bei jeder Entscheidung (Frage) zur Verfügung stehen. Bitte benutzen Sie ausschließlich die zur Verfügung gestellten Informationen für Ihre Entscheidung.

Bitte klicken Sie auf **Weiter'**, um mit der Aufgabe zu beginnen.

Page 7 [English translation]

[Header 1]^o Decision Profiles and Processes [print version]*

[Header 2]^o Selection of potential acquisition targets - Explanations

Put yourself now in the following situation

You are the CEO of the private equity company Alpha Invest AG and intend to extend your portfolio of companies and buy an additional company.

The target company of that transaction has to generate a turnover of 50 to 60 Mio€. The M&A consulted that you have contracted some weeks ago will not offer any company that is outside this range.

Further, you and your management team have agreed additional criteria that ought to be met by the target company, these criteria's importance or weighting, and you have provided this information to your M&A consultant.

You are aware that not all criteria will be met equally well by the potential acquisition candidates.

The target company should...

1. be bought for an **acquisition price of maximum 30 Mio€ (very important, + + +)**
2. generate a **profit (EBIT) of at least 6% of the turnover (very important, + + +)**
3. have a **maximum of 20 Mio€ interest bearing debt** at the time of take-over (**important, + +**)
4. employ a **maximum of 400 employees (important, + +)**
5. require a **maximum of 15 Mio€ investments (less important, +)**
6. be active the **same or a neighbouring industry** than the companies currently in the portfolio (**less important, +**)

Your M&A consultant has provided you a list of 10 companies for which he collected the actuals for each criterion and that he deems suitable ('Longlist').

Your task is to create the list of potential acquisition targets ('Shortlist').

To do so, compare the actual criteria values of each company with the desired criteria values and decide whether or not the respective company should be put on your 'Shortlist' or not.

For comparison of the actual and desired values, a table providing the criteria values, their importance/weight and the desired values will be available for each decision (question).

Please use solely the provided information for your decision.

Please click on 'Next' to start the task.

Page 8 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten

* 41. Unternehmen S

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen S
Kaufpreis (+++)	max. 30 Mio€	27 Mio€
Gewinn (+++)	<i>mind.</i> 6%	7,8%
Mitarbeiter (++)	max. 400	394
Verbindlichkeiten (++)	max. 20 Mio€	14 Mio€
Investitionen (+)	max. 15 Mio€	5 Mio€
Branche (+)	gleich oder angrenzend	gleich

Wollen Sie Unternehmen S auf Ihre 'Short List' setzen?

Ja

Nein

Page 8¹⁸ [English translation]

[Header 1]¹⁹ Decision Profiles and Processes [print version]^{*}

[Header 2]¹⁹ Selection of potential acquisition targets

***41. Company S¹⁹**

Criterion (Importance)	To-Be-Met Value	Company S
Price (+++)	<i>max. 30 M€</i>	27 M€
Profit (+++)	<i>min. 6%</i>	7.8%
Employees. (++)	<i>max. 400</i>	394
Debt (++)	<i>max. 20 M€</i>	14 M€
Investment (+)	<i>max. 15 M€</i>	5 M€
Industry (+)	<i>same or neighbouring</i>	same

Would you like to put company S on your 'Shortlist'?

[Yes/No]

¹⁸ Pages 8 to 16 have been randomised when administering the questionnaire

¹⁹ Company S: incompatibility score is 0; served as well as sanity check during data cleansing; the sequence of the criteria in the table differs from other company tables;

Page 9 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)		
Auswahl von potentiellen Übernahmekandidaten		

* 42. **Unternehmen C**

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen C
Branche (+)	<i>gleich oder angrenzend</i>	angrenzend
Mitarbeiter (+ +)	<i>max. 400</i>	430
Gewinn (+ + +)	<i>mind. 6%</i>	7,3%
Kaufpreis (+ + +)	<i>max. 30 Mio€</i>	27 Mio€
Investitionen (+)	<i>max. 15 Mio€</i>	13 Mio€
Verbindlichkeiten (+ +)	<i>max. 20 Mio€</i>	11 Mio€

Wollen Sie Unternehmen C auf Ihre ‚Short List‘ setzen?

Ja

Nein

Page 9²⁰ [English translation]

[Header 1]¹ Decision Profiles and Processes [print version]^{*}

[Header 2]¹ Selection of potential acquisition targets

***42. Company C²¹**

Criterion (Importance)	To-Be-Met Value	Company C
Industry (+)	<i>same or neighbouring</i>	neighbouring
Employees (+ +)	<i>max. 400</i>	430
Profit (+ + +)	<i>min. 6%</i>	7.3%
Price (+ + +)	<i>max. 30 M€</i>	27 M€
Investment (+)	<i>max. 15 M€</i>	13 M€
Debt (+ +)	<i>max. 20 M€</i>	11 M€

Would you like to put company C on your 'Shortlist'?

[Yes/No]

²⁰ Pages 8 to 16 have been randomised when administering the questionnaire

²¹ Company C: incompatibility score is -2 (criterion 'Employees'); the sequence of the criteria in the table differs from other company tables;

Page 10 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten

* 43. **Unternehmen G**

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen G
Verbindlichkeiten (++)	max. 20 Mio€	22 Mio€
Branche (+)	gleich oder angrenzend	angrenzend
Gewinn (++ +)	mind. 6%	6,1 %
Mitarbeiter (++)	max. 400	341
Kaufpreis (++ +)	max. 30 Mio€	28 Mio€
Investitionen (+)	max. 15 Mio€	21 Mio €

Wollen Sie Unternehmen G auf Ihre 'Short List' setzen?

Ja

Nein

Page 10²² [English translation]

[Header 1]²³ Decision Profiles and Processes [print version]^{*}

[Header 2]²³ Selection of potential acquisition targets

***43. Company G²³**

Criterion (Importance)	To-Be-Met Value	Company G
Debt (++)	<i>max. 20 M€</i>	22 M€
Industry (+)	<i>same or neighbouring</i>	neighbouring
Profit (+++)	<i>min. 6%</i>	6.1%
Employees. (++)	<i>max. 400</i>	341
Price (+++)	<i>max. 30 M€</i>	28 M€
Investment (+)	<i>max. 15 M€</i>	21 M€

Would you like to put company G on your 'Shortlist'?

[Yes/No]

²² Pages 8 to 16 have been randomised when administering the questionnaire

²³ Company G: incompatibility score is -3 (criteria 'Debt' & 'Investment'); the sequence of the criteria in the table differs from other company tables;

Page 11 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten

* 44. **Unternehmen H**

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen H
Branche (+)	gleich oder angrenzend	andere
Mitarbeiter (+ +)	max. 400	380
Gewinn (+ + +)	mind. 6%	7,7%
Kaufpreis (+ + +)	max. 30 Mio€	39 Mio€
Investitionen (+)	max. 15 Mio€	14 Mio€
Verbindlichkeiten (+ +)	max. 20 Mio€	15 Mio€

Wollen Sie Unternehmen H auf Ihre 'Short List' setzen?

- Ja
 Nein

Page 11²⁴ [English translation]

[Header 1]²⁵ Decision Profiles and Processes [print version]^{*}

[Header 2]²⁵ Selection of potential acquisition targets

***44. Company H²⁵**

Criterion (Importance)	To-Be-Met Value	Company H
Industry (+)	<i>same or neighbouring</i>	different
Employees. (+ +)	<i>max. 400</i>	380
Profit (+ + +)	<i>min. 6%</i>	7.7%
Price (+ + +)	<i>max. 30 M€</i>	39 M€
Investment (+)	<i>max. 15 M€</i>	14 M€
Debt (+ +)	<i>max. 20 M€</i>	15 M€

Would you like to put company H on your 'Shortlist'?

[Yes/No]

²⁴ Pages 8 to 16 have been randomised when administering the questionnaire

²⁵ Company H: incompatibility score is -4 (criteria 'Industry' & 'Price'); the sequence of the criteria in the table differs from other company tables;

Page 12 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten

*** 45. Unternehmen J**

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen J
Verbindlichkeiten (++)	max. 20 Mio€	26 Mio€
Investitionen (+)	max. 15 Mio€	9 Mio€
Kaufpreis (++ +)	max. 30 Mio€	24 Mio€
Mitarbeiter (++)	max. 400	320 Mio€
Branche (++)	gleich oder angrenzend	gleich
Gewinn (++ +)	mind. 6%	4,0%

Wollen Sie Unternehmen J auf Ihre ‚Short List‘ setzen?

Ja

Nein

Page 12²⁶ [English translation]

[Header 1]²⁷ Decision Profiles and Processes [print version]^{*}

[Header 2]²⁷ Selection of potential acquisition targets

***45. Company J²⁷**

Criterion (Importance)	To-Be-Met Value	Company J
Debt (+ +)	<i>max. 20 M€</i>	26 M€
Investment (+)	<i>max. 15 M€</i>	9 M€
Price (+ + +)	<i>max. 30 M€</i>	24 M€
Employees. (+ +)	<i>max. 400</i>	320
Industry (+)	<i>same or neighbouring</i>	same
Profit (+ + +)	<i>min. 6%</i>	4.0%

Would you like to put company J on your 'Shortlist'?

[Yes/No]

²⁶ Pages 8 to 16 have been randomised when administering the questionnaire

²⁷ Company J: incompatibility score is -5 (criteria 'Debt' & 'Profit'); the sequence of the criteria in the table differs from other company tables;

Page 13 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

**Auswahl von potentiellen
Übernahmekandidaten**

* 46. **Unternehmen K**

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen K
Kaufpreis (+++)	<i>max. 30 Mio€</i>	28 Mio€
Investitionen (+)	<i>max. 15 Mio€</i>	24 Mio€
Gewinn (++++)	<i>mind. 6%</i>	7,1%
Branche (+)	<i>gleich oder angrenzend</i>	andere
Mitarbeiter (++)	<i>max. 400</i>	442
Verbindlichkeiten (++)	<i>max. 20 Mio€</i>	27 Mio€

Wollen Sie Unternehmen K auf Ihre 'Short List' setzen?

- Ja
 Nein

Page 13²⁸ [English translation]

[Header 1]²⁹ Decision Profiles and Processes [print version]^{*}

[Header 2]²⁹ Selection of potential acquisition targets

***46. Company K²⁹**

Criterion (Importance)	To-Be-Met Value	Company K
Price (+ + +)	<i>max. 30 M€</i>	28 M€
Investment (+)	<i>max. 15 M€</i>	24 M€
Profit (+ + +)	<i>min. 6%</i>	7.1%
Industry (+)	<i>same or neighbouring</i>	different
Employees. (+ +)	<i>max. 400</i>	442
Debt (+ +)	<i>max. 20 M€</i>	27 M€

Would you like to put company K on your 'Shortlist'?

[Yes/No]

²⁸ Pages 8 to 16 have been randomised when administering the questionnaire

²⁹ Company K: incompatibility score is -6 (criteria 'Investment', 'Industry', 'Employees' & 'Debt'); the sequence of the criteria in the table differs from other company tables;

Page 14 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten

* 47. **Unternehmen F**

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen F
Branche (+)	gleich oder angrenzend	andere
Gewinn (+++)	mind. 6%	4,6%
Mitarbeiter (++)	max. 400	383
Verbindlichkeiten (++)	max. 20 Mio€	18 Mio€
Investitionen (+)	max. 15 Mio€	9 Mio€
Kaufpreis (+++)	max. 30 Mio€	36 Mio€

Wollen Sie Unternehmen F auf Ihre 'Short List' setzen?

- Ja
- Nein

Page 14³⁰ [English translation]

[Header 1]³¹ Decision Profiles and Processes [print version]^{*}

[Header 2]³¹ Selection of potential acquisition targets

***47. Company F³¹**

Criterion (Importance)	To-Be-Met Value	Company F
Industry (+)	<i>same or neighbouring</i>	different
Profit (+ + +)	<i>min. 6%</i>	4.6%
Employees. (+ +)	<i>max. 400</i>	383
Debt (+ +)	<i>max. 20 M€</i>	18 M€
Investment (+)	<i>max. 15 M€</i>	9 M€
Price (+ + +)	<i>max. 30 M€</i>	36 M€

Would you like to put company F on your 'Shortlist'?

[Yes/No]

³⁰ Pages 8 to 16 have been randomised when administering the questionnaire

³¹ Company F: incompatibility score is -7 (criteria 'Industry', 'Price' & 'Profit'); the sequence of the criteria in the table differs from other company tables;

Page 15³² [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)
Auswahl von potentiellen Übernahmekandidaten

* 48. Unternehmen E

or

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen E
Verbindlichkeiten (++)	20 Mio€	23 Mio€
Investitionen (+)	15 Mio€	18 Mio€
Kaufpreis (++ +)	max. 30 Mio€	37 Mio€
Mitarbeiter (++)	max. 400	467
Branche (+)	gleich oder angrenzend	angrenzend
Gewinn (++ +)	mind. 6%	6,9%

Unternehmen R

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen R
Verbindlichkeiten (++)	20 Mio€	23 Mio€
Investitionen (+)	15 Mio€	18 Mio€
Kaufpreis (++ +)	max. 30 Mio€	37 Mio€
Mitarbeiter (++)	max. 400	467
Branche (+)	gleich oder angrenzend	angrenzend
Gewinn (++ +)	mind. 6%	22,6%

Wollen Sie Unternehmen E auf Ihre ‚Short List‘ setzen?

Ja

Nein

Wollen Sie Unternehmen R auf Ihre ‚Short List‘ setzen?

Ja

Nein

³² This was the page presenting the 'profit temptation';

Base Sample: 294 participants of the experimental group have been faced with company R, the 'profit temptation', 355 participants of the reference group have been faced with company E (non-temptation);

Student Sample: 41 participants of the experimental group have been faced with company R, the 'profit temptation', 46 participants of the reference group have been faced with company E (non-temptation);

Extension Sample: 32 participants of the experimental group have been faced with company R, the 'profit temptation', 24 participants of the reference group have been faced with company E (non-temptation);

Page 15³³ [English translation]

[Header 1]³ Decision Profiles and Processes [print version]^{*}

[Header 2]³ Selection of potential acquisition targets

***48. Company E³⁴ or R**

Criterion (Importance)	To-Be-Met Value	Company E / R
Debt (++)	<i>max. 20 M€</i>	23 M€
Investment (+)	<i>max. 15 M€</i>	18 M€
Price (++ +)	<i>max. 30 M€</i>	37 M€
Employees. (++)	<i>max. 400</i>	467
Industry (+)	<i>same or neighbouring</i>	neighbouring
Profit (++ +)	<i>min. 6%</i>	6.9 % / 22.6%

Would you like to put company E (R) on your 'Shortlist'?

[Yes/No]

³³ Pages 8 to 16 have been randomised when administering the questionnaire

³⁴ Company E and R: incompatibility score is -8 (criteria 'Debt', 'Investment', 'Price' & 'Employee'); the sequence of the criteria in the table differs from other company tables;

Page 16³⁵ [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentielle Übernahmekandidaten

* 49. Unternehmen D

or

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen D
Branche (+)	gleich oder angrenzend	andere
Mitarbeiter (++)	max. 400	453
Gewinn (++ +)	mind. 6%	4,8%
Kaufpreis (++ +)	max. 30 Mio€	26 Mio€
Investitionen (+)	max. 15 Mio€	19 Mio€
Verbindlichkeiten (++)	max. 20 Mio€	24 Mio€

Unternehmen T

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen T
Branche (+)	gleich oder angrenzend	andere
Mitarbeiter (++)	max. 400	453
Gewinn (++ +)	mind. 6%	4,8%
Kaufpreis (++ +)	max. 30 Mio€	7 Mio€
Investitionen (+)	max. 15 Mio€	19 Mio€
Verbindlichkeiten (++)	max. 20 Mio€	24 Mio€

Wollen Sie Unternehmen D auf Ihre 'Shortlist' setzen?

- Ja
 Nein

Wollen Sie Unternehmen T auf Ihre 'Shortlist' setzen?

- Ja
 Nein

or

³⁵ This was the page presenting the 'price temptation';

Base Sample: 323 participants of the experimental group have been faced with company T, the 'price temptation', 326 participants of the reference group have been faced with company D (non-temptation);

Student Sample: 50 participants of the experimental group have been faced with company T, the 'price temptation', 37 participants of the reference group have been faced with company D (non-temptation);

Extension Sample: 26 participants of the experimental group have been faced with company T, the 'price temptation', 30 participants of the reference group have been faced with company D (non-temptation);

Page 16³⁶ [English translation]

[Header 1]³⁷ Decision Profiles and Processes [print version]^{*}

[Header 2]³⁷ Selection of potential acquisition targets

***49. Company D³⁷ or T**

Criterion (Importance)	To-Be-Met Value	Company D / T
Industry (+)	<i>same or neighbouring</i>	different
Employees. (+ +)	<i>max. 400</i>	453
Profit (+ + +)	<i>min. 6%</i>	4.8%
Price (+ + +)	<i>max. 30 M€</i>	26 M€ / 7 M€
Investment (+)	<i>max. 15 M€</i>	19 M€
Debt (+ +)	<i>max. 20 M€</i>	24 M€

Would you like to put company D (T) on your 'Shortlist'?

[Yes/No]

³⁶ Pages 8 to 16 have been randomised when administering the questionnaire

³⁷ Company D and T: incompatibility score is -9 (criteria all except 'price'); the sequence of the criteria in the table differs from other company tables;

Page 17 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Auswahl von potentiellen Übernahmekandidaten

* 52. Wie wichtig sind für SIE nachfolgende Kriterien beim Unternehmenskauf?

* 50.e ordnen Sie die Kriterien nach ihrer von Ihnen empfundenen Wichtigkeit:

Platz 1 für das **wichtigste** Kriterium,

Platz 2 für das **zweit-wichtigste**,

etc.

Wählen Sie 'n. v.' (=nicht verwendet), wenn Sie das Kriterium zur Auswahl der Unternehmen im Rahmen dieses Fragebogens nicht verwendet haben.

:::	Kaufpreis	<input type="checkbox"/> n. v.
:::	Gewinn	<input type="checkbox"/> n. v.
:::	Verbindlichkeiten	<input type="checkbox"/> n. v.
:::	Anzahl Mitarbeiter	<input type="checkbox"/> n. v.
:::	Investitionen	<input type="checkbox"/> n. v.
:::	Branche	<input type="checkbox"/> n. v.

Page 17 [English translation]

[Header 1]’ Decision Profiles and Processes [print version]*

[Header 2]’ Selection of potential acquisition targets

***50. How important are to YOU the following criteria when buying a company?**

Please rank the criteria following their importance **perceived by YOU**:

Rank 1 for the **most important** criterion

Rank 2 for the **second-most important** criterion

etc.

Please select 'n.a.' (=not applicable), if you have not used the criterion to select companies in the context of this questionnaire.

[rank of criteria to be select or box 'n.a.' to be ticked; a given rank can only be allocated once.]

Page 18³⁸ [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Demographische Fragen

51. Sind Sie männlich oder weiblich?

- Männlich
- Weiblich

52. Wie alt sind Sie?

- Unter 26
- 26-35
- 36-45
- 46-55
- 56-65
- Über 65

53. Welche der folgenden Kategorien beschreibt Ihre aktuelle Stellung im Unternehmen bzw. in der Organisation am besten?

- Eigentümer/Eigentümerin/Geschäftsführung/Vorstand
- Oberes Management
- Mittleres Management
- Mitarbeiterin/Mitarbeiter mit Erfahrung
- Berufseinstiegerin/Berufseinstieger
- Studentin/Student
- Sonstiges (bitte angeben)

³⁸ This page was only shown to the Student Sample

Page 18 [English translation]

[Header 1]° Decision Profiles and Processes [print version]*

[Header 2]° Demographic questions

51. Are you male or female?

[male/female]

52. How old are you?

[under 26 / 26-35 / 36-45 / 46 - 55 / 56 - 65 / above 65]

53. Which of the following categories describes best your current position in your organisation / company?

[Owner, Managing Director, CEO / Upper Management / Middle Management / Experienced Employee / Beginner / Student / Other, please describe...]

Page 19 [original questionnaire in German language]

Entscheidungsprofile und -prozesse (Druckversion)

Ende des
Fragebogens

Glückwunsch! Sie haben es geschafft!

Sie haben den Fragebogen beantwortet!

Herzlichen Dank!

Für Nutzer von SurveyCircle (www.surveycircle.com): Der Survey Code lautet: **Z97E-6YYR-WN3P-366R**

Bitte klicken Sie auf 'Fertig' um den Fragebogen zu beenden!

Page 19 [English translation]

[Header 1]³⁹ Decision Profiles and Processes [print version]*

[Header 2]³⁹ End of the questionnaire

Congratulations! You made it!

You have answered the questionnaire!

Thank you very much!

For the user of SurveyCircle (www.surveycircle.com): The Survey Code is **Z97E-6YYR-WN3P-366R³⁹**

Please click on 'Finish' to complete the survey!

³⁹ This line was only shown to the Student Sample

8.2.2 Extension Sample Questionnaire (German original & English translation)

Page 1 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse

Fragen zur Umfrage?
Senden Sie eine E-Mail an
alexander.muller@student.shu.ac.uk

WICHTIGE HINWEISE (Bitte lesen!):

Die Umfrage ist das Kernstück einer wissenschaftlichen Studie zur Untersuchung von Entscheidungsprozessen.

Die Umfrage sollte nicht mehr als 10 min Ihrer Zeit in Anspruch nehmen und besteht aus insgesamt 15 Fragen.

Ihre Aufgabe ist es, aus einer Liste von Unternehmen potentielle Übernahmekandidaten auszusuchen, die Ihres Erachtens sechs Kriterien ausreichend genug erfüllen.

Alle Antworten sollten Ihr TATSÄCHLICHES Entscheidungsverhalten widerspiegeln und NICHT ein von Ihnen beabsichtigtes oder erwünschtes!

Seien Sie also nicht rationaler, nicht spontaner und nicht intuitiver als Sie dies in einer Entscheidungssituation sind!

Die Teilnahme an dieser Umfrage ist vollkommen anonym.

Wenn Sie auf die unten gezeigte Schaltfläche 'Weiter' klicken, stimmen Sie der Nutzung und Verarbeitung der mit dieser Umfrage erhobenen, anonymen Daten im Rahmen der oben genannten wissenschaftlichen Studie oder anderer, nicht-kommerzieller, wissenschaftlicher Projekte ausdrücklich zu.

Bitte LASSEN SIE SICH ZEIT bei der Beantwortung der Fragen!

Vielen Dank für Ihre Teilnahme!

Page 1 [English translation]

[Header 1]⁴⁰ Decision Profiles and Processes [print version][°]

[Header 2][°] Questions regarding the survey?

[Header 2][°] Send an e-mail to

[Header 2][°] alexander.muller@student.shu.ac.uk

IMPORTANT REMARKS (please read!)

This survey is the centre piece of a scientific study investigating decisions processes.

The survey should not take more than 10 minutes of your time and consists of 15 questions.

Your task is to select from a list of companies, potential acquisition targets that meet sufficiently well six criteria.

All answers should reflect your TRUE decision behaviour and NOT a desired or intended behaviour.

Don't be more rational, more spontaneous or more intuitive than you are in a decision situation.

The participation in this survey is entirely anonymous.

If you click the 'Next' button below, you expressively agree that the anonymous data collected with this questionnaire, can be used and processed for the purpose of this study or any other non-commercial, scientific study.

Please TAKE YOUR TIME when answering the questions!

Thank you very much for your participation!

⁴⁰ Expressions marked with a circle were not shown in the original version of the questionnaire

Page 2 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse

Auswahl von potentiellen Übernahmekandidaten - Anleitung

Versetzen Sie sich nun in folgende Situation:

Sie sind der Vorstand des Private Equity Unternehmens *Alpha Invest AG* und beabsichtigen, Ihr Portfolio von Unternehmen zu erweitern und ein weiteres Unternehmen hinzuzukaufen.

Das Zielunternehmen dieser Transaktion muss einen Umsatz von 50 bis 60 Mio€ vorweisen können. Der von Ihnen vor einigen Wochen beauftragte M&A Berater wird Ihnen keine Unternehmen zum Kauf vorschlagen, die außerhalb dieser Bandbreite liegen.

Zudem haben Sie mit Ihrem Management-Team weitere Kriterien, die das Zielunternehmen erfüllen muss, deren Wichtigkeit bzw. Gewichtung vereinbart und anschließend diese Information Ihrem Berater mitgeteilt.

Ihnen ist bewusst, dass potentielle Übernahmekandidaten nicht alle Kriterien gleich gut erfüllen können.

Das Zielunternehmen soll ...

1. für einen **Kaufpreis von höchstens 30 Mio€** gekauft werden (**sehr wichtig: ++**).
2. einen **Gewinn (EBIT) von mind. 6%** des Umsatzes erwirtschaften (**sehr wichtig: ++**).
3. zum Zeitpunkt der Übernahme **höchstens 20 Mio€ zinstragende Verbindlichkeiten** besitzen (**wichtig: ++**).
4. **höchstens 400 Mitarbeiter** beschäftigen (**wichtig: ++**).
5. **höchstens 15 Mio€ Investitionen** benötigen (**weniger wichtig: +**).
6. in der **gleichen oder einer angrenzenden Branche** tätig sein wie das aktuelle Portfolio (**weniger wichtig: +**).

Ihr M&A Berater hat Ihnen nun eine Auswahl von 14 Unternehmen vorgelegt, für die er die Ist-Werte der sechs Kriterien zusammengestellt hat und die er für geeignet hält ('Longlist').

Ihre Aufgabe ist es nun, eine Liste von potentiellen Übernahmekandidaten ('Shortlist') zu erstellen.

Vergleichen Sie hierzu für jedes Unternehmen die Ist-Werte mit den Soll-Werten der einzelnen Kriterien und entscheiden Sie dann ob das Unternehmen auf Ihre 'Shortlist' aufgenommen werden soll oder nicht.

Zum Abgleich der Ist- und Soll-Werte pro Unternehmen, wird eine Tabelle mit den Kriterien, deren Wichtigkeit/Gewichtung und deren Sollwerte bei jeder Entscheidung (Frage) zur Verfügung stehen. Bitte benutzen Sie ausschließlich die zur Verfügung gestellten Informationen für Ihre Entscheidung.

Bitte klicken Sie auf 'Weiter', um mit der Aufgabe zu beginnen.

Page 2 [English translation]

[Header 1]¹ Decision Profiles and Processes [print version]^{*}

[Header 2]¹ Selection of potential acquisition targets - Explanations

Put yourself now in the following situation

You are the CEO of the private equity company Alpha Invest AG and intend to extend your portfolio of companies and buy an additional company.

The target company of that transaction has to generate a turnover of 50 to 60 Mio€. The M&A consulted that you have contracted some weeks ago will not offer any company that is outside this range.

Further, you and your management team have agreed additional criteria that ought to be met by the target company, these criteria's importance or weighting, and you have provided this information to your M&A consultant. You are aware that not all criteria will be met equally well by the potential acquisition candidates.

The target company should...

7. be bought for an **acquisition price of maximum 30 Mio€ (very important, + + +)**
8. generate a **profit (EBIT) of at least 6% of the turnover (very important, + + +)**
9. have a **maximum of 20 Mio€ interest bearing debt** at the time of take-over (**important, + +**)
10. employ a **maximum of 400 employees (important, + +)**
11. require a **maximum of 15 Mio€ investments (less important, +)**
12. be active the **same or a neighbouring industry** than the companies currently in the portfolio (**less important, +**)

Your M&A consultant has provided you a list of 14 companies for which he collected the actuals for each criterion and that he deems suitable ('Longlist').

**Your task is to create the list of potential acquisition targets ('Shortlist').
To do so, compare the actual criteria values of each company with the desired criteria**

values and decide whether or not the respective company should be put on your 'Shortlist' or not.

For comparison of the actual and desired values, a table providing the criteria values, their importance/weight and the desired values will be available for each decision (question). Please use solely the provided information for your decision.

Please click on 'Next' to start the task.

Pages 3 to 11 of the Extension Sample questionnaire are identical to pages 8 to 16 of the Base & Student Sample Questionnaires.

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Page 12 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse
Auswahl von potentiellen Übernahmekandidaten

* 10. Unternehmen L

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen L
Kaufpreis (+++)	max. 30 Mio€	28 Mio€
Gewinn (+++)	mind. 6%	7,2%
Mitarbeiter (++)	max. 400	389
Verbindlichkeiten (++)	max. 20 Mio€	17 Mio€
Investitionen (+)	max. 15 Mio€	20 Mio€
Branche (+)	gleich oder angrenzend	andere

Wollen Sie Unternehmen L auf Ihre ‚Short List‘ setzen?

Ja

Nein

Page 12⁴¹ [English translation]

[Header 1]¹ Decision Profiles and Processes [print version]^{*}

[Header 2]² Selection of potential acquisition targets

***10. Company L⁴²**

Criterion (Importance)	To-Be-Met Value	Company L
Price (+ + +)	<i>max. 30 M€</i>	28 M€
Profit (+ + +)	<i>min. 6%</i>	7.2%
Employees: (+ +)	<i>max. 400</i>	389
Debt (+ +)	<i>max. 20 M€</i>	17 M€
Investment (+)	<i>max. 15 M€</i>	20 M€
Industry (+)	<i>same or neighbouring</i>	different

Would you like to put company L on your 'Shortlist'?

[Yes/No]

⁴¹ Pages 3 to 16 have been randomised when administering the questionnaire

⁴² Company L: incompatibility score is -2 (criteria 'Investment' & 'Industry'); the sequence of the criteria in the table is the same as for company S;

Page 13 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse
Auswahl von potentiellen Übernahmekandidaten

* 11. Unternehmen X

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen X
Branche (+)	gleich oder angrenzend	gleich
Mitarbeiter (++)	max. 400	384
Gewinn (+++)	mind. 6%	7,0%
Kaufpreis (+++)	max. 30 Mio€	26 Mio€
Investitionen (+)	max. 15 Mio€	19 Mio€
Verbindlichkeiten (++)	max. 20 Mio€	15 Mio€

Wollen Sie Unternehmen X auf Ihre 'Short List' setzen?

Ja

Nein

Page 13⁴³ [English translation]

[Header 1]⁴ Decision Profiles and Processes [print version]^{*}

[Header 2]⁵ Selection of potential acquisition targets

***11. Company X⁴⁴**

Criterion (Importance)	To-Be-Met Value	Company X
Industry (+)	<i>same or neighbouring</i>	same
Employees. (+ +)	<i>max. 400</i>	384
Profit (+ + +)	<i>min. 6%</i>	7.0%
Price (+ + +)	<i>max. 30 M€</i>	26 M€
Investment (+)	<i>max. 15 M€</i>	19 M€
Debt (+ +)	<i>max. 20 M€</i>	15 M€

Would you like to put company X on your 'Shortlist'?

[Yes/No]

⁴³ Pages 3 to 16 have been randomised when administering the questionnaire

⁴⁴ Company X: incompatibility score is -1 (criterion 'Investment'); the sequence of the criteria in the table is the same as for company C;

Page 14 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse
Auswahl von potentiellen Übernahmekandidaten

* 12. Unternehmen N

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen N
Verbindlichkeiten (++)	max. 20 Mio€	18 Mio€
Branche (+)	gleich oder angrenzend	andere
Gewinn (++ +)	mind. 6%	6,7 %
Mitarbeiter (++)	max. 400	440
Kaufpreis (++ +)	max. 30 Mio€	25 Mio€
Investitionen (+)	max. 15 Mio€	19 Mio €

Wollen Sie Unternehmen N auf Ihre 'Short List' setzen?

Ja

Nein

Page 14⁴⁵ [English translation]

[Header 1]¹ Decision Profiles and Processes [print version]^{*}

[Header 2]² Selection of potential acquisition targets

***12. Company N⁴⁶**

Criterion (Importance)	To-Be-Met Value	Company N
Debt (++)	<i>max. 20 M€</i>	18 M€
Industry (+)	<i>same or neighbouring</i>	different
Profit (+++)	<i>min. 6%</i>	6.7%
Employees. (++)	<i>max. 400</i>	440
Price (+++)	<i>max. 30 M€</i>	25 M€
Investment (+)	<i>max. 15 M€</i>	19 M€

Would you like to put company N on your 'Shortlist'?

[Yes/No]

⁴⁵ Pages 3 to 16 have been randomised when administering the questionnaire

⁴⁶ Company N: incompatibility score is -4 (criteria 'Industry', 'Employee' & 'Investment'); the sequence of the criteria in the table is the same as for company G;

Page 15 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse
Auswahl von potentiellen Übernahmekandidaten

* 13. Unternehmen Y

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen Y
Branche (+)	gleich oder angrenzend	andere
Mitarbeiter (++)	max. 400	432
Gewinn (++ +)	mind. 6%	7,7%
Kaufpreis (++ +)	max. 30 Mio€	35 Mio€
Investitionen (+)	max. 15 Mio€	13 Mio€
Verbindlichkeiten (++)	max. 20 Mio€	17 Mio€

Wollen Sie Unternehmen Y auf Ihre 'Short List' setzen?

Ja

Nein

Page 15⁴⁷ [English translation]

[Header 1]¹ Decision Profiles and Processes [print version]^{*}

[Header 2]² Selection of potential acquisition targets

***13. Company Y⁴⁸**

Criterion (Importance)	To-Be-Met Value	Company Y
Industry (+)	<i>same or neighbouring</i>	different
Employees. (+ +)	<i>max. 400</i>	432
Profit (+ + +)	<i>min. 6%</i>	7.7%
Price (+ + +)	<i>max. 30 M€</i>	35 M€
Investment (+)	<i>max. 15 M€</i>	13 M€
Debt (+ +)	<i>max. 20 M€</i>	17 M€

Would you like to put company Y on your 'Shortlist'?

[Yes/No]

⁴⁷ Pages 3 to 16 have been randomised when administering the questionnaire

⁴⁸ Company Y: incompatibility score is -6 (criteria 'Industry', 'Employees' & 'Price'); the sequence of the criteria in the table is the same as for company H;

Page 16 [original questionnaire in German language]

Wissenschaftliche Studie: Entscheidungsprozesse

Auswahl von potentiellen
Übernahmekandidaten

* 14. Unternehmen P

Kriterium (Wichtigkeit)	Sollwerte	Unternehmen P
Verbindlichkeiten (++)	max. 20 Mio€	25 Mio€
Investitionen (+)	max. 15 Mio€	11 Mio€
Kaufpreis (++ +)	max. 30 Mio€	25 Mio€
Mitarbeiter (++)	max. 400	428 Mio€
Branche (++)	gleich oder angrenzend	andere
Gewinn (++ +)	mind. 6%	4,5%

Wollen Sie Unternehmen P auf Ihre 'Short List' setzen?

Ja

Nein

Page 16⁴⁹ [English translation]

[Header 1]⁵⁰ Decision Profiles and Processes [print version]^{*}

[Header 2]⁵¹ Selection of potential acquisition targets

***14. Company P⁵⁰**

Criterion (Importance)	To-Be-Met Value	Company P
Debt (+ +)	<i>max. 20 M€</i>	25 M€
Investment (+)	<i>max. 15 M€</i>	11 M€
Price (+ + +)	<i>max. 30 M€</i>	25 M€
Employees. (+ +)	<i>max. 400</i>	428
Industry (+)	<i>same or neighbouring</i>	different
Profit (+ + +)	<i>min. 6%</i>	4.5%

Would you like to put company P on your 'Shortlist'?

[Yes/No]

⁴⁹ Pages 3 to 16 have been randomised when administering the questionnaire

⁵⁰ Company P: incompatibility score is -8 (criteria 'Employees', 'Industry', & 'Profit'); the sequence of the criteria in the table is the same as for company J;

Pages 17 of the Extension Sample questionnaire is identical to page 17 of the Base & Student Sample questionnaire.

Page 18 of the Extension Sample is identical to page 19 of Base & Student Sample questionnaire (except for the statement "For the user of SurveyCircle (www.surveycircle.com): The Survey Code is **Z97E-6YYR-WN3P-366R**" which was not provided for the Extension Sample questionnaire since it was administered to participants of the respective *SurveyMonkey* online panel only.

8.3 40 items to determine the decision styles

Construct	Item	Factor			Reference	Sequence
		Page	Loading	Variable		
Avoidant	I avoid making important decisions until the pressure is on	5	0.89	AVOIDANT_4	Scott & Bruce (1995)	1 st question on page
	I postpone decision making whenever possible	2	0.94	AVOIDANT_1		
	I often procrastinate when it comes to making important decisions	3	0.86	AVOIDANT_2		
	I generally make important decisions at the last minute	6	0.84	AVOIDANT_5		
	I put off making many decisions because thinking about them makes me uneasy	4	0.77	AVOIDANT_3		
Dependent	I often need the assistance of other people when making important decisions	6	0.74	DEPENDENT_5	Scott & Bruce (1995)	8 th question on page
	I rarely make important decisions without consulting other people	3	0.79	DEPENDENT_2		
	If I have the support of others, it is easier for me to make important decisions	4	0.66	DEPENDENT_3		
	I use the advice of other people in making my important decisions	5	0.69	DEPENDENT_4		
	I like to have someone to steer me in the right direction when I am faced with important decisions	2	0.70	DEPENDENT_1		
Rational	I plan my important decisions carefully	3	unknown	RATIONAL_2	Scott & Bruce (1995)	3 rd question on page
	I double-check my information sources to be sure I have the right facts before making decisions	2	0.63	RATIONAL_1		
	I make decisions in a logical and systematic way	6	0.73	RATIONAL_5		
	My decision making requires careful thought	5	0.76	RATIONAL_4		
	When making a decision, I consider various options in terms of a specific goal	4	0.75	RATIONAL_3		
Spontaneous	I generally make snap decisions	6	0.87	SPONTANEOUS_5	Scott & Bruce (1995)	4 th question on page
	I often make decisions on the spur of the moment	3	0.78	SPONTANEOUS_2		
	I make quick decisions	4	0.75	SPONTANEOUS_3		
	I often make impulsive decisions	2	0.70	SPONTANEOUS_1		
	When making decisions, I do what seems natural at the moment	5	0.66	SPONTANEOUS_4		
Intuitive	When making decisions, I rely upon my instincts	4	0.82	INTUITIVE_3	Scott & Bruce	2 nd question on page
	When I make decisions, I tend to rely on my intuition	3	0.75	INTUITIVE_2		
	I generally make decisions that feel right to me	2	0.70	INTUITIVE_1		

Construct	Item	Factor			Reference	Sequence
		Page	Loading	Variable		
Regret	When I make a decision, it is more important for me to feel the decision is right than to have a rational reason for it	6	0.57	INTUITIVE_5	Schwartz et al. (2002)	5 th question on page
	When I make a decision, I trust my inner feelings and reactions	5	0.79	INTUITIVE_4		
Anxious	Whenever I make a choice, I'm curious about what would have happened if I had chosen differently	5	0.78	REGRET_4		
	Whenever I make a choice, I try to get information about how the other alternatives turned out	4	0.74	REGRET_3		
	If I make a choice and it turns out well, I still feel like something of a failure if I find out that another choice would have turned out better	6	0.62	REGRET_5		
	When I think about how I'm doing in life, I often assess opportunities I have passed up	2	0.61	REGRET_1		
	Once I make a decision, I don't look back (R) ⁵¹	3	0.56	REGRET_2		
Maximising	I feel very anxious when I need to make a decision	4	0.63	ANXIOUS_3	Leykin & DeRubeis (2010)	7 th question on page
	I feel as if I'm under tremendous time pressure when making decisions	6	0.64	ANXIOUS_5		
	I panic when I think that my decision might be wrong	3	0.58	ANXIOUS_2		
	When making a decision, I am afraid that I might be wrong	2	0.41	ANXIOUS_1		
	I can't think straight if I have to make decisions in a hurry	5	0.42	ANXIOUS_4		
Maximising	When I watch TV, I channel surf, often scanning through the available options even while attempting to watch one program	2	0.81	MAXIMISING_1	Schwartz et al. (2002)	6 th question on page
	When I am in the car listening to the radio, I often check other stations to see if something better is playing, even if I'm relatively satisfied with what I'm listening to	4	0.77	MAXIMISING_3		
	I often find it difficult to shop for a gift for a friend	5	0.73	MAXIMISING_4		
	When shopping, I have a hard time finding clothing that I really love	3	0.71	MAXIMISING_2		
	Renting videos is really difficult. I'm always struggling to pick the best one	6	0.68	MAXIMISING_5		

⁵¹ question is reversed scored

8.4 Decision alternatives and their characteristics

8.4.1 Base & Student Sample Questionnaire

Company	Price (+ + +)	Profit (+ + +)	Debt (+ +)	Employees (+ +)	Invest. (+ +)	Industry (+ +)	Incompatibility Score	Temptation
To-Be-Met Values	max. 30 M€	min. 6%	max. 20M€	max. 400	max. 15M€	same or neighbouring	n/a	n/a
Company S	27 M€	7,8%	14 M€	394	5 M€	same	0	no
Company C	27 M€	7,3%	11 M€	430	13 M€	neighbouring	-2	no
Company G	28 M€	6,1%	22 M€	341	21 M€	neighbouring	-3	no
Company H	39 M€	7,7%	15 M€	380	14 M€	different	-4	no
Company J	24 M€	4,0%	26 M€	320	9 M€	same	-5	no
Company K	28 M€	7,1%	27 M€	442	24 M€	different	-6	no
Company F	36 M€	4,6%	18 M€	383	9 M€	different	-7	no
Company E	37 M€	6,9%	23 M€	467	18 M€	neighbouring	-8	no
Company R	37 M€	22,6%	23 M€	467	18 M€	neighbouring	-8	yes - profit
Company D	26 M€	4,8%	24 M€	453	19 M€	different	-9	no
Company T	7 M€	4,8%	24 M€	453	19 M€	different	-9	yes - price

8.4.2 Extension Sample Questionnaire (add on)

<i>Company</i>	<i>Price</i> (+ ++)	<i>Profit</i> (+ ++)	<i>Debt</i> (+ +)	<i>Employees</i> (+ +)	<i>Invest</i> (+)	<i>Industry</i> (+)	<i>Incompatibility</i> Score	<i>Temptation</i>
<i>To-Be-Met Values</i>	max. 30 M€	min. 6%	max. 20M€	max. 400	max. 15M€	same or neighbouring	n/a	n/a
<i>Company X</i>	26 M€	7,0%	15 M€	384	19 M€	same	-1	no
<i>Company L</i>	28 M€	7,2%	17 M€	389	20 M€	different	-2	no
<i>Company N</i>	25 M€	6,7%	18 M€	440	19 M€	different	-4	no
<i>Company Y</i>	35 M€	7,7%	17 M€	432	13 M€	different	-6	no
<i>Company P</i>	25 M€	4,5%	25 M€	428	11 M€	different	-8	no

8.5 Descriptive statistics of the 40 questionnaire items

	<i>N</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>Standard Deviation</i>
AVOIDANT_1	649	1	4	1.98	.818
AVOIDANT_2	649	1	4	2.25	.864
AVOIDANT_3	649	1	4	2.02	.890
AVOIDANT_4	649	1	4	2.16	.888
AVOIDANT_5	649	1	4	1.96	.792
ANXIOUS_1	649	1	4	2.07	.797
ANXIOUS_2	649	1	4	1.90	.863
ANXIOUS_3	649	1	4	1.77	.818
ANXIOUS_4	649	1	4	2.21	.963
ANXIOUS_5	649	1	4	2.02	.849
REGRET_1	649	1	4	2.45	.894
REGRET_2	649	1	4	2.22	.817
REGRET_3	649	1	4	2.40	.853
REGRET_4	649	1	4	2.41	.902
REGRET_5	649	1	4	2.15	.888
MAXIMISING_1	649	1	4	2.05	.900
MAXIMISING_2	649	1	4	2.32	1.033
MAXIMISING_3	649	1	4	1.92	.970
MAXIMISING_4	649	1	4	2.39	1.011
MAXIMISING_5	649	1	4	1.77	.861

	<i>N</i>	<i>Minimum</i>	<i>Maximum</i>	<i>Mean</i>	<i>Standard Deviation</i>
<i>DEPENDENT_1</i>	649	1	4	2.46	.860
<i>DEPENDENT_2</i>	649	1	4	2.40	.860
<i>DEPENDENT_3</i>	649	1	4	2.81	.784
<i>DEPENDENT_4</i>	649	1	4	2.69	.743
<i>DEPENDENT_5</i>	649	1	4	1.94	.832
<i>INTUITIVE_1</i>	649	1	4	3.29	.583
<i>INTUITIVE_2</i>	649	1	4	2.84	.693
<i>INTUITIVE_3</i>	649	1	4	2.89	.687
<i>INTUITIVE_4</i>	649	1	4	2.96	.672
<i>INTUITIVE_5</i>	649	1	4	2.66	.809
<i>SPONTANEOUS_1</i>	649	1	4	2.38	.834
<i>SPONTANEOUS_2</i>	649	1	4	2.44	.768
<i>SPONTANEOUS_3</i>	649	1	4	2.57	.732
<i>SPONTANEOUS_4</i>	649	1	4	2.95	.637
<i>SPONTANEOUS_5</i>	649	1	4	2.10	.738
<i>RATIONAL_1</i>	649	1	4	3.33	.640
<i>RATIONAL_2</i>	649	1	4	3.29	.667
<i>RATIONAL_3</i>	649	1	4	3.14	.666
<i>RATIONAL_4</i>	649	1	4	3.05	.670
<i>RATIONAL_5</i>	649	1	4	2.95	.775

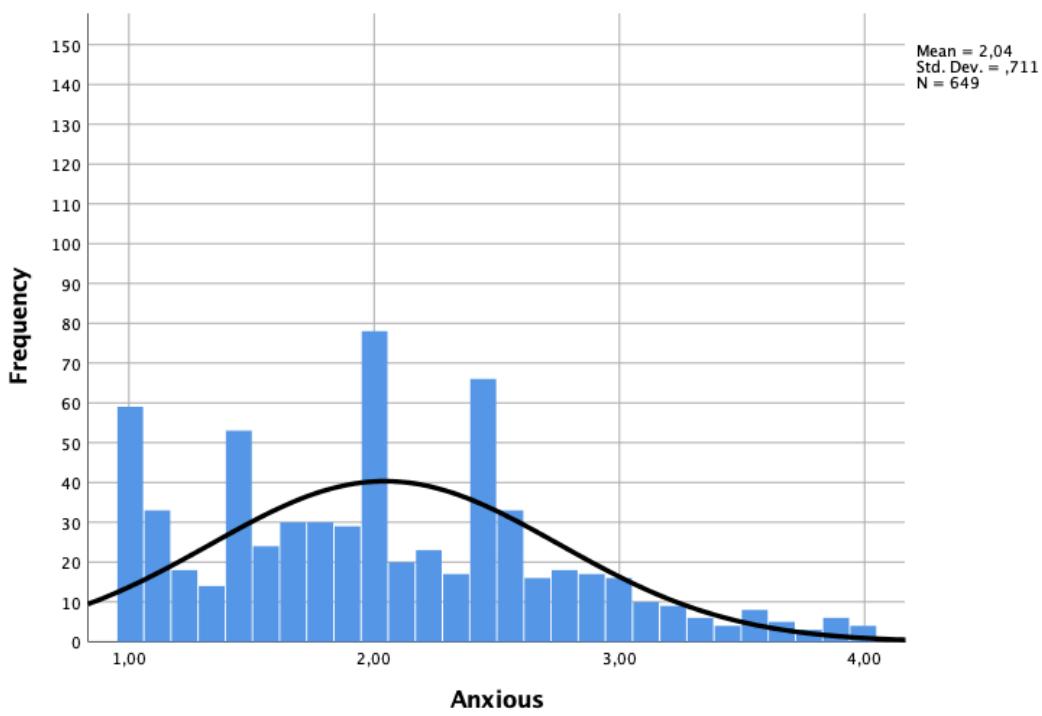
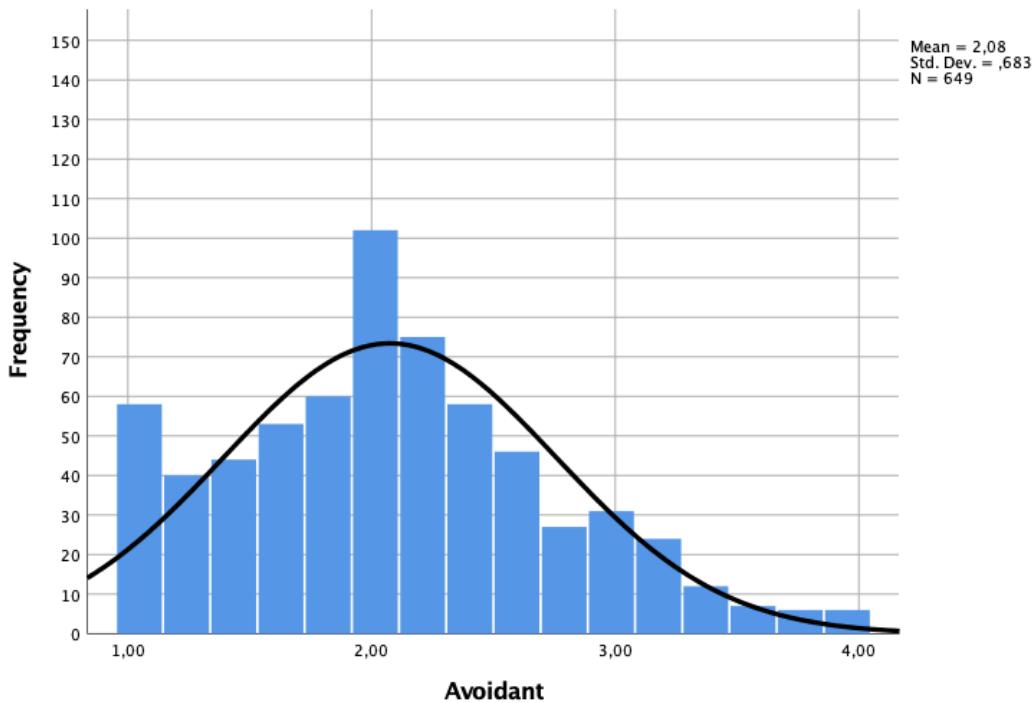
8.6 Factor loadings of the 40 questionnaire items into the 8 extracted components

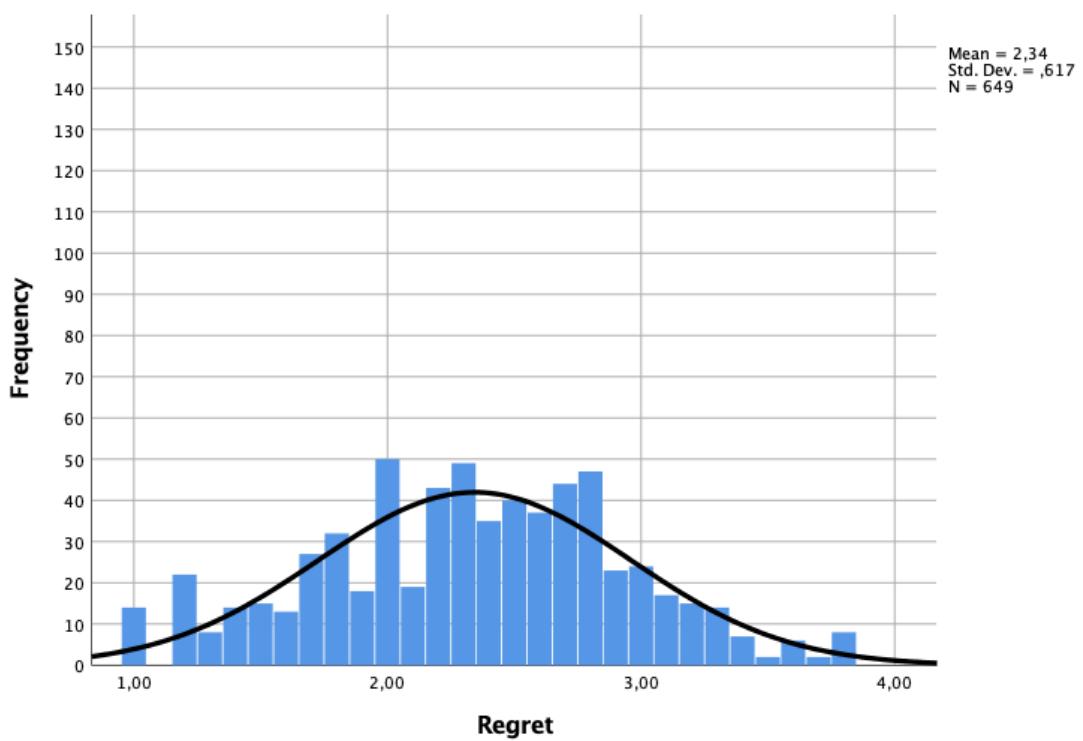
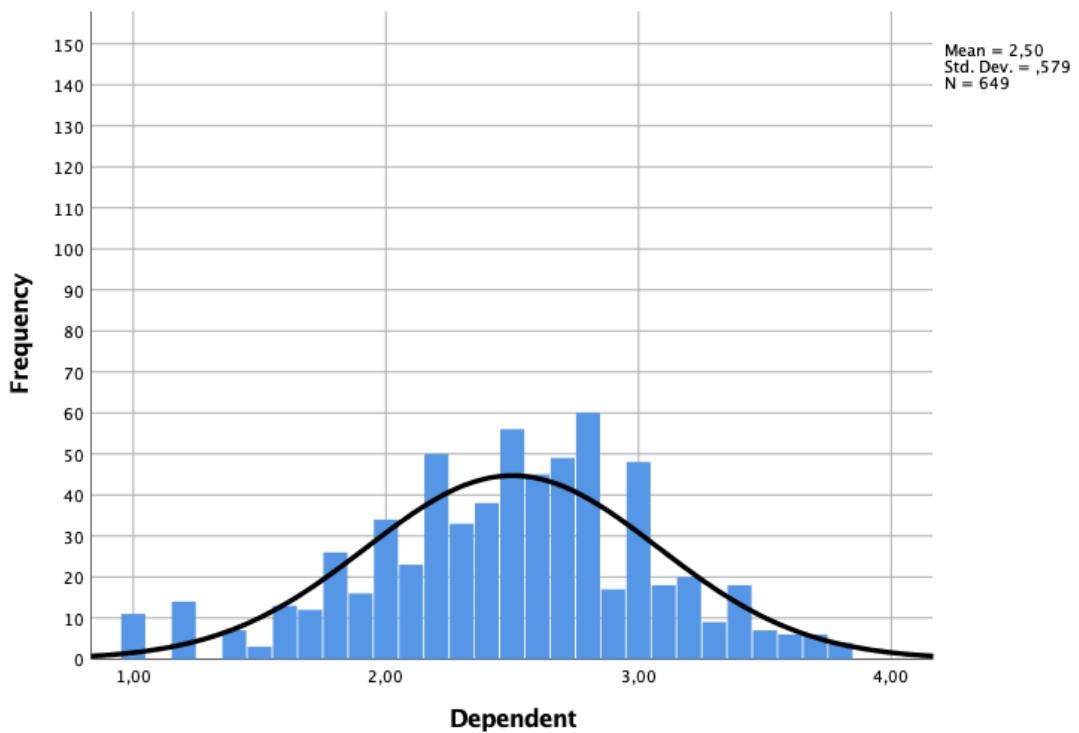
	<i>Components</i>							
	1	2	3	4	5	6	7	8
AVOIDANT_1	.743	-.011	-.099	.129	.161	.202	.156	-.025
AVOIDANT_2	.605	.019	.006	.243	.292	.265	.054	.233
AVOIDANT_3	.653	.023	-.122	.267	.156	.261	.202	.153
AVOIDANT_4	.720	.037	-.054	.039	.112	.193	.273	.046
AVOIDANT_5	.644	.021	-.136	.189	-.002	.235	.234	-.134
ANXIOUS_1	.495	-.011	-.048	.312	.320	.289	.062	.106
ANXIOUS_2	.464	.079	-.076	.294	.259	.292	.189	.164
ANXIOUS_3	.528	.024	-.184	.270	.258	.299	.288	.195
ANXIOUS_4	.274	.187	-.141	.213	.087	.225	.313	.471
ANXIOUS_5	.464	-.001	-.163	.354	.164	.296	.278	.232
REGRET_1	.258	.116	-.006	.566	.074	.187	.027	.075
REGRET_2	.136	-.109	-.176	.490	.107	.069	-.094	.390
REGRET_3	-.041	-.005	.107	.745	.158	.080	.235	-.068
REGRET_4	.041	.039	.102	.778	.148	.058	.183	-.021
REGRET_5	.366	-.035	-.026	.458	.224	.207	.298	.163
MAXIMISING_1	.053	.005	.054	.106	-.019	.122	.736	-.112
MAXIMISING_2	.059	.018	.036	.099	.078	.727	.123	.020
MAXIMISING_3	.058	.005	-.060	.074	.169	.071	.763	-.094
MAXIMISING_4	.117	-.031	-.040	.037	.067	.788	.038	.038

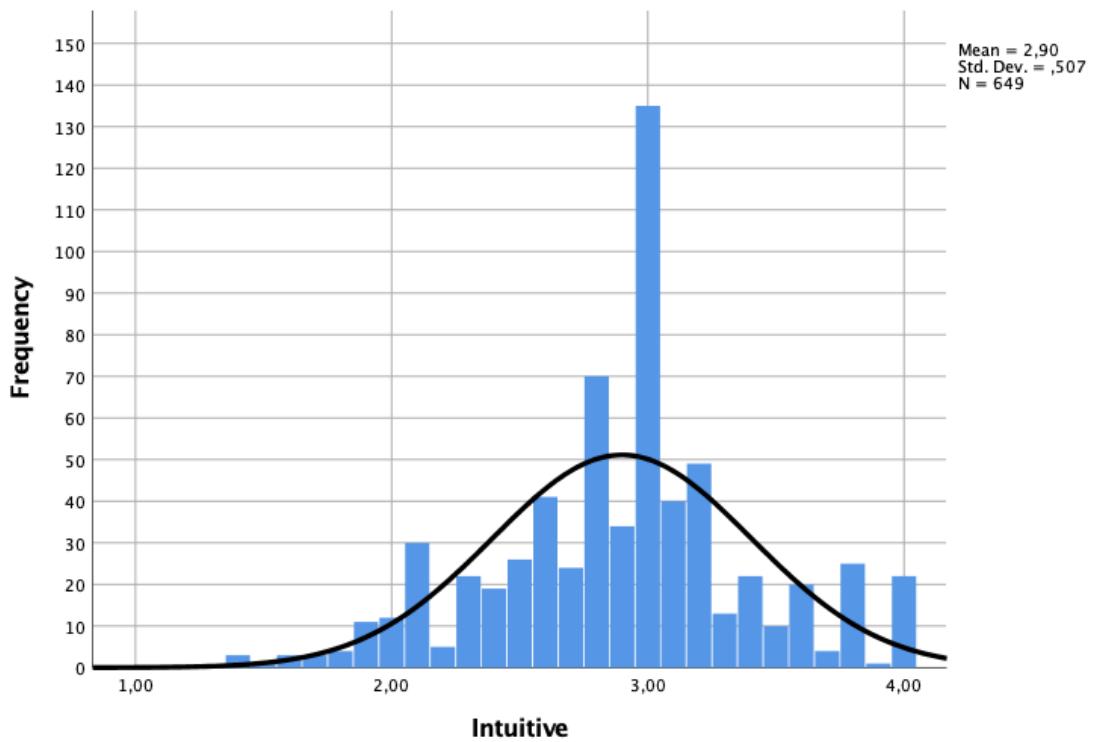
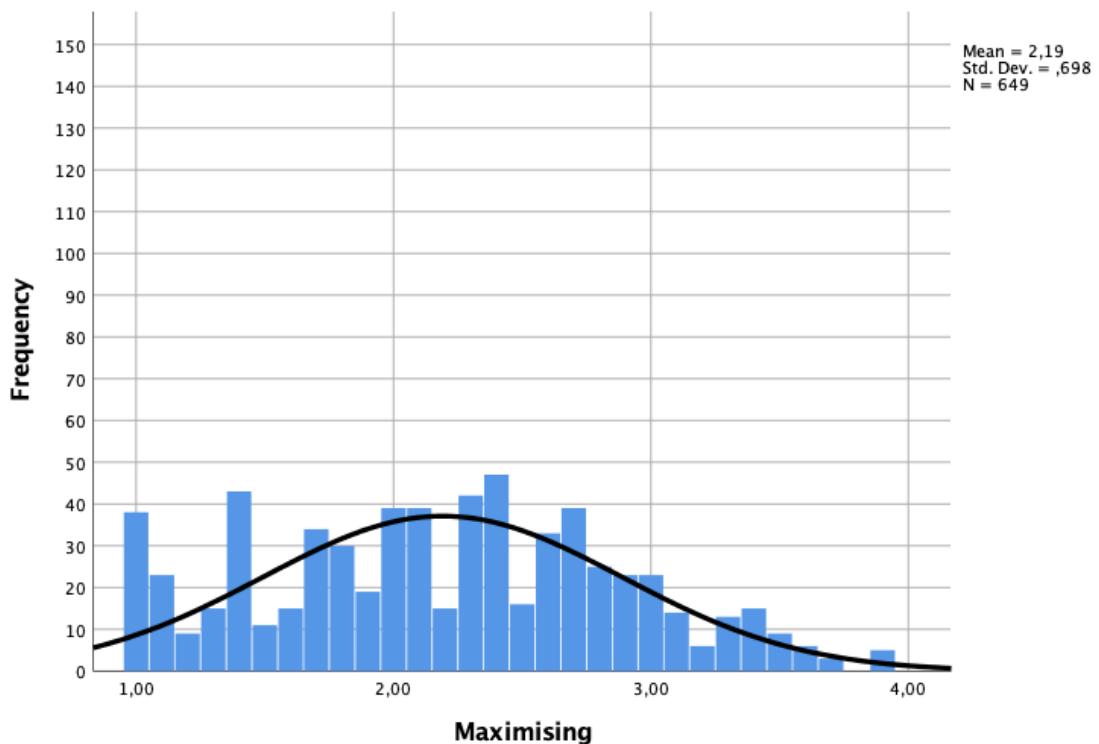
Components

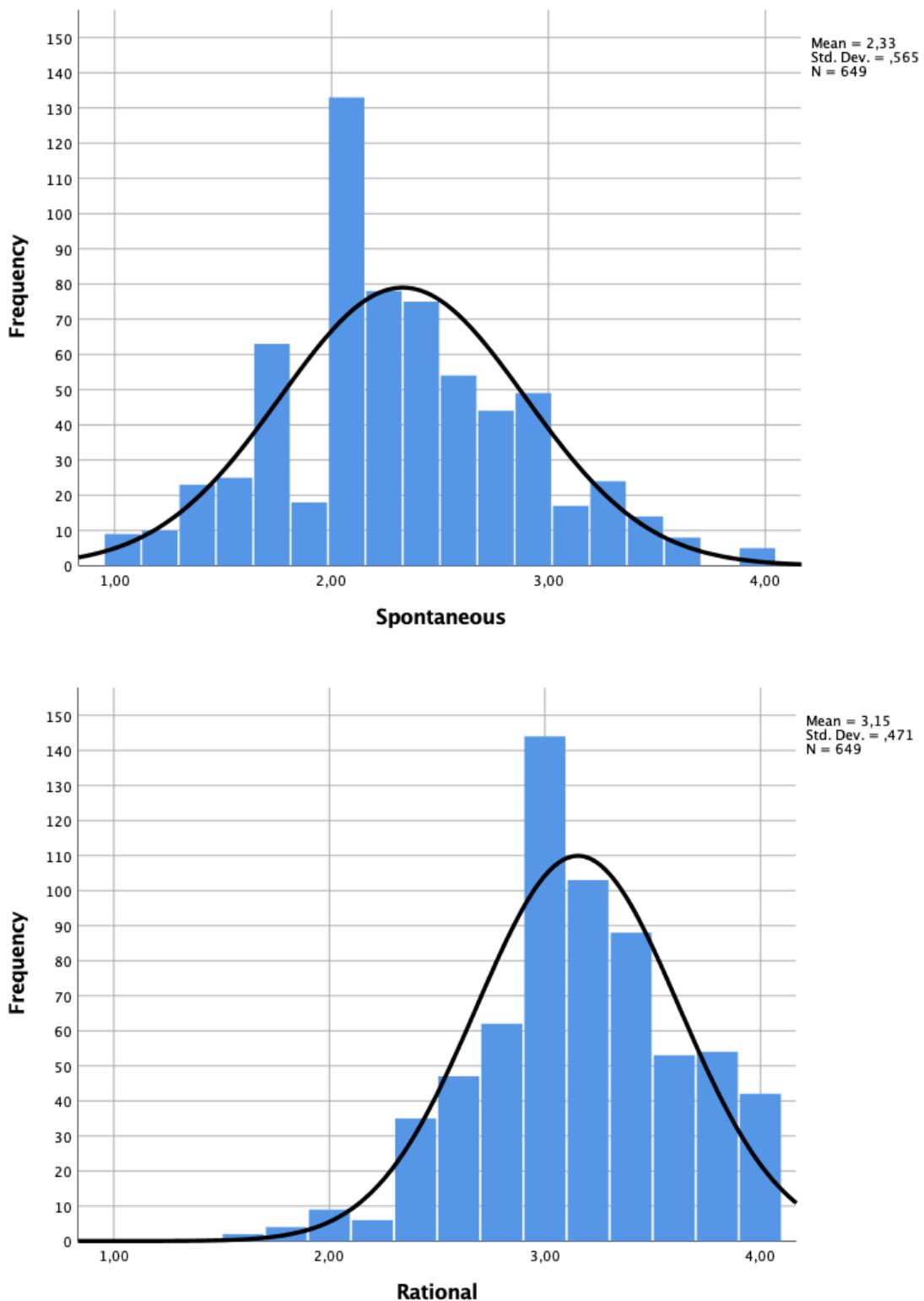
<i>MAXIMISING_5</i>	.200	-.021	-.099	.087	.095	.516	.400	-.002
<i>DEPENDENT_1</i>	.173	.143	.121	.184	.533	.125	.169	.001
<i>DEPENDENT_2</i>	.177	-.020	.046	.025	.649	.088	.096	.044
<i>DEPENDENT_3</i>	.014	.106	.075	.123	.735	.089	.027	.164
<i>DEPENDENT_4</i>	-.051	.017	.087	.130	.801	.038	.031	.012
<i>DEPENDENT_5</i>	.293	.029	-.216	.252	.511	.227	.204	.189
<i>INTUITIVE_1</i>	-.169	.421	.389	-.170	-.078	-.163	.028	.077
<i>INTUITIVE_2</i>	-.055	.757	-.009	.024	.024	.022	.015	-.122
<i>INTUITIVE_3</i>	-.049	.730	-.005	.059	-.029	.023	-.058	-.253
<i>INTUITIVE_4</i>	-.001	.752	-.020	.012	.124	-.028	-.047	-.161
<i>INTUITIVE_5</i>	.167	.634	-.196	-.002	.058	-.051	.208	.023
<i>SPONTANEOUS_1</i>	.071	.387	-.375	.094	.080	.132	.145	-.371
<i>SPONTANEOUS_2</i>	.143	.514	-.228	.213	.069	.140	.171	-.376
<i>SPONTANEOUS_3</i>	-.087	.194	-.048	-.082	-.053	.001	.051	-.737
<i>SPONTANEOUS_4</i>	.034	.705	.097	.004	.080	.024	.037	-.002
<i>SPONTANEOUS_5</i>	.140	.212	-.206	.099	-.141	-.065	.267	-.614
<i>RATIONAL_1</i>	.039	.082	.660	-.068	-.039	-.230	.029	.128
<i>RATIONAL_2</i>	-.197	.072	.654	-.056	.095	-.033	.039	.225
<i>RATIONAL_3</i>	.052	-.078	.698	.089	.086	-.015	-.217	-.147
<i>RATIONAL_4</i>	-.045	.011	.626	.149	.182	.129	-.015	.333
<i>RATIONAL_5</i>	-.090	-.184	.645	.040	.037	.021	-.045	-.154

8.7 Histograms for the Base Sample decision style scores



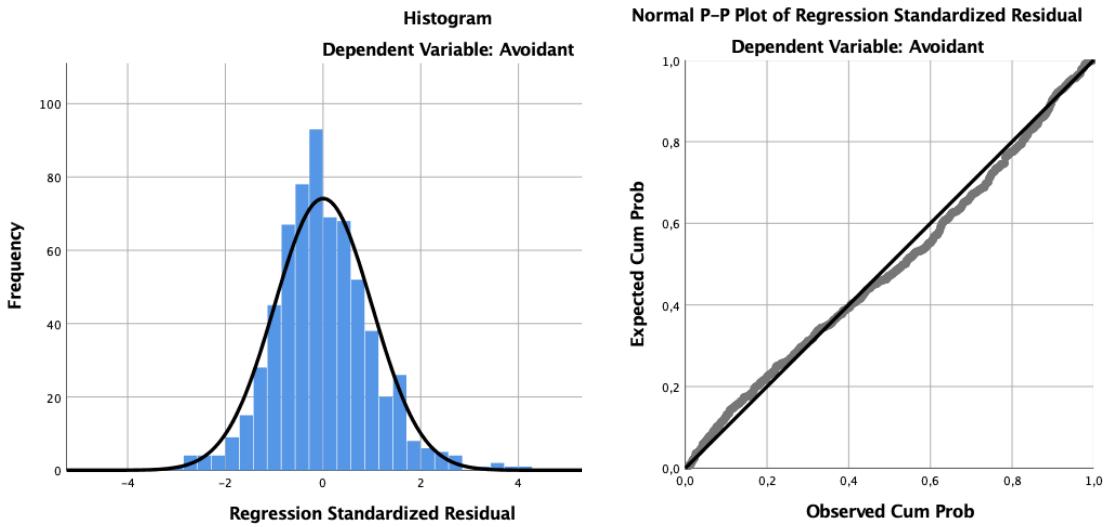




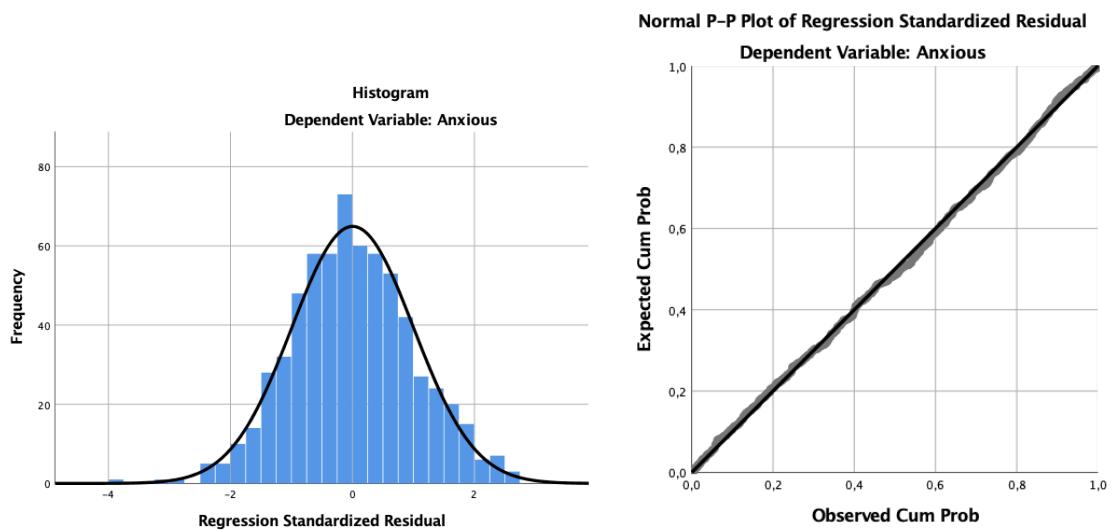


8.8 Histograms of standardised residuals & P-P plots for decision style regressions

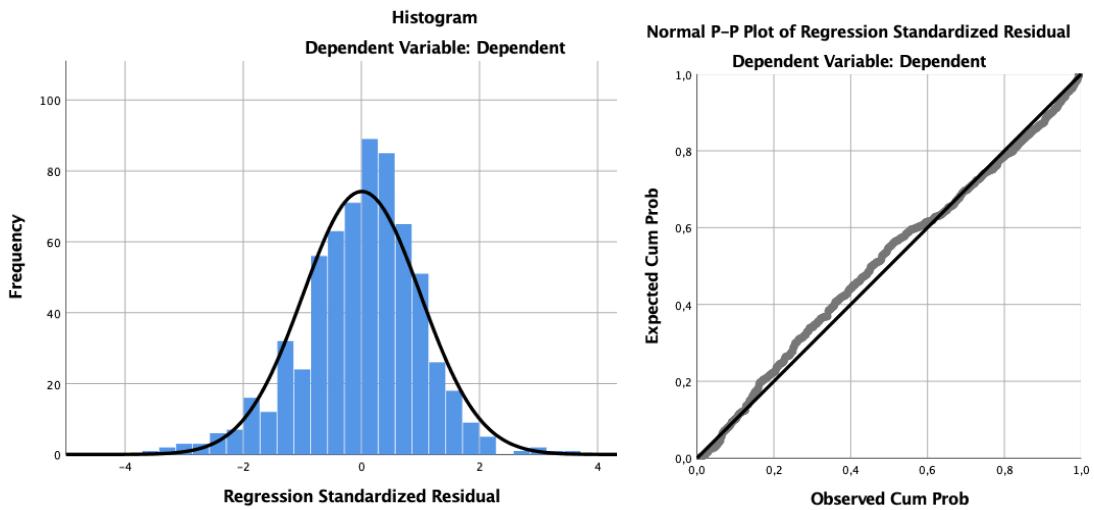
8.8.1 Avoidant as dependent variable



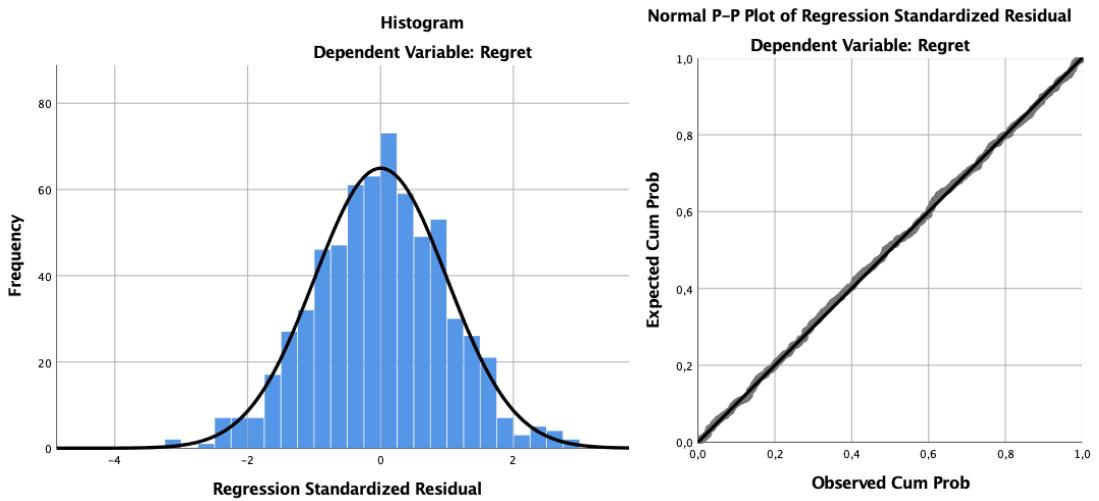
8.8.2 Anxious as dependent variable



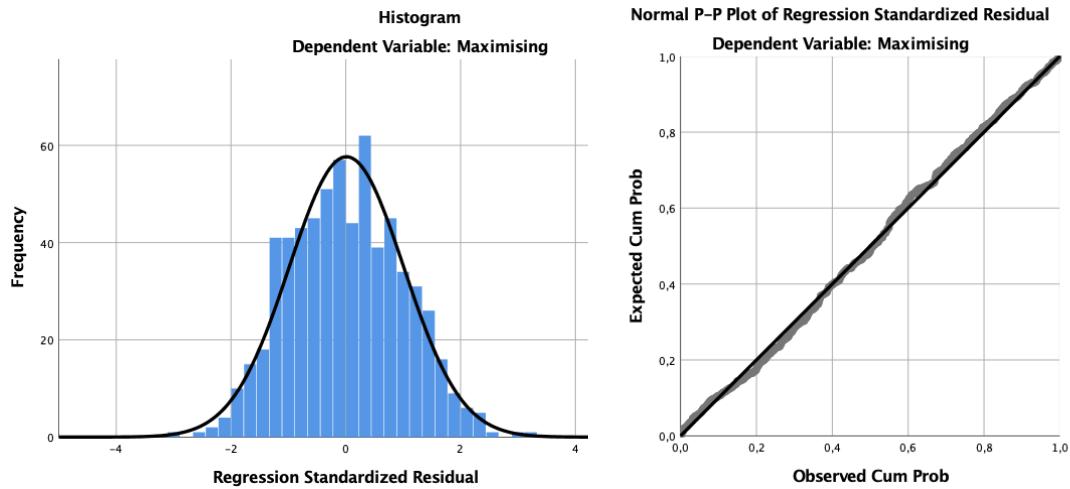
8.8.3 Dependent as dependent variable



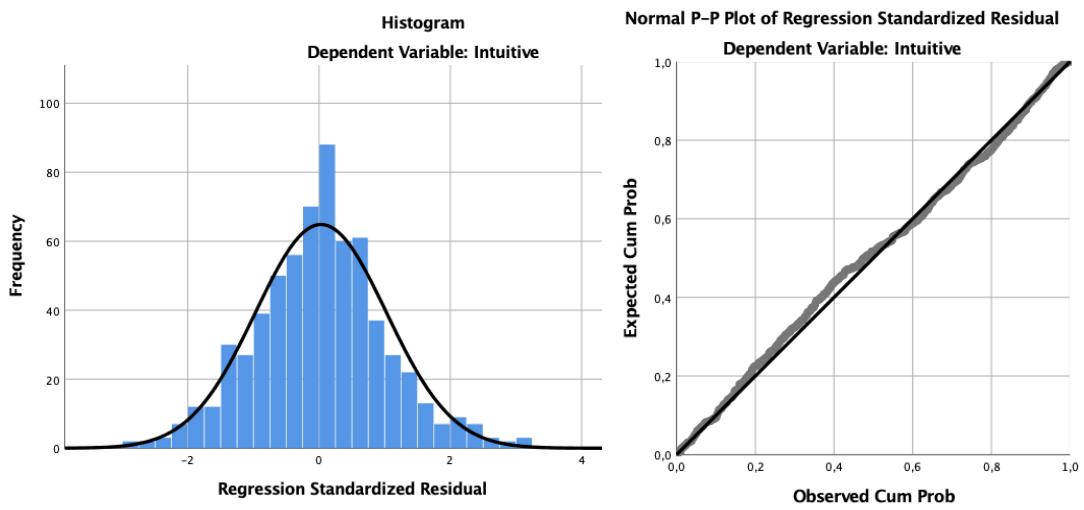
8.8.4 Regret as dependent variable



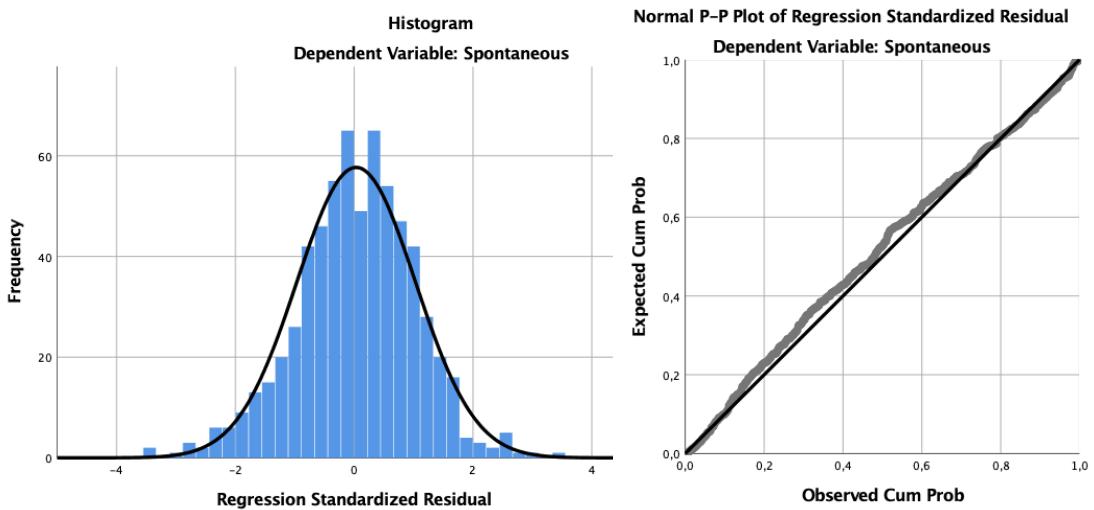
8.8.5 Maximising as dependent variable



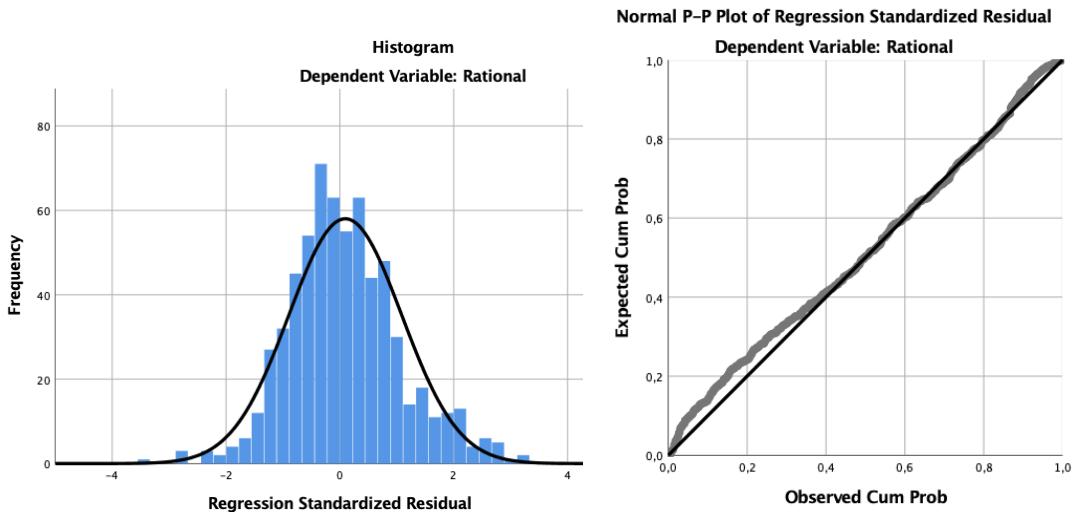
8.8.6 Intuitive as dependent variable



8.8.7 Spontaneous as dependent variable

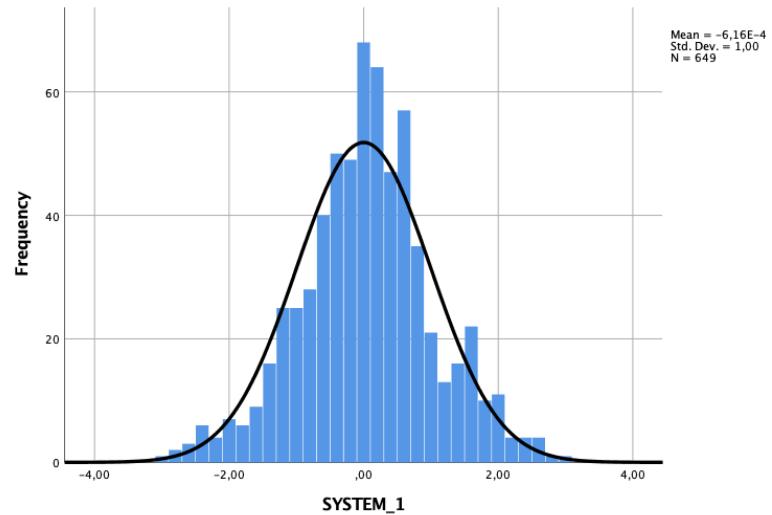
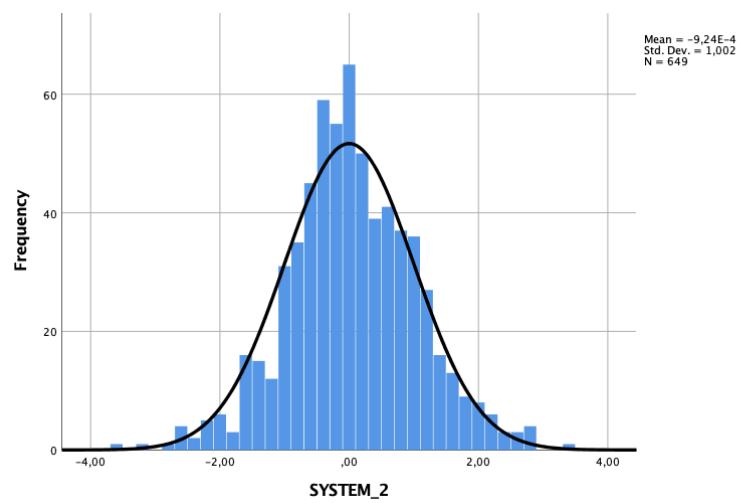
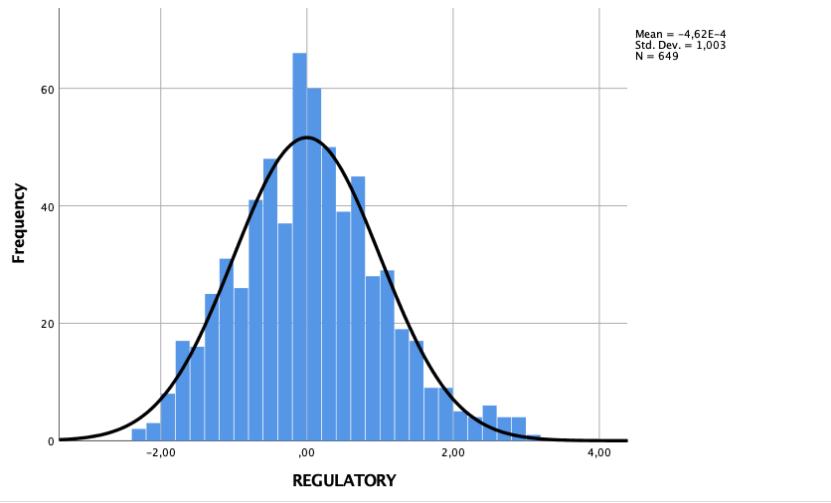


8.8.8 Rational as dependent variable

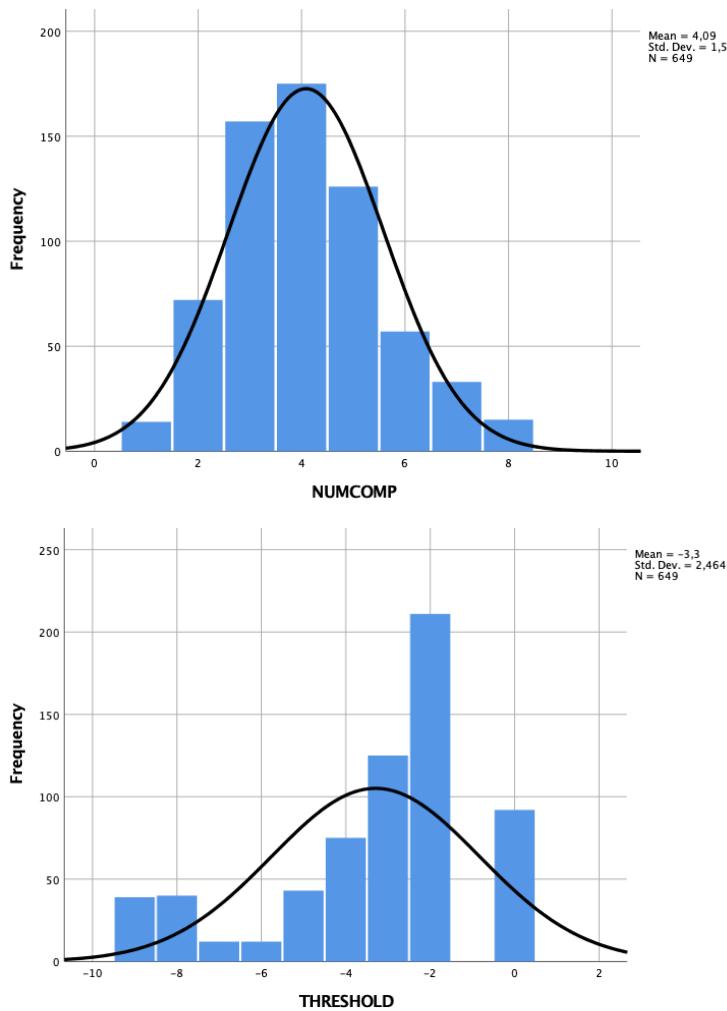


8.9 Histograms for the choice set and process style variables

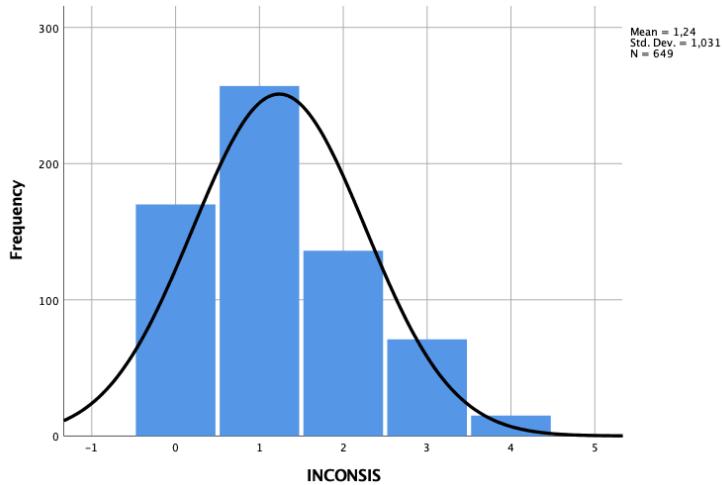
8.9.1 Process styles variables



8.9.2 Choice set variables



Please note that the histogram for THRESHOLD is distorted due to two facts: first, a company (an alternative) with an incompatibility score of -1 was not offer and, second, the profit temptation alternative had an incompatibility score of -8.



8.10 Summary pages for the 15 regression analyses

Convention for this attachment:

**p<0.01;

^a standardised coefficient;

^b non-standardised coefficient

^c the R² cannot be compared with the R² of a regression with a constant term

8.10.1 Number of companies (NUMCOMP)

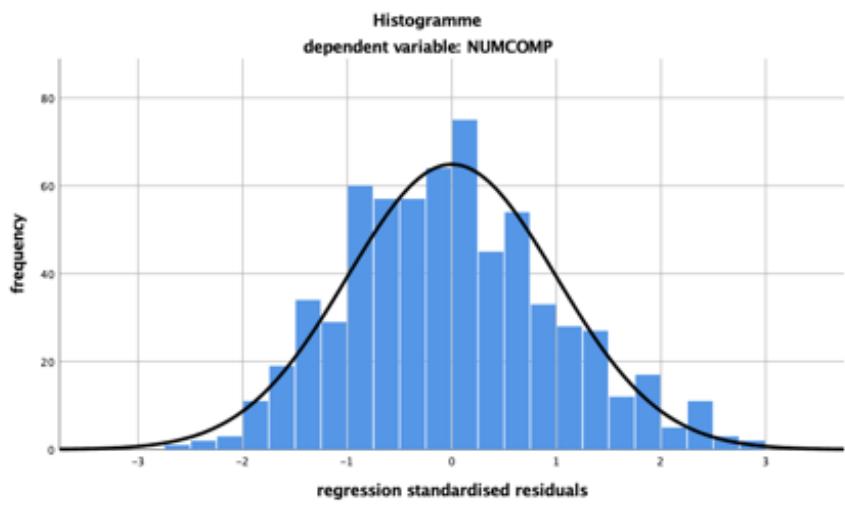
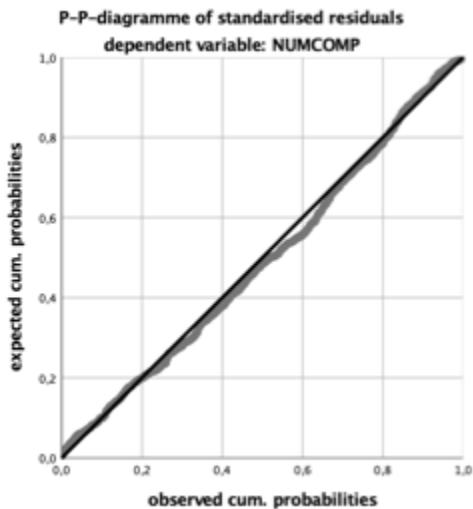
Regression N°1

Dependent variable: NUMCOMP;
 Independent variables: ANXIOUS, AVOIDANT, REGRET, SPONTAEOUS,
 MAXIMISING, DEPENDENT, INTUITIVE, RATIONAL,
 GENDER, AGE, TIME;
 Constant Term: Yes;
 Method: listwise, include $p < .05$, exclude $p < .10$;
 Durbin-Watson statistic: 1.981;
 Corrected R^2 : 0.054;

Regression function:

$$1^b) \text{NUMCOMP} = 2.67 + .32 * \text{DEPENDENT} + .38 * \text{INTUITIVE} - .19 * \text{TIME}$$

	<i>NUMCOMP</i>	<i>Coefficients^{a/b}</i>
CONSTANT b_0		2.665**
ANXIOUS		excluded
AVOIDANT		excluded
REGRET		excluded
SPONTANEOUS		excluded
MAXIMISING		excluded
DEPENDENT		.122/.315**
INTUITIVE		.129/.382**
RATIONAL		excluded
GENDER		excluded
AGE		excluded
TIME		-.142/-1.191**



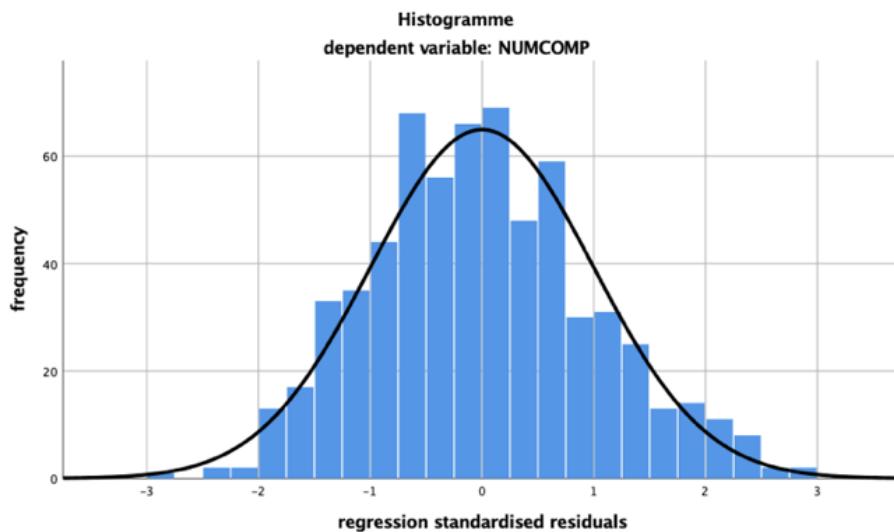
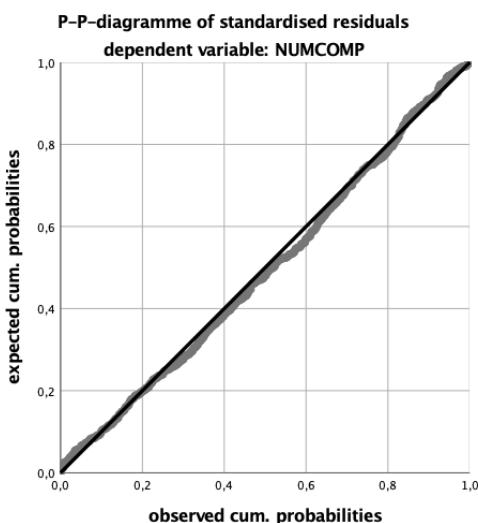
Regression N°2

Dependent variable: NUMCOMP;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, TIME,
 GENDER, AGE;
 Constant Term: Yes;
 Method: listwise, include p<.05, exclude p<.10;
 Durbin-Watson statistic: 1.990;
 Corrected R²: 0.067;
 F-value and p-value: 12.725, p<0.01;

Regression function:

$$2^b) \text{NUMCOMP} = 4.56 + .16 * \text{REGULATORY} + .23 * \text{SYSTEM 1} + .17 * \text{SYSTEM 2} - .19 * \text{TIME}$$

<i>NUMCOMP</i>	<i>Coefficients^{a/b}</i>
CONSTANT b_0	4.556**
REGULATORY	.106/.159**
SYSTEM 1	.156/.234**
SYSTEM 2	.114/.172**
GENDER	excluded
AGE	excluded
TIME	-.140/-1.189**



Regression N° 3

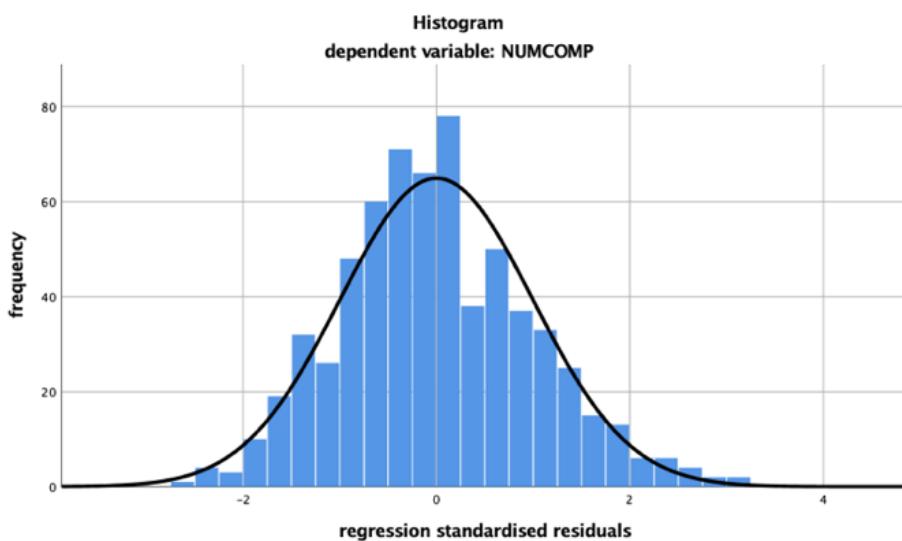
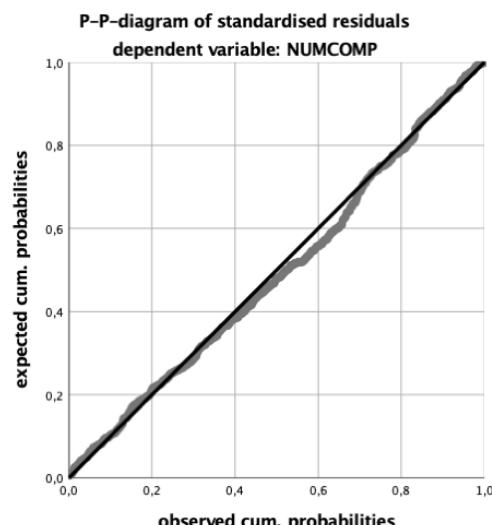
Dependent variable: NUMCOMP;
 Independent variables: DEPENDENT, INTUITIVE, TIME, INDIV_W_PRICE and IMPOR_WEIGHT_FIT;
 Constant Term: Yes;
 Method: listwise, include p<.05, exclude p<.10;
 Durbin-Watson statistic: 2.005;
 Corrected R²: 0.084;
 F-value and p-value: 15.773, p<0.01;

Regression function:

$$3^b) \text{NUMCOMP} = 3.61 + .30 * \text{DEPENDENT} + .33 * \text{INTUITIVE} - 3.71 * \text{INDIV_W_PRICE} - .16 * \text{TIME}$$

NUMCOMP *Coefficients*^{a/b}

<i>CONSTANT b₀</i>	3.614**
<i>DEPENDENT</i>	.114/.296**
<i>INTUITIVE</i>	.113/.334**
<i>IMPOR_WEIGHT_FIT</i>	excluded
<i>INDIV_W_PRICE</i>	-.177/-3.711**
<i>TIME</i>	-.120/-162**



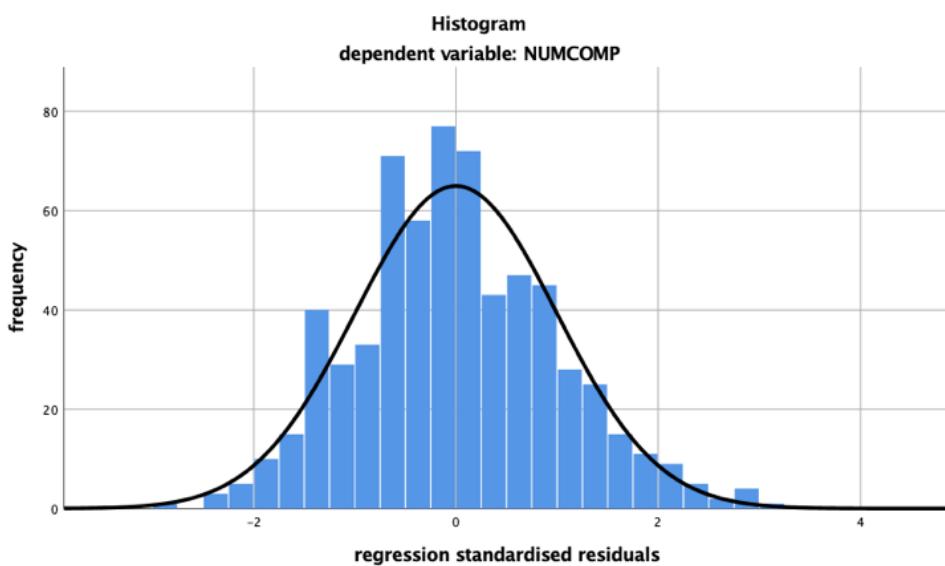
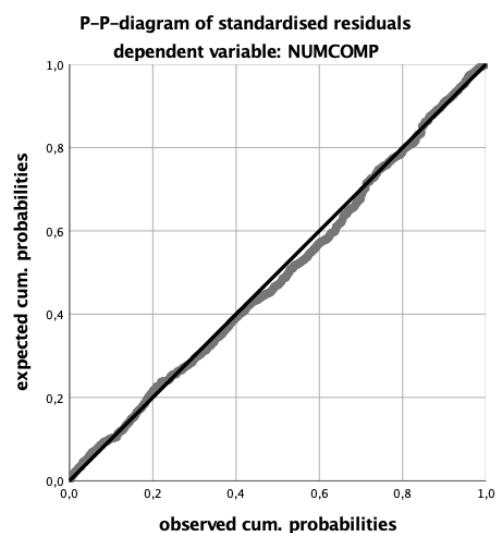
Regression N°4

Dependent variable: NUMCOMP;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, TIME, INDIV_W_PRICE and IMPOR_WEIGHT_FIT;
 Constant Term: Yes;
 Method: listwise, include p<.05, exclude p<.10;
 Durbin-Watson statistic: 2.009;
 Corrected R²: 0.094;
 F-value and p-value: 14.441, p<0.01;

Regression function:

$$4^b) \text{NUMCOMP} = 5.28 + .16 * \text{REGULATORY} + .21 * \text{SYSTEM1} - .15 * \text{SYSTEM2} - 3.55 * \text{INDIV_W_PRICE} - .16 * \text{TIME}$$

NUMCOMP	Coefficients ^{a/b}
CONSTANT b_0	5.284**
REGULATORY	.103/.155**
SYSTEM 1	.138/.207**
SYSTEM 2	.102/.154**
IMPOR_WEIGHT_FIT	excluded
INDIV_W_PRICE	-.169/-3.553**
TIME	-.119/-1.161**

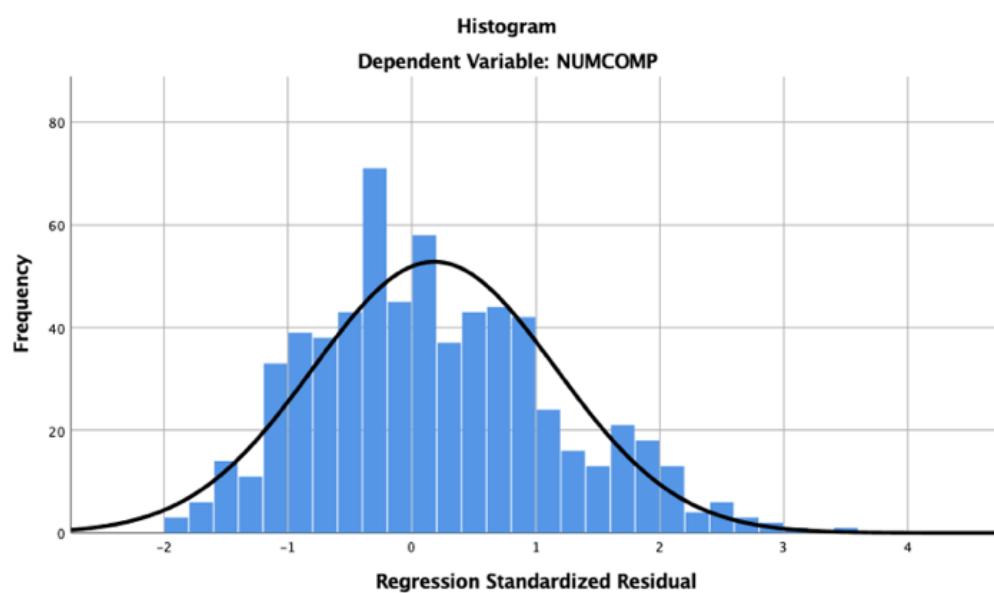
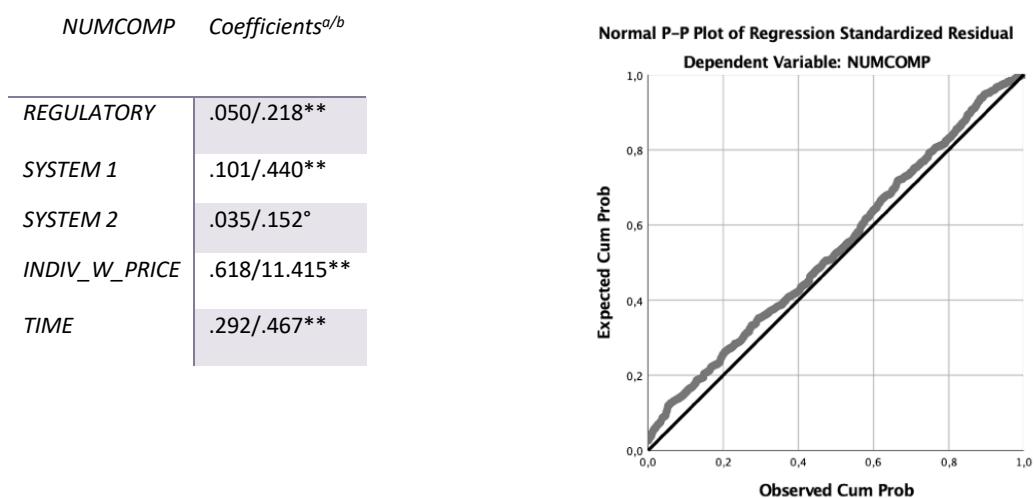


Regression N°5

Dependent variable: NUMCOMP;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, TIME and INDIV_W_PRICE;
 Constant Term: No;
 Method: listwise, include p<.05, exclude p>.10;
 Durbin-Watson statistic: 1.858;
 Corrected R²: 0.791;
 F-value and p-value: 493.477, p<0.01;

Regression function:

$$5^b) \text{NUMCOMP} = .22 * \text{REGULATORY} + .44 * \text{SYSTEM1} + .15 * \text{SYSTEM2} + 11.42 * \text{INDIV_W_PRICE} + .47 * \text{TIME}$$



8.10.2 Rejection Threshold (THRESHOLD)

Regression N°6

Dependent variable:

THRESHOLD;

Independent variables:

ANXIOUS, AVOIDANT, REGRET, SPONTAEOUS,
MAXIMISING, DEPENDENT, INTUITIVE, RATIONAL,
GENDER, AGE, TIME;

Constant Term:

No, since respective regression showed statistical
insignificance;

Method:

listwise, include p<.05, exclude p<.10;

Durbin-Watson statistic:

1.918;

Corrected R²:

0.657^c;

F-value and p-value:

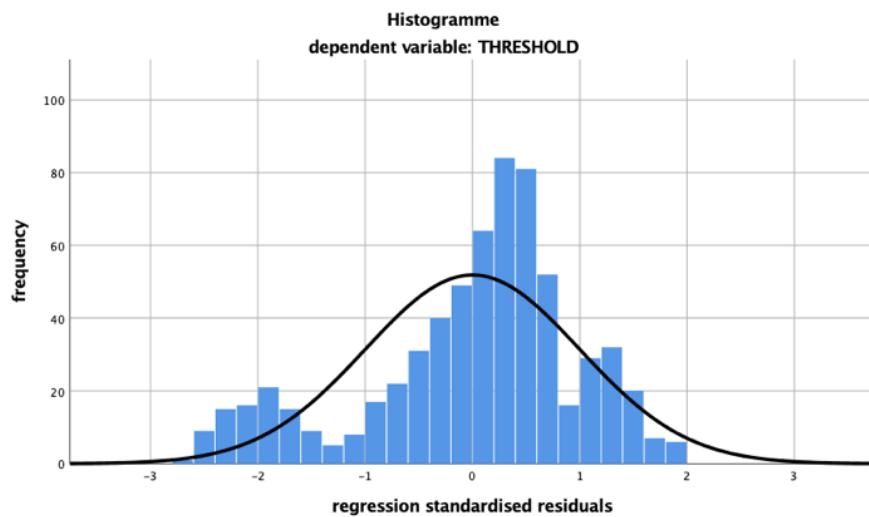
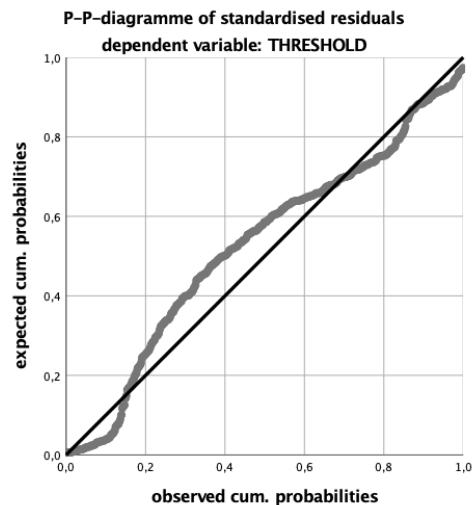
414.957, p<.01;

Regression function:

$$1^b) \text{THRESHOLD} = .26 * \text{TIME} - .62 * \text{INTUITIVE} - .69 * \text{RATIONAL}$$

THRESHOLD Coefficients^{a/b}

ANXIOUS	excluded
AVOIDANT	excluded
REGRET	excluded
SPONTANEOUS	excluded
MAXIMISING	excluded
DEPENDENT	excluded
INTUITIVE	-.442/-618**
RATIONAL	-.531/-685**
GENDER	excluded
AGE	excluded
TIME	.174/.262**



Regression N°7

Dependent variable: THRESHOLD;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, TIME, GENDER, AGE;
 Constant Term: Yes;
 Method: listwise, include p<.05, exclude p<.10;
 Durbin-Watson statistic: 1.941;
 Corrected R²: 0.050;
 F-value and p-value: 9.566, p<0.01;

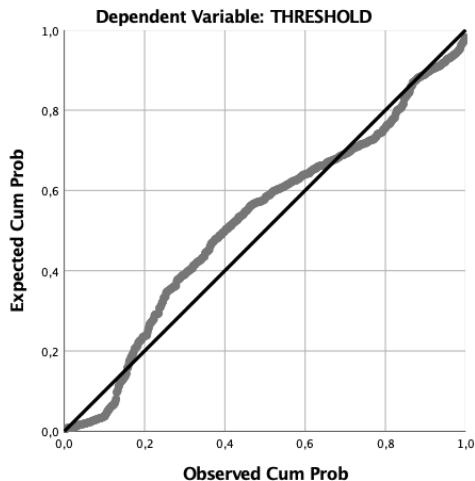
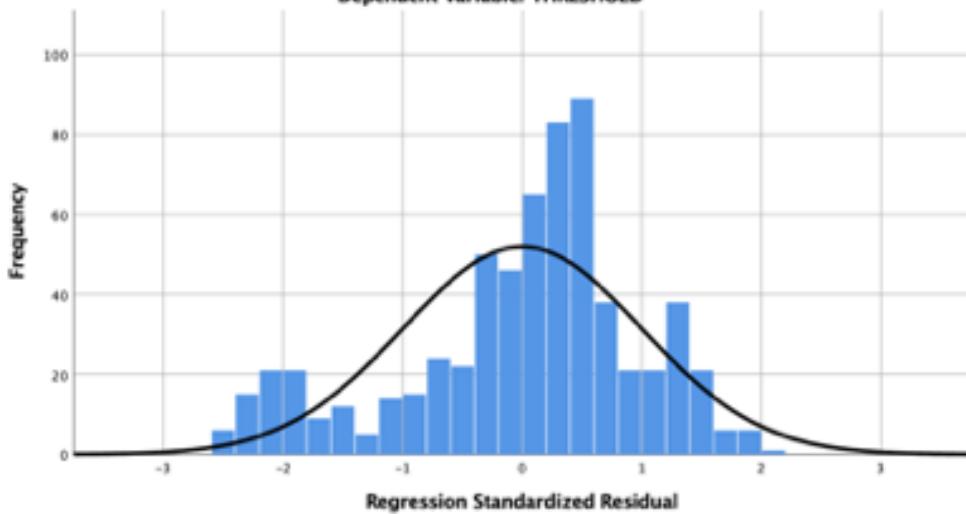
Regression function:

$$^2b) \text{THRESHOLD} = -3.87 + .23 * \text{TIME} - .23 * \text{REGULATORY} - .29 * \text{SYSTEM 1} - .35 * \text{SYSTEM 2}$$

THRESHOLD Coefficients^{a/b}

CONSTANT b_0	-3.868**
REGULATORY	-.093/-229*
SYSTEM 1	-.119/-294**
SYSTEM 2	-.144/-354**
GENDER	excluded
AGE	excluded
TIME	.104/.230**

Normal P-P Plot of Regression Standardized Residual

Histogram
Dependent Variable: THRESHOLD

Regression N°8

Dependent variable:

THRESHOLD;

Independent variables:

INTUITIVE, RATIONAL, TIME, IMPOR_WEIGHT_FIT

and INDIV_W_PRICE;

Constant Term:

No, since respective regression showed statistical

insignificance;

Method:

listwise, include p<.05, exclude p<.10;

Durbin-Watson statistic:

1.930;

Corrected R²:0.663^c;

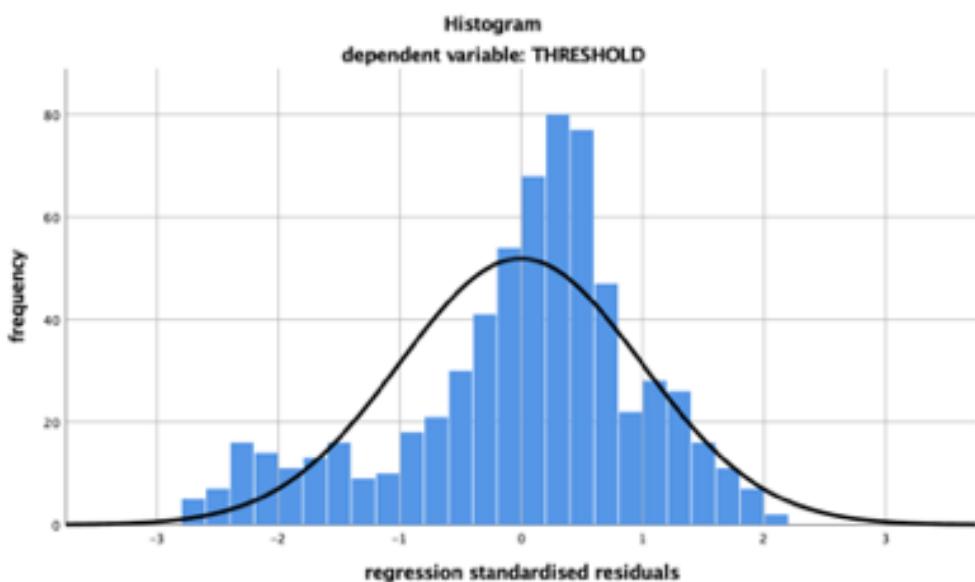
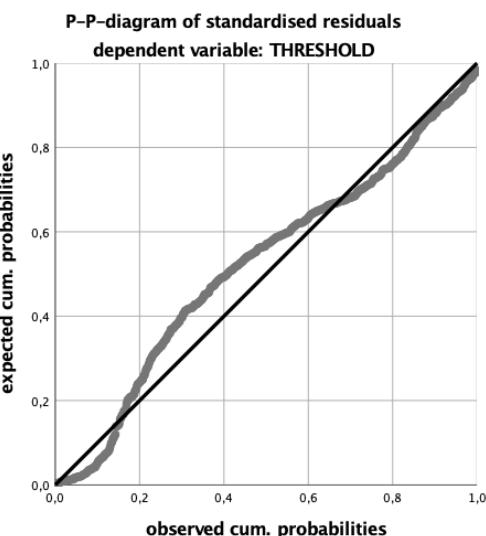
F-value and p-value:

320.360, p<.01;

Regression function:

$$3^b) \text{THRESHOLD} = 4.46 * \text{INDIVWPRICE} - .73 * \text{INTUITIVE} - .84 * \text{RATIONAL} + .20 * \text{TIME}$$

<i>THRESHOLD</i>	<i>Coefficients</i> ^{b/c}
<i>INTUITIVE</i>	<i>-.523/-731**</i>
<i>RATIONAL</i>	<i>-.654/-844**</i>
<i>INDIV_W_PRICE</i>	<i>.256/4.458**</i>
<i>IMPOR_WEIGHT_FIT</i>	excluded
<i>TIME</i>	<i>.132/.199*</i>



Regression N°9

Dependent variable: THRESHOLD;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, TIME, IMPOR_WEIGHTS_FIT and INDIV_W_PRICE;
 Constant Term: Yes;
 Method: listwise, include p<.05, exclude p>.10;
 Durbin-Watson statistic: 1.956;
 Corrected R²: 0.069;
 F-value and p-value: 10.662, p<0.01;

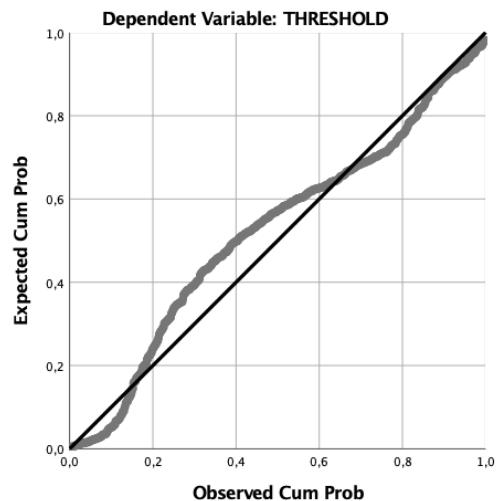
Regression function:

$$4^b) \text{THRESHOLD} = -4.90 + 5.02 * \text{INDIV_W_PRICE} - .26 * \text{SYSTEM 1} - .33 * \text{SYSTEM 2} + 19 * \text{TIME} +$$

THRESHOLD Coefficients^{a/b}

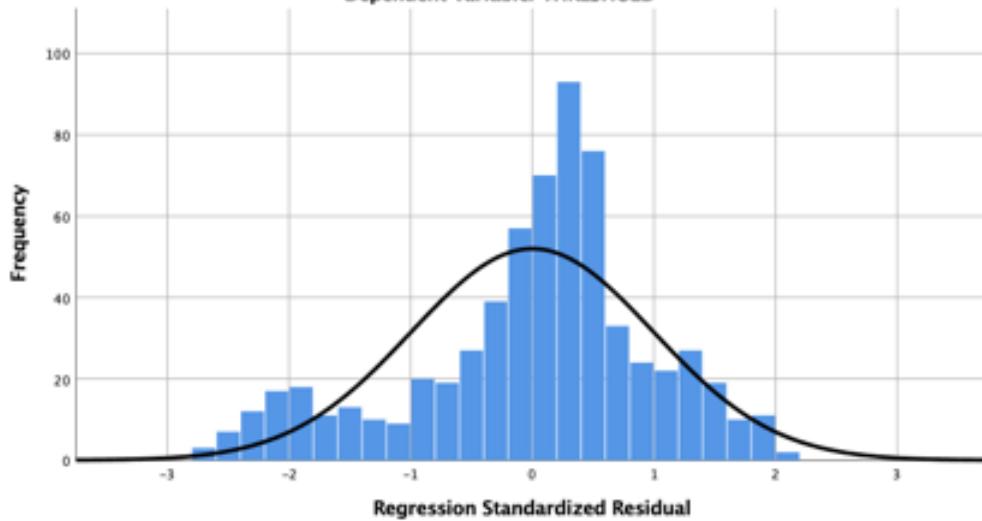
CONSTANT <i>b</i> ₀	-4.896**
REGULATORY	-.090/-,.222*
SYSTEM 1	-.103/-,.255**
SYSTEM 2	-.134/-,.329**
INDIV_W_PRICE	.146/5.019**
IMPOR_WEIGHT_FIT	excluded
TIME	.086/.190*

Normal P-P Plot of Regression Standardized Residual



Histogram

Dependent Variable: THRESHOLD



Regression N°10

Dependent variable: THRESHOLD;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, TIME and
 INDIV_W_PRICE;
 Constant Term: No;
 Method: listwise, include p<.05, exclude p>.10;
 Durbin-Watson statistic: 1.872;
 Adjusted R²: 0.569^c;
 F-value and p-value: 172.698, p<0.01;

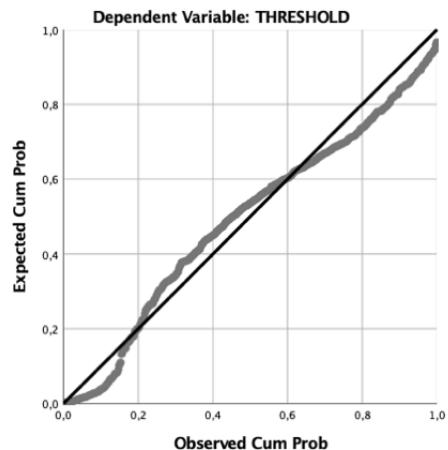
Regression function:

$$5^b) \text{THRESHOLD} = .28 * \text{REGULATORY} - .47 * \text{SYSTEM1} - .33 * \text{SYSTEM2} - 8.85 * \text{INDIV_W_PRICE} - .39 * \text{TIME}$$

THRESHOLD Coefficients^{a/b}

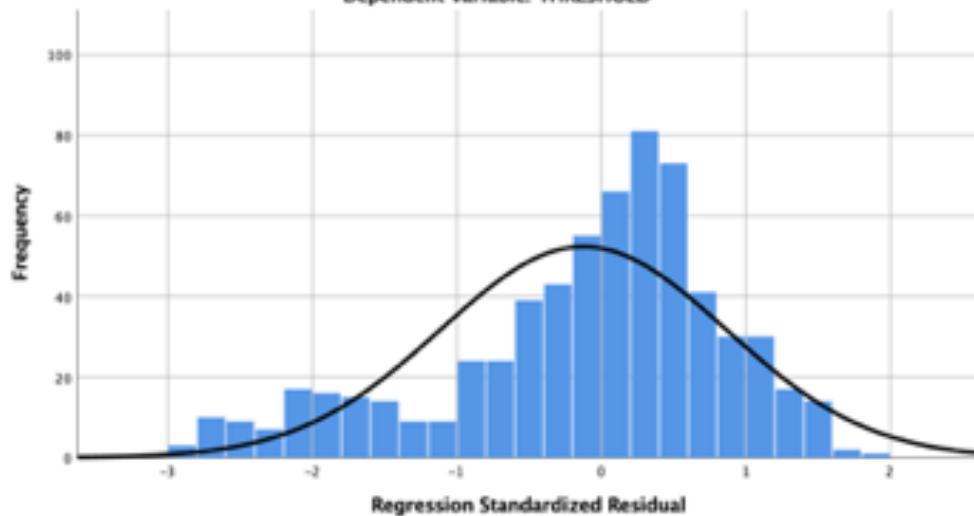
REGULATORY	-.068/-281**
SYSTEM 1	-.114/-471**
SYSTEM 2	-.080/-328**
INDIV_W_PRICE	-.507/-8.850**
TIME	-.259/-391**

Normal P-P Plot of Regression Standardized Residual



Histogram

Dependent Variable: THRESHOLD



8.10.3 Number of inconsistencies (INCONSIS)

Regression N°11

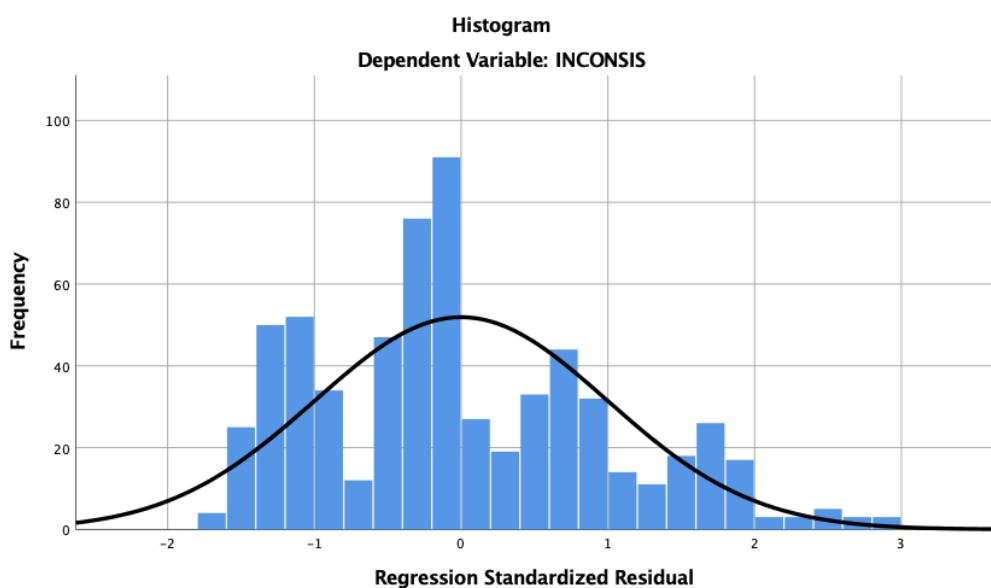
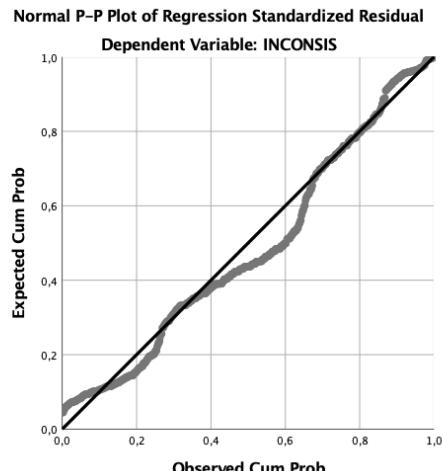
Dependent variable: INCONSIS;
 Independent variables: ANXIOUS, AVOIDANT, REGRET, SPONTAEOUS, MAXIMISING, DEPENDENT, INTUITIVE, RATIONAL, GENDER, AGE, TIME;
 Constant Term: Yes;
 Method: listwise, include $p < .05$, exclude $p > .10$;
 Durbin-Watson statistic: 1.904;
 Corrected R^2 : 0.040;
 F-value and p-value: 10.023, $p < .01$;

Regression function:

$$1^b) \text{INCONSIS} = 1.67 + .18 * \text{SPONTANEOUS} - .17 * \text{RATIONAL} - .12 * \text{TIME}$$

INCONSIS Coefficients^{a/b}

<i>CONSTANT</i> b_0	1.671**
ANXIOUS	excluded
AVOIDANT	excluded
REGRET	excluded
SPONTANEOUS	.096/.176*
MAXIMISING	excluded
DEPENDENT	excluded
INTUITIVE	excluded
RATIONAL	-.079/-1.72°
GENDER	excluded
AGE	excluded
TIME	-.131/-1.121**



Regression N°12

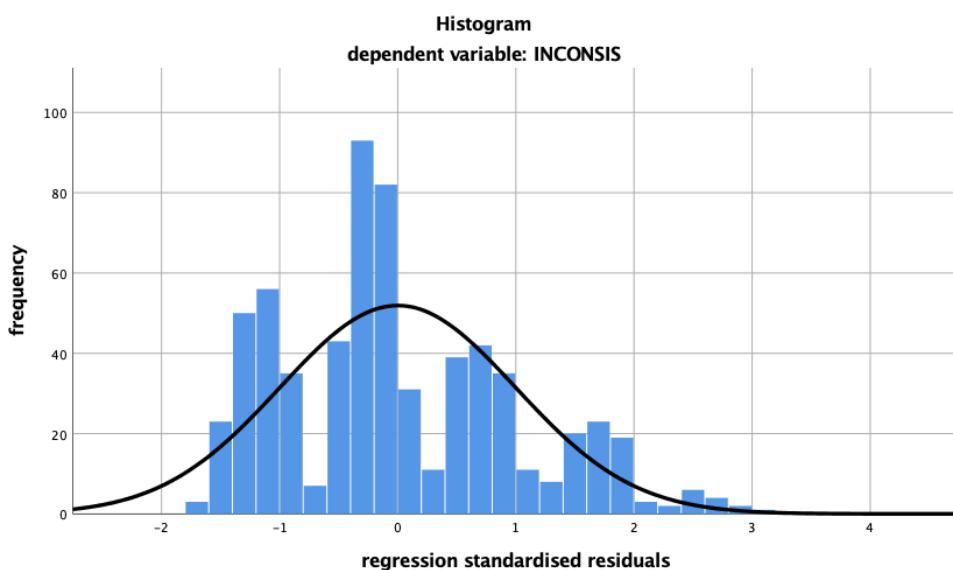
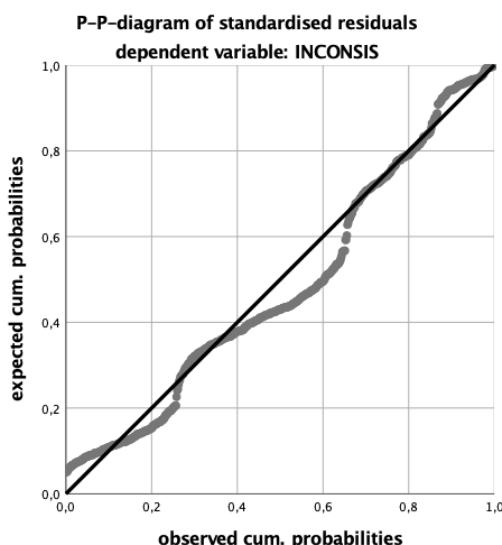
Dependent variable: INCONCIS;
 Independent variables: REGULATORY, SYSTEM 1, SYSTEM 2, GENDER, AGE, TIME;
 Constant Term: Yes;
 Method: listwise, include $p < .05$, exclude $p > .10$;
 Durbin-Watson statistic: 1.910;
 Corrected R^2 : 0.033;
 F-value and p-value: 8.833, $p < .01$;

Regression function:

$$2^b) \text{INCONCIS} = 1.55 - .13 * \text{TIME} + .01 * \text{SYSTEM 1} - .01 * \text{SYSTEM 2}$$

INCONCIS Coefficients^{a/b}

<i>CONSTANT</i> b_0	1.549**
<i>REGULATORY</i>	excluded
<i>SYSTEM 1</i>	.096/.099*
<i>SYSTEM 2</i>	-.078/-081*
<i>GENDER</i>	excluded
<i>AGE</i>	excluded
<i>TIME</i>	-.136/-126**



Regression N°13

Dependent variable:

INCONCIS;

Independent variables:

SPONTAEOUS, RATIONAL, TIME, INDIV_W_PRICE,
INDIV_W_PROFIT, INDIV_W_EMPLOYEE,
INDIV_W_INVEST, INDIV_W_INDUSTRY and
IMPOR_WEIGHT_FIT;

Constant Term:

Yes;

Method:

listwise, include p<.05, exclude p<.10;

Durbin-Watson statistic:

1.944;

Corrected R²:

0.065;

F-value and p-value:

9.967, p<.01;

Regression function:

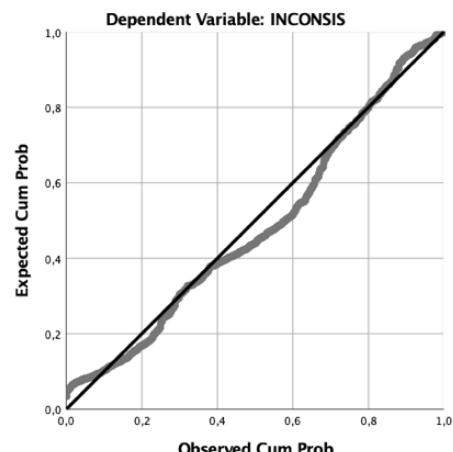
$$3^b) INCONCIS = 1.26 - .19 * RATIONAL + .14 * SPONTANEOUS - .12 * TIME + 1.94 * IMPOR_WEIGHT_FIT + \\ + 1.16 * INDIV_W_EMPLOYEE$$

INCONCIS

Coefficients^{a/b}

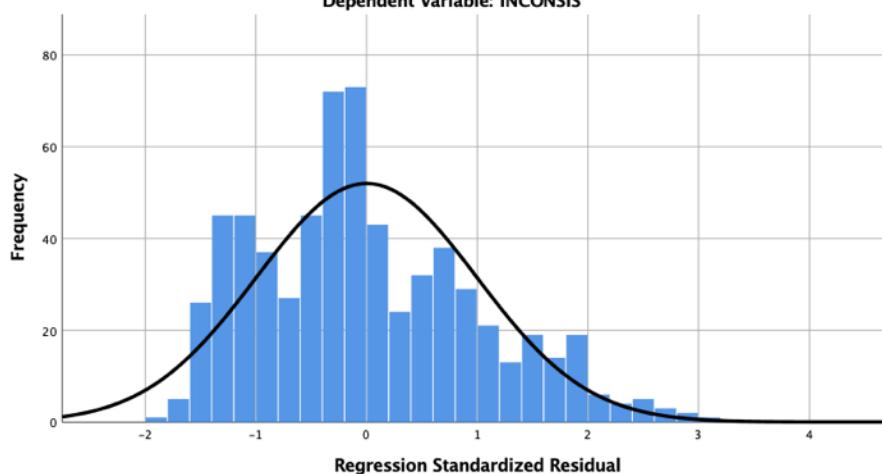
<i>CONSTANT</i> b_0	1.261**
<i>IMPOR_WEIGHT_FIT</i>	.149/1.935**
<i>INDIV_W_PRICE</i>	excluded
<i>INDIV_W_PROFIT</i>	excluded
<i>INDIV_W_EMPLOYEE</i>	.078/1.157*
<i>INDIV_W_INVEST</i>	excluded
<i>INDIV_W_INDUSTRY</i>	excluded
<i>RATIONAL</i>	-0.085/-0.186**
<i>SPONTANEOUS</i>	.079/.144°
<i>TIME</i>	-0.108/-0.117**

Normal P-P Plot of Regression Standardized Residual



Histogram

Dependent Variable: INCONCIS



Regression 14

Dependent variable:

INCONIS;

Independent variables:

SYSTEM 1, SYSTEM 2, TIME, INDIV_W_PRICE,
INDIV_W_PROFIT, INDIV_W_EMPLOYEE,
INDIV_W_INVEST, INDIV_W_INDUSTRY and
IMPOR_WEIGHT_FIT

Constant Term:

Yes;

Method:

listwise, include p<.05, exclude p<.10;

Durbin-Watson statistic:

1.945;

Corrected R²:

0.059;

F-value and p-value:

9.119, p<.01;

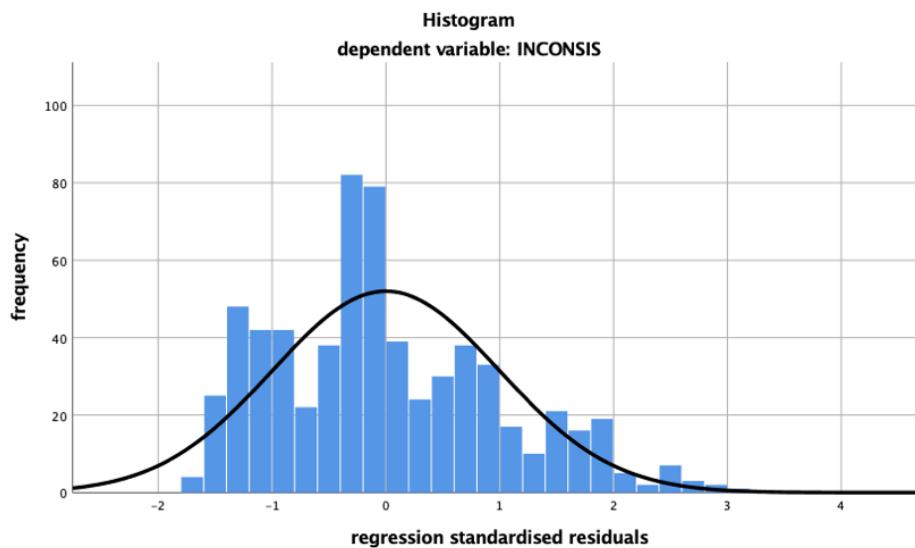
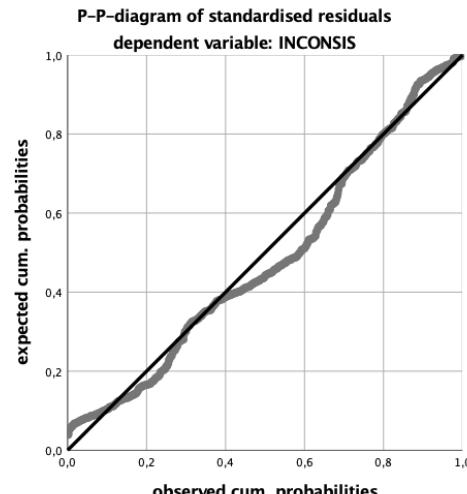
Regression function:

$$4^b) INCONIS = 1.03 + .08 * SYSTEM\ 1 - .09 * SYSTEM\ 2 - .11 * TIME + 1.92 * IMPORWEIGHTFIT + \\ + 1.2 * INDIV_W_EMPLOYEE$$

INCONIS

Coefficients^{a/b}

CONSTANT b_0	1.025**
IMPOR_WEIGHT_FIT	.148/1.916**
INDIV_W_PRICE	excluded
INDIV_W_PROFIT	excluded
INDIV_W_EMPLOYEE	.078/1.162*
INDIV_W_INVEST	excluded
INDIV_W_INDUSTRY	excluded
SYSTEM 1	.073/.075°
SYSTEM 2	-.082/-0.85*
TIME	-.123/-1.14**



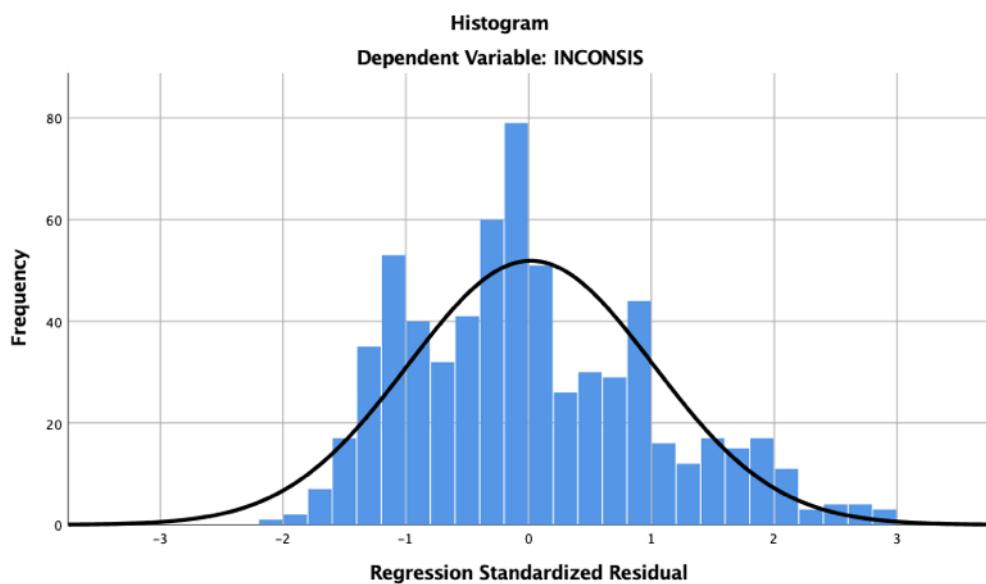
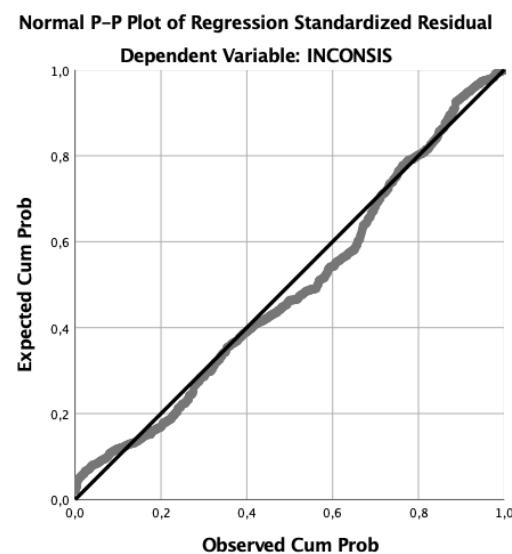
Regression N°15

Dependent variable: INCONCIS;
 Independent variables: SPONTAEOUS, RATIONAL, TIME,
 INDIV_W_EMPLOYEE and IMPOR_WEIGHT_FIT;
 Constant Term: No;
 Method: listwise, include p<.05, exclude p<.10;
 Durbin-Watson statistic: 1.962;
 Corrected R²: 0.611^c;
 F-value and p-value: 204.466, p<.01;

Regression function:

$$5^b) INCONCIS = .33 * SPONTANEOUS - .07 * TIME + 2.36 * IMPOR_WEIGHT_FIT + 1.56 * INDIV_W_EMPLOYEE$$

INCONCIS	Coefficients ^{a/b}
IMPOR_WEIGHT_FIT	.305/2.363**
INDIV_W_EMPLOYEE	.125/1.563**
RATIONAL	excluded
SPONTANEOUS	.485/.326**
TIME	-.110/-065*



8.11 Syntax for the various analysis in MPlus

8.11.1 CFA to extract 8 factors to test Dewberry model with 5 items per decision style

TITLE:

CFA to confirm 8 factors of 40 questionnaire items

DATA:

...

VARIABLE:

NAMES = u1-u40;

CATEGORICAL ARE u1-u40;

ANALYSIS:

ROTATION IS CF-EQUAMAX (ORTHOGONAL);

MODEL:

f1-f8 BY u1-u40 (*1);

8.11.2 CFA to extract 3 factors of the 8 decision styles data

TITLE:

CFA to extract 3 factors from 8 styles (calculated
with loading factors)

DATA:

```
FILE = AM-Thesis-Data Set A 3-Hypothesis 3 factors-  
19-01-22.dat;  
FORMAT ARE FREE;
```

VARIABLE:

```
NAMES ARE AVOID INTUIT RATIONAL SPONTAN REGRET  
MAXIMIS ANXIOUS DEPEND;
```

ANALYSIS:

```
ROTATION IS GEOMIN;
```

MODEL:

```
f1-f3 BY AVOID INTUIT RATIONAL SPONTAN REGRET MAXIMIS  
ANXIOUS DEPEND (*1);
```

8.11.3 First SEM analysis to test hypothesis 3

TITLE:

```
First SEM on Base Sample data for test of Hypothesis  
3
```

DATA:

```
FILE = AM-Thesis-Input-MPlus-Data Set SEM 3-11-03-  
17.dat;
```

VARIABLE:

```
NAMES ARE TIM52 AVO INT RAT SPO REG MAX ANX DEP NUM  
THR INC REY SY1 SY2 IWF PRI EMP;  
  
USEVARIABLES ARE TIM REY SY1 SY2 NUM THR INC IWF PRI  
EMP;
```

MODEL:

```
THR on TIM REY SY1 SY2 PRI;  
INC on TIM SY1 SY2 IWF EMP;  
NUM on TIM;  
NUM on THR;  
NUM with INC;
```

OUTPUT:

```
SAMP;  
STAND;
```

⁵² abbreviations were used since MPlus has limited size for an input line. The abbreviations are explained in the abbreviations section at the beginning.

8.11.4 Second SEM analysis to test hypothesis 3

TITLE:

Second SEM Analysis to test Hypothesis 3, full structural model;

DATA:

FILE = AM-Thesis-Input-MPlus-Data Set SEM 3-11-03-17.dat;

VARIABLE:

NAMES ARE TIM AVO INT RAT SPO REG MAX ANX DEP NUM THR INC REY SY1 SY2 IWF PRI EMP;
USEVARIABLES ARE TIM INT RAT SPO REG DEP ANX MAX AVO NUM THR INC IWF PRI EMP;

ANALYSIS:

ROTATION IS CF-EQUAMAX(ORTHOGONAL);
ROWSTANDARDIZATION IS KAISER;

MODEL:

F1-F3 by RAT INT SPO DEP REG ANX MAX AVO (*1);
THR on TIM F1-F3 PRI;
INC on TIM F1-F3 IWF EMP;
NUM on TIM;
NUM on THR;
NUM with INC;

OUTPUT:

SAMP;
STAND;

Warning message provided by MPlus:

" WARNING: THE RESIDUAL COVARIANCE MATRIX (THETA) IS NOT POSITIVE DEFINITE. THIS COULD INDICATE A NEGATIVE VARIANCE/RESIDUAL VARIANCE FOR AN OBSERVED VARIABLE, A CORRELATION GREATER OR EQUAL TO ONE BETWEEN TWO OBSERVED VARIABLES, OR A LINEAR DEPENDENCY AMONG MORE THAN TWO OBSERVED VARIABLES. CHECK THE RESULTS SECTION FOR MORE INFORMATION. PROBLEM INVOLVING VARIABLE SPO."

8.11.5 Third SEM analysis to test hypothesis 3 with Student Sample data

TITLE:

Third SEM Analysis to test Hypothesis 3 on Student Sample data, full structural model;

DATA:

FILE = AM-Thesis-STUDENT-3rd SEM-Hypothesis 3-19-03-18.dat;

VARIABLE:

```
NAMES ARE TI AV IN RA SP RE MA AN DE NC TH IC RY S1
S2 WF PRI PRO DEB EMP INV IND;
USEVARIABLES ARE TI IN RA SP RE DE AN MA AV NC TH IC
WF PRI EMP;
```

ANALYSIS:

```
ROTATION IS CF-EQUAMAX(ORTHOGONAL);
ROWSTANDARDIZATION IS KAISER;
```

MODEL:

```
F1-F3 by RA IN SP DE RE AN MA AV (*1);
TH on TI F1-F3 PRI;
IC on TI F1-F3 WF EMP;
NC on TI TH;
NC with IC;
```

OUTPUT:

```
SAMP;
STAND;
```

Mplus Message:

"NO CONVERGENCE. NUMBER OF ITERATIONS EXCEEDED. WARNING: THE RESIDUAL COVARIANCE MATRIX (THETA) IS NOT POSITIVE DEFINITE. THIS COULD INDICATE A NEGATIVE VARIANCE/RESIDUAL VARIANCE FOR AN OBSERVED VARIABLE, A CORRELATION GREATER OR EQUAL TO ONE BETWEEN TWO OBSERVED VARIABLES, OR A LINEAR DEPENDENCY AMONG MORE THAN TWO OBSERVED VARIABLES. CHECK THE RESULTS SECTION FOR MORE INFORMATION.

PROBLEM INVOLVING VARIABLE IN.

THE CHI-SQUARE STATISTIC IS NEGATIVE.

THE LOGLIKELIHOOD VALUES MAY NOT BE RELIABLE."

8.11.6 Fourth SEM analysis to test hypothesis 3 with Student Sample data

TITLE:

Fourth SEM Analysis to test Hypothesis 3, right-hand side structure only;

DATA:

FILE = AM-Thesis-STUDENT-3rd SEM-Hypothesis 3-19-03-18.dat;

VARIABLE:

NAMES ARE TI AV IN RA SP RE MA AN DE NC TH IC RY S1 S2 WF PRI PRO DEB EMP INV IND;
USEVARIABLES ARE TI RY S1 S2 NC TH IC WF PRI EMP;

MODEL:

TH on TI RY S1 S2 PRI;
IC on TI S1 S2 WF EMP;
NC on TI TH;
NC with IC;

OUTPUT:

SAMP;
STAND;