Ambition patterns in strategic decision-making

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Dedicated to Theo Vandewalle,

a true academic.

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Chapter 1
Introduction

Designing a methodology to model aspects of strategic decision-making

This thesis is about designing a methodology to model aspects of strategic decision-making into a generically applicable calculation rule. The model is based on the input from large numbers of employees to support an organization’s upper management. Modelling strategic decision-making can be done, for example, by means of a conceptual model (e.g. Kotter, 1995), with a set of mathematical equations (e.g. Gureckis & Love, 2009) or by using specific visualizations (e.g. Kohl & Miikkulainen, 2009). When involving the input of large numbers of employees, strategic decision-making is mainly a bottom-up flow of information: the employees become the ‘eyes and ears’ of upper management. But, when decisions are made and targets are set, it is the subsequent change management where information flows top-down: upper management instructs the rest of the organization what the targets, milestones, budgets and mandates have become.

So, when modelling aspects of strategic decision-making, we prefer to apply a modelling technique that would benefit this change management as well and would factor in the probably lesser modelling competencies of lower management and employees. Given the latter, we deem conceptual models too generic and mathematical models too difficult to deploy in daily practice. Hence, in this thesis, we set out to build a simple statistical model by finding a way to harness a parameterized set of probability distributions about a key aspect of strategic decision-making: the ambition of the organization’s personnel itself. Based on these parameters we intend to create an entity-relationship model to describe how management might intervene in potentially negative side-effects of the employees’ ambition.

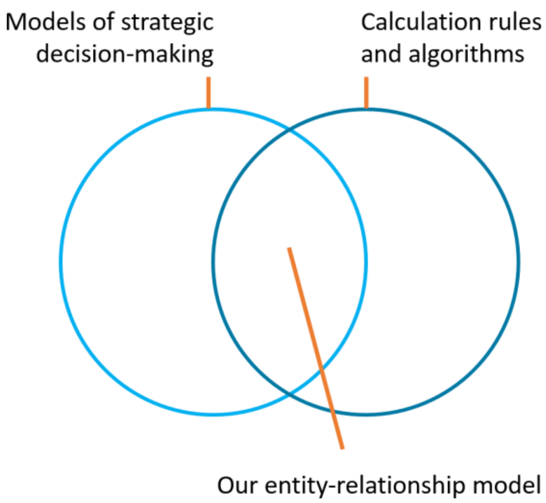

Figure 1.1: Choosing our model

We aim to integrate the probabilities and interventions into a generically applicable calculation rule. This could be referred to as an example of an algorithm: ‘a step-by-step procedure for solving a problem or accomplishing some end especially by a computer’ (Algorithm, n.d.).

Strategic decision-making is about managing an organization in world’s everyday change. Every organization takes strategic decisions that require change management: a combination of a sense of urgency, a vision to follow, the empowerment of the organization, planning for wins and institutionalizing new approaches to make these decisions a reality (Kotter, 1995). Strategic decisions are fueled by publicly available data (e.g., market forecasts) and the data in the organization’s administration; both augmented by the insight of people. Calculation rules that might support this decision process are fed by these data. Already, managers are seeking to incorporate various sorts of data in their strategic decision-making process. These data give, for example, insight into strategically important aspects of innovation (Chenhall, Kallunki, & Silvola, 2011), into the (im-) possibilities of internal alignment (Burrus & Mann, 2011) and how organizational complexity affects employees (Birkinshaw & Heywood, 2010).

Various authors have also indicated the scientific merits of the development of calculation rules, for example to reduce uncertainty about alternative strategic options and to improve the optimization of a specific course of action (in medicine, Hornberger, 2013), to stimulate theoretical research to improve the calculation rules’ performance prediction (in mechanics, Förstner, 1996), and to unify previously unrelated theories (in science philosophy, Kühn, 1977). Additionally, calculation rules drive simulations that in turn may speed up theory development, e.g., when calculation rules mirror theoretical logic to provide construct validity (in mathematics, Davis, Eisenhardt, & Bingham, 2007).

Applying these advantages when modelling strategic decision-making would propel the insight into the topic itself as well as in underlying theories. These underlying theories include, for example, theories about 'groupthink' (a phenomenon described by Turner and Pratkanis, 1998) and 'process clarity' where a shared team identity and clear tasks, roles and responsibilities could propel the (strategic) performance of a team (Parker & Collins, 2010; Hu & Liden, 2011). These theories are especially interesting given more recent organizational developments as the reduction of management layers to stimulate production (Qi, Tang, & Zhang, 2014) or to drive innovation (Koukis & Koulioumpas, 2015) and the rise of self-controlling, autonomous teams (Lambe, Webb, & Ishida, 2009). In turn, these developments have an influence on the strategic decision-making process that our modelling may further nuance.

Modelling strategic decision-making relates to a compelling, currently unfolding societal trend

In 2013, Harvard Business Review wrote about consulting on the cusp of disruption (Christensen, Wang & van Bever, 2013). The main conclusion was that management consultants, who are the prime experts to support management with strategic decision-making, suffered from a lack of standardization and quantification in their approach to tackle their clients' strategic issues. And no one less than Nobel economics laureate Daniel Kahneman, a behavioral economist, recently shared how he was *under*whelmed by the quality of decision-making in organizations (Wharton, 2016). "The amount of folly in the way these places are run, [..] the really, really poor thinking [..] is actually fairly troubling." In this interview, Kahneman sees an urgent need to improve strategic decision-making to match the increasing complexity in which organizations operate. From behavioral economy we learn that this decision-making is haunted by, among others, limited understanding of the impact of decisions (McElhinney & Proctor, 2005), human's cognitive biases (Hilbert, 2012), overconfidence (Fast, Sivanathan, Mayer, & Galinsky, 2012) and conformity pressure (in finance, Smith, 2011); all of which create errors in (strategic) decision-making. In the interview, Kahneman illuminates this 'organizational noise' by experiments proving a very large variability in experts' judgement of the very same business issues. Kahneman sees algorithms (our 'calculation rules') as a noise-free enhancement to organizational decision-making where this 'artificial intelligence' increasingly performs tasks done by managers.

This lack of standardization and quantification to which the Harvard Business Review referred is even more remarkable given a study of the McKinsey Global Institute (Disruptive technologies, 2013). This study ranked 'automation of knowledge work' as the number two disruptive technology of the coming decade with a projected industry revenue of five to seven trillion dollar. As such, this trend is, ahead of, among others, the Internet of Things, cloud computing, 3D printing and renewable energy. Automation of knowledge work was defined as "sophisticated analytics tools that augment the talents of highly skilled employees" and has applications in sectors such as Pharma, Legal, and Economics. 'Tools that augment talents' could also very well apply to models of strategic decision-making. The impact of automation of knowledge work is especially visible in how the nature of work changes (e.g., ask a computer in natural language like Apple Siri or Google Now), how organizational structures change (e.g., new ways of employment, education and training of workers, as well as new ways of working) and how economic growth and productivity will accelerate (e.g., the ability to serve more clients better via automated customer-service centers). All these examples are strategic aspects of an organization. McKinsey estimated that 20% of the five to seven trillion dollars will be related to the work managers do, such as monitoring activities, understanding the root causes of issues, and accurately forecasting future trends. McKinsey reckons that there are over 50 million knowledge workers in this field who will experience an overall productivity gain of 30% to 40% by 2025.

To achieve these levels of productivity gain, we see not only a need for advancement in calculation methods but also - and especially - a need for strategic decision-making models that can scale within and among organizations. This leads to more profound changes in the consulting market (De Man, 2015) as the need to scale strategic decision-making models fuels the need for automated consulting. Technology trends require organizations to redesign their business model (Kavadias, Ladas, & Loch, 2016). Consequently, the 'traditional' consultants' approach to supporting strategic decision-making (stakeholder interviews, business case calculation in Excel® and then a Powerpoint® presentation to the Board) is not enough. Hence, strategic decision-making models should not only automatically provide the graphs/visuals that analyze the employees' input but also automate the interpretation of these graphs/visuals and that without the fewest possible errors and bias. That means that the strategic decision-making process can be done much faster and better as conclusions are updated in real time when each next employee's input adds to the granularity of the outcomes. This granularity is further augmented as the traditional 'presentation to the Board' gets replaced by dashboard and improvement roadmaps per department, region, managerial level and even for each individual employee. Specific software/analytics then reaches the (potentially) ten thousands of employees in the organization in (near) real-time. All this is in line with management guru Gary Hamel's plea "Build a change platform, not a change program" (Hamel & Zanini, 2014).

Still, involving large numbers of employees automatically means one has to deal with Kahneman's 'organizational noise' as well (Wharton, 2016). It requires, for example, that the employees' input is as objective as possible (i.e., not influenced by personal feelings, cognitions, emotions, interpretations, or prejudice; based on facts; unbiased) to reduce the noise early in the process.

As we seek for a generally applicable model of aspects of the strategic decision-making process, we want to search for phenomena that happen in a wide variety of organizations. Phenomena that can be regarded as an intricate part of strategic decision-making; as a recurring pattern of strategic decision-making that can be clearly separated from Kahneman's 'organizational noise'.

If advanced calculation methods are able to detect recurring patterns in strategic decision-making and subsequent change management, it may help management to improve its strategic decision-making process by using these patterns to their advantage. The above-mentioned aspects can be visualized in a positively self-reinforcing cycle as depicted in Figure 1.2.

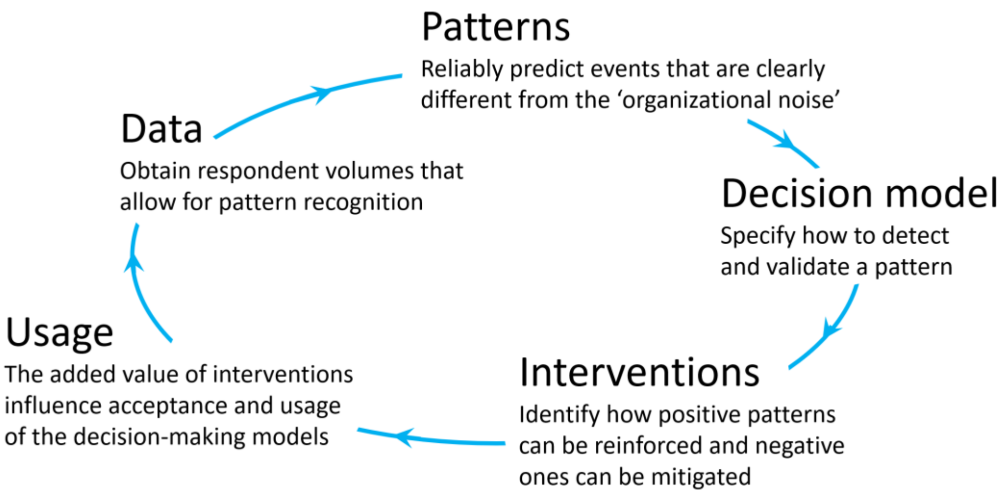

Figure 1.2: A positively self-reinforcing cycle of a data-driven strategic decision-making model

Studying large amounts of data enables to discover whether phenomena in strategic decision-making reappear as recurring patterns, as shown in Figure 1.2. Understanding how patterns develop is required to design a strategic decision-making model (the entity-relationship model we intend to develop). The model describes how patterns come to develop, how to influence the origin of these patterns, and/or how to manage, or intervene in, their effects (cf. Javed, Abgaz, & Pahl, 2013). If the interventions indeed favor better strategic decision-making and the subsequent change management, the usage of such strategic decision-making models will increase, in turn creating even more data.

Employees' input feeds strategic decision-making modelling.

As said, our model is fed by data. Management has three types of data to feed such a strategic decision-making model. These three types are distinguished by the process through which these data are collected and processed to yield informative value: (1) structured data, (2) semi-structured data, and (3) unstructured data. First, structured data usually reside in the organization's administration or enterprise data warehouse (e.g., sales records, production figures, number of employees, and profit numbers) and are immediately ready for analysis (e.g., the number of units sold last month). Second, semi-structured data usually come from the organization's networks and sensors (such as telephone records, clickstreams from social media, and data from geolocations) that require some further quantitative processing before they yield any informative value. Finally, an example of unstructured data is the input from employees (or clients and suppliers) that may need further processing and interpretation to allow for analysis in the first place (Russom, 2011). Examples of that input tell management about the level of team effectiveness, the level of the salesforce's preparation, the extent to which there is organizational alignment, the level of integration of suppliers into the organization's logistical processes and the quality of project management. Structured and semi-structured data represent the state of the organization until a few nanoseconds ago. Anything to do with the future is an extrapolation of that data.

However, obtaining the input from employees is a way of obtaining data about where the organization is going, straight from the source. Systems and databases have neither intentions nor plans, but people do. Analyzing the digital traces that people leave (e.g., clickstreams in the corporate intranet or Google search terms) is about what they did just a moment ago. Engaging with them in a conversation, however, unlocks their intentions, their mutual alignment and much more. All of these are key to strategic decision-making.

When engaging employees in strategic decision-making, a so-called 'network effect' takes place. Aggregated views from large numbers of individuals – the 'wisdom of the crowd' – have proven to outperform financial market models as well as models in other areas like project management (Surowiecki, 2005; Giles, 2005). The combined knowledge and expertise of the entire body of employees in an organization may outperform the knowledge and expertise of the organization's management. For that to happen, Surowiecki (2005) lists five requirements for a crowd to be able to be 'wise'.

The first requirement is a true diversity of opinions: "diversity adds perspectives that would otherwise be absent [... as diversity …] takes away, or weakens, some of the destructive characteristics of group decision making" (p. 29). Surowiecki states that "the negative case for diversity is that the group easier makes decision on facts than on influence, authority or group allegiance" (p. 36). The second requirement is an independence of opinion: "the relative freedom from the influence of others" (p. 41). Surowiecki states that "independence keeps the mistakes that people make from becoming correlated" (p. 41) and that "independent individuals are more likely to have new information rather than the same old data everyone is already familiar with" (p. 41). The third requirement is decentralization: "[… decentralization is crucial to capture…] knowledge that can't be easily summarized to others because it is specific to a particular place or job or experience, but is nonetheless tremendously valuable" (p. 71). Surowiecki also states "decentralization's great weakness is that there's no guarantee that valuable information which is uncovered in one part of the system will find its way through the rest of the system" (p. 71). That leads to Surowiecki's fourth requirement which is a suitable mechanism for aggregation: "a way for individuals to […] acquire local knowledge - which includes the total amount of information available in the system – while also being able to aggregate that local knowledge and private information into a collective whole. A [… corporation …] needs to find the right balance between […] making individual knowledge globally and collectively useful while still allowing it to remain resolutely specific and local" (p. 72).

Asking all managers and employees in an organization would fulfill the requirements for diversity and decentralization. If we would do an unsupervised survey, we might reasonably fulfill the requirement for independence of opinion. If we could address the other two requirements (i.e., factual data and a means for aggregation) too, this wisdom is highly likely a useful additional and smart source of information that may reduce several strategic decision-making biases as listed by Mudd (2015), and is an input for informal networks that influence organizational performance (Vega-Redondo, 2012). Metcalfe's law states that the value of a network is proportional to the square of the number of connected persons (Shapiro & Varian, 1999). Applying this to organizations, one could postulate that the more employees are connected within an organization (literally in terms of technology like email, and figuratively in terms of knowledge and experience) the greater the value of their network (i.e., their combined knowledge and expertise) is as connected employees should be considered as being better informed than their isolated colleagues. This provides a greater 'wisdom of the crowd' leading to better analytics, in turn leading to better decision-making and, finally, to more competitive advantage (cf. LaValle, Lesser, Shockley, Hopkins, & Kurschwitz, 2011).

Employee surveys insufficiently support employee-driven strategic decision-making

If there is one regular feature in asking large groups of employees, it is the employee engagement survey. Employee engagement surveys are focused on the employees: their well-being, performance goals, remuneration, personal development, motivation, etc. (Mone, Eisinger, Guggenheim, Price, & Stine, 2011; Wollard 2011). Predominantly, the question format is asking for opinions, e.g. ‘Overall, I find the work that I do meaningful’ (Mone & London, 2014).

There is a wide variety of literature- and cross-industry empirical studies on employee surveys (Langford, 2009; Trotman, Tan, & Ang, 2011; Joshi & Sodhi, 2011; Bailey, Madden, Alfes, & Fletcher (2017). Yet, *none* of these even mentions that employees could or should contribute to the strategic decision-making in an organization. Eventually, we found one study where employees could indicate their (dis-)agreement with strategic alternatives like “Project XYZ will increase our sales/revenues/ profits” (Sonenshein & Dholakia, 2012, p. 11).

So, shouldn’t employees contribute to strategic decision-making? There *is* literature on employees contributing to strategic decision-making but it is always about asking only a small part of the organization. It should be the ‘employee representatives’ that should be asked (García, Munduate, Elgoibar, Wendt, & Euwema, 2017), or the ‘employees closest to the decision source’ and ‘emotionally intelligent employees’ (Scott, Ladd & Chan, 2004). Other scholars advise to ask ‘stakeholders’ (Simmons, Iles, & Yolles, 2005), ‘local entrepreneurs’ (Andersen, 2008), or ‘strategic entrepreneurs’ (Monsen & Wayne Boss, 2009). Given Surowiecki’s (2005) desire to capture knowledge specific to a particular place or job or experience and to capture local knowledge, we can postulate that asking all managers and employees would yield more benefit than asking just any subset, most notably because of Surowiecki’s diversity and decentralization arguments. An aspect of the employee survey is anonymity/confidentiality and the freedom for employees to speak out without fear (Lusty, 2007), for example, when answering questions about their direct supervisor. That would favor Surowiecki’s (2005) requirement for independence while simultaneously hamper aggregation.

From employees’ input to designing calculation rules requires specific steps

The strategic decision-making process has many different facets. It may focus on improving processes, on choosing among commercial options, on how to become a more innovative organization or on how to change the organization’s culture: any aspect that will influence the organization in the long term (Frishammar, 2003). Strategic decision-making is a complex process, so there is likely a need for more than just one calculation rule (i.e., an ‘algorithm library’) to support the strategic decision-making process. Hence, we have to make a choice which aspect of the strategic decision-making process we want to use for further research. A fundamental aspect of strategic decision-making is change. So, the first area for analyzing strategic decision-making is the employees’ ambition, and their priority setting among strategic options. In its simplest form, strategic decision-making usually boils down to three questions: (1) “Where are we now?”, (2) “Where do we want to go?”, and (3) “How do we get there?”. So, to start extracting the employees’ input is to ask the entire organization about their observations of the current situation and what they think should be changed. Next, that wisdom has to be extracted in a form with which we can calculate.

Unfortunately, current research on 'employee-driven' data sources other than employee surveys still leaves little to work with. These researched data sources generally have limited or no applicability in a strategic decision-making setting. These sources include web- and sensor-based data (Chen, Chiang, & Storey, 2012), collections of browser search trend data (Brynjolfsson, Geva, & Reichman, 2014), social media data in general (Hussain & Vatrapu, 2014) or from Facebook (Aral & Walker, 2014) and extracts from blogs and tweets (Lau, Yang-Turner & Karacapilidis, 2014). Additionally, research on qualitative applications in management focuses, for example, on customer segmentation (Provost & Fawcett, 2013), talent management (Russell & Bennett, 2014), job satisfaction (Judge, Thoresen, Bono, & Patton, 2001) and business process redesign (Reijers & Liman Mansar, 2005) rather than on strategic decision-making. Not surprisingly, in a study of 1,357 Business Intelligence-related and 450 Big Data-related job advertisements there was no specialization/job announcement found for positions related to strategic decision-making or strategic change management (Debortoli, Müller, & Vom Brocke, 2014).

To extract the wisdom of the crowd might involve several thousands of employees. That might require weeks, if not months in case we would resort to interviews. However, the availability of new technologies and new approaches to data analysis could bring implementation time closer to days, if not hours. Online technologies like artificial neural networks (Hosseini, & Bideh, 2014) and netnography (Sinkovics, Penz, & Molina-Castillo, 2014) in combination with data analysis approaches (Sinkovics, Penz, & Ghauri, 2008; Chen, Chiang, & Storey, 2012) could potentially help to reduce the time spent on data collection and analytics. Unfortunately, for none of the abovementioned approaches we have found proven applications in combination with reliable implementation time estimates for either strategic decision-making or change management.

Reverting to traditional interviews is an impossibility given the large number of employees involved (Yin, 2003). Therefore, we opt to use online surveys. We distinguish in this thesis the following three building blocks: (1) reviewing survey scale requirements, (2) pattern detection, and (3) definition of the calculation rule, and describe these as follows:

1) We have to analyze our online survey approach to ensure that the input of large numbers of employees about where the organization currently is and should be going in the near future is sufficiently objective to reduce Kahneman's 'organizational noise' and to comply with Surowiecki's (2005) requirement for factual data. A literature study of papers on team ambition (in Chapter 3) resulted in an average sample size in those papers of approximately 300 respondents. In Chapter 5 we will analyze over 66,000 respondents. This 220-fold increase in sample size warrants a formal evaluation of a suitable survey scale in terms of data requirements which we borrow from scientific literature on Big Data.

2) The resulting survey scale must give an insight into both the actual and the preferred state of the organization, according to the employees. Therefore, we must describe the analytics we build on top of the survey scale and how these analytics work out in a larger set of respondents. Then, we must verify whether the outcomes of these analytics reveal recurring patterns and, preferably, if there are factors to manage these patterns to the benefit of the organization. The management of the patterns is obtained by comparing the employees' ambition pattern with circumstances that management is able to influence.

3) In order to confidently predict – and if possible manage – the patterns we need a calculation rule that gives a step-by-step procedure of how to detect, verify and manage the pattern. The detection is done by a survey (step 1 above). The verification is done by comparing patterns obtained from a so-called first data set (step 2 above) and verified by a

larger, second data set (Duin & Pekalska, 2007). The calculation rule must then be converted into a set of instructions (e.g., ’if-then’ statements) that describes the calculation rule and that integrates into software programming code in order to be able to contribute to the (automated) interpretation of the aggregated employees’ input.

Research problem and aim of the thesis

In general, the present thesis aims to develop an entity-relationship model that harnesses possible patterns in the ambition of employees given strategic options provided by the organization’s upper management as part of a strategic decision-making process. This leads to several research topics as depicted below.

- We want to research ways to obtain the input of large numbers of employees about strategic options presented by management. This must take place unsupervised, and in near real-time to support Surowiecki’s (2005) requirement of independence of opinion. Hence, we need to review whether the traditional employee survey approach would suffice and whether improvements might be necessary.
- By analyzing the response from a large number of employees, the thesis aims to detect patterns in the employees’ ambition in order to recognize employees’ behavior in relation to this aspect of strategic decision-making. These patterns will likely give management more predictability in the strategic decision-making process and possibilities to best use them to their own purpose.
- Then, realizing that the employees’ ambition is only one factor in the strategic decision-making process and our pattern/s being likely only one of many patterns needed to support strategic decision making, this research aims to allocate the research activities in the various chapters (for example, survey design, data quality, visual representation, generalization of conclusions) into an overall pattern recognition process.

Consequently, the research questions in this thesis are:

1.) How applicable are the usual employee surveys given data requirements needed for the development of an entity-relationship model *based on large-scale employee input gathered on strategic options? If not, would specific survey improvements be necessary? And what would these improvements have to look like?*

2.) Can we detect ambition types in the employees’ choice out of the strategic options presented by their management? Can these types be meaningfully labelled/interpreted? Will these types differ across industries? Do these ambition types recur as such that we could identify them as patterns?

3.) Are these ambition types manageable (amplify the positive aspects and mitigate the negative aspects) to support or improve the quality of the strategic decision-making process?

4.) How do our research activities compare to the process steps in a formal pattern recognition process as described in scientific pattern recognition literature? Have we left out certain process steps?

Overview of the present thesis

The present thesis consists of six chapters. In Chapter 2 we first investigate data requirements for our entity-relationship model. The amounts of data we predict to capture are clearly more than management would be used to in case of strategic decision-making: asking managers or a few specialists or stakeholders clearly differs from asking everyone in the organization. Hence, we borrow these data requirements from literature on Big Data. Plus, Big Data aspects like veracity (dealing with bias, noise and abnormality) and validity (correct and accurate data for the intended use) might very likely be an issue in our situation as well. Traditional organization-wide employee surveys are about averaging opinions and satisfaction, usually focusing on the work conditions for individual employees and looking back in time. However, we want to tally verifiable observations on where the organization is and opinions on where it should go to on certain strategic options provided by management. Hence, new approaches to data capture and analytics seem warranted. Therefore, we review how employee surveys compare to these requirements and – if needed – how to improve them. The informative value for the strategic decision-making of a proposed new survey scale format is studied in a German energy company. Chapter 2 aims to answer research question 1.

Chapter 3 presents the results of two different yet related empirical studies. The first study reveals four types of ambition by researching input from close to 3,000 respondents in four different strategic decision-making situations. The second study explores how the ambition of almost 1,200 other respondents compare on how their teams are managed. Finally, it is described how changes in the team management approach might favorably mitigate the ambition types that may potentially be harmful to the organization. Chapter 3 tries to answer research questions 2 and 3, respectively.

In Chapter 4 two topical aspects of working with surveys are researched: (1) non-response, and (2) Extreme Response Styles (ERS). This chapter elaborates further on whether the types of ambition as discovered in Chapter 3 would have been polluted by non-response and ERS and will indicate how to partly mitigate non-response.

All the above findings are strung together in Chapter 5 where our activities are compared with the process steps of a formal pattern recognition process. Also, the types of ambition discovered in Chapter 2 are validated as patterns by researching the input from an additional 66,000 respondents. Moreover, Chapter 5 summarizes the findings of the earlier chapters into a set of instructions: an entity-relationship diagram consisting of a decision tree with if-then statements on behalf of automated interpretation software.

Then, Chapter 6 will provide the main conclusions and a general discussion of this thesis. It will also show several critical methodological and theoretical reflections on the study as a whole. We will review to what extent the discovered ambition patterns may indeed be considered as generically applicable patterns. An outlook on how patterns converted into a decision-model may support strategic decision making will be given as well.

Finally, Appendix A will list sample issues and questions used in our research. In Appendix B, we will give another application of pattern recognition to support strategic decision-making using our proposed survey scale.

Chapter 2

Applying a modified Guttman scale to enrich strategic decision-making

This chapter is largely based on:

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). A new survey scale to capture employee input to support strategic decision making. *Society for Judgment and Decision Making.* Under review.

2.1 Introduction

Every organization takes strategic decisions that require change management: a combination of a sense of urgency, a vision to follow, the empowerment of the organization, planning for wins and institutionalizing new approaches to make these decisions a reality (Kotter, 1995). Yet, organizations realize that in recent years strategic decision-making is getting ever more complex (Conteh, 2013) and the time available for decision-making is getting increasingly shorter (Kotter, 2012). This requires a rethinking of change management (Worley & Mohrman, 2014), for example by means of making smart choices from a supply of data bigger than ever before (McAfee & Brynjolfsson, 2012). These data need to be integrated in an overall decision model (Horkoff, Barone, Lei, Yu, Amyot, Borgida, & Mylopoulos, 2014).

Aggregated views from large numbers of individuals – the 'wisdom of the crowd' – have proven to outperform financial market models (Giles, 2005) as well as models in other areas, provided that the crowd meets certain requirements: diversity, factual data, independence of its members, decentralization, and some mechanism for data aggregation (Surowiecki, 2005). Conversely, though the combined knowledge and expertise of the entire body of employees in an organization may outperform the knowledge and expertise of management, it is highly likely a useful additional and smart source of information that reduces strategic decision-making biases (as listed by Mudd, 2015) and an input for informal networks that influence organizational performance (Vega-Redondo, 2012). Metcalfe's law states that the value of a network is proportional to the square of the number of connected persons (Shapiro & Varian, 1999). Applying this to organizations, one could postulate that the more employees are connected within an organization (connected employees should be better informed than their isolated colleagues), the greater the value of their network (i.e., their combined knowledge and expertise) is. This provides a greater 'wisdom of the crowd' leading to better strategic decision-making and, finally, to more competitive advantage (LaValle, Lesser, Shockley, Hopkins, & Kurschwitz, 2011). Simply put, by tapping the knowledge and expertise of nearly all their employees, organizations have more chance to win in the marketplace.

In this paper we aim to investigate how to tap employees' knowledge and expertise of an entire organization in making a choice out of strategic options provided by management using data requirements as described in literature about Big Data. An additional requirement is to investigate how to obtain employees' input and perform subsequent analysis in a very short time frame.

Data requirements

Comparing the analysis of system data versus mining the wisdom of the entire organization, the former is definitely in the lead in terms of availability of data, software tools and management attention (Russom, 2011). We therefore conclude that it is wise to research what kind of requirements structured data impose on the employee-driven outcomes we aim to tap in order to harvest the wisdom of the crowd in a way that is complimentary to the data in the organizational administration. For example, employee-generated input should preferably be turned into 'binary (no/yes), numerical or categorical representations' (Plewis & Mason, 2007). Another requirement is that data is magnetic (attracting all the data sources that crop up within an organization regardless of data quality niceties), agile (allow analysts to easily ingest, digest, produce and adapt data at a rapid pace), and deep (study larger datasets without resorting to samples and extracts) (Cohen, Dolan, Dunlap, Hellerstein, & Welton, 2009). Put differently, these data should be as unequivocal as possible. Also, a requirement is that the data provides sufficient sample sizes on small subpopulations or even individuals (Monroe, Pan, Roberts, Sen & Sinclair, 2015), that data provides equifinality and can interpret misfits (Mahoney & Goertz, 2006), and that data provides options to construct indices to reduce and summarize complex, multidimensional data and that data allows for data reduction (to reduce "bigness") (Patty & Penn, 2015).

Short time frame

Engaging literally in a conversation with hundreds or even thousands of employees (and/or clients and suppliers) would require weeks, if not months. However, the advent of online technologies and new data analysis approaches could bring implementation time closer to days, if not hours. Hence, online technologies like artificial neural networks (Hosseini & Bideh, 2014) and netnography (Sinkovics, Penz, & Molina-Castillo, 2014) whether or not in combination with subsequent data analysis approaches (Sinkovics, Penz, & Ghauri, 2008; Chen, Chiang, & Storey, 2012) would help to reduce implementation time. Unfortunately, for none of these approaches we could find proven smart applications in combination with reliable implementation time estimates for strategic decision-making in a change management setting.

2.2 Objective

The purpose of this paper is to test a method to obtain the feedback of large amounts of employees about their view regarding strategic options provided by the organization's management. This method should factor in data requirements and should be executable in a short time frame. Also, the method must yield new, smart insights indicating, for example, to what extent hierarchical layers and departments within the organization align in their outlook on the organization's future. And, preferably, the analysis should provide concrete handles to improve strategic decision-making and subsequent change management processes around the implementation of the management's strategy.

2.3 Method

Procedure and participants

We conducted an online survey in one of the largest Energy companies in Germany with over €40b in revenue, with over 50,000 employees and with three divisions in electricity, gas and nuclear power. The organization had formed a new technology division of close to 600 employees coming from each of the three divisions and from three countries (Germany, UK, the Netherlands). Hence, various ways of working needed to be merged into a new strategy with new divisional objectives. The organizational structure consisted of a management Board (3 members), a level with 18 managers reporting to that Board and another level of 30 managers reporting to these 18 while managing approximately 550 employees (the so-called 'All Staff'). With so many different backgrounds and viewpoints, the Board justifiably asked itself whether their strategy had truly landed on the work floor. Clearly, this test was about strategic decision-making (what to do if the strategy hadn't truly landed?) in a change management situation (employees from different backgrounds coming together in a new division) with an interesting data aspect (asking a complex question to close to 600 employees but extendable to other divisions as well) in a time-constrained setting (the total change management process was budgeted to roughly 1.5 years of which this initial analysis could take no more than a few weeks).

The survey was sent out to all the 51 managers (3 managers in the Board, 18 managers in the 1st management layer below the Board and 30 managers in the 2nd management layer below that one) and to the approximately 550 employees working in the departments Project Engineering, Project Management, Project Support, Site Engineering, Specialist Engineering and (general) Support. The questionnaire was available online. One of the Board members sent out the invitation to participate. The questionnaire required approximately 20 minutes to answer. The actual questionnaire was preceded by a few questions about the respondent him-/herself like job role (for example, Board, manager level 1, etc.) and department (Site Engineering, Project Management, etc.). The duration of entire process was 4 weeks: 1 week for questionnaire design and review, 2 weeks for respondents to submit their answers and 1 week for reporting and interpretation of the results. All 51 managers responded and all stated their names. Of the 550 employees, 260 (47%) had responded at the time of analysis (as some groups were still in transit from their old work location) and 154 (59%) responded anonymously. In case respondents did not know the answer to a question or deemed the question not applicable to themselves, they were instructed to skip the question.

Measures

For strategic decision-making in a change management setting, the wisdom of the crowd is aggregating each individual’s view on how to change in order for upper management to decide on a course of action. That means we must capture – for each individual and for each question in the questionnaire – four different components: (1) an actual situation, (2) a preferred situation (preferred by the respondent), (3) a management target (the situation preferred by management), and (4) a time frame. The smallest part of an organization’s change management ‘vector’ is the individual vector of each respondent’s answer on a single survey question. Add all these responses together – by summarizing these individual vectors – and arrive at the aggregated ambition vector per team, per management level, for the entire organization, etc. As we can safely assume that management will not copy the ambition for 100% (for example, because of budget constraints or limited organizational capacity), this ambition vector should be corrected for the impact of upper management’s final decision on how to proceed. With new online qualitative data capturing techniques (for example neural networks or netnography) neither proven in strategic decision-making and subsequent change management nor having a fast-enough implementation time, we decided to use an online survey as a feedback collection method.

Yet, the complementarity requirements (required for subsequent correlation/causation of our findings with structured data already available in the organization’s databases) prompt to carefully choose the survey scale. An employee survey may ask for agreement on statements. An example is a survey that asks for agreement with strategic alternatives like “Project XYZ will increase our sales/revenues/profits” (Sonenshein & Dholakia, 2012, p. 11). Such a survey with, for example, a 7-point Likert scale only partly captures these four components (Actual, Preferred, Target, Time). Different contextual interpretations of the scale numbers and item bias may deteriorate the informative value. Two individuals who want to move from a score ‘3’ to a score ‘6’ on the statement “The organization has a clear strategic direction” might have vastly different improvement steps in mind. Hence, the time frame can be fixed (for example, the actual situation is now and the preferred situation refers to six months from now) yet the content of the actual and preferred situation is not clear: in the above example, we know what respondents want to improve (a clearer strategic direction) but not how. Asking for agreement on, or asking for an applicability score of, statements may require corrections for response latitudes (as a sign of respondent non-involvement) (Lake, Withrow, Zickar, Wood, Dalal, & Bochinski, 2013), for extreme response styles (De Jong, Steenkamp, Fox, & Baumgartner, 2008), for various sampling errors (Piterenko, 2013) and for various types of bias (Roulston & Shelton, 2015). Statements do not make it easy to come up with an ambition score or allow management to set a target to drive the change management. Assume a female respondent who slightly disagrees with the statement: "I get sufficient opportunities to develop myself". It has not very much sense to ask this respondent whether she will continue to slightly disagree with the statement in 6 months from now. Will there be a new learning and development system be available by then? Will she still have the same manager? Do the new profit figures allow the HR department to double the training budget? She doesn't know now. Hence, asking for it would be pure guessing. Conversely, it has little sense for management to set a target score for the question "The organization has a clear strategic direction" at, e.g., 5 out of 7. It would become a target that every lower manager would achieve with a stroke of a pen. For that very reason, we modified a commonly used Guttman scale to capture present status and future outlook of respondents while simultaneously working on complying with the data requirements. Guttman is a cumulative scale (Uhlaner, 2002) measuring 'breaking points'. This scale design is different from the longitudinal Guttman scale (for example, Hays & Ellickson, 1991) which compares response patterns of a Guttman-designed questionnaire (the 'Now'-score) in time. Yet, a Guttman scale's answer options might refer to levels of agreement with statements too, e.g.:

Q. How will Project XYZ increase our sales/revenues/profits?
Answer 1: it will NOT affect our sales/revenues/profits
Answer 2: it will NOTABLY affect our sales/revenues/profits
Answer 3: it will DRAMATICALLY affect our sales/revenues/profits

What we wanted to know is: exactly how far is an employee on a specific aspect of the strategy? What does he plan to improve in the foreseeable future? Would that ambition fit with the view of upper management? An example of a question with three answers (coming from our team effectiveness assessment, see Appendix A) that *does* give an answer to these three questions is:

Q. How have you defined your team objectives?
Answer 1: We have no team objectives (yet)
Answer 2. We have a qualitative description
Answer 3. We have formal, SMART key performance indicators.

Currently, a respondent might not have team objectives, plans to have a qualitative description of these team goals in 6 months' time while management would like to see that all teams have formal, SMART key performance indicators by then (actual, ambition, target). Superfluously, a statement like "Our team has defined team objectives" using a 7-point Likert scale with an actual score of '2', an ambition score of '6' and a management target of '5' makes no sense.

Guttman scaling works with current-status data (a term used by Diamond, McDonald, and Shah, 1986) and can also cover the Time dimension, for example, *now* there isn't yet a reporting infrastructure but *in 6 months' time* there will be one. We added the time dimension in the Guttman scale in the following way to represent the vector of a respondent's answer to a single question:

Q. How have you defined your team objectives?	Now	In 6 months' time
1. We have no team objectives (yet)	☐	☐
2. We have a qualitative description	☐	☐
3. We have formal, SMART key performance indicators.	☐	☐

The answers given by the respondents are objective and verifiable in such a way that they could classify as 'objectively real' or 'a testable proposition' (cf. Ahrens & Chapman, 2006). This is because we abstain from adjectives and adverbs to reduce interpretation bias and insert words like, e.g., 'formally', 'regularly', 'periodically', 'documented' and 'described' to reduce respondent self-report bias (a problem raised by Donaldson and Grant-Vallone, 2002) and to help with verification. Given the requirement for 'binary (no/yes), numerical or categorical representations' (Plewis & Mason, 2007), we could say that this way of formulating answers is a 'no/yes' check for categories: "Yes, we have qualitative objectives but, no, these objectives are not SMART". Appendix A gives a list of sample questions using this modified Guttman scale.

Yet, there certainly remains subjectivity. The questions and answers are subjectively chosen. They usually represent the strategic reality as perceived by upper management or the consultant firm that creates the questionnaire rather than being the output of a scientific model. Then, the best answer as used in a questionnaire is not theoretically the best answer. For example, an even better answer than Answer 3 in the above team objectives question is "We have formal, SMART key performance indicators *that get formally reviewed every 3 months*". Clearly, there might be a need for more than three answers in some cases. The 'In 6 months' time' is just a placeholder: it could be any moment in time later than 'Now'. And how objective and verifiable we try to make the actual score, the ambition score in 6 months' time will always be a respondent's opinion.

The division's Board of the multinational German energy company wanted to know to what extent their strategy had been adopted by the lower management layers and employees and how these layers and employees wanted to improve on that strategy. We dissected the strategy by interviewing the Board first and reviewing the resulting topics and options with the Strategy staff-department afterwards. This resulted in a survey of 108 questions for the three managerial levels and a condensed questionnaire of 62 questions for the All Staff about people-, process- and technology-aspects of the strategy. These three subjects were further divided into dimensions. For example, for Process: Individuals, Time, Centers' of Competence, Governance and Culture. The dimensions contained the individual questions. For example, for Governance: "Are project and line responsibilities aligned?"

Each of these questions were constructed according to the following template of a question with three answers:

Q. Element of the strategy
- Answer 1. Current situation
- Answer 2. Intermediate step towards the required situation
- Answer 3. The required situation according to the Board's strategy

In total, the response resulted in 38,146 data points: 51 managers * 108 questions * 2 answers + 260 employees * 62 questions * 2 answers – 5,110 answer options unanswered = 38,146 data points.

The Guttman scale shows the transformation trajectory from the old to the new situation. Here are two examples of how that worked out in the questionnaire used in the test: the first example refers to the strategy's focus on more tailor-made work for larger clients and the second example to the focus on archiving and sharing best practices.

Q. Have you received specific requirements from clients?
Answer 1. No, not received any (so far)
Answer 2. We received some general questions/remarks
Answer 3. We have received formal requests from clients.

Q. Has your team defined best practices?
Answer 1. No
Answer 2. Our team has a document guideline defining best practices
Answer 3. Our team has a document guideline AND
it gets regularly reviewed and updated.

In order to ensure objective answers and eliminate socially desirable answering (cf. Frese & Zapf, 1988), we made the answer options as verifiable/auditable as possible (like "Please, show me your formal client requests" or "Show me the team's best practices document").

Data analysis

Each question had three answers. The first answer of three (the current situation) was rated with a score of 0, the second answer (the intermediate step) with a score of 1 and the third answer (reflecting the content of the strategy that needed to be achieved) with a score of 2. The resulting score was then multiplied by 5 to achieve a score on a 0-10 scale. The respondents' answers were aggregated in a pivot table with six dimensions "Question", "Actual score", "Planned score" (the ambition per question as given by the individual respondent), "Desired score" (the required situation according to the Board's strategy), "Hierarchical level" and "Department". An average score for a dimension (a group of questions covering one topic of the strategy) was achieved simply by averaging the scores of the individual questions. Grandtotal scores were based on individual questions too in order to avoid averaging averages. The effort to improve from one answer to the next (achieving a higher 'breaking point') differs per question, as well as per hierarchical level and department. For example, referring to the two question examples above, getting the first generic client requirements is likely a somewhat different amount of effort than having a document guideline defining best practices. And defining such a guideline might be somewhat more effort for an engineering department than a sales department. Yet, we abstained from any form of weighting among these questions and answers for three reasons. Firstly, we deemed the choice of questions and answers to include in the questionnaires a far greater error than the error that would be solved with weighting. Secondly, the effort of determining the proper weights would require a very considerable time effort that was at odds with the requirement of a short time frame. Thirdly, the Board wanted to focus the managerial attention not on a discussion on weights but on a discussion of (re-)prioritization and implementation steps. Any total group score should not be considered as a precise outcome but as an indicative value at best. Skipped questions were not considered in the calculation of the scores (as we assumed the question's non-applicability for that individual respondent). The same score methodology was applied for the Ambition ('In 6 months' time') score. Hence, both Actual and Ambition scores could be calculated per hierarchical level and per department.

Other than just looking at the delta between Actual and Ambition, we also studied the type of ambition within the entire questionnaire. We looked at the ambition Width: how many questions (as a percentage of the total number of questions in the questionnaire) did a single respondent plan to improve? And we looked at the ambition Depth: by how much did that respondent plan to improve those questions (as percentage improvement over the Actual score)? Both ambition Width and Depth could be added up per hierarchical level and per department. This analysis gave insight into the ambition focus of a group of respondents. Did the group spread its attention too thin? Or were they focusing on only a few items? Additionally, we also looked at the percentage of respondents that did not indicate an Ambition score and at the percentage of respondents that did not submit their name. To investigate whether hierarchical levels differed in their ambition we statistically tested these levels' score per question on their variance (Fisher's F-test and Levene's test) and distribution (Kolmogorov-Smirnov test).

Next, we studied to what extent groups of respondents (for example, Managerial level 2 or the Site Engineering department) were mutually aligned in their ambition. We compared pair-wise all respondents in such a group. We assigned a 0% alignment value to the respondent pair(s) that were least aligned (their ambition scores were most dissimilar). We assigned a 100% alignment value to the pair(s) that were most aligned (their ambition scores were most similar). We assigned all the other respondent pairs an alignment value in between 0% and 100% using steps of 12.5% based on their relative alignment to the 0%- and 100% pair(s). Having compared every respondent with every other respondent, we sorted the respondents from most aligned to least aligned. Then, we added up the average misalignment % per respondent and, subsequently for the group. This analysis gives insight into the expected implementation speed of the group's ambition. Does the group plan to improve in unison? Or are the respondents planning to improve in all kinds of directions? Appendix B gives more insight into this calculation method with an example of how to model team alignment.

With 108 questions for the managers and 62 for the All Staff, it was clear that the 'required situation according to the Board's strategy' couldn't be achieved on all questions within the timeframe of 6 months. Hence, the Board had developed a target for the next 6 months indicating what questions needed to be addressed, what answer options needed to be achieved and in what sequence. For example, it is logical to work on client requirements first before engaging in defining best practices about these requirements. With that specific target set for the next 6 months, we compared the alignment of an individual respondent with the management target. Similarly, as before, we calculated that target alignment per hierarchical level and per department. This analysis gave insight into the expected implementation speed of the Board's strategy.

Given the availability of the Board's target (the Desired score), we calculated per individual question per individual respondent the gap between the Actual situation and the target. Subsequently, we aggregated this gap for each question per hierarchical level and per department and investigated what percentage of the questionnaire would close 50% of the gap between the Actual situation and the management target. This analysis gives insight into the expected implementation speed of the Board's strategy as well as it indicates to what extent a group of respondents can focus on a manageable amount of questions to improve. Next, we studied to what extent there were respondents scoring the best answer on an individual question. For example, the Board's target score required that each group had at least a document that defined how they would approach the identification and archiving of best practices. So, it would be useful if various respondents in the group had already worked on such a document. We identified the percentage of questions in a questionnaire where 2 or more respondents scored the best answer (the second respondent as a 'back-up' to ensure the knowledge/ experience was indeed present in the group). This analysis gave insight to what extent the required experience and progress was somewhere present in the group (an example of the wisdom of the crowd) and, thus, facilitated the implementation speed of the strategy.

Related to that was the average number of questions a respondent could share given each and everyone's high scores. For example, one respondent may be far ahead with defining client requirements but has little/no knowledge how to archive these requirements in a best practice. Conversely, it would also be good that a specialist in defining best practices understands more about the intricacies of client requirements. Hence, there is a need to share knowledge between these two employees. This analysis gave insight to what extent sharing knowledge was a doable amount of work or just a too heavy burden.

The above attention for alignment served also another purpose. Misalignment may be an indicator of shortcomings in the Board's strategy. Therefore, we also investigated per hierarchical level and per department which Top-3 of the 14 dimensions (groups of questions) in the questionnaire resulted in the biggest misalignment among the group's respondents. Moreover, we verified to what extent this Top-3 was responsible for the total amount of misalignment (expressed in a percentage of total misalignment).

2.4 Results

The Board had very specific information requirements to help them in their change management and required detailed answers on questions like: How far are the hierarchical levels and departments in implementing the strategy? Will that change in the next 6 months? Where? What topics? By how much? Are the three managerial levels aligned in their priorities for the next 6 months? In what areas do we have to address the biggest misalignment? Can one manager or department that has reached the best answer help another manager/department that still needs to improve on that specific item?

We presented the results in four different tables. Table 2.1 gives an overview of the aggregated scores, ambition types and group alignment percentage solely based on the input from the respondents. Table 2.2 visualizes how the hierarchical levels differed in terms of actual- and ambition scores. Table 2.3 gives an overview of the effect of the Board's target on alignment, priority setting and knowledge sharing. Finally, Table 2.4 gives an overview of what dimensions created the biggest misalignment in the groups.

Table 2.1

Analyzing the aggregated scores (N=311)

	Ambition			Group	
	Width	Depth	None	alignment	Anon.
Hierarchial					
Level 1 (Board)	75%	54%	0%	64%	0%
Level 2	97%	40%	0%	53%	0%
Level 3	100%	54%	6%	51%	0%
All Staff	33%	44%	35%	*N.A.*	32%
Departmental					
Specialist Engineering	100%	29%	44%	57%	41%
Site Engineering	73%	38%	40%	71%	60%
Project Engineering	100%	26%	38%	53%	30%
Project Management	100%	22%	31%	52%	18%
Project Support	98%	36%	64%	55%	26%
Support (general)	100%	47%	32%	58%	17%

Anon. = percentage of respondents that answered anonymously

Table 2.1 shows a variety of insights that helped the Board in implementing its strategy. The first three columns dissect the ambition of the four hierarchical levels in Width (what percentage of the total number of questions in the questionnaire did a single respondent plan to improve?), Depth (by how much did that respondent plan to improve those questions as percentage improvement over the Actual score?) and what percentage of respondents in that level did not indicate an ambition in the first place (indicated by 'None').

A second insight is in the fourth column of Table 2.1: group alignment. It was the Site Engineering department - together with the Board - that was most focused in its ambition - showing lower values for ambition Width and higher values for ambition Depth - than the other departments or managerial levels. Consequently, Site Engineering and the Board showed the highest group alignment scores compared to the others. With respect to this group alignment scores: it was highly surprising that Level 2 – right below the Board – showed such a low group alignment percentage. This was also true for Level 3. The Board realized that it had to invest a lot of energy in aligning the managerial levels before they could direct their attention to All Staff where 35% did not gave an indication for the ambition score (the fifth column in Table 2.1).

We postulate that if the ambition is synchronized across hierarchical levels the variance and distribution in the levels' planned 'In 6 months score' are statistically similar. That means that the ambition from the Board can move down the ranks swiftly. This benefits the strategic decision-making and subsequent change management process. Hence, for a further comparison of hierarchical levels (managerial level L1, L2 and L3 and All Staff), we compared these groups in terms of the variance (are the scores dispersed?) and distribution of their scores (are the scores skewed?). And we analyzed this for actual score as well as ambition. The distribution of the respondents' actual scores was more or less normal (the left graph in Figure 2.1), while the distribution in their ambition (planned score -/- actual score) was asymmetrical (left skewed; the right graph in Figure 2.1).

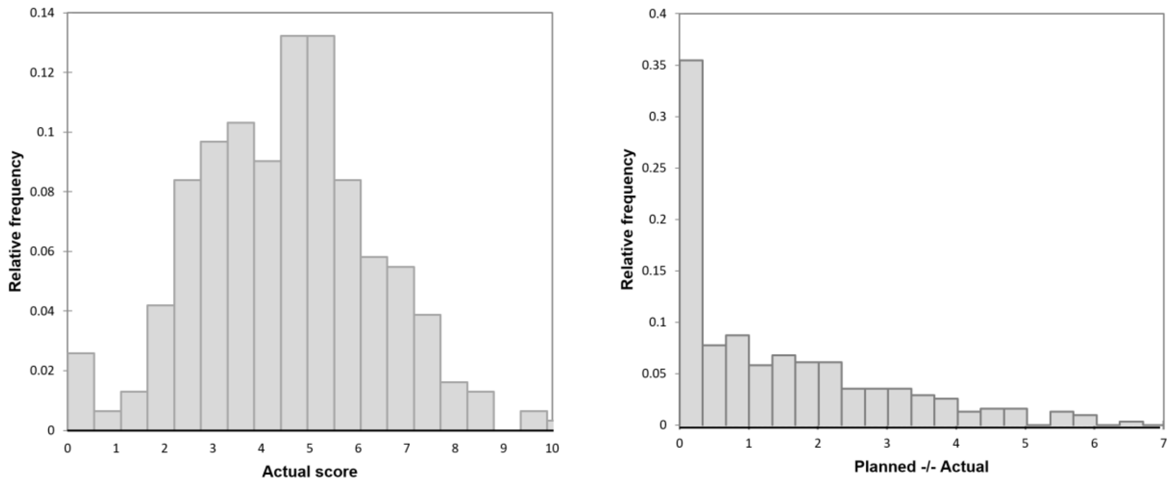

Figure 2.1: Mapping the respondents' actual score (left) and ambition (right, Planned -/- Actual)

Given these distributions, we compare in Table 2.2 the hierarchical levels on variance in the Actual scores with Fisher's F-test as the Actual score have a normal distribution. We tested the variance in ambition with Levene's test using the median instead of mean because of the skewedness (as the Fisher F-test is sensitive to data that do not follow a normal distribution). We tested:

H_1 = The variances in managerial levels' scores is different.

And we also compare in Table 2.2 the hierarchical levels looking at the distribution of their Actual- and Ambition scores using a Kolmogorov-Smirnov test. Consequently, we tested:

H_1 = The scores of managerial levels have different distributions.

Table 2.2

Analyzing similarity between respondent groups

Hierarchical levels versus **Actual score**: similarity in **Variance**

	Level 1				Level 2				Level 3				All Staff			
	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2
Level 1 (Board)	-	-	-	-	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.
Level 2					-	-	-	-	.264**	2.273	17	29	.159***	1.828	17	259
Level 3									-	-	-	-	.601	1.634	29	259
All Staff													-	-	-	-

*The table shows the observed and critical F, the degrees of freedom. α = 0.05. * p < .05, ** p < .01, *** p < .001. 'N.a.' means the value is not available.*

Hierarchical levels versus **Actual score**: similarity in **Distribution**

	Level 1	Level 2	Level 3	All Staff
	D	D	D	D
Level 1 (Board)	-	.556	.833	.704
Level 2		-	.367	.431*
Level 3			-	.149
All Staff				-

*The table shows hypothesized difference (D) = 0, α = 0.05. * p < .05, ** p < .01, *** p < .001.*

Hierarchical levels versus **Ambition** similarity in **Variance**

	Level 1				Level 2				Level 3				All Staff			
	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2
Level 1 (Board)	-	-	-	-	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.	N.a.
Level 2					-	-	-	-	.206	4.052	1	46	.265	3.875	1	276
Level 3									-	-	-	-	.005	3.874	1	288
All Staff													-	-	-	-

*The table shows the observed and critical F, the degrees of freedom. α = 0.05. * p < .05, ** p < .01, *** p < .001. 'N.a.' means the value is not available.*

Hierarchical levels versus **Ambition**: similarity in **Distribution**

	Level 1	Level 2	Level 3	All Staff
	D	D	D	D
Level 1 (Board)	-	.611	.600	.735
Level 2		-	.200	.432**
Level 3			-	.403***
All Staff				-

*The table shows hypothesized difference (D) = 0, α = 0.05. * p < .05, ** p < .01, *** p < .001.*

A comparison of the variance in Actual score of the Board with the other levels in the organization is not available as the Board consisted of only three respondents. In terms of Actual score, Level 2 managers were significantly different in their variance than Level 3 managers (F_{obs} = .294, p < .01) and All Staff (F_{obs} = .159, p < .001). It is also interesting to see how in terms of ambition (Planned score -/- Actual score; bottom part of Table 2.2) the managerial levels (Level 1, Level 2, Level 3) seem comparable in distribution but Level 2 (D = .432, p < .01) and Level 3 (D = .403, p < .001) were significantly different from the All Staff. In that sense, we concluded that the managerial level 1 and 2 were not aligned in terms of ambition with the All Staff.

Table 2.3 gives several insights that helped the Board to understand how their target would land in the organization.

Table 2.3

Comparing the effect of the Board's strategy

	Target Alignment	50% gap	% Questions >=2 resp. best	Questions to share/resp.
Hierarchial				
Level 2	70%	26%	70%	7
Level 3	59%	29%	82%	29
All Staff	*N.A.*	27%	100%	5
Departmental				
Specialist Engineering	49%	24%	90%	6
Site Engineering	54%	16%	15%	5
Project Engineering	50%	29%	94%	9
Project Management	55%	26%	97%	8
Project Support	48%	27%	98%	6
Support (general)	47%	24%	89%	5

Abbreviations: '% Questions >= 2 resp. best' = the percentage of questions where two or more respondents already score the best answer.
'Questions to share/resp.' = The average number of questions about which a respondent can share knowledge with one or more colleagues not scoring the Board's target that question.

In terms of alignment with the Board's target, managerial Level 2 scored 70% for 'Target Alignment' (Level 2 managers' scores aligned for 70% with the target of the Board) and Level 3 scored somewhat lower with 59%. Yet, the departmental scores did leave much to desire with alignment percentages hovering around 50%. The Board was very happy, though, to discover that their target resulted in achievable percentages for the 50% gap. For example, for the departments it meant that approximately 16% to 29% of the questions (10 to 18 questions) covered already 50% of the gap between the Actual situation and the Board's target.

Moreover, the departments (with the exception of Site Engineering) did have almost all the capabilities/knowledge/experience in house: for between 89% and 98% of the questions in the questionnaire there were at least two respondents already scoring the best answer. The exception was Site Engineering with a low 15% of questions where at least two respondents scored the best answer. Related to this were the relatively attractive low scores for the amount of questions to share between respondents: if groups are large, the chance that several respondents score already the best answer is higher and the amount of knowledge to share per respondent decreases as a result.

Yet, this was also offset by the notion that for several questions the Board's (intermediate) target for the next 6 months was not the best answer but the middle answer. Finally, the Board also noted that the amount of questions to share among the respondents in managerial Level 3 was high enough to engage in knowledge sharing and to get other support from both managerial Level 2 as well as from outside consultants.

Table 2.4 shows how misalignment turned out to be a great source of employees' knowledge and expertise.

Table 2.4

Alignment and misalignment

	Dimensions with most misalignment			% Top-3 of
	#.1	#.2	#.3	misalignm.
Hierarchial				
Level 2	Supplier M'ment	Client M'ment	Individuals	37%
Level 3	Supplier M'ment	Client M'ment	Health & Safety	40%
All Staff	Client M'ment	Team / Unit	Individuals	29%
Departmental				
Specialist Engineering	Client M'ment	Team / Unit	People	33%
Site Engineering	Client M'ment	Supplier M'ment	Team / Unit	68%
Project Engineering	Client M'ment	Team / Unit	Supplier M'ment	29%
Project Management	Client M'ment	Team / Unit	Supplier M'ment	27%
Project Support	Client M'ment	Team / Unit	Individuals	30%
Support (general)	Client M'ment	People	Team / Unit	31%

Abbreviations: misalignm. = misalignment; M'ment = Management

We researched for each of the 14 dimensions (groups of questions) the misalignment within the various hierarchical levels and departments. And we also calculated how much the Top-3 of misaligned dimensions accounted for the total group misalignment (in percentages). Clearly, Client Management turned out to be the biggest debate, which was understandable for a new division that in a supply-driven Energy market now had to nurture its own clients. And for Site Engineering (a department which was all about clients as they engineered and maintained the sites - with energy plants on it - for their clients) the Top-3 accounted for 68% of the misalignment. Likely, a heated debate was going on there. Yet, it was also very notable how the hierarchical levels 2 and 3 had no Top-3 misalignment about the 'Team/Unit'-dimension while it remained a Top-3 item for each of the departments. Lesson learned for the Board: what is a topic for debate in the boardroom might be totally not an issue on the work floor. And vice versa. Finally, the Board realized that the #.3 score for 'Individuals' for All Staff indicated a wide variety of thoughts of how individuals would find their role in the new division. The Board sensed a strong insecurity among the employees about their personal future in the organization, which the Board found confirmed by the high percentages of anonymous respondents (see Table 2.1) and respondents that did not indicate an Ambition score. As a result of the above analysis, the Board dramatically intensified the communication on 'Client Management', 'Supplier Management' and 'Team/Unit' and redesigned part of their strategy as well as the implementation timetable associated with it. Also, the Board reallocated responsibilities among the managerial Levels 2 and 3 to redistribute workload and put more knowledgeable people in specific key-positions. Finally, the Board issued clear marching orders on how individuals and teams were thought to work together.

2.5 Discussion

This chapter aimed at harnessing the views of an entire organization to support management in making a choice out of its strategic options and the subsequent implementation of these choices. We designed a simple, smart and innovative online survey method to collect both the employees' knowledge about the actual situation and their vision of how the organization should improve. As a first empirical example and test, we collected data from several hundreds of employees within a division of a leading multinational German energy company that needed to know whether its strategy had truly landed on the work floor. And, finally, we designed some new analytics to present the collected 'wisdom of the crowd' in an actionable way including ambition, bottom-up versus top-down (mis-)alignment, strategic gaps to close, priority setting, available knowledge and knowledge sharing.

Results showed that by asking the entire organization about its actual situation regarding the roll-out of the organizational strategy as well as its planned ambition on how to further implement that strategy, the division's Board escaped some serious mishaps. Among these were an unwarranted high ambition of the Board itself, misaligned management layers, unfocused departments and possibly frightened employees. Given the objective nature of the answer options in the questionnaire, we may conclude there was some sort of disconnect between Level 2 managers and the rest of the organization. It confirms that either Level 2 managers knew that things had been arranged or set in motion and that the lower levels in the organization had not yet been aware or had not been enough engaged to confirm that, or that Level 2 managers thought that things had been arranged or set in motion but the lower levels in the organization knew it wasn't (yet) the case. We consider it another organizational disconnect as the managerial levels significantly deviated from All Staff in terms of their ambition as was shown in Table 2.2 This wedge between management and All Staff was something the Board *had* to act upon. The Board also learned that their target was in several areas sufficiently easy to implement with the right resources available while simultaneously not overstretching the organization. In summary, employee-supplied data combined with new kinds of analysis turned out to be a very welcome addition to the data already available in the corporate administration on which the initial Board strategy had been based.

Thinking about a scaling up, we believe that if we had to process input from 30,000 employees rather than 300 (with the number of data points increasing to several millions), the amount of data-processing work would not have been significantly higher. Although a correlation of the employee-driven data with data in the corporate administration (for example, "Do teams with more anonymous respondents report more sick days per person per year?") was out of scope for our research, we believe that the straightforward math we applied to the submitted answers (addition, averaging, dividing and sorting) created sufficiently 'binary-, numerical or categorical representations' that would easily lend itself to correlations. The verifiable nature of the answers greatly supports data stability and reliability. We also saw that the data was applicable to small sample sizes/individuals (for example the Board consisted of three people; the All Staff of 260 people). The self-assessment was done without supervision and catered to respondents from different national, cultural and job-specific backgrounds. Non-response was treated as a valuable source of information. For example, there was significant non-response on a question about an upcoming Center of Excellence which made the Board realize more communication about that center was necessary. Finally, the outcomes were quick and easy to implement, were simple to apply and had high information content as well as impact as these outcomes showed disparities that could not be ignored at all by the Board (for example a management reshuffle, other priority setting, adjusted implementation timetables, readdressing internal communication). As such, our test passed the data requirements as specified earlier in this paper. The final requirement was a short time frame. In our test, this was driven by the Board's hurry to get their strategy implemented. In general, this requirement has to do with processing large numbers of respondents (for example several thousands of people) in a time frame that keeps the outcomes still relevant.

Summarizing, in terms of internal versus external validity, this approach scores very well in terms of the connection between study findings and a "belief of reality" (cf. Koro-Ljungberg, 2008, p. 984). The strategy was much more multi-faceted and complex than was described in the survey. Yet, the survey was a direct translation of the strategy's key-topics and the quality of the answers reflected what needed to be achieved in order to have the Board rate the implementation of the strategy as successful. Hence, it was a useful enough approximation of reality. With regard to external validity (could the findings be applied to other situations), we see no reason why the approach tested couldn't be replicated for change management in other organizations.

Limitations and future research

At the same time, there are several cautionary remarks to be made about this approach, which also fuel the need for more research. Firstly, the choice of questions is – despite being well-intended – scientifically arbitrary. Management was given a questionnaire of 108 questions while one could argue that for a true picture at least, say, 500 questions were necessary. Here, practicality and managers under time constraints in the middle of a change management process turned out to be more important than granularity. In terms of content validity ("whether operationalization captures the ideas contained in the systematized concept", Adcock & Collier, 2001, p. 536), the Board's selection was the given content to work with.

Secondly, the choice of what described the first answer, second and third answer was also arbitrary. It was possible to make the answer options that easy that everyone would score 10 out of 10. Likewise, it was possible to make the answer options that difficult that everyone would score 0 out of 10. Yet, the absolute score was nowhere important; it was the relative score that helped to compare respondent groups.

Thirdly, there is not enough research yet to determine what combination(s) of ambition Width and –Depth would most benefit an organization. We have used generic assumptions that spending more organizational energy on fewer topics would be beneficial. Hence, more research is needed here.

Next, we haven't researched why large groups of respondents did not submit an Ambition score. This could have been due, for instance, to fear (which would mean a material fact for the change management process) but also to incomplete instructions from our side (which would be much less detrimental for the conclusions).

Finally, we also realize that we have used only two criteria to segment the respondents: the hierarchical level and the department. Clearly, there are many more segmentation criteria that could benefit the change management approach including age, gender, education and previous change management experience. Plus, we only studied 311 respondents in only one organization. Further research in larger respondent bodies in various organizations will show whether the ambition types and phenomena that emerged in this organization will materialize elsewhere too. This will also show whether and how this survey structure and related analytics will be able to scale into larger respondent samples when the number of data points will grow from the ten thousands like in our test to the hundred thousands or even millions.

2.6 Conclusions

Strategic decision-making is not only about discovering exciting new insights by analyzing large numbers of structured data in corporate data warehouses. Engaging large numbers of employees, if not the input from the entire organization, results in equally exciting insights. In a short period of time, using only a 'low-tech' survey and some elementary math, we were able to provide the Board enough ammunition to structurally alter their change management approach, both from a process- as a from a content point of view.

Extending this to any organization with strategic issues, this is a fast and affordable way to blend the wisdom of employees in an organization with data already available to management. Moreover, as people have (unlike data in the corporate administration) a rationale and subsequent intentions, a whole new field of analytics lays bare. Studying more organizations in a similar way may lead to exploring certain patterns that will provide pivotal insights to managers. Not only in strategic decision-making or change management but in many other organizational fields such as human resource management, sales and marketing, information technology and supply chain management as well.

Chapter 3

Identifying and mitigating team ambition patterns in change management

This chapter is largely based on:

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). A cross-industry research into employee ambition patterns in change management. *Journal of Change Management.* Under review.
Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). Mitigating employee ambition patterns in change management". *Journal of Organizational Change Management.* Under review.

3.1 Introduction

Modern organizations face several changes that increasingly force employees to make decisions - independently or within a team setting - that influence the strategic direction of an organization. These changes include a development towards reduction of management layers (Qi, Tang, & Zhang, 2014; Koukis & Koulioumpas, 2015) and the rise of self-controlling, autonomous teams (Lambe, Webb, & Ishida, 2009). At the same time, modern organizations face technological developments (availability of computers, bandwidth and storage) that empower employees (Lackey, Pandey, Moshiri, Lalwani, Lall, & Bhargava, 2014) in strategic decision-making. If employees have technology that enables to connect and share knowledge with one another (Ferreira & du Plessis, 2009), Metcalfe's Law weighs in. This law states that the value of a network is proportional to the square of the number of connected persons (Shapiro & Varian, 1999). Applying this to an organization, one could postulate that the more employees are connected, the better informed they are and the greater the value of their network is. Consequently, these employee networks provide a certain 'wisdom of the crowd' where the insight of the group outperforms the smartest, most informed individuals (Surowiecki, 2005; Giles, 2005). If management uses this wisdom (i.e., employees' knowledge and experience) adequately to help them choose among management's strategic options, this could lead to better strategic decision-making. This is especially true when this kind of strategic decisions require an empowerment of the entire organization and subsequent change management in the organization to implement that strategy (Kotter, 1995).

To ensure that the employees' knowledge and experience is paired with data already available in the corporate administrative systems, organizations must find a way to harness input (i.e., opinions, observations, intentions) directly from their employees and preferably as objectively as possible (i.e., to minimize cognitively- and emotionally-laden questions and answers, cf. Frese & Zapf, 1988). As employee input is available throughout the entire organization, it is necessary to obtain the collective input of potentially thousands of employees where respondent samples are reasonable proxies for the population of the entire organization (Dhar, 2013). This employee input can be an enormous help for management and a main source for competitive advantage (LaValle, Lesser, Shockley, Hopkins, & Kurschwitz, 2011). Yet, these amounts of data do require new approaches to analytics (cf. Russom, 2011). Simply put, it's useful to research (1) how to obtain input from all employees quickly and reliably, and (2) how to apply smart survey analytics to enable management to improve their strategic decisions and implement these decisions faster.

It is important for management to understand where - and in how far - there is ambition among employees throughout the organization with regard to the strategic options management presents them. We define employee ambition as 'what employees hope to achieve within a given time frame when they are asked to participate in structural organizational changes'. Management should involve these employees because specific knowledge of the organization is positively associated with organizational performance (Ayers, 2013), because certain expertise and creativity fuels innovation and growth (Zhu & Chen, 2014), and because consensus drives team performance (Hyatt & Ruddy, 1997). In this paper, the ambition of employees is measured using an online survey on strategic topics issued by management.

Box 3.1
Definition of 'employee ambition'

"What employees hope to achieve within a given time frame when they are asked to participate in structural organizational changes".

Surveying literature on employee and/or team ambition we found no studies that covered all four criteria that define the scope of our study, as shown in Table 3.1:

1. Covering a large group of respondents (for example, more than 1,000 respondents) that would emulate asking an 'entire' organization (most studies had less than 250 respondents) …

2. … in a business setting (most studies involved students or other artificial teams composed just for the research or studied teams in a non-business environment like sports or politics) …

3. … and in a change management setting (most studies that researched teams focused on a stable 'as-is' situation specifically to be able to compare 'before' vs. 'after' a specific intervention) or were not focused on teams facing strategic decisions (for example, papers studying teams that had to perform a game or group puzzle) …

4. … and measuring the ambition in a real-world setting, as much as possible how it happens within an organizational setting (the full purpose of the ambition measurement not announced before or during the capturing of the respondents' input).

Table 3.1
Comparing papers on ambition

Author(s)	Topics	N > 1,000	Business Setting	Change M'ment	In action
Borchert, 2011	Ambition for managerial position	-	✓	✓	-
Brandon et al., 2004	Team's transactive memory system	-	✓	✓	-
Brunstein et al., 2004	Task enjoyment influences ambition	✓	✓	-	-
Burns, 1993	Team performance	-	✓	✓	-
Cannon-Bowers et al., 2001	Team's transactive memory system	-	-	-	✓
Capa et al., 2008	Team members' health influences ambition	-	-	-	✓
Cruz et al., 2007	Team member competencies influence ambition	-	-	-	-
Cury et al., 2006	Team member competencies influence ambition	-	-	-	✓
de Lange et al. 2010	Task enjoyment influences ambition	-	-	-	✓
Ellemers et al., 2004	Past success influences ambition	-	✓	-	✓
Ensley et al., 2001	Shared cognition	-	-	-	-
Foote et al, 2011	High ambition teams commit to a vision	-	-	-	✓
Ghosh et al., 2014	Ambition and focus	-	✓	-	✓
Gupta et al., 2010	Team's combined domain knowledge influences ambition	-	-	-	✓
Judge et al., 2012	Team members' personality influences ambition	-	✓	-	-
Koch et al., 2009	Reward schemes influence ambition	-	-	-	✓
Matteson, 2007	Team members' status influences ambition	-	-	-	✓
Miller et al., 2014	Team members' (TMS) influences ambition	-	✓	-	✓
Prichard, 2007	Transactive memory and performance	-	✓	-	-
Ready et al., 2011	Purpose-driven teams have clear priorities	-	✓	-	-
Sharma et al., 2007	Team size influences ambition	-	✓	-	✓
Slapin et al., 2014	Team size influences ambition	-	-	-	-
Story et al., 2009	Achievement motivation	-	✓	-	✓
Swaab et al., 2007	Shared cognition, shared identity	✓	✓	-	-
Tournemaine et al., 2010	Perceived team inequality influences team ambition	-	✓	-	-
Turner et al. 2014	Team's transactive memory system influences ambition	-	-	-	-
van Vianen, 1999	Ambition for managerial position	-	-	-	-
Wegner et al., 1985	Team's transactive memory system influences ambition	✓	✓	-	-

Abbreviation: M'ment = Management

The aim of the current study is to investigate whether individual respondents across industries and countries have similar types of ambition. If we are indeed able to identify these similarities, we want to investigate whether there are possibilities to influence/mitigate these in favor of a rapid and professional implementation of any management's strategic decisions, and how to mitigate potentially harmful ambition types. To enable this, we obtained the input of more than 1,000 employees in several modern organizations in a business setting about their future outlook regarding pending strategic options, and/or about the implementation/change management of these strategic options.

3.2 Material and methods

We conducted two separate empirical studies. In the first empirical study, we identified generic types of ambition of employees. In the second empirical study, we investigated the possibility of influencing/mitigating these ambition types.

For the first study, we had access to four different databases of respondents, each with their own specific strategic issue and a variety in either organizations or countries covered. Group 1 consisted of 491 managers and employees of one of the largest family-owned multinationals in USA (over 100,000 employees) covering 46 business unit management teams in a wide variety of locations around the globe (5 continents) answering a 13-item questionnaire on how to improve the company's approach to innovation. The second group consisted of 94 managers and employees from 12 teams on three continents of one of the largest reinsurance firms globally (headquartered in Switzerland) answering a 30-item questionnaire on IT customer service objectives for a next fiscal year. Group 3 consisted of 831 managers/employees in 39 teams in various business units in an industrial company in the Netherlands answering a 45-item questionnaire on team effectiveness. The fourth and final group consisted of 1,486 teachers from 104 different teams in various higher vocational education colleges in the Netherlands answering a 67-item questionnaire on how to comply over time with teacher competencies as specified in a new government guideline on teacher professionalism. In total, these four groups combined 2,902 respondents from 201 teams who submitted 257,475 answers. In the second study, we investigated the possibility of influencing/mitigating ambition types by comparing the answers on a 'team effectiveness'-questionnaire filled out by 1,122 respondents in 126 teams from 31 organizations in eight different industries with the ambition types of these respondents calculated from that same questionnaire. These 1,122 respondents gave a total of 133,795 answers.

Method

A strategic decision-making process cannot be stopped for a few weeks or months to query the organization. So, obtaining large quantities of respondents' answers must be done quickly and cost-effectively which rules out interviews and favors online surveys. In order to facilitate the change management following the strategic decision-making, these surveys must record four different components: (1) an actual situation, (2) a preferred situation (preferred by the respondent), (3) a management target (the situation preferred by management), and (4) a time frame. Therefore, we used closed questions with a modified Guttman scale. Guttman scaling works with current-status data (a term coined by Diamond, McDonald, and Shah, 1986) and we modified the Guttman scale with a time aspect. Each of the questions was constructed according to the following template:

Q. Element of the strategy	Now	In 6 months' time
1. The old situation we have to leave behind	☐	☐
2. Intermediate step towards the new situation	☐	☐
3. The new situation as desired by management	☐	☐

Thus, the Guttman scale shows the transformation trajectory from the current to a new situation. Clearly, there might be a need for more than three answers in some cases. Here is an example from the questionnaire on team effectiveness:

Q. How have you defined your team objectives?
Answer 1: We have no team objectives (yet)
Answer 2. We have a qualitative description
Answer 3. We have formal, SMART key performance indicators.

The Guttman scale shows the answers in an increasing level of 'quality': each next answer is better than the previous one. The multiple-choice answers have been formulated in an objective, verifiable/auditable way in contrast to indirect assessments of 'highly complex and uncertain situations where team members provide cognitive content themselves' (a problem raised by Kitaygorodskaya, 2006). These verifiable/auditable formulations reduce personal interpretation of the respondent and – when sourced from throughout the organization – help to improve comparisons between 'precise populations of interest' (as studied in political science by Monroe, Pan, Roberts, Sen and & Sinclair, 2015). It also helps to neutralize extreme-answer or mid-answer responding styles (issues raised by De Jong, Steenkamp, Fox, & Baumgartner, 2008 and by Plieninger & Meiser, 2014) and various biases like experimenter- and observer bias (Roulston & Shelton, 2015). Finally, it helps to correct for a respondent suffering from self-report bias and for the motivation of a respondent to bias his or her responses, for example, by submitting social desirable answers (issues raised by Donaldson and Grant-Vallone, 2002).

Respondents were free to omit answers ("If you do not know the answer or the question is not applicable to you: please skip it") or score a question identical on both actual situation and ambition. Additionally, there were also respondents that left the Actual situation blank and only indicated an 'In 6 months' time'-score or did the reverse by leaving all the 'In 6 months' time'-scores blank and only indicated an Actual situation. Hence, we distinguished between individuals that responded (gross response) and individuals who both submitted – but not necessarily for every question – an Actual- as well as an Ambition score (net response).

To compare individual respondents and teams, we calculated a score per person per question. The first answer of three was rated with a score of 0, the second answer with a score of 5 and the third answer (reflecting the content of the strategy best) with a score of 10. The scoring for questions with four answers worked the same way with the following scores: 0, 3.3, 6.7 and 10. An average score for a group of questions covering one topic was achieved simply by averaging the individual questions' scores. Questions were not weighted in comparison to each other. The questions left blank were not tallied for the calculation of the score.

With this thesis' objective of testing for the availability of generic ambition patterns, we did not study *what* or *how* respondents wanted to improve but only by *how much*. Therefore, we dissected 'ambition' in two components. The first component was Width: the number of questions a respondent chooses to improve within the next 6 months. The Width ranged from 0% (none of the questions in the questionnaire had to be improved) to 100% (all questions in the questionnaire had to be improved). The second component of the ambition was Depth: the percentage with which these selected questions had to be improved. The Depth ranged from 0% (the score of the selected questions in the questionnaire was not to be improved) to 200% (the score of the selected questions in the questionnaire had to triple). An example: Respondent 1 scores a 4.0 in the actual situation, wants to improve to a 6.0 in the next 6 months by improving 1/3 of the questions. That gives a Width of 33% and a Depth of 50% (6.0 divided by 4.0 minus 1). The Width and Depth have been plotted in a matrix with Width on the X-axis and Depth on the Y-axis. The resulting scatter plot shows the ambition of the individual respondents as well as of their teams. The corners of this matrix represent four different ambition types:

1. No Ambition: this is the bottom-left corner of the matrix where hardly any of the questions gets improved and if they do, then only by a small margin.

2. No Focus: this is the bottom-right corner of the matrix where most, if not all, questions have to be improved but only by a small margin.

3. No Realism: this is the upper-right corner of the matrix where most, if not all, questions have to be improved and then by a wide margin. Given the constraints that the ambition score refers to "In 6 months' time", we refer these respondents as having no realism.

4. Focused Change: this is the upper-left corner of the matrix where only a small amount of questions has to be improved but by a wide margin. The name 'Focused Change' is based on the premise that changing a few topics and change them well (and repeat that cycle with other topics in a next period of 6 months, and so on) is the most effective of the four ambition types (cf. in leadership, Foote, Elsenstat, & Fredberg, 2011; in technology innovation, Ghosh, Martin, Pennings, & Wezel, 2014).

There is no hard guideline on where to draw the line between No Ambition and No Focus (x-axis; Width) and between No Focus and No Realism (y-axis; Depth). Hence, we calculated for various cut-off values for Width and Depth what the division of the respondents and teams over the four types would be. By choosing one set of cut-off values for Width and Depth we 'lock' the assigned ambition types to an individual or team. Then, we calculate for each question the average score for all 'No Ambition'-teams, for all 'No Focus'-teams, and so on, for both the Actual situation and the 'In 6 months' time situation. The scores for the Actual situation resulted in a profile for each type of ambition.

But, more importantly, to inform management on how to intervene in possibly negative ambition types, we performed the second empirical study to analyze how ambition types compared among 1,122 respondents in 126 teams on a team effectiveness questionnaire. For example, do individual respondents or teams with SMART team objectives on average have more Width or less? And more Depth or less? Comparing the team effectiveness scores for all individual respondents and teams that have, for example, a No Ambition type gives a profile of an average No Ambition respondent/team. Similarly, we can calculate a profile for the average No Realism respondent/team, the average No Focus respondent/team and the average Focused Change respondent/team. Having calculated a ‘team effectiveness-profile’ for each of four types, we can calculate what helps to reduce Width and what helps to increase Depth. Therefore, we compared the No Ambition and No Focus respondents/teams to understand what influenced Width: No Focus respondents/teams score high on Width while No Ambition respondents/teams score low on Width. Hence, we subtracted per question the average score of the No Focus teams from the average score of the No Ambition teams. We expressed their difference as a percentage of the No Focus teams’ score. Subsequently, we analyzed if there would be a pattern in the questions that constituted the biggest difference between these two ambition types. Similarly, we compared the No Focus and No Realism types to understand what influenced Depth. So, we could determine what team effectiveness aspects would increase Depth for No Ambition respondents and what aspects would decrease Width for No Realism respondents. No Focus respondents would benefit from both a reduced Width as well as an increased Depth. Finally, we compared the intervention priorities for each of the ambition types with the individual respondents’ own ambition scores to see whether the improvements already planned by the individual respondents would align with the required interventions as calculated before. For example, how similar (or different) are the plans of No Ambition respondents from what management would like them to plan based on the results of our analyses?

3.3 Results Study 1: Defining ambition types

Table 3.2 shows the results of Study 1 of both individuals and teams for each of the four organizations participating in the first study.

Table 3.2

Scores for each of the respondent groups

	Reponse (n =)			Width				Depth			
	Gross	Nett	Nett%	Min	Max	Avg	StDev	Min	Max	Avg	StDev
Individuals											
Multinational - Innovation	491	312	64%	5%	63%	22%	15%	2%	150%	26%	26%
Reinsurance - IT objectives	94	80	85%	3%	100%	70%	24%	6%	196%	79%	48%
Industrial - Team effectiveness	831	280	34%	2%	100%	21%	20%	1%	200%	24%	31%
Teachers - Professionalism	1,486	1,377	93%	1%	100%	43%	26%	1%	200%	39%	34%
Total / *average*	**2,902**	**2,049**	**71%**			***38%***	***26%***			***37%***	***35%***
Teams											
Multinational - Innovation		46		18%	76%	60%	17%	6%	142%	29%	23%
Reinsurance - IT objectives		12		93%	100%	99%	2%	44%	144%	74%	31%
Industrial - Team effectiveness		39		30%	100%	83%	20%	0%	30%	14%	7%
Teachers - Professionalism		104		48%	100%	94%	9%	6%	60%	31%	11%
Total / *average*		**201**				***85%***	***20%***			***31%***	***20%***

The table shows gross response (all respondents) and the nett response (respondents that submitted both Actual- as Ambition scores). The table further shows the minimum and maximum score that a respondent (or team) had on Width. The Avg column shows the average Width for all individuals (or teams) in the organization. The StDev shows the standard deviation. The columns for Depth have been similarly constructed.

The first notable point is the difference between gross and net response that can be partly explained by situational factors in the four organizations. For example, the multinational had a rather rigid top-down approach to innovation where its Organization Alignment department at headquarters usually decided how to orchestrate an organization-wide innovation program.

Additionally, it never happened before that 46 business units could all have a say in how to run innovation. Hence, we suspect that many respondents could not fully comprehend what was required from them. Looking at the Width and Depth figures for the individual respondents we see an extreme bandwidth in the scores: between 0% and 100% in Width and between 0% and 200% in Depth. Figure 3.1 shows the individual respondents mapped in a matrix. The Width is plotted on the X-axis and Depth on the Y-axis. Each dot represents a respondent. The green line is the trendline through the scatterplot. Note the clustering of No Ambition respondents in the 'No Ambition'-corner.

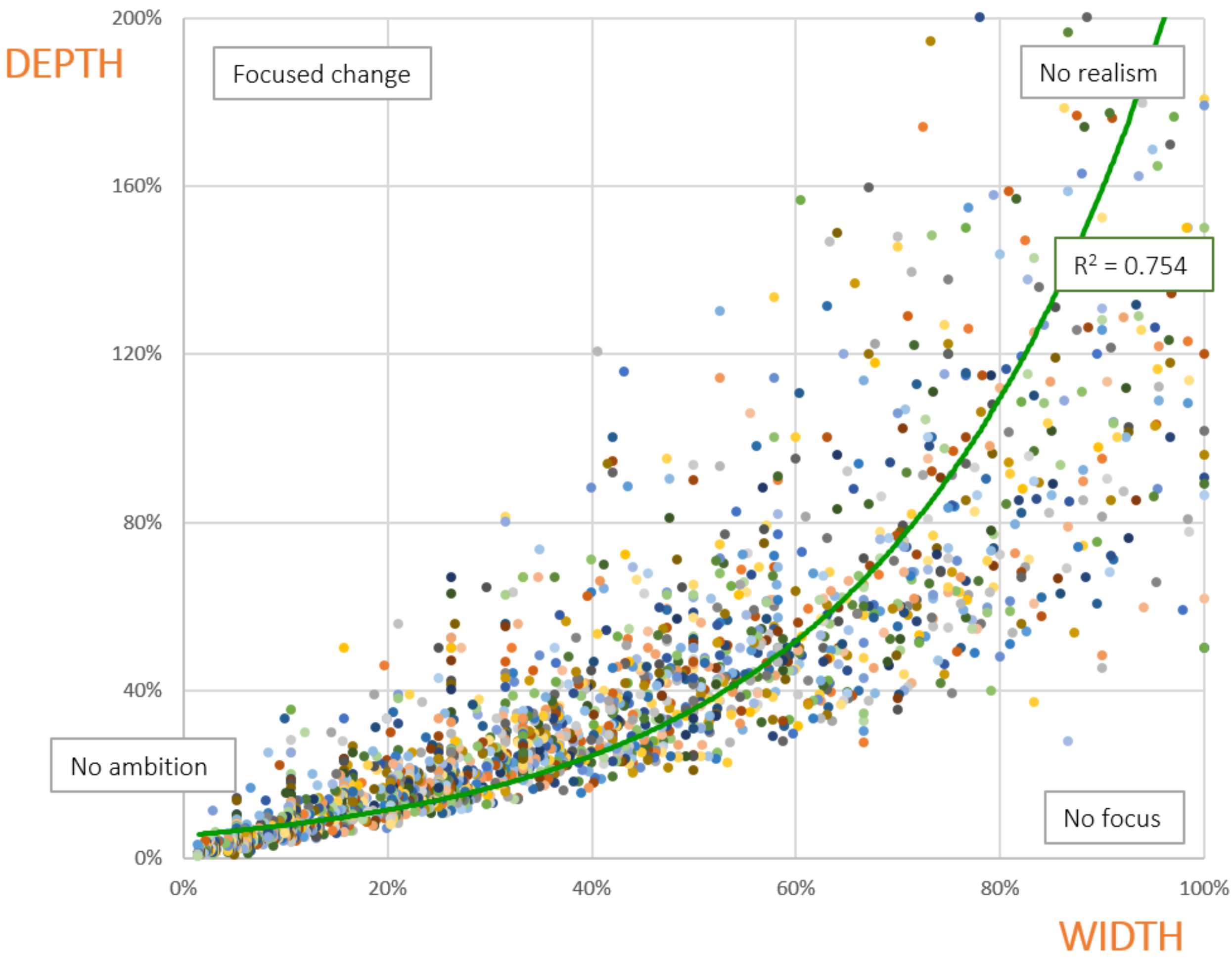

Figure 3.1: Mapping the ambition Width and Depth of the individual respondents (n = 2,049)

The same mapping done for the 201 teams shows a clustering into the No Focus corner, as shown in Figure 3.2 (next page). This clustering can be explained by two factors. A team will likely consist of a mix of respondents with one of the ambition types. The more equal the mix between these ambition types, the higher Width will be: as the respondents' ambition mix varies, more questions will be earmarked by one or more team members. At the same time, this variety dampens the Depth: No Ambition and No Realism respondents meet each other half-way and average each other out.

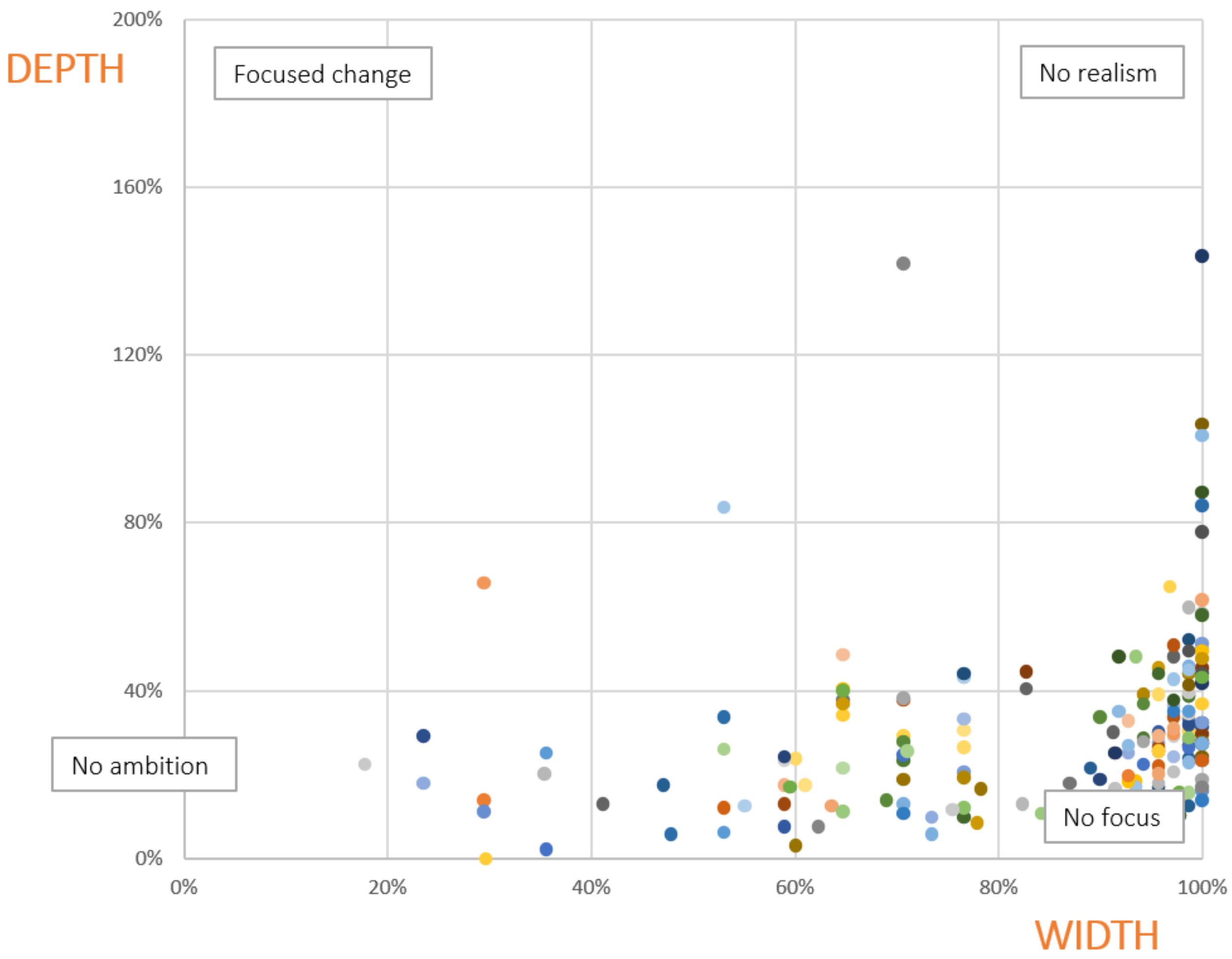

Figure 3.2: Mapping the ambition Width and Depth of the teams (n = 201)

Next, we calculated where in the matrix the x- and y-axes should be divided in two to separate No Ambition from No Focus (x-axis) and No Focus from No Realism (y-axis). Table 3.3 (next page) shows the effect of changing the cut-off values of Width and Depth on the mix of the four ambition types.

Table 3.3

Cut-off values and the effect on the pattern mix

	No Ambition	No Focus	No Realism	Focused Change
Individuals: Width - Depth				
20% - 20%	29%	12%	56%	2%
30% - 30%	43%	13%	42%	2%
40% - 40%	55%	12%	30%	3%
50% - 50%	66%	10%	21%	4%
60% - 60%	74%	8%	14%	4%
10% - 20%	16%	25%	58%	1%
20% - 40%	31%	36%	32%	1%
30% - 60%	45%	36%	18%	0%
Teams: Width - Depth				
20% - 20%	0%	30%	70%	0%
30% - 30%	3%	54%	42%	0%
40% - 40%	4%	74%	21%	0%
50% - 50%	6%	85%	8%	0%
60% - 60%	12%	82%	4%	1%
10% - 20%	0%	30%	70%	0%
20% - 40%	0%	78%	22%	0%
30% - 60%	3%	92%	5%	0%

For example, looking at the first row in the table (20% - 20%), if we divide the X-axis in two parts (everything below 20% Width and everything above 20%) and do the same on the Y-axis for Depth, 29% of the individual respondents fall into the No Ambition category. And if we would apply the same 20% - 20% division to the teams, 30% of the teams would fall into the No Focus category. To be able to work with only one version of the matrix, we preferred to use one set of cut-off values for both individuals and teams. Therefore, we looked which set of cut-off values divided the individuals and teams most equally over the four ambition types. From the sets listed in Table 3.3 the set of 30% - 30% did that best.

Table 3.4

Cut-off values and the outcome of the confusion matrices

Width ↓	Depth →	20%	30%	40%	50%	60%
20%		89%	84%	84%	85%	N.a.
30%		88%	89%	85%	89%	89%
40%		N.a.	87%	88%	92%	90%
50%		84%	N.a.	88%	90%	89%

Values are the overall % of correct predicted ambition types using that pair of Width- and Depth values based on the underlying respondent answers.
N.a.: it was not possible to calculate a value for this pair.

These cut-off values also came forward when we calculated the confusion matrices for each of the pairs of cut-off values for individual respondents in Table 3.4. The 40%-50% and 50-50% pairs would do marginally better for the individual respondents then a 30%-30% cut-off but the mix of teams resulting from these pairs would be less practical. For example, with the 50%-50% cut-off values, 85% of the teams would be of the same type (No Focus).

We also investigated if the length of the questionnaire would influence Width and Depth. For example, we initially thought that a respondent would be more easily inclined to earmark all questions for improvement in a 13-question-questionnaire than in a 67-question questionnaire. Yet, for individuals the association between the length of the questionnaire and Width was modest (r = .25, p < .001). Initially, we assumed that in larger teams more information would be available for individual respondents to make more informed choices reducing their Width and improving their Depth. However, for individual employees, team size was not significantly related to either Width (r = -.01, p = .225) or Depth (r = .01, p = .903). There was a negative association between the score for the “Actual Situation” and both Width (r = -.36, p < .001) and Depth (r = -.70, p < .001).

3.4 Results Study 2: Influencing/mitigating ambition

Ambition types appear generic enough to warrant one specific intervention

Study 1 was about detecting ambition types. In Study 2, the focus was on intervening in these types. Table 3.5 gives an overview of the Width and Depth for each of the teams. It shows roughly comparable figures among the surveyed organizations and industries.

Table 3.5
Width and Depth in the surveyed organizations in the second study

	Width				Depth				
	Min	Max	Avg	StDev	Min	Max	Avg	StDev	Remark
Communication & Media									
Management magazine	45%	64%	58%	10%	29%	150%	76%	65%	Editorial board
Media firm	45%	64%	55%	9%	50%	64%	57%	7%	USA
Telecommunications provider	9%	91%	48%	22%	7%	183%	61%	45%	
Consultancy									
Consulty firm - 1	36%	91%	65%	22%	17%	163%	90%	67%	Strategy consulting
Consulty firm - 2	4%	88%	41%	27%	3%	167%	56%	45%	Engineering
Consulty firm - 3	18%	67%	46%	25%	13%	155%	74%	73%	Big-4
Consulty firm - 4	9%	91%	44%	22%	17%	138%	46%	35%	Big-4
Consulty firm - 5	9%	64%	39%	22%	10%	180%	60%	62%	IT
Consulty firm - 6	9%	82%	45%	23%	11%	75%	41%	23%	Strategy consulting
Consulty firm - 7	8%	54%	26%	16%	5%	47%	19%	14%	Marketing & Sales
Trade organization	11%	82%	43%	26%	20%	200%	71%	63%	In consulting
Financial services									
Insurance company	4%	54%	23%	15%	2%	42%	17%	12%	Life insurance
Mortgage company	4%	73%	33%	21%	3%	129%	37%	32%	
Government									
Alumni network	4%	43%	23%	13%	2%	78%	23%	18%	Part of a university
Hospital	4%	92%	33%	24%	4%	150%	43%	39%	
Tourist promotion office	4%	72%	39%	30%	4%	107%	49%	45%	
University	18%	73%	49%	20%	13%	149%	62%	47%	
Industrial services									
Installation company - 1	2%	100%	23%	19%	0%	194%	26%	29%	1st round - by location
Installation company - 1	2%	100%	22%	18%	0%	194%	25%	29%	1st round - by department
Installation company - 1	2%	75%	25%	19%	1%	108%	26%	28%	2nd round - by location
Installation company - 1	2%	75%	27%	19%	2%	108%	27%	29%	2nd round - by department
Plant maintenance firm	4%	46%	22%	14%	2%	42%	15%	12%	
Manufacturing									
Agriculture supply manufacturer	4%	79%	36%	21%	5%	163%	44%	44%	
Computer manufacturer	18%	73%	43%	17%	10%	69%	35%	19%	USA
Instrument maker	4%	96%	27%	24%	2%	136%	33%	39%	Optical
Medical equipment manuf. - 1	36%	64%	55%	10%	31%	175%	66%	54%	
Medical equipment manuf. - 2	4%	59%	21%	20%	2%	52%	16%	18%	
Production line manufacturer	4%	59%	17%	18%	2%	51%	13%	17%	
Truck manufacturer	7%	79%	33%	26%	5%	118%	40%	42%	
Retail									
Kitchen reseller	4%	82%	34%	23%	2%	162%	38%	40%	
Supermarket - 1	11%	50%	25%	12%	11%	71%	31%	21%	Distribution center
Supermarket - 2	4%	75%	32%	21%	6%	100%	42%	32%	Distribution center
Transportation									
Airline	9%	82%	37%	24%	3%	143%	47%	47%	
Transportation firm	4%	58%	25%	24%	6%	167%	43%	62%	Buses, taxis
Average	**11%**	**73%**	**36%**	**20%**	**9%**	**124%**	**43%**	**37%**	

Legend: Min = the minimum width recorded for a respondent in that organization. Max = the maximum width recorded for a respondent in that organization. Avg = the average width of all respondents in that organization. StDev = the standard deviation in the respondent's width. The four Depth-columns are constructed the same way.

But to verify whether the ambition types are generic types, irrespective of industry, we need to statistically compare these industries. If we analyze the individual respondents in these eight industries, we see an asymmetrical distribution for both Width and Depth (see Figure 3.3):

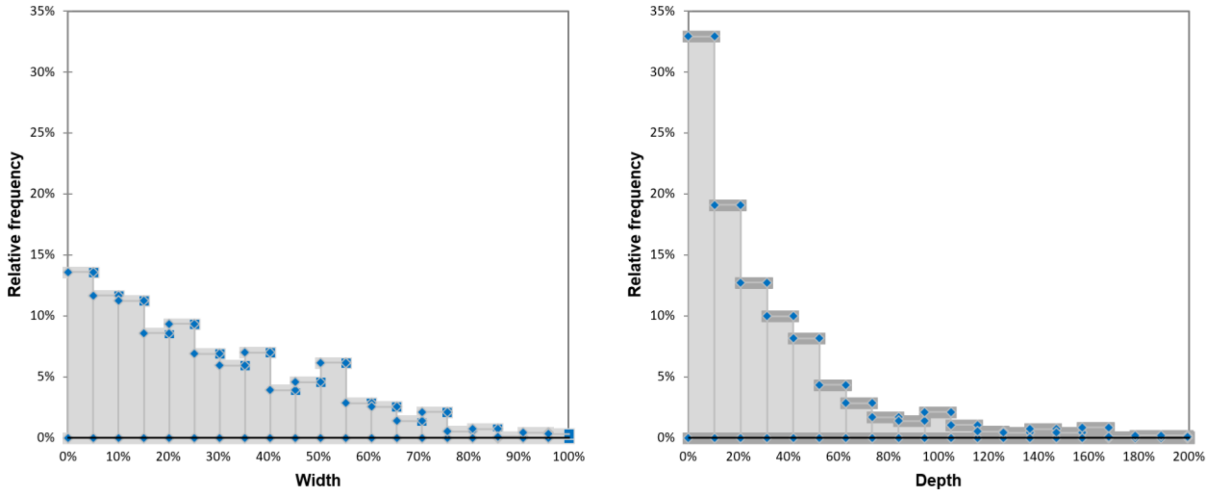

Figure 3.3: Individual respondents' distribution of Width and Depth scores

Hence, for comparison purposes, we chose Levene's test (median) over Fisher's F-test to analyze whether industries are significantly alike in terms of their variance in the ambition scores. The Levene's tests in Table 3.6 (on the next page) compare for all individual respondents from the eight industries, for both Width and Depth, whether the variance in pairs of industries is alike or not:

H_1 = The variance in a pair of industries' scores is different.

Table 3.6 shows that 9 out of 56 pairs (Width and Depth combined), or 16% of the pairs, were not considered to be significantly equal in terms of variance. One industry – Industrial Services – was responsible for 7 of the 9 'not alike'-pairs. When we excluded this Industrial Services industry, only 2 pairs, or 4% of the total amount of remaining pairs, were significantly different; for example, Financial Services and Transportation ($F_{obs} = 4.47$, $p < .05$). This implies that for 96% of the remaining pairs of industries, hypothesis H_1 has to be rejected: these pairs had significantly similar variances in terms of Width and Depth and could be considered alike in terms of ambition types. In turn, that suggests that as a rule-of-thumb our ambition types exist irrespective of the industry.

Table 3.6

Similarity in variance among industries for ***WIDTH***

	Communication & Media				Consultancy				Financial Services				Government			
	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2
Communication & Media	-	-	-	-	2.58	3.94	1	94	0.00	3.98	1	67	0.33	3.96	1	81
Consultancy					-	-	-	-	3.63	3.93	1	107	1.37	3.92	1	121
Financial Services									-	-	-	-	0.47	3.94	1	94
Government													-	-	-	-

	Industrial Services				Manufacturing				Retail				Transportation			
	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2
Communication & Media	0.04	3.86	1	620	2.35	3.92	1	125	0.10	3.99	1	66	1.73	4.06	1	44
Consultancy	11.20***	3.86	1	660	0.06	3.90	1	165	1.99	3.93	1	106	0.03	3.95	1	84
Financial Services	0.06	3.86	1	633	3.33	3.91	1	138	0.14	3.96	1	79	2.36	4.01	1	57
Government	1.82	3.86	1	647	1.12	3.90	1	152	0.08	3.94	1	93	0.84	3.98	1	71
Industrial Services	-	-	-	-	12.66***	3.85	1	691	0.59	3.86	1	632	4.02*	3.86	1	610
Manufacturing					-	-	-	-	1.73	3.91	1	137	0.11	3.92	1	115
Retail									-	-	-	-	1.30	4.01	1	56
Transportation													-	-	-	-

Similarity in variance among industries for ***DEPTH***

	Communication & Media				Consultancy				Financial Services				Government			
	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2
Communication & Media	-	-	-	-	0.12	3.94	1	94	2.85	3.98	1	67	0.52	3.96	1	81
Consultancy					-	-	-	-	5.52	3.93	1	107	1.83	3.92	1	121
Financial Services									-	-	-	-	1.41	3.94	1	94
Government													-	-	-	-

	Industrial Services				Manufacturing				Retail				Transportation			
	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2	$F_{obs.}$	$F_{cri.}$	df1	df2
Communication & Media	6.67**	3.86	1	620	0.90	3.92	1	125	0.83	3.99	1	66	0.28	4.06	1	44
Consultancy	21.37***	3.86	1	660	3.20	3.90	1	165	2.20	3.93	1	106	0.12	3.95	1	84
Financial Services	0.06	3.86	1	633	0.99	3.91	1	138	0.87	3.96	1	79	4.47*	4.01	1	57
Government	4.53*	3.86	1	647	0.06	3.90	1	152	0.07	3.94	1	93	1.63	3.98	1	71
Industrial Services	-	-	-	-	4.95*	3.85	1	691	2.13	3.86	1	632	9.50**	3.86	1	610
Manufacturing					-	-	-	-	0.00	3.91	1	137	2.24	3.92	1	115
Retail									-	-	-	-	2.03	4.01	1	56
Transportation													-	-	-	-

*Table shows the observed and critical F, the degrees of freedom. $\alpha = 0.05$. * $p < .05$, ** $p < .01$, *** $p < .001$.*

For further comparison, we want to compare industries not only in terms of the variance (are the respondents' ambition scores dispersed?) and distribution of their scores (are these scores skewed?). Table 3.7 shows this comparison using a Kolmogorov-Smirnov test:

H_1 = The scores in a pair of industries have different distributions.

Table 3.7

Similarity in distribution among industries for ***WIDTH***

	C & M	Consultancy	Fin. Serv.	Government
	D	D	D	D
Communication & Media	-	0.223	0.542**	0.460**
Consultancy		-	.0301**	0.260**
Financial Services			-	0.126
Government				-

	Ind. Serv.	Manuf.	Retail	Transport.
	D	D	D	D
Communication & Media	0.590***	0.424**	0.464**	0.373
Consultancy	0.383***	0.201	0.273	0.257
Financial Services	0.219*	0.180	0.154	0.201
Government	0.230*	0.109	0.116	0.189
Industrial Services	-	0.202**	0.291**	0.298*
Manufacturing		-	0.168	0.116
Retail			-	0.250
Transportation				-

Similarity in distribution among industries for ***DEPTH***

	C & M	Consultancy	Fin. Serv.	Government
	D	D	D	D
Communication & Media	-	0.241	0.491**	0.421**
Consultancy		-	0.344**	0.220
Financial Services			-	0.157
Government				-

	Ind. Serv.	Manuf.	Retail	Transport.
	D	D	D	D
Communication & Media	0.421**	0.438***	0.357*	0.448*
Consultancy	0.342***	0.259**	0.178	0.289
Financial Services	0.212	0.153	0.218	0.218
Government	0.213*	0.149	0.123	0.154
Industrial Services	-	0.174**	0.283**	0.259
Manufacturing		-	0.180	0.222
Retail			-	0.183
Transportation				-

Hypothesized difference (D) = 0, $\alpha = 0.05$. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 3.7 shows that 25 out of 56 pairs (Width and Depth combined), or 45% of the pairs, were considered to have significantly different distributions of the respondents' scores. Two industries – Communication & Media and Industrial Services – were together responsible for 21 of the 25 'not alike'-pairs. When we excluded these Communication & Media- and Industrial Services industries, only 4 pairs, or 11% of the total amount of the remaining pairs, were considered to have significantly different distributions. This means that in 89% of the pairs, H_1 has been rejected: the pairs had significantly similar distributions in terms of Width and Depth and could be considered alike in terms of ambition types.

Analyzing what intervention is needed per ambition type

Given the premise that Focused Change is the desired type, the interventions are relatively simple. 'No Ambition'-respondents should increase their Depth, 'No Realism'-respondents should decrease their width and 'No Focus'-respondents should do both. With 30%-30% as cut-off values, there are very few respondents with 'Focused Change'. That means that researching what decreases Width can only be done by comparing how 'No Ambition'-respondents score differently than 'No Focus'-respondents. Conversely, for Depth, by comparing how 'No Realism'-respondents score differently than 'No Focus'-respondents. Table 3.8 shows the Top-10 best scoring questions (in terms of the biggest gap between the two respondent groups) for Less Width.

Table 3.8

Questions influencing Width

← Less Width	Score 'No Ambition'	Score 'No Focus'	No Ambition -/- No Focus	$F_{obs.}$
'No Ambition' scores higher on formal/top-down: top-10 questions				
✓ There are sufficient resources available to do one's job	8.5	6.1	2.4	3.79*
✓ Respondent is part of a formal mentor/mentee couple	8.2	5.8	2.4	7.61**
✓ There is sufficient access to information to do one's job	7.8	6.5	1.3	0.21
✓ Respondent doesn't need to ask for assistance to do the job	6.1	5.1	1.0	3.17
✓ The team members are involved in setting the team goals	5.5	6.5	-1.0	15.89***
✓ Regular celebration of team success by the entire team	3.2	4.2	-1.0	1.78
✓ Team members can determine their own way of working	6.5	7.4	-0.9	0.18
✓ The teammanager publicly recognizes member's performance	5.6	4.7	0.9	0.50
§ Communication of company news incl. feedback, criticism	7.4	6.6	0.8	0.12
✓ Respondent gets involved in process step previous to him/her	5.8	5.1	0.7	0.56
'No Focus' scores higher on formal/top-down: top-3 questions				
§ There is a formal mentor system available	2.8	3.4	-0.6	0.64
§ Manager clearly states his/her opinion of the work at hand	6.0	6.2	-0.2	0.5
§ Regular review of objectives versus achievements	6.9	7.0	-0.1	5.07*

✓ *Less width due to a formal/top-down approach*

§ *Less width due to an informal/bottom-up approach*

*F_{obs} is the observed F with * $p < .05$, ** $p < .01$, *** $p < .001$.*

The columns in Table 3.8 show per question the average score for all the No Ambition respondents, the average score for all the 'No Focus'-respondents and their difference in score expressed in an absolute delta ('No Ambition'-score -/- 'No Focus'-score). The sign for this column is related to the indicator left of the column with the content of the question. This column shows how 'No Ambition'-respondents differed from 'No Focus'-respondents in terms of having a formal/top-down approach to team effectiveness (indicated by a ✓) compared to an informal/ bottom-up approach (indicated by a §). A question that is about an informal/bottom-up approach that has a negative delta is therefore counted as supportive to a formal/top-down approach. Similarly, a question that is about formal/top-down approach that has a negative delta is therefore counted as supportive to an informal/bottom-up approach. To further analyze whether the variance in scores between the 'No Ambition' respondents and the 'No Focus' respondents was significantly different we included in the table the observed F for Levene's test comparing the variance in scores between these two respondent groups. We tested:

H_1 = The variances in respondent groups' scores are different

We have sorted Table 3.8 using the third column: the absolute delta in the score between the 'No Ambition' respondents and the 'No Focus' respondents. The question with the biggest delta for Less Width was "There are sufficient resources available to do one's job". The full question in the team effectiveness questionnaire was:

Q. Do you have enough resources to do your job?
Answer 1. No
Answer 2. There are resources BUT limited availability OR not available to me
Answer 3. There are sufficient resources AND I have access to them.

The delta in the score of 2.4 for this question means that the average 'No Ambition'-respondent scored better than the average 'No Focus'-respondent. In other words, 'No Ambition'-respondents had more resources than 'No Focus'-respondents. Based on the results presented in Table 3.8, the interesting point with regard to management intervention of the ambition patterns is that less Width predominantly appeared to be a matter of a formal/top-down approach (for example, having SMART team goals, team members know their own tasks/responsibilities). That said, we realize that not every formal/top-down question is equally influential in reducing width. In the F_{obs} column in Table 3.8 we see that there are two questions ("There is sufficient access to information to do one's job" and "Team members can determine their own way of working") where the variance between 'No Ambition' respondents and 'No Focus' respondents was not significantly different.

Additionally, there were also formal/top-down questions outside this Top-10. Most interestingly, there were a few questions that can be characterized as aspects of a formal/top-down approach where 'No Focus' respondents score better than the 'No Ambition' respondents. These higher scores are marginally higher, yet the F_{obs} shows that for two of these questions ("Manager clearly states his/her opinion of the work at hand" and "Regular review of objectives versus achievements") the variance was significantly different between the two respondent groups. The Top-3 of these questions can be found in the bottom half of Table 3.8. This finding nuances our statement that a formal/top-down approach reduces Width. The *overall tendency* in the Top-10 seems to point at an effect from such an approach to reduce Width, yet there are exceptions.

Table 3.9 shows the comparable analysis for Depth by subtracting the No Focus respondents' scores from the No Realism respondents' scores resulting in a Top-10 best scoring questions (in terms of the biggest delta.

Table 3.9

Questions influencing Depth

↑ More Depth	Score 'No Realism'	Score 'No Focus'	No Realism -/- No Focus	$F_{obs.}$
'No realism' scores higher on informal/bottom-up: top-10 questions				
§ Getting formal feedback from manager	4.4	7.3	-2.9	16.08***
§ The managers signals deviations from the preferred way of working	3.9	6.2	-2.3	2.38
§ Manager clearly states his/her opinion of the work at hand	5.5	7.6	-2.1	0.03
§ Manager and team members give each other formal feedback	4.8	6.7	-1.9	1.18
§ Team members have a formal personal development plan	3.2	5.0	-1.8	2.93
✓ The team members are involved in setting the team goals	4.8	6.5	-1.7	7.30**
§ The team has SMART team goals	5.4	7.1	-1.7	22.36***
§ The team goals have been translated into a year planning	4.0	5.6	-1.6	2.51
§ There is a formal mentor system available	1.9	3.4	-1.5	8.60**
✓ Regular celebration of team success by the entire team	2.7	4.2	-1.5	3.18
'No Focus' scores higher on informal/bottom-up: top-10 questions				
✓ Team goals get translated into one's personal goals	4.7	6.0	-1.2	1.3
✓ There is a possibility to disagree	7.0	8.2	-1.1	20.69***
✓ Employees volunteer for new tasks	6.4	7.4	-1.0	1.1

✓ *More depth due to a formal/top-down approach*

§ *More depth due to an informal/bottom-up approach*

*F_{obs} is the observed F with * $p < .05$, ** $p < .01$, *** $p < .001$.*

Table 3.9 has a comparable structure to Table 3.8. We sorted the questions by the biggest delta in score between 'No Realism' and 'No Focus' respondents (third, first and second column, respectively) and then compared the variance in score between the two groups with a Levene's test. The 'No Realism' respondents scored worse than No Focus respondents on all Top-10 questions for individuals. And looking at the content of these Top-10's it is clear that 'No Realism' respondents scored better on informal/bottom-aspects but scored worse on formal/top-down aspects. Rating all questions in both the 'Less Width' and 'More Depth' columns along 'formal/top-down', 'informal/bottom-up' clearly shows that increasing Depth can be linked to a more informal/bottom-up management style.

Yet, in Table 3.9 there is also the cautionary remarks that one question ("Manager clearly status his/her opinion of the work at hand") did not significantly differ between the two groups in terms of variance and that there were informal/bottom-up questions outside this Top-10. Especially, the Top–3 questions where 'No Focus' respondents score better than 'No Realism' respondents on informal/bottom-up questions deserves attention. The same nuance as with Table 3.8 appeared: the *overall tendency* seems to point at an effect from an informal/bottom-up to increase Depth, yet there are exceptions.

From the above we infer that – given exceptions aside – formality is associated with influencing Width and informality is associated with influencing Depth. Consequently, in terms of management intervention and the requirement to achieve a situation of Focused Change, 'No Ambition' respondents need to work on their informality, 'No Realism' respondents on their formality and 'No Focus' respondents should work on both. With that conclusion in mind, it is interesting to research whether individual respondents would already plan to move in the required direction given the required mitigation for their ambition type.

In Table 3.10 on the next page, we summarized in how far the Top-10 of questions from Tables 3.8 and 3.9 had already been planned to be improved in the next 6 months (the Ambition score minus the Actual score) by the respondents of each of the three ambition types.

For example, the first question in 'No Ambition' is "There are sufficient resources available to do one's job". On average, the 'No Ambition'- respondents would plan an improvement of from an average score of 8.5 (first column) to a score of 9.4, a delta of 0.9 points (on a scale of 10, second column) that being a 10% improvement (the 'As %'-column), in the next six months. The 'down arrows' indicate those questions that represent an improvement in areas that are contrary to our main line of reasoning that No Ambition respondents should primarily improve on the informal/bottom-up questions (to increase Depth) whereas No Realism respondents should primarily improve on the formal/top-down questions (to reduce Width). Note that two questions appear in both Top-10's (indicated by a ❷). Some questions have a '(- sign)'-suffix. For example: "The team members are involved in setting the team goals (- sign)" in the Top-10 questions that reduce Width. This suffix indicates that improving that particular question has the opposite effect. For this sample question, further involving team members in the setting the team goals favours an informal/bottom-up approach and, thus, increases Width, not decreases it.

The 'No ambition' respondents should become more informal/bottom-up in their management approach in order, yet Table 3.10 shows that a lot of ambition was still pointed at further improving formal/top-down aspects. The 'No Focus' respondents benefit from both formal/top-down as informal bottom-up aspects. However, we indicated two questions where 'No Focus' respondents were scoring high enough that the effort involved could be better spend elsewhere. Finally, the 'No Realism' respondents were planning to further improve on informal/bottom-up aspects like "The team members are involved in setting the team goals". Given the 'No Realism' respondents' priority to improve on the formal/top-down aspects, we deem several planned improvements of likely having a less overall effect in the direction of Focused Change.

In other words, the 'No Ambition' respondent/teams plan a lot of improvements that further reinforce the formal/top-down approach rather than the required informal/bottom-up approach. Conversely, the same is true for the 'No Realism' respondents/teams: they plan a lot of improvements that further reinforce the informal/bottom-up approach rather than the required formal/top-down approach.

Table 3.10

What was actually planned of the Top-10 topics

Respondent group →	No Ambition			No Focus			No Realism		
	Actual	Delta	As %	Actual	Delta	As %	Actual	Delta	As %
Top-10 that reduces Width									
There are sufficient resources available to do one's job	↓ 8.5	0.9	10%	6.1	1.2	19%	7.1	1.0	15%
Respondent is part of a formal mentor/mentee couple	↓ 8.2	0.2	3%	5.8	0.3	5%	4.9	0.5	11%
There is sufficient access to information to do one's job	↓ 7.8	1.1	14%	6.5	1.2	18%	6.1	1.3	22%
Respondent doesn't need to ask for assistance to do the job	↓ 6.1	0.9	15%	5.1	1.1	22%	5.8	0.9	15%
❷ The team members are involved in setting the team goals (- sign)	5.5	1.1	21%	6.5	1.2	19%	↓ 4.8	1.3	26%
❷ Regular celebration of team success by the entire team (- sign)	3.2	1.7	51%	4.2	1.7	41%	↓ 2.7	2.5	91%
Team members can determine their own way of working (- sign)	6.5	1.1	17%	↓ 7.4	1.0	13%	↓ 7.0	1.0	15%
The teammanager publicly recognizes member's performance	↓ 5.6	1.1	20%	4.7	1.3	28%	4.2	1.3	32%
Communication of company news incl. feedback, criticism	7.4	1.1	15%	6.6	1.4	21%	↓ 6.5	1.2	19%
Respondent gets involved in process step previous to him/her	↓ 5.8	1.2	21%	5.1	1.6	31%	4.4	1.6	37%
Top-10 that increases Depth									
Getting formal feedback from manager (- sign)	↓ 6.9	1.2	18%	7.3	1.3	18%	4.4	2.0	45%
The managers signals deviations from the preferred way of working (- sign)	↓ 6.0	1.2	21%	6.2	1.4	22%	3.9	1.7	44%
Manager clearly states his/her opinion of the work at hand (- sign)	↓ 7.2	1.0	14%	↓ 7.6	1.0	14%	5.5	1.4	26%
Manager and team members give each other formal feedback (- sign)	↓ 6.6	0.8	12%	6.7	1.0	15%	4.8	1.1	24%
Team members have a formal personal development plan (- sign)	↓ 7.6	1.0	14%	7.7	1.1	14%	↓ 7.2	1.2	16%
❷ The team members are involved in setting the team goals	5.5	1.1	21%	6.5	1.2	19%	↓ 4.8	1.3	26%
The team has SMART team goals (- sign)	↓ 7.2	1.1	16%	7.1	1.4	20%	5.4	1.7	31%
The team goals have been translated into a year planning (- sign)	↓ 5.8	1.0	17%	5.6	1.3	23%	4.0	1.3	33%
There is a formal mentor system available (- sign)	2.8	2.3	80%	3.4	2.4	70%	1.9	3.4	180%
❷ Regular celebration of team success by the entire team	3.2	1.7	51%	4.2	1.7	41%	↓ 2.7	2.5	91%
↓ *What probably has less effect*	13 questions			2 questions			7 questions		
❷ *Question appears in both top-10's*									

3.5 Discussion

This paper aimed at (1) identifying generic ambition types in teams, (2) studying how these ambition types could be influenced, and (3) understanding what ‘team-effectiveness’-related interventions management should be applied to align the teams’ ambition with the overall organizational strategy.

Our study shows that many employees clearly want to move forward given the strategic options presented by management. Yet, our findings also show that these employees most likely have either no ambition, no focus or no realism. When comparing ambition types and scores on the team effectiveness assessment, we did find directions for specific interventions for several of the ambition types. To study employees’ knowledge and experience, it is required to survey relatively large bodies of respondents within an organization and to apply specific analytical techniques. Surveying a large number of employees has several theoretical implications. For example, we substituted the use of statements for a Guttman scale and added a time aspect to it to allow for an unsupervised assessment, for more objective respondent input about actual situation and planned improvement in 6 months’ time, and to allow management to set a target. Given the need for short throughput times we were able to work with very simple math. We studied close to 3,000 respondents giving over 257,000 answers in the first empirical study. We were specifically interested how the ambition of the crowd could be compared among teams, whether specific types of ambition could be detected and whether these types could be regarded as generally applicable.

A theoretical implication is that despite the attention in literature for, for example, groupthink (Turner & Pratkanis, 1998), vision clarity (Patanakul, Chen, & Lynn, 2012), goal alignment (Ayers, 2013) and team cognition (DeChurch & Mesmer-Magnus, 2010), the net result is disappointing. We realize that the overwhelming majority of teams – if not all – have ambition types that are potentially harmful, costly and/or time-consuming for the organizations as a whole. Perhaps there is goal clarity and alignment on skill, knowledge, and expertise (Bezrukova, Thatcher, Jehn, & Spell, 2012) but apparently not on *how* to achieve it. A shared team cognition (Swaab, Postmes, Van Beest, & Spears, 2007) or understanding team members’ narratives (Fiander-McCann, 2013) can serve to align leaders with team members to build integral business relationships but apparently are not a guarantee for a shared view how to execute the changes. Delegating strategic responsibility to teams and individual team members does not mean they feel accountable (De Leede, Nijhof, & Fisscher, 1999) and it apparently does not fuel their need to align on the change management implementation either.

This aligned view on how to achieve strategic goals is something else than ‘process clarity’. The latter focuses on administrative aspects like, for example, coordination of team tasks, managing interpersonal relationships and clear procedures, roles and responsibilities (Parker & Collins, 2010; Hu & Liden, 2011). The former, shared view on change management could be defined as ‘roadmap clarity’. This roadmap clarity differs from vertical strategic alignment (Andrews, Boyne, Meier, O'Toole, & Walker, 2012) and middle management alignment (Ouakouak, Ouedraogo, & Mbengue, 2014). These authors describe a predominantly top-down exercise about making lower managers and employees understand how their work contributes to the strategic goals of the organization (Andrews et. al. refer to a “principal-agent theory”, p. 79). The seemingly omnipresence of potentially harmful team ambition types may suggest one of three undesirable situations that result in the dominant ‘No Focus’ team ambition type. Either employees do not understand their contribution to the strategic goals. Or, employees understand their contribution but their goals are not aligned. Or management has failed to involve the employees in the first place.

So, when the empowerment of teams to engage in strategic decision-making coincides with a lack of roadmap clarity, there is a new argument in the debate of pushing responsibilities down the organization versus stimulating a more autocratic management style (Nowicki & Summers, 2003). Is it about "engaging in a conversation [.. with employees..] and listening well" as Groysberg and Slind (2012, p.2) propose or about defining goals *and* detailed implementation roadmaps and only then pursue the vertical strategic alignment? Related to this, the question is whether improving roadmap clarity is a case of organizational culture (self-managing versus autocratic) or a case of finding the right team effectiveness intervention mechanisms.

Practical implications

By researching the team effectiveness assessments of 126 teams with over 1,100 useful respondents submitting over 130,000 answers in the second empirical study, it became clear that specific management interventions may overcome the negative aspects of these ambition types. Our first rule-of-thumb is that a formal/top-down approach to team management likely reduces Width. That includes, for example, a focus on formal objectives, on a year plan with milestones, on formal 1-on-1's between manager and employee and public recognition for good work done. Our second rule-of thumb is that an informal/bottom-up intervention likely increases Depth. That includes, for example, the translation of team goals to personal goals, informal team gatherings, celebrating team successes and facilitating knowledge sharing among employees. That said, we have found individual questions that seemed exceptions to these rules of thumb. Future research could shed a light on which approaches yield the best effect when reducing Width and/or increasing Depth. We fully realize that the sample of 'No Focus' respondents answering a particular question eventually becomes so small that we cannot draw conclusions whether specific questions go against our rules of thumb; just that there will be questions doing that.

Note that, when intervening, management will likely find respondents only partly aligned with their adjustments (one of ten critical alignment issues listed by Griffith and Gibson, 2001): a considerable part of the priorities planned by respondents themselves were at odds with the required intervention.

Although we did not research in depth the content of the scores for each of the four organizations in our first study, the management in each of the organizations benefitted certainly from a 'wisdom of the crowd'. The multinational discovered that most of the teams had lots of meetings, but also that most of them had no innovation objectives to discuss. The reinsurance firm realized to what extent employees were currently involved in the various objectives. The industrial company got a feel for what ways of working had not yet been implemented. And the colleges realized where they were lagging behind in certain aspects of teacher professionalism.

On a higher level of abstraction, our outcomes suggest that any organization's management might be faced with these ambition types in teams. And, given the development that employees more and more have to take decisions with a strategic impact autonomously, these outcomes should worry (top-)managers. The majority of respondents have either No Ambition, No Realism or No Focus. In that particular sense, there is not only a 'wisdom of the crowd' (analyzing the Actual scores and using the employees as 'the eyes and ears' of the organization), but also a 'folly of the crowd' as three of the four ambition types require management intervention. Respondents with No Realism need to work on a reasonable ambition: keep the Depth but reduce the Width. Respondents with No Ambition have to do the reverse: keep the Width but improve the Depth. And respondents with No Focus should both reduce the Width and improve the Depth. Simply put, there is certainly a wisdom of the crowd in change management but, when considering how inefficiently diverse team ambition is, there is also wisdom in analyzing and intervening the folly of the crowd. That said, we *infer* that as rules of thumb a formal/top-down approach likely reduces Width and an informal/bottom-up approach likely increases Depth. More studies are necessary to confirm which interventions will move what kind of respondents to the Focused Change area.

In our first empirical study, we have not researched why or how the respondents came to choose these four ambition patterns, just that these patterns do exist empirically. Additionally, due to the content of the available databases, we have not been in the position to correlate individuals' ambition with for example age, gender, nationality, managerial position, years of work experience, team composition, and team performance. Also, there is a need to further research why a significant portion of the respondents left the entire section on "In 6 months" blank. This could have been due, for instance, to fear (which would mean an important insight for the change management process) but also to incomplete instructions from our side

The prospect that these ambition types indeed have a generic character, affect most, if not all, teams and can be considered a pattern is very alluring. The comparison of likeness among industries hints at a generic nature of these types. Yet, we are also fully aware that we compared only eight industries of which half consisted of only two or three teams. In terms of Width, excluding the Industrial Services industry reduced the number of dissimilar industry pairs from 16% to 4%. The deviant score for the Industrial Services segment could be explained by a relative large percentage of lower-skilled employees in comparison to the other segments.

So far, our database did not provide an explanation for the scores of the Communication & Media industry. Comparing Tables 3.6 and 3.7, we can infer that we have indications – but certainly not conclusive – that the ambition types appear to be of a generic nature and can be regarded as patterns. Repeating this analysis in many more teams would help to confirm to what extent teams can be generally classified in one of the four patterns. As said, we have not researched why or how the respondents came to choose these ambition patterns, just that these patterns exist. So, the connection between the four ambition patterns and the two intervention styles is purely a mathematical one and has not yet been commented on by the respondents themselves nor tested on other groups of respondents. Future research could include team effectiveness factors that haven't been included in the available questionnaires, for example, alignment of business goals and process goals (Hartmann, 2011; Lepmets, McBride, & Ras, 2012), groupthink and group composition (Devine, 1999; Edman, 2006), and top management's trustworthiness (Henttonen, Johanson, & Janhonen, 2014). Knowing this might help to move teams into the desired Focused Change direction.

We have artificially drawn cut-off lines between the four patterns. Shifting the cut-off values will not only change the distribution of teams among the four patterns but might have an effect on the interventions as well. Moreover, we can imagine that there are 'No Ambition'-situations that are not bad at all, or at least not detrimental. This can be in a situation where rapid change is not required (for example in very stable businesses) or even discouraged (say, in a nuclear plant). The same holds for 'No Realism'-situations where 'moonshots' (Hamel, 2009) force organizations to think outside the box. Or, for example, such a 'No Realism'-situation can happen in an 'all or nothing'-situation where a team must dramatically break with its past situation and collateral damage is a lesser priority than its survival. Last but not least, we studied ambition patterns using a questionnaire on team effectiveness. More research is necessary to verify whether the proposed interventions equally hold value in, say, assessments of innovation- or IT service processes to support a more generic application of these patterns.

3.6 Conclusions

The prospect that very many – if not practically all – employees have generally applicable ambition patterns as we have identified here may dramatically change the way management will implement its strategic decisions. If the 'folly of the crowd' (i.e., harmful ambition patterns) is indeed more standard than not, management must alter its change management approach and, hence, strategic decision making, to include interventions to mitigate these patterns. By doing so, management might be much more successful (i.e., higher execution quality, shorter implementation time, fewer investments needed) in implementing its strategic decisions. The limited availability of research in this area combined with the apparently generic nature of these patterns and the methodological ease with which these patterns can be unearthed suggests that an exciting new avenue in team research lies ahead of us.

Chapter 4

Non-response and extreme response styles change appearance when using a modified Guttman scale

This chapter is largely based on:

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). Non-response/ERS change appearance in large scale employee surveys based on a modified Guttman scale. *Journal of Business and Psychology.* Under review.

4.1 Introduction

Organizations periodically go through phases of strategic decision-making and change management driven. Traditionally, strategic decision-making is about a sense of urgency, a vision, the empowerment of the organization, planning for improvements and ensuring that new approaches make these decisions a reality (Kotter, 1995). Yet, in recent years, strategic decision-making is getting ever more complex (Conteh, 2013) and the available time to implement these decisions is getting increasingly shorter (Kotter, 2012). This requires a structural approach to change management (Worley & Mohrman, 2014), which includes making smart choices from a supply of data bigger than ever before (McAfee & Brynjolfsson, 2012) as well as tapping the knowledge and experience of the entire organizational population (Surowiecki, 2005; Giles, 2005; Horkoff, et al., 2014). This 'wisdom of the crowd' offers additional insights to feed the strategic decision-making process and adds to the organization's competitive advantage (LaValle, Lesser, Shockley, Hopkins, & Kurschwitz, 2011). So, by tapping the knowledge and experience of nearly all employees, organizations may win in the marketplace.

Compared to tens to hundreds of employees within teams, an entire body of employees may involve several ten thousand or more employees within an organization. Certainly, these are much larger bodies of respondents than are usually required as a minimal sample size (Marshall, Cardon, Poddar, & Fontenot, 2013). When asking the entire organization, corrections for sampling errors such as not covering a representative cross section of the organization (Dillman, 2011) and key participation selection where "[participant] selection is conceptually driven by the theoretical framework" (Cleary, Horsfall, & Hayter, 2014, p. 473) are much less or no longer an issue. However, with these amounts of respondents and the time-pressure in change management situations, interviews would be too time-consuming and too labor-intensive. In those cases, certain types of online assessments are a good alternative (cf. Kang & Gratch, 2014).

When choosing for an online assessment of potentially thousands of employees, open ended questions are too cumbersome in terms of data processing (Reja, Manfreda, Hlebec, & Vehovar, 2003) given that automation through text mining in strategic decision-making and change management is still in in development (cf. Chen, Chiang, & Storey, 2012). As an alternative for the usual statement-driven employee surveys, we propose to use an assessment based on a modified Guttman scale. The answer options of this scale are formulated in more objective and verifiable terms to reduce, for example, self-perception bias and -leniency. By using new analytics, strategic decision-making and subsequent change management aspects like ambition, alignment, priority setting and knowledge sharing can be supported. Furthermore, the use of a modified Guttman scale may reveal patterns in how individual employees choose their priorities for the organization's near future. These analytics and resulting patterns help management to improve their strategic decision-making and the implementation of these decisions in terms of quality, cost and speed.

Company-wide online assessments are by and large unsupervised. On the one hand, this rules out experimenter and observer bias (issues described by Roulston & Shelton, 2015) and evaluator discomfort and evaluation leniency (issues described by Saffie-Robertson & Brutus, 2013). Using more objective rather than subjective survey scales (i.e., with a minimum of cognitive and emotional wording) should also reduce language bias (a problem raised by Harzing et al., 2009) and discourages a respondent to bias his or her responses (Donaldson & Grant-Vallone, 2002). We do realize that objective questions and answers are not so much an objective reality as a "reality created through people's experiences" (an issue raised by Sale, Lohfeld, and Brazil, 2002, p. 7): management and respondents accept that the questionnaire as such is an artifact of the organization's reality.

On the other hand, however, using a Guttman scale – even when paired with objective, verifiable answers– might lead to respondents compromising survey outcomes. Examples of compromising survey outcomes include giving random responses (Schwartz, 1986), applying extreme response styles (De Jong, Steenkamp, Fox, & Baumgartner, 2008) like an acquiescence response style or ERS (De Beuckelaer, Weijters, & Rutten, 2009), faking responses (Scherbaum, Sabet, Kern, & Agnello, 2012), committing self-deception (Zerbe & Paulhus, 1987) or giving no response at all (Scholz & Zuell, 2012). Fake responses and self-deception can only be estimated by a question-by-question verification of the responses. Given a number of hundreds, if not thousands of respondents that estimation is out of scope here. However, extreme response styles and non-response can be analyzed in a quantitative way.

There is much literature about factors influencing ERS and non-response (see Table 4.1, next page, for an overview). Some of these factors get recorded in organizations' Human Resources (HR) administration, like, for example, certain respondents' demographics and education. However, many respondents' demographics that may have an influence on response aren't usually administrated in organizations like the respondent's IQ (Meisenberg & Williams, 2008), -ethnicity (Morren, Gelissen, & Vermunt, 2012), -culture (Hoffmann, Mai, & Cristescu, 2013) and level of urbanism (Thomas, Abts, & VanderWeyden, 2014). Furthermore, HR departments usually do not record respondent's personality aspects like intolerance of ambiguity, the respondent's level of security (Diamantopoulos, Reynolds, & Simintiras, 2006), perfectionism (Stoeber & Hotham, 2013) or the respondent's level of maladjustment (Crandall, 1982). Also, HR departments usually do not record respondent's behavioral aspects like hard to elicit respondents (in medicine, Kypri, Samaranayaka, Connor et al., 2011) and respondents' attitude towards risky behavior (in medicine, Fergusson & Boden, 2015). Table 4.1 (next page) gives a sample overview of these factors, their effect on ERS and the applicability to our study.

Table 4.1

Factors influencing Extreme Response Styles (ERS)

Topic	Sample author(s)	Effect on ERS	Applicable to study	Applied in study
Demographics				
"Cultural" factors	Hoffmann, Mai, & Cristescu, 2013	+	--	--
"Demographics"	Weijters, Geuens, & Schillewaert, 2010	+	--	--
"Demographics"	Scholz & Zuell, 2012	+	--	--
Asian (vs. European) respondents	Hamamura, Heine, & Paulhus, 2007	+	--	--
Cultural minorities	Morren, Gelissen, & Vermunt, 2012	+	--	--
High average IQ	Meisenberg, & Williams, 2008	--	--	--
Higher education	He, Bartram, Inceoglu, & Van de Vijver, 2014	--	✓	--
Older age	He, Bartram, Inceoglu, & Van de Vijver, 2014	+	✓	✓
Urban (vs. rural) respondents	Thomas, Abts, & VanderWeyden, 2014	+	--	--
Personality				
Decisiveness	Wetzel, Carstensen, & Böhnke, 2012	++	--	--
Intolerance of ambiguity	Diamantopoulos, Reynolds, & Simintiras, 2006	++	--	--
Level of maladjustment	Crandall, 1982	+	--	--
Masculinity	Wetzel, Carstensen, & Böhnke, 2012	+	--	--
Perfectionism	Stoeber & Hotham, 2013	++	--	--
Personality	He & van de Vijver, 2013		--	
Power distance	Wetzel, Carstensen, & Böhnke, 2012	+	--	--
Respondent's sense of security	Diamantopoulos, Reynolds, & Simintiras, 2006	+	--	--
Simplistic thinking	Wetzel, Carstensen, & Böhnke, 2012	++	--	--
Behavior				
Hard to elicit respondents	Kypri, Samaranayaka, Connor, et. al., 2011	++	✓	--
Risky behavior	Fergusson & Boden, 2015;	+	--	--
	Maclennan, Kypri, Langley, & Room, 2012	++		
Environment				
Motivational aspects	Scholz & Zuell, 2012	+	✓	--
Wording				
Item relevance	Van der Kloot, Kroonenberg, & Bakker, 1985;	++	✓	✓
Lack of ambiquity	Diamantopoulos, Reynolds, & Simintiras, 2006	+	✓	✓

Effects: positive (++), somewhat positive (+), no effect (0), somwhat negative (-) and negative effect (--)

So, despite a wide variety of literature about factors influencing response styles, only a few of these factors are usually available on a wider scale for large numbers of employees (i.e., are a structural part of the employees' personal HR file) in organizations. However, in the databases available to us there was only access to basic demographics as the respondent's age, the number of years the respondent has been an employee of the present organization and his/her managerial position and that only for a selection of the respondents.

The objective of this study is to contribute to an approach for tapping the knowledge and experience of large numbers of employees about their organization in a strategic decision-making and/or change management situation. We want to study to what extent there is non-response and to what extent there are Extreme Response Styles (ERS) when using a modified Guttman scale in a large-size, unsupervised online assessment. Moreover, we also aim to study how the organization's management might intervene to reduce non-response and to mitigate extreme response styles.

4.2 Method

Procedure and participants

The present study was based on online, unsupervised team effectiveness assessments in 31 organizations coming from eight industries (both profit and non-profit). The assessments had been executed by various consultancy firms. Of these organizations, 29 were based in the Netherlands and two in the USA. The average team size was 12 employees. In these 31 organizations, 2,344 respondents gave a total of 133,795 answers. When looking at demographic information about these respondents, these assessments asked for one or more of the following three demographics: the respondents' age (average for the sample: 39.3 years, SD = 15.5), their years of service in the organization (average for the sample: 6.8 years, SD = 7.2) and their managerial level (37% was manager, 63% was employee).

Measures

As said, the scope of this study was to research whether large-scale employee surveys using a more objective Guttman scale (i.e., with a minimum of cognitive and emotional wording) would reduce non-response and extreme response styles. In order to capture each individual's view on how the organization needs to change, we assessed – for each individual and for each question in the questionnaire – three aspects: (1) how the employee sees the current situation, (2) how he/she would like to change that, and (3) in what time frame. The change that an individual respondent indicates for a single question in the questionnaire is the smallest 'vector of change'. When we aggregate these individual vectors (add up all the responses), the aggregated vector for the organization is the likely result. We modified a Guttman scale to capture – for each respondent and for each question – the actual status as well as the preferred situation. Therefore, we abstained from a dichotomous Fail/Pass Guttman scale (Hojo, 2008) and opted for a cumulative Guttman scale (Uhlaner, 2002) using more objective, comparable 'breaking points': it defines how far a respondent is or wants to go on a specific topic. A sample question is:

Q. How have you defined your team objectives?
Answer 1: We have no team objectives (yet)
Answer 2. We have a qualitative description
Answer 3. We have formal, SMART key performance indicators.

A Guttman scale works with current-status data (a term coined by Diamond, McDonald, and Shah, 1986). But, we can also cover the aspect of Time. For example, "Now we haven't any SMART key performance indicators but in 6 months we will". Below an example of how we added the time dimension. It represents the vector of a respondent's answer to a single question:

Q. How have you defined your team objectives?	Now	In 6 months' time
1. We have no team objectives (yet)	☐	☐
2. We have a qualitative description	☐	☐
3. We have formal, SMART key performance indicators.	☐	☐

The choice of questions and answers in the current studies have been subjectively chosen by the consultants and agreed by the organizations' management. Note the absence of adjectives and adverbs to reduce ambiguity (Diamantopoulos, Reynolds, & Simintiras, 2006) and interpretation bias (Van IJzendoorn, 1984): the answers given by the respondents could be seen as more objective and as verifiable as possible (cf. Frese & Zapf, 1988; Ahrens & Chapman, 2006) and there is no negative item content (Johnson, 2013). We used questions with three answer options to facilitate respondents in making a choice (Pongou, Tchantcho, & Tedjeugang, 2014).

Each of the surveyed teams was in the process of (re-)defining their team's way-of-working for which they needed a team effectiveness assessment. The individual questions had a generic angle with relevance to any team (Van der Kloot, Kroonenberg, & Bakker, 1985). For example: setting team objectives, involvement of team members in setting these targets, reviewing objectives, feedback within the team, handling conflicts, training opportunities, celebrating team success, possibility to disagree with the overall group opinion, clear team roles and 1-on-1 meetings with one's own manager. Our questionnaire was divided in three major clusters: (1) Objectives, (2) Communication, and (3) Collaboration. The abovementioned 'team objective'-question was an example from the first cluster. An example in Communication is:

Q. How is company news communicated internally?
  Answer 1. Not at all OR hardly
  Answer 2. Irregularly and mainly 'top-down'
  Answer 3. Regular updates and 2-way communication, visible to all.

And an example in Collaboration is:

Q. Do you celebrate team successes?
  Answer 1. Not at all OR hardly ever
  Answer 2. When the opportunity arises
  Answer 3. We make it a habit to celebrate team successes with the entire team.

The online survey set-up was in line with literature about the preferred 'logistics' regarding a survey. The assessment was sent out by the team manager or a higher-ranking manager or director. The link to the online assessment was included in the manager's/director's email and was addressed to the team as a whole. The assessment took approximately ten minutes at maximum to answer. Respondents could decide whether to include their name or not. However, respondents were encouraged to leave their name for getting in return an anonymous comparison of their personal scores with the scores of all other respondents sent to their email address. Respondents were also asked to provide their team name, age, presence (in years) in the organization and management position to underline the importance of their personal involvement in the assessment. This in contrast to anonymous employee surveys. Finally, respondents were asked whether they wanted to share knowledge with colleagues as an indicator for personal behavior and organizational culture. This knowledge sharing links to Surowiecki's requirement (2005, p. 72) for a means of aggregating knowledge.

Respondents were free to omit answers ("If you do not know the answer or the question is not applicable to you: please skip it"). Consequently, there was no specific "Don't know"- option. Also, respondents were free to score a question identical on both actual situation and ambition. Respondents were given roughly ten days to submit their answers after the survey launch. Given the business setting of these teams, there were no incentives, payments or other rewards: participating in an assessment required by management was considered 'part of the job'.

Data analysis

As shown above, each question had three answers. At the most granular level this score was available per individual respondent, per individual question and for both the 'actual' and a 'planned' situation. The first answer out of three was rated with a score of 0, the second answer with 5 and the third answer at 10. An average score for a group of questions covering one topic was achieved simply by averaging the individual questions' scores. Questions were not weighted in comparison to each other. The questions left blank were not tallied for the calculation of the score.

We dissected the Planned score (the ambition in 6 months' time) for the entire questionnaire in two components. The first was Width: the number of questions a respondent choose to improve within the next six months. The Width ranged from 0% (none of the questions in the questionnaire had to be improved) to 100% (all questions in the questionnaire had to be improved). The second component of the ambition was Depth: the percentage with which these selected questions had to be improved. The Depth ranged from 0% (the score of the selected questions in the questionnaire were not to be improved) to 200% (the score of the selected questions in the questionnaire had to triple).

An example: respondent 1 scores a 4.0 in the actual situation, and she wants to improve to a 6.0 in the next 6 months by improving 1/3 of the questions. That gives a Width of 33% and a Depth of 50% (6.0 divided 4.0 minus 1). Another example: respondent 2 scores a 3.0 in the actual situation and intends to improve to a 9.0 in the next 6 months by improving all of the questions. That gives a Width of 100% and a Depth of 200% (9.0 divided 3.0 minus 1). We then defined nine respondents' patterns: 5 'incomplete' response patterns (pattern 1 to 5) and 4 'complete' response patterns (pattern 6 to 9). The nine response patterns were:

1. No Actual score indicated: these respondents did not indicate their actual situation but did give (some) indication of their planned situation. We consider this 'incomplete' as the ambition score cannot be compared to a baseline actual score. Hence, the scores obtained give no indication of the size or the content of the respondent's ambition.

2. Questionnaire left blank: these respondents left the entire questionnaire blank. This is an 'incomplete' as the respondent opened the questionnaire, entered his personal data (name, department, role, age, etc.) but decided to quit the questionnaire after seeing the questions.

3. No Planned score indicated: these respondents did indicate their actual situation but did not give any indication of their planned situation. We consider this as 'incomplete' with the same argument as response pattern 1. Here, there is a baseline actual score, but no ambition score to gauge the ambition of the respondent.

4. Negative ambition: these respondents answered for some questions the actual situation and gave an indication of their planned situation for just a few others. The calculated ambition was negative because these respondents' Planned scores were lower than their Actual scores. We consider this an 'incomplete' as well being a combination of incomplete patterns 1 and 3. Some questions miss the ambition, other the baseline actual score. Hence, we deem this response pattern too polluted to be included in the overall analysis.

5. Actual score = Planned score: these respondents answered identically for both the Actual and the Planned score. As ambition is about change, we considered this the final 'incomplete' pattern. As organizations cannot be completely fixed in time (the literal interpretation of this response pattern). Other than refining the view on the actual situation such a response pattern doesn't help the organization's management in any way with regard to ambition and change management.

6. No Ambition: these respondents answered (most if not) all questions but only a few questions (less than 30% of the questionnaire) were planned to improve and then only by a small margin (less than 30% improvement). Hence, we consider this a 'complete' pattern as it provides – even if it isn't for all questions – an actual score and an ambition to compare it with. And this argument is valid for response patterns 7 to 9 as well.

7. No Focus: these respondents answered (most if not) all questions and many questions were planned to improve (more than 30% of the questionnaire) but only by a small margin (less than 30% improvement).

8. No Realism: these respondents answered (most if not) all questions, many questions were planned to improve (more than 30% of the questionnaire) and then by a wide margin (more than 30% improvement). Given the constraints that the ambition score refers to "in 6 months' time", we refer to respondents scoring here as having no realism.

9. Focused Change: respondents answered (most if not) all questions but only a small amount of questions was planned to improve (less than 30% of the questionnaire) but by a wide margin (more than 30% improvement). The name 'Focused Change' is based on the premise that changing a few topics and change them well (and repeat that cycle with other topics in a next period of – for example – six months, and so on) is the most effective of the four complete response patterns (cf. Foote, Elsenstat, & Fredberg, 2011; Ghosh, Martin, Pennings, & Wezel, 2014).

Next, we analyzed how these nine response patterns compared on the percentage of questions left blank and on the willingness to share knowledge among anonymous respondents. Also, we analyzed how these nine response patterns compared on extreme response styles. Therefore, we defined four different extreme response styles (partly derived from Diamantopoulos, Reynolds, and Simintiras, 2006; as well as from Wetzel, Carstensen, and Böhnke, 2012):

1. Midpoint responding: a respondent qualifies for this response style when s/he indicates for 90% or more of the questions the middle answer as the actual score.

2. Extreme Low: a respondent qualifies for this response style when s/he indicates for 90% or more of the questions the first answer as the actual score. This response style would be comparable to a 'disacquiescence' response style.

3. Extreme High: a respondent qualifies for this response style when s/he indicates for 90% or more of the questions the best answer as the actual score. In our Gutmann scale there is a clear best answer that could also be seen as the situation most desired by management. This response style would be comparable to an ‘acquiescence’ response style.

4. Extreme Both: a respondent qualifies for this response style when s/he indicates for 90% or more of the questions either the first or the third answer as the actual score.

To see where we could attach ‘hooks’ for management intervention to these response styles, we investigated what demographic variables were available in our database. We then compared the nine response patterns with respondent data available in each of the assessment: age, work experience at the organization, and management position. The rationale for this comparison was that each of these three aspects might help upper management to improve response. Older employees could be reminded about their expertise, younger employees about their youthful, fresh viewpoints. Employees already long employed in the organization know what didn’t work in the past, recent hires might have experiences at other organizations. Higher managers could be pointed at their responsibility to give the right example, employees could be pointed at their opportunity to speak up. To complete the comparison of the response patterns, we compared the non-response per individual question and for response patterns 3, 4 and 5 the Top-10 low-scoring questions. Because of lack of relevance, pattern 1 (no actual scores) and pattern 2 (no scores at all) were left out of the analyses.

4.4 Results

We present the results in seven different tables. Table 4.2 gives an overview per response pattern of anonymous respondents, questions left blank and willingness to share knowledge. Table 4.3 gives an overview per response pattern of the four different response styles. Table 4.4 gives an overview of factors affecting ERS. Tables 4.5, 4.6 and 4.7 show how age, presence in the organization and managerial position, respectively, differ for the nine response patterns. Finally, Table 4.7 shows the Top-10 low-scoring questions for response patterns 4 and 5.

Table 4.2

Some characteristics of response types

	N=	Answered anonymously	Questions left blank	Willing to share knowledge
Incomplete response types				
No Actual score indicated	10	0%	--	0%
Questionnaire left blank	26	39%	100%	23%
No Planned score indicated	370	40%	23%	17%
Negative ambition	361	27%	13%	28%
Actual score = Planned score	413	31%	22%	30%
Total / *Average*	**1,180**	***32%***	***21%***	***25%***
Complete response types				
No Ambition	735	20%	8%	34%
No Focus	79	11%	7%	56%
No Realism	303	13%	6%	54%
Focused Change	47	42%	16%	28%
Total / *Average*	**1,164**	***19%***	***8%***	***40%***
Grandtotal / *Average*	**2,344**	***26%***	***26%***	***33%***
Other aspects				
Anonymous respondents	606	100%	24%	5%
Named respondents	1,738	--	11%	43%
Those willing to share knowledge	780	4%	26%	100%
Those not willing to share	1,564	96%	45%	--

Table 4.2 shows the clear presence of incomplete response patterns in the database. The "N="-column shows how many respondents had an incomplete response pattern: 1,180 out of a total of 2,344 respondents (50%). Apart from "No Actual score indicated" and "Questionnaire left blank", the incomplete patterns are roughly divided equal (370, 361 and 413 respondents, respectively). For the 4 complete patterns "No Ambition" (735 respondents) and "No Realism" (303 respondents) are the prime patterns. Incomplete patterns have 32% of respondents responding anonymously. Complete patterns have 19% of respondents responding anonymously. The number of 'questions left blank' is 21% for the incomplete patterns and 'willingness to share knowledge' is 25%. For the complete patterns these percentages are 8% and 40%, respectively.

This high percentage of "Questions left blank" and the low percentage of "Willingness to share knowledge" for the incomplete response patterns may seem to indicate that these patterns are not just attributable to technical reasons (for example, not understanding the assignment of indicating a second answer, the Planned score, on the same question) but also to, for example, disengagement from the respondent.

In the "Other aspects"-section, we compare anonymity and the willingness to share knowledge. Of the named respondents 43% are willing to share knowledge. Of the anonymous respondents 5% is willing to share knowledge.

Comparing response patterns on extreme response styles

Table 4.3 gives an overview per response pattern of the four different response styles.

Table 4.3

Extreme response styles (ERS)

	Respondents with …						
	90% Mid	90% Extr-L	90% Extr-H	90% Extr-B	Tot. Resp w. ERS	Tot Resp.	Resp. w. ERS
Incomplete response types							
No Actual score indicated	--	--	--	--	--	10	--
Questionnaire left blank	--	--	--	--	--	26	--
No Planned score indicated	2	6	7	2	17	370	4.6%
Negative ambition	0	0	4	3	7	361	1.9%
Actual score = Planned score	6	21	13	1	41	413	9.9%
Total / *Average*	**8**	**27**	**24**	**6**	**65**	**1,180**	***5.5%***
Complete response types							
No Ambition	0	0	1	3	4	735	0.5%
No Focus	0	2	0	1	3	79	3.8%
No Realism	0	0	0	0	0	303	0.0%
Focused Change	0	0	0	0	0	47	0.0%
Total / *Average*	**0**	**2**	**1**	**4**	**7**	**1,164**	***0.6%***

Abbreviations: Mid = respondents showing a 'Midpoint' response style; Extr-L = respondents showing an 'Extreme Low' response style; Extr-H = respondents showing an 'Extreme High' response style; Extr-B = respondents showing an 'Extreme Both' response style; w. = with; Resp = Respondents; ERS = Extreme Response Styles

In an assessment asking for respondents' opinions using, say, a 5-point Likert-scale, it is not difficult to imagine that a percentage of respondents will answer in a neutral way by choosing for the vast majority of the questions the middle score of '3'. However, in our Guttman scale with more objective, verifiable answer options, choosing predominantly the middle answer would bring a respondent quickly into a moral dilemma: there is no need to score a lower 'middle' answer if the 'best' answer reflects the actual situation. Consequently, only 0.7% of the 'incomplete respondents' (8 divided by 1,180) and none of the 'complete respondents' have a Mid-response style. The 0.7% can further be explained by respondents who had answered only a few questions and had chosen the middle answer for these few questions. The Extreme Low and –High are more or less absent in the complete response patterns (3 divided by 1,164= 0.3%). This number can further be explained by that some respondents were verifiably scoring well across most, if not all, questions (there are respondents that work in very effective teams) and some very low (for example, respondents just getting on board in the team and not yet integrated in the daily operations of a team or in a situation of strongly disengaged team members). The Extra Both respondents (10 divided by 2,344 = 0.4%) might be respondents with a true extreme response style (not immediately interpreted like the other three response styles), yet, this 0.4% is practically negligible. In summary, with the use of this type of verifiable Guttman scale, extreme response styles do not seem to be a concern.

Table 4.4 shows how age differs for the nine response patterns.

Table 4.4

Age vs. response type

	Age ...							Chi-square			
	25 or younger	26-35 years	36-45 years	46-55 years	Older than 55	N =	As % of Total	Obs. χ^2	Crit. χ^2	df	Fisher's Cramer's V
Incomplete response types											
No Actual score indicated	--	--	--	--	--	10	--				
Questionnaire left blank	0%	1%	0%	1%	0%	8	31%				
No Planned score indicated	0%	1%	1%	2%	2%	40	11%				
Negative ambition	2%	4%	4%	3%	2%	55	15%				
Actual score = Planned score	0%	1%	0%	1%	1%	14	3%				
Total	**2%**	**7%**	**5%**	**7%**	**6%**	**117**	**10%**				
Complete response types											
No Ambition	5%	14%	10%	12%	7%	180	24%	15.16**	9.49	4	0.214**
No Focus	1%	1%	0%	1%	1%	16	20%	3.16	9.49	4	0.121
No Realism	3%	6%	4%	5%	0%	68	22%	24.81***	9.49	4	0.315***
Focused Change	1%	1%	0%	0%	0%	10	21%	10.96**	9.49	4	0.229**
Total	**9%**	**23%**	**15%**	**18%**	**8%**	**274**	**24%**				
Grandtotal	**11%**	**30%**	**20%**	**25%**	**14%**	**391**	**17%**				

The percentages for the patterns/age brackets add up diagonally to 100%
The "As % of total"-column shows per pattern for how many respondents "age" had been recorded
Right part of the table shows the observed and critical χ2, the degrees of freedom. α = 0.05.
** p ≤ .05, ** p ≤ .01, *** p ≤ .001.*

In this table, the "N="-column shows how many respondents in the database were asked and had indicated their age: 391 out of a total of 2,344 (i.e., 17%). Reading the table horizontally only shows how respondents were distributed along their age. Reading the table vertically shows how much more respondents with complete response patterns indicate the age compared to their colleagues with incomplete response patterns. Remind that in Table 4.1 we showed that the number of 'complete' respondents was almost equal to the number of 'incomplete' respondents (1,164 versus 1,180).

We tested three separate contingency tables with the four types of ambition as rows and the categories for age, presence in the organization and managerial level as columns. The right part of Table 4.4 shows the outcome. We tested the following hypotheses:

H_1 = There is a relation between the ambition types and age

H_2 = There is a relation between the ambition types and years of presence in the organization.

H_3 = There is a relation between the ambition types and managerial level

We phrase these hypotheses in a neutral way. It may be equally true that younger respondents have more ambition (the proverbial brash youth who do not oversee the consequences of their ambition) as that they have less ambition (their inexperience doesn't give them the guidelines to make a choice among the options presented by management). A similar reasoning can be made for respondents new to the organization and for lower managers/employees.

As some of the categories had less than five respondents (for example, both the No Focus- and Focused Change respondents for each of the age categories), we added a Fisher's exact test to the Chi-square test as an additional analysis. We calculated Cramer's V instead of Pearson's Phi as the contingency tables are larger than 2*2. For example, there are four types of ambition and five age categories. We interpreted Cramer's V following Van den Berg (2016). We may conclude that 'Age' is significantly associated with ambition when combining all four types of ambition. When breaking these up we see significant associations between 'Age' and No Ambition and No Realism respondents. Younger respondents will more likely be a No Realism- or Focused Change type. Older respondents are more likely to be of a No Ambition type. However, remind that sample sizes for No Focus (16 respondents) and Focused Change (10 respondents) may be not large enough to draw any firm conclusions.

Table 4.5 shows how the years the respondent had been an employee of the organization differs for the nine response patterns.

Table 4.5

Presence in the organization vs. response type

	Presence ...							Chi-square			
	< 1 year	1 - 5 years	6 - 10 years	11 - 15 years	Longer than 15	N =	As % of Total	Obs. χ^2	Crit. χ^2	df	Fisher's Cramer's V
Incomplete response types											
No Actual score indicated	--	--	--	--	--	10	--				
Questionnaire left blank	0%	1%	1%	0%	0%	10	38%				
No Planned score indicated	0%	2%	2%	1%	2%	44	12%				
Negative ambition	2%	7%	2%	2%	2%	62	17%				
Actual score = Planned score	0%	2%	1%	1%	1%	15	4%				
Total	**3%**	**12%**	**6%**	**3%**	**5%**	**131**	**11%**				
Complete response types											
No Ambition	7%	19%	9%	4%	9%	188	26%	34.19***	9.49	4	0.441***
No Focus	1%	1%	2%	0%	1%	16	20%	13.70**	9.49	4	0.509**
No Realism	2%	9%	3%	2%	3%	70	23%	30.28***	9.49	4	0.575***
Focused Change	1%	1%	1%	0%	0%	10	21%	17.73***	9.49	4	0.604***
Total	**10%**	**29%**	**14%**	**6%**	**12%**	**284**	**24%**				
Grandtotal	**13%**	**41%**	**19%**	**9%**	**17%**	**415**	**18%**				

The percentages for the patterns/age brackets add up diagonally to 100%
The "As % of total"-column shows per pattern for how many respondents "age" had been recorded
Right part of the table shows the observed and critical χ2, the degrees of freedom. α = 0.05.
** p ≤ .05, ** p ≤ .01, *** p ≤ .001.*

A pattern similar to Table 4.4 unfolds here. Roughly the same number of respondents indicated their years of presence (18%) compared to age (17%). In terms of 'Years of presence in the organization', the combined ambition shows no association. Yet, when breaking up Presence across the four ambition types there seems to be a significant association. Some of the percentages in Table 4.5 represent (very) small numbers of respondents. For example, there were only three 'No Focus' respondents that were less than one year in their organizations. As said, we added a Fisher's exact test as an additional analysis and calculated Cramer's V instead of Pearson's Phi as the contingency tables are larger than 2*2. However, the high Cramer's V values might indicate a *too* strong association (above 0.5): the two variables are probably both measuring some other concept. Hence, we remain inconclusive whether there is a significant association between 'Years of presence in the organization' and the four ambition types.

Table 4.6 shows the managerial level versus the response type.

Table 4.6

Managerial level vs. response type

	Level ...					Chi-square			Fisher's
	Higher M'ment	Lower M'ment	Employee	N =	As % of Total	Obs. χ^2	Crit. χ^2	df	Cramer's V
Incomplete response types									
No Actual score indicated	--	--	--	10	--				
Questionnaire left blank	0%	0%	0%	11	42%				
No Planned score indicated	0%	1%	17%	287	78%				
Negative ambition	1%	2%	12%	245	68%				
Actual score = Planned score	1%	2%	17%	313	76%				
Total	**3%**	**5%**	**46%**	**856**	**73%**				
Complete response types									
No Ambition	6%	6%	21%	515	70%	6.45*	5.99	2	0.163*
No Focus	1%	1%	1%	39	49%	1.92	5.99	2	0.283
No Realism	2%	2%	5%	146	48%	3.37	5.99	2	0.214
Focused Change	0%	0%	2%	33	70%	14.76***	5.99	2	0.834***
Total	**8%**	**9%**	**29%**	**733**	**63%**				
Grandtotal	**11%**	**14%**	**75%**	**1,589**	**68%**				

Abbreviation: M'ment = Management

The percentages for the patterns/age brackets add up diagonally to 100%

The "As % of total"-column shows per pattern for how many respondents "age" had been recorded

Right part of the table shows the observed and critical χ2, the degrees of freedom. α = 0.05.

** p ≤ .05, ** p ≤ .01, *** p ≤ .001.*

Many more respondents indicated their managerial position (68%) than presence in the organization (18%) and age (17%). For Managerial Level, we see two contradicting outcomes when combining the four types of ambition. When breaking into the four types, we see a very weak Cramer's V for No Ambition, too high p-values for No Focus and No Realism, while the sample size for Focused Change (33 respondents, see Table 4.6) is very small. Therefore, we conclude there is no significant relation between 'Managerial Level' and the four types of ambition.

Comparing response patterns on non-response

Despite the design of the survey scale and the more objective wording of the questions and answers, there might be employees who may just not be capable – or willing – to answer the questions. To really ensure that the 'item relevance' and 'lack of ambiguity' had been warranted, we investigated the non-response percentages for response patterns 3 to 9 per individual question (the "No actual score indicated"- and "Questionnaire left blank"-patterns are not relevant here).

In our databases, the percentages of non-response per question varied between 43% ("Is there financial support for new initiatives/activities?") and 5% of the respondents ("Are there sufficient resources available to do your job?"). We can imagine that many respondents (including lower management) cannot answer a question like "Is there financial support for new initiatives/activities?" It's perhaps too managerial for employees. Yet, 23% of respondents did not answer "How do you volunteer for new tasks?" 13% of respondents did not answer "To what extent do you celebrate team successes?” and 8% of respondents did not answer “Do you have 1-on-1 meetings with your manager?” It comes to mind that the term ‘1-on-1 meeting’, ’structured’ or ‘periodic’ was perhaps too ambiguous, a too unfamiliar wording or perhaps too managerial. Whether one volunteers for new tasks or not or whether one celebrates or not with the team is something one knows. Yet, slightly less than 1 out of 7 respondents did not answer that question. In summary, despite the more objective, non-ambiguous question set-up, non-response is still present.

To research what factors drive the incomplete response patterns, Table 4.7 (next page) shows the Top-10 low-scoring questions for response patterns 3, 4 and 5.

For each of the incomplete response patterns 3, 4 and 5 (the “No actual score indicated”- and “Questionnaire left blank”-patterns are again not relevant here), we have calculated the score on that question for those respondents that did answer it and compared it to the average score of all ‘complete’ respondents on that same question.

We see that the ‘No planed score indicated’-respondents (31% of the incomplete patterns and 16% of total respondents; see Table 4.2) indeed score lower than the ‘complete’ respondents on questions that likely indicate engagement: less celebration of success, are not teaming up with a mentor or mentee, meet less out of work, know less their own task/responsibilities, are less involved in defining team goals, get less recognition and are least able to set their own agenda. Note that only for some questions we found a significant difference between the ‘No Planned score indicated’-respondents and the average score for the ‘complete respondents’ on that question. For example, the “Own tasks/responsibilities known” (F_{obs} = 34.03, p < .001) question shows such difference.

The conclusion for the ’Actual score = Planned score”-respondents is more mixed. On some questions they score higher than the average of the ‘complete’ respondents. For example, on “Involved in team goals” and “Celebrating team success”. On other questions the ’Actual score = Planned score”-respondents score low. For example, with regard to “Agreement on personal development” and to “Support for new initiatives”. Yet, of the top-10 lowest scoring questions we found one question with a significant difference with regard to the average ‘complete’ respondent: “Personally part of mentor/mentee couple” scored F_{obs} = 4.56, p < .05). However, a clear and consistent profile can’t be drawn.

The ‘Negative Ambition’-respondent scores also better on some questions – and worse on others – than the ‘complete’ colleagues. ‘Negative ambition’-respondents’ top-10 lowest scoring questions. The latter scored higher on “Manager informs team” (F_{obs} = 4.77, p < .05) but less on “Support for new initiatives” (F_{obs} = 5.03, p < .05).

4.5 Discussion

Tapping the knowledge and experience of (nearly) all employees in an organization to support management in their strategic decision-making and subsequent change management is more than a welcome addition to data already available in the corporate data warehouses. Data in the corporate data warehouses do not have intentions or plans, but employees do. So, we captured in an online assessment both the actual situation of the organization as well as the intentions and plans of a large body of employees given the strategic options as laid out by upper management in an online assessment. This is the 'wisdom of the crowd' (Surowiecki, 2005; Giles, 2005) in action: a large group of employees may outperform (here: offer additional insight to) a small group of specialists (here: management). We chose an unsupervised, online, multiple-choice survey to allow for getting input from a large body of employees quickly. We forewent on the traditional employee survey structure featuring statements and instead opted for a modified Guttman scale with more objective, verifiable 3-option answer patterns with an additional time dimension. The aim of the present study was to investigate the effect of our modified Guttman scale on two methodological drawbacks of working with surveys: extreme response styles (ERS) and non-response.

We identified five different incomplete response patterns. The incompleteness existed in the failure of the respondent answer pattern to represent a 'vector of change': what did a respondent want to change and by when? We also identified four complete respondent patterns: although not every question needed to be answered, there were sufficient answers to determine such a vector.

The results indicated that the incomplete response patterns were not just attributable to technical reasons (for example, not understanding the assignment of indicating a second answer, the Planned score, on the same question). These incomplete patterns also likely indicated respondent disengagement as these 'incomplete' respondents were more anonymous, left more questions blank and were much less willing to share knowledge than the 'complete' respondents. So, there is a value of non-response as an indicator of employee disengagement.

We also investigated the presence of extreme response styles, a topic of much debate with Likert scales (De Jong, Steenkamp, Fox, & Baumgartner, 2008). In our modified Guttman scale with more objectively worded answer options, extreme response styles were almost absent.

Next, we compared how age, years of presence in the organization and the respondents' managerial position (data that is usually registered in HR files) were related to the incomplete patterns. Our analysis showed that older respondents (the importance of age has been indicated by He, Bartram, Inceoglu, and Van de Vijver, 2014) and employees (compared to managers) had significantly higher percentages of incomplete response types. We found that 'Age' was significantly associated with ambition. However, neither 'Years of presence in the organization' nor 'Managerial Level', had a significant relation with ambition.

We then investigated whether non-response per individual question may explain the incomplete response patterns. On the one hand, we saw – across all the patterns – relatively large percentages of respondents omitting questions on which they must have known the answer. Focusing on how the incomplete patterns scored on individual questions revealed – despite the non-response – for one of the patterns ('No planned score indicated') a possible explanation: strong disengagement of the respondent. For two other incomplete patterns ('Actual score = Planned score' and 'Negative ambition'), we could not find an explanation, and two more incomplete patterns ('No Actual score indicated' and 'Questionnaire left blank') contained no data to work with at all.

Theoretical implications

We have approached our analysis of Extreme Response Styles (ERS) similar to how ERS has been analyzed by for example, Wetzel, Carstensen, and Böhnke (2013): we looked at extreme answering and midpoint answering. Our results show that these response styles hardly appear with our Guttman scale. Yet, the incomplete response patterns could be regarded as just other examples of extreme response styles. Conversely, as there is literature on how to mathematically correct for ERS (cf. Plieninger & Meiser, 2014), there is much to be gained in mathematical solutions to correct for our incomplete patterns, for example using association rules.

We were able to conclude that a part of the 'incomplete' respondents were the result of disengagement. We realize there are many other factors that could be relevant as well, for example, the employees' dependence on the manager, the employees' caring about the strategic issue at hand and management's behavioral integrity (whether management does what it says; an issue raised by Simons, 2002) may influence respondent participation. If we consider that, for example, respondents whose participation is hardest to elicit report riskier behavior (in medicine, Kypri, Samaranayaka, Connor, Langley, & Maclennan, 2011) and that peer-ratings influence ERS (Naemi, Beal, & Payne, 2009) there are many other aspects to integrate for a complete understanding of incomplete respondents. Unfortunately, these aspects were not part of the databases available to us. And we doubt that these aspects are structurally monitored in the organizations' HR-files. To conclude, non-response can likely be attributed to disengagement, but only for roughly one third of the incomplete patterns.

Practical implications

An upper management of any organization may benefit of the 'wisdom of the crowd': asking lower managers and employees about their priorities among strategic options the organization has. Then it is of the utmost importance that the input gathered is as objective and noise-free as possible. Our modified Guttman scale provided as objective as possible answers (i.e., not influenced by personal feelings, cognitions, emotions, interpretations, or prejudice; based on facts; unbiased). Yet, it is also important to verify whether respondents are able to tamper with the results or - perhaps unknowingly – introduce some sort of pollution of the data.

The near absence of ERS almost eliminates this kind of pollution. It makes the processing of outcomes easier than with other methods to capture the input from large numbers of employees (like, for example, the employee engagement survey build on questions asking for opinions): there is no need for management to apply additional calculations or filters to accommodate the ERS.

With regard to non-response, we saw on the one hand that roughly half of the respondents were incompletes. On the other hand, the large number of employees might quickly result in insightful response (cf. Cleary, Horsfall, & Hayter, 2014), whatever the percentage of incomplete respondents. It is always good to know from each team how they are doing to apply the proper interventions in favor of the change management process. Yet, from a certain percentage of response (in our databases that percentage was around 35% of the final number of respondents), the overall picture of the organization's situation will not materially change with any next additional respondent. That means, that a possible damaging effect of 'incomplete' respondents on the quality of the overall survey outcome might only in occur in small respondent samples combined with a high percentage of 'incomplete' respondents. Therefore, and similar to ERS, there seems little need for additional calculations or filters to accommodate or absorb the non-response.

Cheap online assessment software in combination with dedicated analytics might very likely reduce the barrier to perform strategic, organization-wide surveys. In turn, that will lead to more longitudinal studies. Our scale design is different from the Longitudinal Guttman Simplex (e.g., Hays & Ellickson, 1991). This Simplex compares response patterns of a Guttman-based answers (the 'Now'-score) over time and does not require respondents to define a delta between actual and preferred situation. We saw that the near absence of ERS and the likely small or absent influence of non-response on the quality of the overall survey outcomes likely eliminates the need for additional calculations or filters. That facilitates the comparison over time when comparing survey outcomes longitudinally. With more sequential surveys with longitudinal data, it will be interesting to see whether incomplete respondents become complete respondents (a phenomenon described by Gray, 2015) or whether respondents with a certain pattern move to another (for example, 'No Ambition'-teams moving over time to a 'Focused Change'-pattern).

Limitations and future research

There are several cautionary remarks that could be made about our approach which also fuel the need for more research. Firstly, the choice of questions is – despite being well-intended – scientifically arbitrary. In hindsight, we deemed some questions perhaps too managerial for employees to answer. Maybe other questions had yielded much more insight and explanatory value. Secondly, the choice of what described the first, second and third answer was also arbitrary. It was possible to make the answer options that easy that everyone would score 10 out of 10. Likewise, it was possible to make the answer options that difficult that everyone would score 0 out of 10. Yet, as said, we do realize that the selected questions and answers are not so much an objective reality as a "reality created through people's experiences" (an issue raised by Sale, Lohfeld, and Brazil, 2002): management and respondents accepted that the questionnaire as such was an artifact of the organization's reality. Thirdly, there was not enough data available to investigate two of the incomplete response patterns. In fact, we had not enough data to compare incomplete response patterns among various industries (similar to what we did with complete patterns in Table 3.6 and 3.7). Implicitly, we have referred to incomplete response *patterns* while we could only refer to incomplete response *types.* Clearly, further research is needed here.

We concluded that a part of the respondents with incomplete response patterns scored very low on team effectiveness aspects that would otherwise characterize an engaged employee (e.g., be part of a mentor/mentee couple, getting support for new initiatives, having the possibility to determine one's own work agenda). We haven't researched whether changing these aspects would over time convert these respondents to a more engaged state. We also realize that we have used only a few criteria to segment the respondents: anonymity, questions left blank, willingness to share knowledge, age, years of presence in the organization and management position. There are many more segmentation criteria that are regularly and relatively easily available in the organizations' HR administration that could further benefit the understanding of incomplete response patterns like team turnover, annual review scores, percentage of workdays absent, bonuses received, highest formal education received, etc.

Future research in larger respondent bodies in various organizations may show whether the response patterns and phenomena that emerged in these organization will materialize elsewhere too.

4.6 Conclusions

In recent years, strategic decision-making has become more complex and under heavy time constraints. Hence, it is wise for upper management to capture the collective input of the lower managers and employees in the organization. Traditional interviews-based assessments of aspects of strategic decision-making and change management usually focus on small amounts of respondents who indicate their agreement with, or give a rating of, certain statements. The main sampling question is then “Who shall we interview?” and mostly opinions are recorded.

As we have used a different survey scale to capture more objective input of respondents, we need assure that we cover two important issues of working with surveys: extreme response styles (ERS) and non-response. Our approach focused on using a more objective, verifiable Guttman scale. Consequently, this scale might have helped to nearly eliminate ERS. Whatever the imperfections of our approach that we have encountered, we do feel that the use of our modified Guttman scale in company-wide employee assessments adds to the granularity of the insights provided to the upper management of an organization. The lack of ERS and the link of no response with engagement provide further handles for upper management to enrich their strategic decision-making and change management.

Then there is the other aspect of non-response. The main sampling issue in our approach was “Who has *not* answered?”. Apparently, tapping this ‘wisdom of the crowd’ means that far away from upper management, perhaps in the periphery of the organization, groups of employees are not willing to let management tap their knowledge and experience or perhaps are not even capable to have any strategic wisdom to share. In case respondents are capable but not willing, disengagement is one of the factors to consider. For management that truly wants to tap the wisdom of their employees, this means that they have both to engage employees and train them as the ‘eyes and ears’ of the organization.

Modifying a Guttman scale to cater for new analytics of large bodies of employees does affect certain unfavorable aspects of current employee surveys. While ERS appears to be completely neutralized, non-response does surface again, albeit in a complete different appearance.

Chapter 5
Assembly into a pattern recognition process

This chapter is partly based on:

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2017). Identifying team ambition patterns in change management. *Journal of Change Management.* Under review.

5.1 Introduction

The discovery of the ambition types in Chapter 3 should be verified as truly being patterns if we ensure that all steps of a pattern recognition process have been followed. Pattern recognition has taken a big step since the Big Data trend allowed to move from statistical pattern recognition to stochastical pattern recognition. Recognition of handwriting, images, speech and text have since become almost commonplace. Mumford has elaborated on pattern recognition with his Manifesto of Pattern Theory (Mumford & Desolneux, 2010, pages 1-4):

> "1. A wide variety of signals result from observing the world, all of which show patterns of many kinds. These patterns are caused by objects, processes, and laws present in the world but at least partially hidden from direct observation. The patterns can be used to infer information about these unobserved factors."
>
> "2. Observations are affected by many variables that are not conveniently modeled deterministically because they are too complex or too difficult to observe and often belong to other categories of events."
>
> "3. Accurate stochastic models are needed that capture the patterns present in the signal while respecting their natural structures. These models should be learned from the data and validated by sampling: inferences from them can be made by using Bayes' rule, provided that the models' samples resemble real world signal."
>
> "4. The various objects, processes, and rules of the world produce patterns that can be described as precise pure patterns distorted and transformed by a limited family of deformations, similar across modalities."

This is all applicable to this thesis. We have used real world signals/data. We have generalized interventions. Yet, we haven't done formal validation and we have only partly indicated deformations (for example, by analyzing the incomplete response patterns in Chapter 4). So, a step-by-step evaluation of a formal, generic pattern recognition process is in place. The field of pattern recognition is so immense that we cannot create an all-encompassing recognition process. Pattern recognition consists of five different schools of thought as summarized in Table 5.1 (Domingos, 2015).

Table 5.1
Five 'schools' in Pattern Recognition (c.f. Domingos, 2015)

School	Representation	Evaluation	Optimization
Symbolists	Logic	Accuracy	Inverse deduction
Connectionists	Neural networks	Squared error	Gradient descent
Bayesians	**Graphical models**	**Posterior probability**	**Probabilistic inference**
Evolutionaries	Genetic programs	Fitness	Genetic search
Analogizers	Support vectors	Margin	Constrained optimization

As we cannot exclude that certain schools of thought will be applied for pattern recognition in strategic decision-making and change management, it is on the one hand necessary to include each of these schools into our formal pattern recognition process template. It is on the other hand impossible to do justice to each of these schools while keeping the pattern recognition process template practical enough. Hence, our 10-step process is a gross oversimplification of an enormous field in science. As the source of the patterns in this thesis is the 'Focus Field'-matrix – a graphical model – as depicted in Chapter 3, Figure 3.1, we have highlighted in Table 5.1 the Bayesian row in bold.

Hence, we have searched for authors describing such a process and for authors zooming in on parts of that process. For a formal, step-by-step evaluation we preferred the work of Duin (Duin & Pekalska, 2007) over that of, for example, Fayyad (Fayyad, Piatetsky-Shapiro, & Smyth, 1996) due to the more elaborate steps of the former, the focus on describing a pattern recognition vocabulary and definitions as well as a higher attention to classification techniques. The pattern recognition process of Duin is an 8-step process from defining an 'object to be recognized' to 'evaluation'. This pattern recognition process is meant for pattern recognition in, for example, handwriting. These patterns do not need interventions. In this example, how should a person change his handwriting to make it more legible is not an issue to address. However, in our study we do have interventions. For example, a No Ambition team should work on increasing depth by working on informal/bottom-up aspects of team management.

Hence, I discussed with the author (Duin) how to extend the 8-step process with interventions. The result is summarized in a 10-step process with 40 underlying aspects in Table 5.2 (next page). Additionally, the table shows sample literature provided by the author (Duin) for each of the pattern recognition process steps' underlying aspects. Each aspect is shortly discussed in the text below.

With this 10-step generic process as a basis, it is possible to verify whether we have taken all the necessary steps in our own pattern recognition process and fill any voids left out so far. The first-time process steps and aspects get indicated, we will use italics. Plus, when applicable, we indicate per step what could be improvements for studying a next pattern. Table 5.3 shows how these ten steps relate to the five schools of pattern recognition:

Table 5.3

Five 'schools' in Pattern Recognition, applied to our process steps

School	Representation	Evaluation	Optimization
Our steps	*Step 1 to 4*	*Step 5 to 8*	*Step 9 and 10*
Symbolists	Logic	Accuracy	Inverse deduction
Connectionists	Neural networks	Squared error	Gradient descent
Bayesians	**Graphical models**	**Posterior probability**	**Probabilistic inference**
Evolutionaries	Genetic programs	Fitness	Genetic search
Analogizers	Support vectors	Margin	Constrained optimization

Table 5.2

Pattern recognition process

Process steps	Sample aspects	Sample author(s)
1. Object to be recognized	Unknown classes	Ripley, 2007
	Invariants	Spencer, 1971
2. Sensor	Specific class	Schalkoff, 1992
	Question type/scale	Albaum, 1997
3. Representation	Learning methods	Hastie, Tibshirani, & Friedman, 2009
	(Un-)labelled data	Li & Zhou, 2015
	Feature set	Questier, Arnaut-Rollier, Walczak, & Massart, 2002
	Features	Bishop, 2006
	Feature space	Frasch, Lodwich, Shafait, & Breuel, 2011
	Attributes	Schalkoff, 1992
4. Design set	Train set	Duin, 2002
	Real-world data	Mumford & Desolneux, 2010
	No overtraining/overfitting	Jain, Duin, & Mao, 2000
5. Adaptation	Data cleansing/neutralization	Gemp, Theocharous, & Ghavamzadeh, 2017
	Incompleteness	Parsons, 1996
6. Generalization	Structural pattern recognition	Bunke & Riesen, 2012
	Reasoning patterns	Kuosa, 2011
	Curse of dimensionality	Bellman, 1961
	Feature reduction	Świniarski, 2001
7. Classification	Identification accuracy	Yu, 2011
	Examples of classification techniques:	
	Dissimilarity-based pattern recognition	Duin & Pekalska, 2007
	Multi-layer perceptron	Zahiri, 2008
	Nearest neighbor	Zahiri, 2008
	Particle swarm	Zahiri, 2008
	Binary classification	Proctor & Cho, 2006
	Class density	Silverman, 1986
	Pattern abnormality	Lu, Shao, & Li, 2011
8. Evaluation	Validation data set	Ljung & Guo, 1997
	3-times validation	Spiliopoulos, 2013
	Quantify the evidence quality	Guil & Marín, 2013
9. Intervention	Supervised learning	Zhu, 2005
	Semi-supervised learning	Zhu, 2005
	Reinforcement learning	Sutton & Barto, 1998
	Pattern activation	Du Castel, 2015
10. Binarization	Stochastic-to-binary conversions	Canals, Morro, & Rosselló, 2010
	Flow charts, decision trees	Rokach & Maimon, 2014

Step 1: Object to be recognized

The definition of the object is "it has an unknown class and it is the task of the system to derive this class from its observations. An example is the heart beat of patient that should be classified as normal/abnormal" (Duin & Pekalska, 2015, p. 17). In our ambition pattern study, the object could be defined as the aggregated view of the employees regarding strategic options provided by management. The strategic options are defined by management by choosing specific questions and answers in the survey. But it is not the alignment of the employee- and management view per se. In our experience at Transparency Lab, in almost all projects management wants to gauge the employee view as 'testing the water' before deciding for a final course of action. In sports analogy, management defines the playing field and lets the employees do a test game/dry run. In that sense, at the most granular level in our study, the individual employees' ambition (their answers in the questionnaire) is the object.

Taken literally, invariants are expressions that do not change during the execution of a program. In pattern recognition, they are object properties that are not relevant for class differences are named. For example, in facial recognition, it may be the position of the nose in an image. In our study, while looking for generic ambition patterns, we assumed, for example, in Chapter 3 the assessment topic, the organizations' industry, the length of questionnaire, the team's size and the 30%-30% cut-off values as invariants. In Chapter 4, we assumed respondents' personality as an invariant. A possible void to fill here is the requirement to formally list the invariants. Some of these invariants can be statistically confirmed as an invariant (e.g., the length of the questionnaire). Other invariants are so because of an arbitrary choice.

Step 2: Sensor

In pattern recognition, the sensor can be the microphone that picks up a signal. In our study, the sensor is not just the phenomenon of the online questionnaire itself, but also the choice of a Guttman scale and the comparison with employee surveys as discussed in Chapter 2. To a wider extent, our sensor also includes the 'logistics' surrounding an online assessment. These were mentioned implicitly in Chapter 4. Sensor design may have an influence on the recognition of the pattern, so a formal accountability of all sensor aspects is in place. Hence, to fill the void, we have summarized a sample overview of logistics in Table 5.4 (next page) searching for papers on survey design. Recommendation for a next pattern is to verify whether the logistics that we did not apply (for example, incentives to respond) should be considered.

Table 5.4

Questionnaire 'logistics' and the effect on response

Sample aspect(s)	Sample author(s)	Effect	Applicable to study	Applied in study
Question content				
Meaningful questions neutralize ERS	Van IJzendoorn, 1984	++	✓	✓
Other respondent data				
Anonimity as an option	Damrin, 1947	0	✓	✓
Managing "Don't knows"	Zeglovits & Schwarzer, 2016	++	✓	✓
Delivery & timing				
Preliminary notification	Yu & Cooper, 1983	+	✓	-
Personal delivery (e.g. envelope)	McCoy & Hargie, 2007	--	✓	-
Personalization	Sauermann & Roach, 2013	++	✓	✓
Questionnaire printing format	Jobber, 1989	--	-	
Contact time of the day	Sauermann & Roach, 2013	0	-	-
Allowed response time	McIntyre, 2011	0	-	-
Sequence of data collection	Covell, Sidani, & Ritchie, 2012	0	-	-
Warnings	Clifford & Jerit, 2015	++	✓	-
Late respondents	Studer et. al, 2013	--	✓	-
Wording of reminders	Sauermann & Roach, 2013	++	✓	-
Incentives to respond				
Sponsorship	Schneider & Johnson, 1995	++	-	-
Help-the-sponsor	Schneider & Johnson, 1995	++	-	-
Monetray rewards	Schneider & Johnson, 1995	++	-	-
Lotery incentives	Sauermann & Roach, 2013	++	-	-
Pre-paid cash incentives	LaRose & Tsai, 2014	++	-	-
Sweepstakes	LaRose & Tsai, 2014	+	-	-
Other				
Computer based survey	Kang & Gratch, 2014	+	✓	✓

Effect: positive (++), somewhat positive (+), no effect (0), somewhat negative (-) and negative effect (--)
Applicable/Applied: ✓ = Yes, - = No

Step 3: Representation

The representation of the object is a prerequisite for classification. As there were no pre-established ambition-classes, we focused on unlabeled data/unsupervised learning (cf. Li & Zhou, 2015) based on a feature set consisting of Width and Depth as two features of a stacked histogram showing per question the Actual- and Ambition scores of respondents. The feature space is then the ‘Focus Field’-matrix (see Chapter 3, Figure 3.1) that has Width on the X-axis and Depth on the Y-axis. Its attributes are, for example, the axes-dimension (percentages) and axes-range (Width: 0% - 100%, Depth: 0% - 200%). No specific voids to fill. For a next pattern, it is recommended to formally review this list of aspects when choosing another representation than we did here, e.g., when using non-graphical representations.

Step 4: Design set

The design set is a set of objects, preferably drawn at random from the same source as the future objects to be classified. All or many of these objects should have a known class label: their true class memberships should be known. They are used for optimizing the representation (the adaptation of an initial representation to the demands of the classifier) and for classifier training. (Duin & Pekalksa, 2007). We consider the available database of respondents as the design data set and they have indeed been drawn at random from the same source as the future objects to be classified. In Chapter 2, we used the data from five teams and three organizational layers within one organization. In Chapter 3, we first used 201 teams in four organizations and then used data from 126 teams in 31 organizations in eight industries. In Chapter 4, we used the same data set of 126 teams but focused on the subset of 'incomplete responses'. But in all cases, there was the same strategy/change management angle, the same assessment structure and choice of survey scale and the same set of assessment logistics.

To a certain extent, we identified class labels like, for example, managerial level, age and years-at-the-company in Chapter 4. Yet, we did not yet engage in classifier training. We studied the existence of the ambition patterns but did not engage in predicting, for example, the probability whether a certain manager of a certain age and a certain period at the company will have No Realism. Reason being the inconsistencies among the various individual team effectiveness assessments with regard to data about the respondents: only 73 respondents (3% of the respondents in the second study in Chapter 3) had all three class labels registered. For studying a next pattern – and given the possibility to select or even better design the database beforehand – it is recommended to add more time to cover a wider and more consistent set of class labels.

Step 5: Adaptation

The adaptation of data is sometimes a necessity. Data *cleansing is* necessary in case of, for example, pattern recognition in social studies (cf. Gemp, Theocharous, & Ghavamzadeh, 2017) to align interpretations to a formal standard. Our choice to use a Guttman scale with objective, verifiable answers almost eliminated the need for data neutralization. A bigger problem was data *incompleteness* due to anonymous respondents, indications of not be willing to share knowledge and, most importantly, the incomplete patterns as discussed in Chapter 4. Whereas, for example, anonymity helped to paint a picture of disengaged respondents in Chapter 4, the percentage of incomplete patterns (50% of total respondents despite complying with most, if not all, of the assessment logistics) was a serious drawback in building up the database for our analysis. Because the databases were a given there is no void left to fill: we cannot go back to the respondents. However, a strong recommendation for studying any next pattern – again given the possibility to design the database beforehand – is to mitigate any opportunity for respondents to submit an incomplete response pattern.

The last aspect of adaptation is overtraining (i.e., to generalize without adapting to peculiarities in the data, cf. Jain, Duin, & Mao, 2000) or overfitting (Fayyad, Piatetsky-Shapiro, & Smyth, 1996) when a statistical model describes random error or noise instead of the underlying relation. This happens when a model is very complex and has too many parameters relative to the number of observations. This is related to the curse of dimensionality in Step 6 but not an aspect of our study.

Step 6: Generalization

In Chapter 2, we discussed the data requirement for easy processing (Cohen, Dolan, Dunlap, Hellerstein, & Welton, 2009), on the one hand to be able to handle large amounts of data and on the other hand to facilitate a short processing throughput time. Structural pattern recognition allows one to use powerful and flexible representation formalisms but offers only a limited repertoire of algorithmic tools needed to solve classification and clustering problems (Bunke & Riesen, 2012). Although structural pattern recognition has certain drawbacks, its flexibility to name domain-based classifiers, its accurateness and relatively simple math makes it attractive for the scope of our study. Yet, other patterns in strategic decision-making and change management might require statistical pattern recognition.

Given an approach for pattern recognition there are reasoning patterns including 'empirical calculation', 'proving a theory with observations' and 'real combining' (Kuosa, 2011; cf. Korzilius, Raaijmakers, Rouwette, & Vennix, 2014). In Chapter 3, our pattern was based on empirical calculation. In Chapter 4 we were proving a theory ('non-response is a sign of respondent disengagement') with observations. Reasoning patterns do have their pros and cons and are often used in combination with other reasoning patterns (Sadler & Zeidler 2005). In our study, the reasoning pattern was implicit. Next pattern recognition efforts could improve by explicitly evaluating the most applicable (combination of) reasoning pattern(s).

Maintaining a healthy relation between the number of variables to research and the available data points is the point of avoiding the curse of dimensionality (Bellman, 1961) or 'combinatorial explosion' (Domingos, 2015). If we would research a phenomenon using 30 variables with, for example, only two states ('on' and 'off') there would be 2^{30} different options to research (slightly over 1 billion options) and most databases would not even contain enough data points to research all options. In the first study in Chapter 3, we only used two variables (Width and Depth) and had close to 3,000 respondents submitting over 250,000 answers. Hence, we stayed away from this curse. Yet, when researching other patterns, it is wise to check in advance how to avoid the curse of dimensionality.

Only marginally applicable to our study but a fixture in a pattern recognition process is the aspect of feature reduction (for which techniques have been proposed by Świniarski, 2001) in case of rough (contrary to 'crisp') data sets (Pawlak, 1997). Specific algorithms then help to reduce noise in the data set. The applicability of feature reduction in our study could be the omission on incomplete patterns in Chapter 4.

Also, hardly applicable to our study, yet a key element in a pattern recognition process is reduction in variability of the probability of occurrences (Han, Wilson, & Hancock, 2015). This concept originated from patterns in images and might be very applicable in patterns that might occur in other strategic decision-making / change management visualizations like Heat Maps (for example Klemm et al., 2016) and Dendrograms (Dodge, 2008).

Step 7: Classification

In order to properly classify patterns there is the need to verify the identification accuracy as unnatural patterns can be associated with certain assignable causes for process variation (Yu, 2011). Although identification accuracy is related to, for example, image recognition (e.g., in low light situations), the concept might be worth considering when studying other patterns. As a form of identification accuracy, we made sure in Chapter 4 that we had the majority of assessment logistics in order and had removed the incomplete patterns. In Chapter 3, we divided the X- and Y-axes of the 'Focus Field'-matrix in two parts in order to divide the matrix in 4 quadrants. The analysis of cut-off values helped to indicate where to put the dividers. With this being one of the crudest and simplest form of a classification technique it would be extremely recommendable when studying other patterns to evaluate the use of other classification techniques like 'Dissimilarity-based pattern recognition' (Duin & Pekalska, 2012) or 'Multi-layer perceptron', 'Nearest Neighbor' and 'Particle swarm' to name a few (Zahiri, 2008). Using these techniques, we would be really *training* the Train database. Figure 5.1 shows how quadrants (left visual, as applied in Chapter 3) and k-Nearest Neighbor (an 'artist impression' in the right visual, not based on a real kNN calculation) could differ:

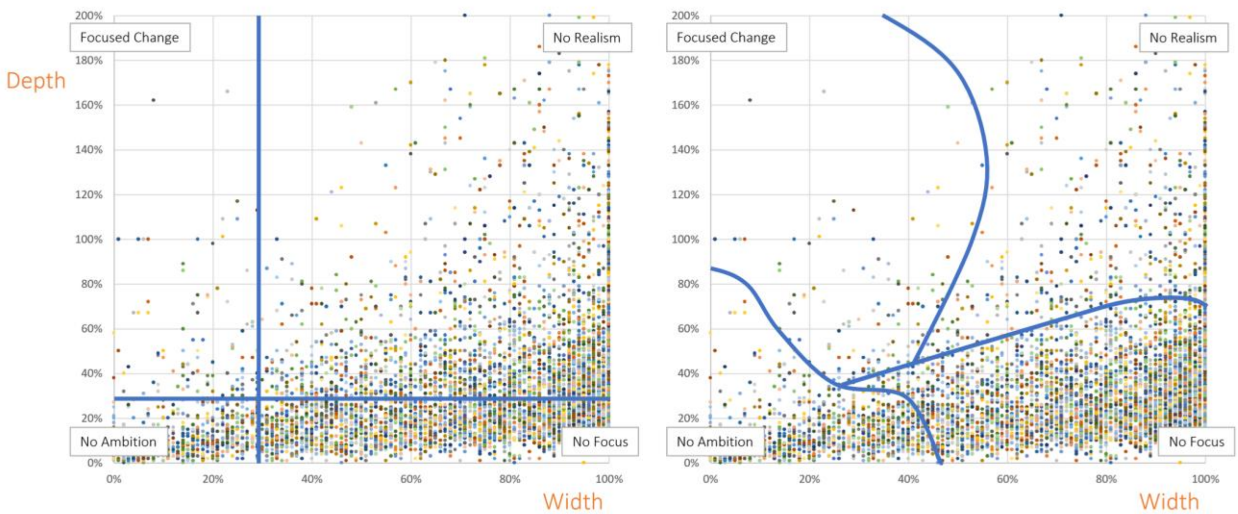

Figure 5.1: Alternative ways to segment ambition types

Another classification technique is the 'binary classification' (Proctor & Cho, 2006). Although used for research in stimulus–response mappings, the concept of binary classification results in speedy processing times. For our study it means that simple classification methods are not necessarily inferior: we classify both With and Depth in a binary way: 'high' (above 30%) versus 'low' (below 30%).

The aspect of class density is very much related to the use of histograms, which is the source visual that delivered the values for Width and Depth. There are specific drawbacks of the use of histograms (Silverman, 1986) incl. that a histogram has bins and, therefore, is not continuous. However, this drawback is not applicable to our study as we used discrete rather than continuous values: each bin in our histogram represented one single question in the questionnaire. However, for future pattern studies it would be recommendable to ensure that a priori choices regarding class density might unexpectedly influence outcomes.

The last item in classification is the recognition of pattern abnormalities. The effective identification of control chart patterns (what is a 'normal' versus an abnormal abnormality) is important since abnormal patterns that are visible in control charts can be associated with certain causes which affect the process (Lu, Shao, & Li, 2011). Most specifically in our study are the incomplete patterns as studied in Chapter 4. This concept is included in this pattern recognition process template as researching a next pattern might be helped with a formal approach to the control chart patterns and any resulting pattern abnormalities.

Step 8: Evaluation

One of the main elements in any pattern recognition process is the distinction between a train data set and a validation data set (e.g., Ljung & Guo, 1997). Although these authors underline, for example, the need for applying specific statistics to split data residuals in an error part and a disturbance part, it is clear that our ambitions patterns were based on a train set. We could not find specific indicative literature on the required sample size but in neural networks 'small samples' are for example 5 million test iterations (Faußer & Schwenker, 2015). With that number as an informal reference we were able to create a validation database of 48,514 'complete respondents' submitting 5,263,734 answers and 18,335 'incomplete respondents' using the same Guttman scales as in Chapters 2 and 3 and the approximately the same assessment logistics as described in Chapter 4. The resulting matrix with the four patterns is shown in Figure 5.2 that resembles the 2,049 respondents as mapped in Figure 3.1 of Chapter 3. The Width is plotted on the X-axis and Depth on the Y-axis. Each dot represents a respondent. The green line is the trendline through the scatterplot. Note the clustering of No Ambition respondents in the 'No Ambition'-corner.

Figure 5.2: The 'complete' respondents (n = 48,514) of the validation set

Note that the trend line in Figure 5.2 is comparable in form to the one in Chapter 3: it's making a curve from No Ambition to No Focus and then upward to No Realism, almost circumventing the Focused Change corner. Comparing Width and Depth, the regression in Figure 3.1. in Chapter 3 scored $R^2 = .75$, n = 2,049. The same regression in Figure 5.2 scores $R^2 = .49$, n = 48,514. The curvilinear regression line has as formula:

$$\text{Depth} = 0.1155e^{2.4781*\text{Width}}$$

Figure 5.3 shows the same mapping but then for the 3,362 teams in the validation set. This chart shows a similar clustering in the No Focus corner as we saw in Figure 3.2 and discussed in Chapter 3.

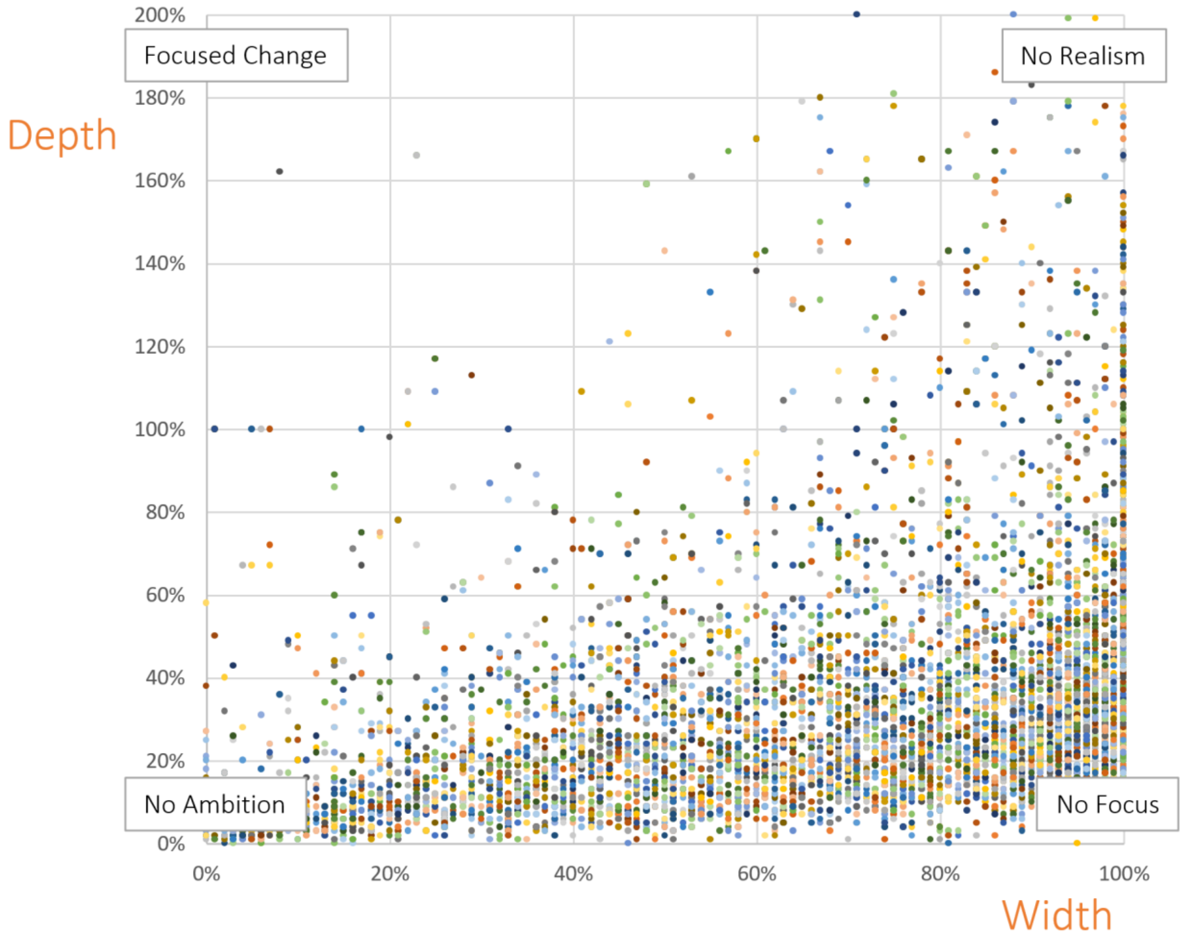

Figure 5.2: The 'complete' teams (n = 3,362) of the validation set

To specify the difference between Figures 3.1 and 3.2 of Chapter 3 on the one hand and Figures 5.2 and 5.3 on the other, we show the difference among respondents between train- and validation data set in Table 5.5 (next page).

The added insight of the validation set is immediately clear: with a total number of respondents more than 28 times higher than the train set several differences pop up. First of all, the number of incomplete patterns is as a percentage almost half in the validation set compared to the train set (27% compared to 50%). That gives already more credibility to the online use of our type of Guttman scale. Zooming in on these incomplete response patterns, we see also a change in the mix of these patterns. The "No plan indicated"-respondents – who we connected to disengagement in Chapter 4 – turn out to be a (relatively speaking) smaller group (16% in the train set versus 8% in the validation set). Also, in the validation set there are fewer "Negative ambition"-respondents (15% versus 4%) while the "Actual score = Planned score"-respondents remain roughly the same (18% versus 15%).

With respect to the complete response patterns, we see how much the train set deviates from the validation set when comparing the "Weight%"-columns that indicate the weight of the individual complete response patterns compared to the total number of complete response patterns.

Table 5.5

Comparing the mix of response types in two different data sets

Response type	Train set (Chapter 3 & 4) N=	Share %	Weight%	Validation set (Chapter 5) N=	Share %	Weight%
Incomplete response types						
No Actual score indicated	10	0%		1	0%	
Questionnaire left blank	26	1%		494	1%	
No Planned score indicated	370	16%		5,429	8%	
Negative ambition	361	15%		2,499	4%	
Actual score = Planned score	413	18%		9,912	15%	
Total	**1,180**	**50%**		**18,335**	**27%**	
Complete response types						
No Ambition	735	31%	63%	17,336	26%	36%
No Focus	79	3%	7%	6,889	10%	14%
No Realism	303	13%	26%	22,615	34%	47%
Focused Change	47	2%	4%	1,674	3%	3%
Total	**1,164**	**50%**	**100%**	**48,514**	**73%**	**100%**
Grandtotal	**2,344**	**100%**		**66,849**	**100%**	
Average Actual score		5.8			5.3	
Average Planned score		6.6			7.2	
Average ambition (Planned -/- Actual)		0.8			1.9	

Most notably, in the train set, the “No Ambition”-respondents clearly dominated, representing 63% of all ‘complete respondents. In the validation set this reduces to 36%. Equally interesting is the difference in “No Realism”-respondents (26% versus 47%).

Literature about validation refers to three aspects of validation: (1) within a data set, (2) between data sets, and (3) generalized between data sets. In that thought, we have done the within- and between-parts in the two studies in Chapter 3, while the generalized-part is about fixing value parameters at levels estimated by unrelated experimental tasks (cf. Spiliopoulos, 2013). The size of the validation set might help to relatively ‘fix’ the division among response patterns. Of course, an even larger validation set might still alter the division among the response patterns.

A last item in the validation step is to quantify the quality of the evidence (Guil & Marín, 2013). Yet, this step is usually reserved for patterns based on continuous variables (contrary to the discrete variables – the questions’ answers – that we have used) or when patterns are very frequently mined (for example, in image recognition). There is much literature on the subject but of little applicability to the tallying of answers we have applied in our study. Studying the quality of the evidence would not be a numerical approach but would entail interviewing respondents to verify evidence that would support their answers. However, for a next pattern the validation step might be pivotal. Hence, the inclusion of this step in our formal pattern recognition process.

Step 9: Intervention

In Chapters 2 and 3, we stumbled upon the four complete ambition patterns using unsupervised learning: discovering a hidden structure from unlabeled data with no error or reward signal to evaluate a potential solution (a phenomenon described by Sathya and Abraham, 2013). The respondents' data was labelled in terms of Width and Depth but the resulting patterns were error-free as interpretation had not started. Neither were the patterns a priori predictable from an earlier data source. Once, we started working on interventions in Chapter 3 and non-response in Chapter 4, we added labels – and thus engaged in supervised learning (cf. Zhu, 2005) – to predict how certain patterns could be mitigated for their unfavourability. For example, we concluded that "No Ambition"-respondents would best be served with an informal/bottom-up approach to change management. As the field of supervised learning tools and techniques is very wide, we do want to add this aspect to our formal process without adding too much detail to complicate the step-by-step process overview. Yet, when studying next patterns, a formal verification of supervised learning opportunities seems to be mandatory.

A blend of unsupervised- and supervised learning is semi-supervised learning where a few labelled data are used to train a larger set of unlabeled data (Zhu, 2005). In a way, one could say that our 'Step 8 – Validation' is a very mild form of semi-supervised learning. Closely related is reinforcement learning. Reinforcement learning learns through trial and error interactions with its environment by assigning rewards and/or penalties (Sutton & Barto, 1998). For example, many robots learn via reinforcement learning.

We would be applying semi-supervised learning if we, for example, would want to replace the non-response for the "Actual score = Planned score"- and "Negative ambition"-respondents with estimated scores based on similarities within each of these two groups. In Chapter 4 these two patterns could not be attributed to a specific setting that could be mitigated, similar to the "No Planned score indicate"-respondents who very likely suffer from disengagement. Replacing the non-response by estimated scores might give more clues about how these two patterns could be mitigated. We would be applying reinforcement learning if we, for example, would want to allocate respondents of each of the incomplete response patterns (excluding "Questionnaire left blank") to one of the complete response patterns.

Similarly, to (un-)supervised learning, the fields of semi-supervised- and reinforcement learning are very wide and encompass many tools and techniques not used in our study. Yet, we do want to add these aspects to our formal process but without adding too much detail to complicate the step-by-step process overview for now. That said, discovering new patterns might very well be happening using these other learning strategies.

All of these learning strategies may result in intervention insights but it is the pattern activation (a term coined by Du Castel, 2015) itself that makes the invention come to life: the checking, organizing, and augmentation of patterns become patterns in their own right. This concept is preliminary focused on neural networks rather than on the employee networks that are involved in strategic decision-making and change management. Yet, it being such a much-referenced aspect of pattern recognition processes it has been included here. In our study, the pattern activation would be specific action steps that describe what to do in case a formal/top-down and/or informal-/bottom-up approach to team effectiveness is necessary.

Step 10: Binarization

As mentioned in ‘Step 8: Evaluation’, there were 66,894 respondents and 3,362 teams in the validation data set. That could equally be the size of a somewhat larger multinational. Consequently, when supporting such a multinational by tapping the wisdom of the crowd in support of strategic decision-making and subsequent change management, it would be too time-consuming and too costly to have consultants or staff members visit all these team and discuss interventions. Hence, computer software could not only discover the patterns but also provide made-to-measure intervention instructions/suggestions to each team. That would require to translate the stochastic probabilities into a decision tree of instructions what to do (and what not) in order to have, for example, online software deliver the intervention instructions/suggestions to the teams. It is then important to decide on the granularity of the instructions and interdependencies between these instructions/suggestions (cf. Maravall & De Lope, 2011). The integrated pattern recognition- and pattern activation process can then be integrated into, for example, a flow chart or decision tree. Such a flow chart could for our ambition patterns and interventions for individual respondents look like Figure 5.4.

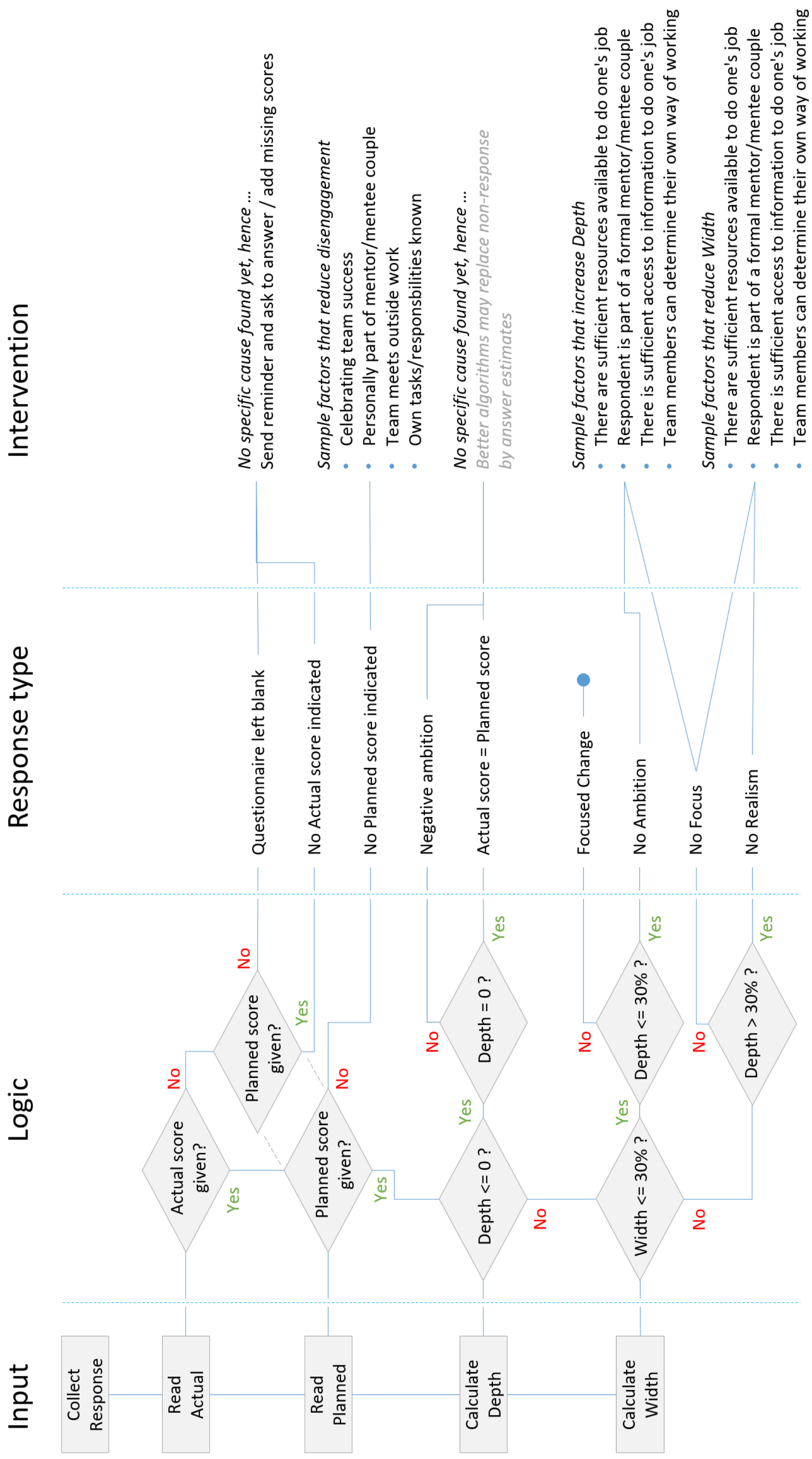

Figure 5.4: Chapters 2 to 4 in a simplified flow chart (entity relationship diagram)

The flow chart is divided in four steps, similar to work of Maravall and De Lope (2011) with an input layer, a hidden logic layer, a hidden end-state layer and a set of recommendations. Note that the applied logic is very simple. The first two incomplete patterns (“Questionnaire left blank” and “No Actual score indicated”) have an intervention in the field of the questionnaire logistics (for example, “send respondents a reminder”). The third incomplete pattern (“No Planned score indicated”) does have an intervention based on reducing disengagement, the likely source for the differences in score between that pattern and the average score of the complete patterns. The fourth and fifth incomplete pattern (“Negative ambition” and “Actual score = Planned score”) have no interventions and, for example, applying more elaborate algorithms to substitute the non-response by estimated answers would help to distill interventions after all.

Note that the “Focused Change” pattern has no associated interventions which makes the flow chart stop (the sign). The three other complete patterns link to the Reduce Width and Increase Depth inventions.

5.2 Conclusion

In Chapters 2 to 4, we developed a methodology to model the ambition of large groups of employees about strategic options presented by their upper management. This resulted in four ambition patterns. The aim of this chapter is to allocate the various steps taken in Chapters 2 to 4 into an overall pattern recognition process template including sensoring, representation, adaptation, generalization, classification and evaluation. One the one hand such a template is a checklist to see whether we have followed in our study all the necessary steps to rightly name our ambition types ‘patterns’. On the other hand, such a template helps to process future patterns quicker and diligently.

In Table 5.1, we have highlighted in bold the Bayesian approach that we followed in Chapters 2 to 4. We represented data in graphical models (histogram and Focus Field). We concluded retroactively that a 30%-30% cut-off values for Width and Depth divided the respondents as equally as possible over 4 ambition patterns. We concluded a probability of the occurrence for each of those patterns in the train data set and refined that probability using the validation data set. We defined optimization as the Focused Changed pattern and inferred that, for example, less Width is most likely reduced by focusing on a formal/top-down approach.

The five schools presented at the start of this chapter all have in common that the optimization is focused on an intervention of a mathematical or computational nature. For example, Symbolists find ways to filter spam even better and Evolutionaries learn how to bread individual algorithms to achieve even fitter ones. However, in a strategic decision making- and change management environment, we may find ways to calculate optimal processes or behaviors but it is still to the managers and employees in the organization to implement these. We can provide a team with precise instructions on how to make strategic decisions or change the organization to implement these instructions, but that is no guarantee that they will behave as instructed. Simply put, machines always listen but people not necessarily. The theoretical and practical implications of this chapter have been integrated in the overall conclusions in the next chapter.

Chapter 6

Main conclusions and general discussion

6.1 Recapitulation

This thesis is about developing an entity-relationship model based on the input of large numbers of employees to support an organization's upper management with their strategic decision making. In this thesis, the model's end is to support management with understanding the strategic ambition of these employees, by grouping their ambition into manageable clusters and by calculating proper interventions. The preparatory studies to develop the model included survey scale design, pattern recognition, pattern intervention, and pattern validation.

The increase in the application of calculation rules in managing organizations combined with the perceived absence of such rules to support strategically changing an organization (strategic decision-making and the subsequent change management) led us to research whether we could design a model that would describe – and help manage – these strategic changes. Designing models built around calculation rules requires among others two important underlying elements: (1) (large amounts of) data, and (2) patterns that evolve from the data. The model describes how to detect these patterns and – possibly – how to use them best for the purpose of a strategic decision-making process.

In this thesis, we have focused our model design on ambition patterns of individual employees and their teams, given strategic options presented by their management. In order to compare employees' ambition across industries we have not been studying *what* issues employees wanted to improve but only *how many* issues and *by how much*. To research the employees' ambition patterns, we used a modified Guttman survey scale. Our study about data requirements indicated how to get an as objective as possible measurement of current and preferred situation without a myriad of biases. In order to analyse the input of thousands of employees, we successfully matched our modified Guttman scale with data requirements borrowed from scientific Big Data literature. These requirements referred for example to sample size, informative value of data, data validity, data precision and several other aspects. We applied this survey scale in a large number of online surveys to research the ambition patterns of more than 66,000 employees with a wide variety of strategic issues in a wide variety of industries and countries. We have discovered four different ambition patterns regarding how employees chose their priorities given strategic options presented by management. A tiny fraction of employees showed a 'Focused Change'-pattern: improve only a few of the strategic options but improve them significantly. However, the vast majority of employees had either No Ambition, No Focus or No Realism when setting their strategic priorities. These last three patterns are potentially harmful to the organization. But, we also discovered possible interventions to mitigate these last three patterns. Finally, we have converted this ambition pattern recognition process and subsequent matching with the appropriate intervention in an entity-relationship model for use in analytics software

In this final chapter, the general conclusions that can be drawn from the research findings are presented in Section 6.2. Next, some methodological issues will be discussed that should be taken into account when interpreting the results of our study (Section 6.3), followed by theoretical and practical implications of our studies (Sections 6.4 and 6.5, respectively). Section 6.6 will suggest some avenues for future research.

6.2 General conclusions

In the Introduction of this thesis we identified four research questions. We will frame these research questions in this section:

1.) How applicable are the usual employee surveys given data requirements needed for the development of an entity-relationship model *based on large-scale employee input gathered on strategic options? If not, would specific survey improvements be necessary? And what would these improvements have to look like?*

The first research question was fueled by a set of data requirements, for example, the requirement to have employee input that is as objective as possible (i.e., not influenced by personal feelings, cognitions, emotions, or prejudice; based on facts; unbiased), in order to allow for new analytics driven by – for strategic employee input – large amounts of data. In Chapter 2 we wrote about analytics and the data requirements for large-scale surveys among employees. We listed a significant number of drawbacks of employee surveys that ask for agreement with, or the rating of, statements. Statement-based surveys may lead to socially acceptable answers, various types of bias and score low on data quality for feeding the model. Plus, statements do not allow management to set a target. So, the answer to the first part of the first research question is a highly likely 'Not applicable'.

These drawbacks resulted in modifying a commonly used Guttman scale (a.o. with scale improvements like objective wording and an added time aspect) to be more compatible with these data requirements (e.g., stable, binary/numerical/categorical representation, easy to process, applicable to various sample sizes). In Chapter 2, we saw that our low-tech survey in combination with very elementary math yielded new, useful insights from both a process and content point of view.

New and useful from a *process* point of view as we designed some new analytics using our modified Guttman scale. We looked at simple yet indicative aspects like ambition Width (how many questions does a respondent plan to improve) and ambition Depth (by how much does the respondent plan to improve). We also analyzed group alignment (to what extent do respondents plan the same improvements) and alignment with management's target (to what extent do respondents plan their improvements in accordance with what management has in mind for improvement). In terms of organizational effort, we looked at the number of questions to improve equaling 50% of the gap between actual situation and management target. We looked at the percentage of questions where two or more employees have already scored the best answer. And we looked at the average number of questions that can be shared per team member. Our research into the ambition patterns focused not on the 'what' but on 'how many' (questions/issues) and 'how much' in terms of improvement. Still, it is reassuring to know that, in terms of 'what', our modified Guttman scale offers additional avenues for research.

Our approach also yielded new and useful insights from a *content* point of view. Applying our analytics to the German energy company, for example, we discovered the misalignment within management layers and we saw how in terms of ambition (Planned score -/- Actual score) the managerial levels (L1, L2, L3) seemed comparable in variance and distribution but significantly deviant from the All Staff. And we discovered how change management aspects (e.g., people management aspects) were unjustified taken for granted by management.

2.) Can we detect ambition types in the employees' choice out of the strategic options presented by their management? Can these types be meaningfully labelled/interpreted? Will these types differ across strategic industries? Do these ambition types recur as such that we could identify them as patterns?

Our second research question was fed by the notion that strategic decision-making could not be modelled in one single calculation rule but would rather require an entire rule library. One of the first aspects when involving large numbers of employees into a strategic decision-making process is to obtain their input on where the organization is and, more importantly, where those employees think the organization should be going. Hence, starting a library of calculation rules regarding strategic decision-making would certainly be served with insight about the employees' ambition.

In Chapter 3, we used our modified Guttman scale to discover ambition patterns when asking employees in organizations about their strategic outlook within the realm of strategic options provided by management. For that very reason, an empirical study was conducted in four different strategic business situations in various industries in more than 32 countries. Based on that study we identified four distinct ambition patterns. We decided on the naming of these four patterns from a (top-)management's viewpoint: are lower managers and employees moving sufficiently ahead given the questionnaire's strategic window of 6 months? (Although a 'six months'-window may not sound strategic, it helps to focus respondents to make concrete choices). We saw respondents that planned a 'Focused Change' opting to improve a small part of the strategic options presented by management - the questions in the questionnaire - but improve these significantly (cf. Foote, Elsenstat, & Fredberg, 2011; Ghosh, Martin, Pennings, & Wezel, 2014). There were respondents with 'No Ambition' planning to improve only a small part of the questions and then only marginally. There were respondents with 'No Focus' planning to improve a lot of questions, yet only marginally. And there were respondents with 'No Realism' planning to significantly improve a majority of the questions, and that within the short time span of 6 months. A first clustering of respondents showed that 97% of them had ambition patterns that were potentially harmful to their organization (any pattern except Focused Change). Harmful, because No Ambition respondents might slow down a strategic change too much; because No Focus respondents might waste resources by not pinpointing their specific priorities; because No Realism respondents might create havoc by attempting to improve too much, too quickly. However, in specific cases, teams without realism, focus or ambition could be something acceptable (e.g., a team with only a very limited ambition in a nuclear power plant). To answer the second research question: yes, we can detect meaningful ambition patterns (four different ones) that seem generically applicable irrespective of industry. For example, Table 3.6 in Chapter 3 showed that for 9 out of 56 pairs of industries we compared (Width and Depth combined), or for 16% of the pairs, the pair was not considered alike in terms of variance. When we excluded the Industrial Services industry (responsible for 7 of the 10 'not alike'-pairs), only 2 pairs, or 4% of the total amount of remaining pairs of industries were considered 'not alike'. Yet, we use the phrase '*seem to be generically applicable'* as we have studied only a limited number of teams in a limited number of industries.

3.) Are these ambition types somehow manageable (amplify the positive aspects and mitigate the negative aspects) to support or improve the quality of the strategic decision-making process?

Research question 3 was fueled by the understanding that, in a generic pattern recognition process, there is always a generalization phase and an intervention phase. So, it makes little sense 'just' discovering a pattern, but it makes tremendous sense managing that pattern to the advantage of an organization.

In the second study in Chapter 3, we looked at how these ambition patterns could be mitigated in case they would prove to be harmful to their organizations. Individuals that had No Ambition would do well with a focus on more informal/bottom-up aspects of team effectiveness. For example, gathering as a team outside work, informal mentoring and celebrating team successes. Individuals that had No Realism would do well with a focus on more formal/top-down aspects of team effectiveness. For example, having formal team objectives, use more systematic work planning and have formal feedback moments between manager and employee. And individuals that had No Focus would do well with attention for both formal/top-down as informal/bottom-up aspects of team effectiveness. Yet, we also saw that these interventions are to be considered as a rule of thumb: not *every* aspect of a formal/top-down approach influences Width. And not *every* aspect of an informal/bottom-up approach influences Depth. Plus, we also saw that less than half of employees had planned the interventions they would need (according to our calculations) given their ambition pattern.

Next, in Chapter 4, we reviewed what the effect of using this modified Guttman scale would be on non-response and Extreme Response Styles (ERS); both important aspects influencing the quality of the output when using survey questionnaires. We saw that the use of the modified Guttman scale nearly eliminated ERS while non-response changed appearance: we identified 'incomplete' response styles where respondents did answer parts of the questionnaire but in a way that made their input hardly (or not) usable. We also discovered in Chapter 4 that part of the non-response could be explained by respondent disengagement.

Plus, we found that 'Age' was associated with the 'complete' ambition types: younger respondents were more likely to have a No Realism- or Focused Change type while older respondents were more likely to have a No Ambition type. We found no significant relation between ambition and 'Years of presence in the organization' nor between ambition and 'Managerial Level').

To answer the third research question: the ambition patterns seem to be manageable. 'Seem' as we have measured different correlations of the ambition patterns with aspects of team effectiveness but have not conducted a longitudinal study that would measure the net positive effect of the interventions. Furthermore, the studied respondent characteristics (age, years of presence in the organization and managerial level) did not provide sufficient handles to manage the 'incomplete' response types. Would we have been able to convert these into 'complete' responses, we would probably have a better picture of the most likely mix of the ambition types.

4.) How do our research activities compare to the process steps in a formal pattern recognition process as described in scientific pattern recognition literature? Have we left out certain process steps?

Research question 4 was fed by realizing that we needed to compare our research activities in Chapters 2, 3 and 4 against pattern recognition literature to ensure all necessary research steps had been covered. This literature covers pattern recognition process steps like object- and class definition, representation, adaptation and data neutralization, generalization and feature reduction, classification techniques and pattern validation.

In Chapter 5, the various research activities of the former chapters have been aggregated in a formal pattern recognition process. It was noticed that the simple math we applied can be extended by a myriad of other pattern recognition approaches and technologies. Many aspects of questionnaire 'logistics' as suggested in literature have been followed. In this chapter, we also validated the patterns we found in Chapter 3 in a validation data set of more than 48,514 'complete respondents' submitting 5,263,734 answers. And the lessons learned in Chapters 3 and 4 have been aggregated into a flow chart for use in, for example, self-interpreting dashboard.

To answer the fourth research question: it looks like that we haven't committed any major mistakes from a pattern recognition process point of view. That said, we haven't been very advanced in our analytics either. Simple math might be methodologically elegant, but if the analysis will be anyhow executed by a computer, that simplicity is not a big win over – perhaps – better outcomes due to more advanced analytics.

6.3 Methodological implications

There are three groups of methodological implications that require specific notion: (1) improving the survey scale design, (2) better understanding the response, and (3) solidifying the fundament for the interventions. We will discuss them below.

Improving survey scale design

A Big Data literature review suggested several data requirements for gathering large amounts of employee-generated input (e.g., Plewis & Mason, 2007; Cohen, Dolan, Dunlap, Hellerstein, & Welton, 2009). Also, the reviewed literature showed that methodological drawbacks of using statements to gather employee input - for example, self-perception bias (Roulston & Shelton, 2015) and sampling errors (Piterenko, 2013) - can be (partly) addressed by mathematical corrections. However, there is no *overall* correction to cover all these drawbacks simultaneously. Yet, it should also be noted that notwithstanding the match between the modified Guttman scale with data requirements, we haven't made a formal methodological comparison of using statements or Guttman or other types of survey scales to select the best match with these requirements. Hence, the modified Guttman showed to be a good match with the data requirements, but not necessarily *the* best. The good match included, amongst other, addressing different contextual interpretations of the questions in larger respondent samples (for instance because of culture, a phenomenon described by Lee, Jones, Mineyama, and Zhang, 2002). Surveying large samples of respondents makes the survey unsupervised by nature. The specifically described answer options – each improving in quality (a cumulative scale, Uhlaner, 2002) – in our modified Guttman scale greatly reduces the possibility for a respondent to bias his or her responses (cf. Donaldson & Grant-Vallone, 2002). In turn, that greatly diminishes pollution through, e.g., extreme response styles (an issue raised by De Jong, Steenkamp, Fox, and Baumgartner, 2008) and midpoint responding (an issue raised by Plieninger and Meiser, 2014), which we proved to be near zero for our modified Guttman scale (Chapter 4).

There are specific data requirements where also Guttman doesn't score particularly well. For example, the answers in the modified Guttman scale might be defined as verifiable as possible but as such do not prevent faking (cf. Scherbaum, Sabet, Kern, & Agnello, 2012). Faking (and, in general, the quality of the answers) could be verified but if, for example, 500 employees would give two answers (actual situation and ambition) on 30 questions, there are 30,000 answers to be verified. Then, there is a need for an approach to determine which respondents (or questions or answers) should be most likely to be verified to assess the overall quality of the employees' input. Although an approach to verifiability was out of scope for our research, one could think of using a measurement from Chapter 2: the number of questions to improve equaling 50% of the gap between actual situation and management target. In our study at the German Energy company, this percentage was roughly 25%. Another percentage to use could be the number of respondents that score, e.g., 85% of the 'actual situation'-questions already on or above the preferred planned 'in 6 months'-situation. These respondents could be the 'change agents' (a phenomenon researched by Battilana and Casciaro, 2012) on the work floor to assist management with knowledge sharing. We can safely assume that a minority of respondents would score that well. If we assume 5% of the respondents scoring this well, we have 25 change agents (500 respondents * 5%) and only 375 data points to verify (30,000 answers * 25% * 5%) which is slightly over 1% of the total number of responses to ensure the proper knowledge sharing to cover half of the gap between the actual situation and the management target. Such a simple focused verification might be preferred over complex calculations to, e.g., generally estimate the level of socially desirable answers (cf. Paulhus, 1984).

From a methodological point of view, it was surprising to see the wide occurrence of the four ambition patterns. We surveyed teams of different sizes and in a wide variety of organizations in eight different industries. The number of respondents per organization ranged between four and 837 respondents. The team size ranged between four and 26. And there were comparable Width and Depth values across the 31 surveyed organizations in eight different industries as demonstrated in Table 3.5 of Chapter 3. In Chapter 4 we saw that these Width and Depth values weren't polluted by ERS and hardly by non-response. And in Chapter 4 we also discovered that the survey 'logistics' we applied didn't pollute the results either. Hence, a wide applicability of the patterns to other organizations is to be considered highly likely.

It is also remarkable that the validation data set in Chapter 5 showed a confirmation of the pattern mix while this database contains a wide variety of questionnaires of which the vast majority was not based on a specific scientific theory. In other words, in Chapters 2 and 3 we referred to the issue of the arbitrary choice of questions in the questionnaires at hand. From the 900+ projects in the validation database it is inferred that the patterns existed irrespective of the questionnaire topic at hand. In some of these projects, a specific scientific theory was the fundament of the questionnaire at hand. Yet, in the vast majority of cases the questionnaire was a representation of the strategic issues that management was fretting about. That also leads to the methodological implication that the arbitrary choice of what contained the first, second and third answers did not seem to have a great effect as well.

However, especially given the wide applicability of the results, we realize that we did not have access to a large database of comparable research on employee ambition with other scales than our modified Guttman scale to discern what part of pattern is attributable to the scale design and what part truly reflects employee ambition.

Evaluating the response

Another methodological concern remains the large difference between gross and net response. Our own separate in-depth analysis of the response of the projects in the validation data set (out of scope for this thesis) showed that when approximately 35% of the final number of respondents of a certain project have been captured, the results in terms of score, ambition, etc. do not materially change anymore. In that sense, the number of 'incomplete' respondents in Chapters 2 and 3 could be seen as some sort of 'collateral damage' of the obtained wisdom of the crowd: if one just would ask as many respondents as necessary to improve the strategic decision-making process (the exact number of 'sufficient' respondents is out of scope of this thesis), the large number of incomplete respondents could be regarded as an unavoidable side-effect. Yet, in terms of methodological elegance, this large collateral damage might be regarded too big to be tolerable as, for example, it requires a lot of employee capacity that might be better used otherwise. On the other hand, the validation data set brought the ratio between complete and incomplete respondents back from 50%/50% (1,164 complete respondents versus 1,184 incomplete respondents) in Chapters 2 and 3, to 73%/27% (48,514 complete respondents versus 18,335 incomplete respondents) in Chapter 5. And then there was some sort of constant: 18% of respondents in Chapters 2 and 3, and 15% of respondents in the validation data set in Chapter 5 had an "Actual score = Planned score" response pattern. As said before, this response pattern could be, for example, attributable to either respondents' misunderstanding of instructions (an issue raised by Schober, Conrad, and Fricker, 2004), to management not explaining or underlining the importance of adding not only an actual score but a planned score as well (cf. Clifford & Jerit, 2015) or to respondents being indifferent to (cf. Crandall, 1982) - or just compliant with - current management.

Solidifying the fundament for intervention

A final methodological concern remains the number of respondents representing the 'Focused Change' ambition pattern (the only pattern out of the four we identified that we regard not harmful). Despite the size of the validation data set (with 1,674 Focused Change respondents) there were too few such respondents in the available Team Effectiveness projects to support the analysis of what reduces Width (the amount of questions respondents wanted to improve) and what increases Depth (by how much respondents wanted to improve). Methodologically speaking, we might commit an error by assuming, for example, that the Team Effectiveness factors that distinguish No Focus respondents from No Realism respondents (factors that increase Depth) should equally be applicable between No Ambition respondents and Focused Change respondents: factors that influence vertical movements that occur in the right two quadrants in our Width/Depth matrix not necessarily apply to the left two quadrants. Similarly, factors that distinguish No Focus respondents from No Ambition respondents (and that reduce Width) perhaps cannot be equally applied to distinguish No Realism respondents and Focused Change respondents: factors that influence horizontal movements that occur in the bottom two quadrants in our Width/Depth matrix do not necessarily apply to the top two quadrants.

Similarly, there was not enough data to further segment the teams. An organization's (top-) management will always involve the middle management layers (team managers inclusive) in strategic decision-making and will never bypass these layers in order to (only) communicate with the work floor. We showed in Figure 5.3 of Chapter 5 how the majority of teams clustered in the No Focus corner. Hence, a further segmentation of teams would have been welcome to better understand which interventions would work where in the organization.

Also, the length of the questionnaires did not allow for a wide variety of team effectiveness aspects to be considered for intervention. The length of a questionnaire usually influences reliability (Ziegler, Poropat, & Mell, 2014). But, as employees do not have unlimited time (or attention span), the length of the questionnaires was usually around 30 questions. So, methodologically speaking, we favored sample size over intervention variety as we had access to the responses of many organizations answering small variations of the same, limited, questionnaire.

Further advances in the development of strategic decision-making models built on our modified Guttman scale could help to replace some of the blanks in some of the incomplete response patterns by calculated best-estimate answers: calculation rules replacing non-response by estimated answers (cf. Karanja, Zaveri, & Ahmed, 2013). For example, by comparing the answers of a single incomplete respondent with answers of a group of similarly scoring complete respondents. An incomplete respondent with a "No Planned score indicated"-pattern could have his/her Actual score be compared with a group of nearly similarly scoring complete respondents (a so-called 'k-Nearest Neighbor' algorithm). And other calculation techniques (e.g., similarity matrices) could provide additional insight into patterns within graphical representations constructed using our modified Guttman scale (for example, Tax, Cheplygina, Duin, & Van de Poll, 2016).

6.4 Theoretical implications

There are three main theoretical implications of this thesis: (1) the notion that the discovered ambition patterns are seemingly at odds with various existing theories, (2) the view that a more refined segmentation might help to further explain this oddity, and (3) that these explanations could refine the interventions to reduce Width and increase Depth and manage the potential harmfulness of the ambition patterns. These three implications will be discussed in the next paragraphs.

A pattern seemingly at odds with various existing theories

In the era we are living in, there are more and more data sources available to conduct large-scale analyses. As the statement-driven employee surveys clearly show disadvantages as mentioned in Chapter 2, one could argue that redoing earlier research based on statements – by using the modified Guttman scale – could result in modifying or even thwarting existing theories. The wide applicability of the four ambition patterns – whether or not based on theory-driven questionnaires – has such theoretical implications.

As discussed in Chapter 3, the high percentage of unfavorable ambition patterns appears to be perpendicular to concepts as groupthink (Turner & Pratkanis, 1998), goal clarity (Patanakul, Chen, & Lynn, 2012; Ayers, 2013) and team cognition (DeChurch & Mesmer-Magnus, 2010). Perhaps there is goal alignment on skill, knowledge, and expertise (Bezrukova, Thatcher, Jehn, & Spell, 2012) but apparently not on *how* to achieve it. A shared team cognition (Swaab, Postmes, Van Beest, & Spears, 2007) or understanding team members' narratives (Fiander-McCann, 2013) can serve to align leaders with team members to build integral business relationships but apparently are not a guarantee for a shared view how to execute the changes. Delegating strategic responsibility to teams and individual team members does not mean they feel accountable (De Leede, Nijhof, & Fisscher, 1999) and it apparently does not fuel their need to align on the change management implementation either. This aligned view on how to achieve strategic goals is something else than process clarity. The latter focuses on administrative aspects like, for example, clear roles and responsibilities (Parker & Collins, 2010; Hu & Liden, 2011). The former, shared view on change management could be defined as 'roadmap clarity'. This roadmap clarity differs from vertical strategic alignment (Andrews, Boyne, Meier, O'Toole, & Walker, 2012) and employee strategic alignment (Ouakouak, Ouedraogo, & Mbengue, 2014). These authors describe a predominantly top-down exercise about making employees understand how their work contributes to the strategic goals of the organization (Andrews et al. refer to a 'principal-agent theory', p. 79). The seemingly omnipresence of potentially harmful team ambition patterns may suggest the likelihood of one of three undesirable situations that result in the dominant 'No Focus' team ambition pattern. Either employees do not understand their contribution to the strategic goals. Or, employees understand their contribution but their goals are not aligned. Or management has failed to inform or involve the employees in the first place.

The advent of Big Data has led to the prediction of 'the end of theory' (Anderson, 2008) as machine learning independently discovers associations in huge data sets. These associations do not explain why phenomena are happening but alert scientists that something is happening and understanding of the possible underlying causation is needed. Yet, in many situations that is good enough: get a first view on the data from a mathematical angle and only then establish a context for it (Mayer-Schönberger, & Cukier, 2013). However, a more balanced view is the merging of insights of data-driven research and hypothesis-driven research (Mazzocchi, 2015). In that light, we argue that the confrontation of ambition patterns (data-driven research) with existing theory of, for example groupthink, goal clarity and team cognition (hypothesis-driven research) is just an example of what there is more to come. More specific data-driven research could shed a further light on the durability of abovementioned theories.

The need for further segmentation

In the previous section on methodological aspects, it was stated that the confirmation of the patterns through the validation data set implied that team size, industry, whether or not the questionnaire was based on a solid theoretical framework, and whatever the first, second and third answers were, were all not a deciding factor for the mix of ambition patterns. In Chapters 3 and 4, we indicated the limited segmentation of the respondents in terms of age (Weijters, Geuens & Schillewaert, 2010; Scholz & Zuell, 2012), in terms of years in the organizations (cf. He, Baruch & Lin, 2014), and in managerial level (cf. Griffith & Gibson, 2001; MacCurtain, Flood, Ramamoorthy, West & Dawson, 2010; Henttonen, Johanson & Janhonen, 2014). This limited availability of segmentation data was also due to what usually gets, and gets not, registered in the files of Human Resource departments. For example, there is abundance of literature on the effect of personality aspects like decisiveness (Wetzel, Carstensen, & Böhnke, 2012), perfectionism (Stoeber & Hotham, 2013) and the respondent's sense of security (Diamantopoulos, Reynolds, & Simintiras, 2006) on response styles. But all of these personality aspects usually do not get registered in organizations. But then, similar to the beforementioned items, one could argue that the variety among the 48,514 'complete respondents' in the validation data set suggests that segmentation among personality traits or other criteria like education (cf. He, Bartram, Inceoglu, & Van de Vijver, 2014) would not show large segments of respondents being totally exempted from the three unfavorable ambition patterns (No Ambition, No Focus, No Realism). We find it hard to believe (although, again, we have not the evidence to back this up) that our database just happened to miss, for example, all the decisive-, the insecure- or the specifically educated respondents that would have jolted the mix of the four ambition patterns. This would further add to the likely general applicability of the ambition patterns. However, as we lacked the data to divide the 48,514 respondents in the validation data set into teams, we haven't been able to compare the ambition patterns with, for example, team composition (Devine, 1999; Edman, 2006; Bezrukova, Thatcher, Jehn, Kharbey, Choi, & Kursancew, 2007; Bradley, Baur, Banford, & Postlethwaite, 2013), team history (cf. Fagerholm, Ikonen, Kettunen, Münch, Roto, et al. 2014) or team performance (cf. McGlynn et al., 2004; Henningsen & Henningsen, 2013; Zhu & Chen, 2014). So, we had to eschew further segmentation given the fact that for historical reasons we did not have consistent segmentation criteria in the database for this number of teams. The need for further segmentation is that when averaging the ambition of individual respondents in their team ambition the vast majority of teams (more than 70%) end up in the No Focus areas. Hence, if most teams end up in the No Focus zone, management could do with further segmentation to refine their change management approach.

We could then, for example, further segment on alignment profiles (Swaab, Postmes, & Eggins, 2011; Fiander-McCann, 2013; Lepmets, McBride & Ras, 2012). In Chapter 2, we already calculated the percentages with which teams were aligned internally and with the management target. Similar to ambition patterns, we might discover alignment patterns as well and then correlate the two. Or we could segment on knowledge sharing (for example, Oliveira, Curado, Macada, & Nodari, 2015). In the same chapter, we worked with the number of respondents that scored the best answer and the average amount of questions there were to share per individual respondent. Similar to ambition and alignment patterns, we might find knowledge sharing patterns and then correlate all three. In Chapter 4, we compared the ambition patterns against the individual respondents' age, managerial level and years of presence in the organization. We could expand that by further segmentation along team structure (cf. Chow & Chan, 2008) and compare, for instance, old, established teams to newly formed teams or compare teams with a low average respondents' age to teams with a high average age.

Refining the interventions to reduce Width and increase Depth

If the general applicability of the ambition patterns is assumed for a moment, it is also possible to assume that the factors that reduce Width and increase Depth are generally applicable as well. Doing so, it should be noted that the intervention styles have been calculated purely mathematically and have not been proven in longitudinal studies to measure their (causal) effect over time. We have neither been able to measure the impact of the proposed interventions nor have we studied how the respondents and teams actually changed; with or without interventions. In addition, there is neither insight yet in why these patterns exist nor how employees reasoned when they indicated their ambition score in the first place. Assuming this general applicability of the ambition patterns and the possibility to intervene means that, mathematically, it is possible to calculate an optimal change management roadmap for an organization. However, behaviorally speaking, employees might still choose to not to follow up this optimal roadmap (cf. Dietvorst, Simmons, & Massey, 2015). Remember, for example, that in Chapter 4 we could explain only a part of the non-response by respondent disengagement.

The implementation success of rationally calculated optimized solutions (like the interventions to mitigate harmful ambition patterns) still depend on factors like, for example, fear (Thuraisingham & Lehmacher, 2013), commitment, beliefs and work methods (Losonci, Demeter, & Jenei, 2011): despite the apparent logic, decisions have an irrational component (Tversky & Kahneman, 1986). Memories can deceive, experience can become a reflex, and optimism and ambition can cloud a mathematically optimal decision. And logic decisions can be perpendicular to political interests (Pettigrew, 2014) and financial structures (Drover, 2014). Hence, there are theoretical implications on how to create the right environment to let these calculated interventions properly land in a strategic decision-making environment (cf. Hayes, 2014). For example, we had not the possibility to research whether No Ambition respondents would react differently than No Focus- or No Realism respondents would do to the same interventions. And, for example, whether respondents would choose a more focused approach when being confronted with their results and given a chance to resubmit their answers. Still, the discovery of these ambition patterns and the existence of intervention possibilities may help to modify existing theory in topics like decision-making (for example, cf. Bang, Fuglesang, Ovesen, & Eilertsen, 2010; Zhang & Chiu, 2011).

The organization's upper management is now not only aware of the *wisdom* of the crowd but of the *folly* of the crowd as well. This may have an impact on, e.g., their approach to developing leadership within self-controlling, autonomous teams (cf. Taggar, Hackett, & Saha, 1999). Also, the existence of patterns and interventions will affect how we view the communication of change management (cf. Sauermann & Roach, 2013). Clifford and Jerit (2015) researched how warnings (e.g., "We try to only use data from participants who clearly demonstrate that they have read and understood the survey.", p. 792) helped to improve the quality of response. Knowing that mathematically calculated interventions might initially not fall well with certain respondents will fuel the need for more refined change management communication protocols, of which an example will be given in the next paragraph.

6.5 Practical implications

In terms of practical implications of this thesis, we like to emphasize three aspects: (1) our modified Guttman scale yields useful insights other than visualizing ambition patterns, (2) privacy issues have an effect on data collection and implementation of the interventions, and (3) how a positively self-reinforcing cycle is developing with 'More Data' at its core.

New insights

In Chapter 2, we developed some smart analytics on top of the modified Guttman scale including ambition Width/Depth, the percentage of group alignment, the group alignment with the management target, the percentage of questions covering 50% of the gap between actual situation and management target, and the percentage of questions where two or more respondents score the best answer. The first analysis in this line-up became the topic of Chapters 3, 4 and 5. As a wide variety of real-world signals show patterns (Mumford & Desolneux, 2010), there is no reason to believe these other abovementioned analytics would not reveal patterns either. That said, a first practical implication of our research is that our joint train and validation databases combined with our modified Guttman scale and analytics from Chapter 2 as well as the pattern recognition techniques as mentioned in Chapter 5 could reveal a *set* of patterns. This means that by correlating our ambition patterns with other patterns, more practical ways for analysis and intervention will appear. And by cross-referencing the patterns there could emerge a set of patterns of patterns. For example, we already saw a glimpse of that in Chapter 4 when, teams with No Ambition turned out to be among the least willing to share knowledge and we could correlate knowledge sharing *capabilities* (calculated in Chapter 2, Table 2.4, column 5) with knowledge sharing *willingness* (calculated in Chapter 4, Table 4.2, column 5).

Next, in Chapter 4 we calculated that only part of the required interventions was also planned by the teams. So, it may be inferred that the teams' self-corrective capability is relatively low. In the 'Theoretical implications' above it was concluded that a mathematically calculated optimum is not automatically a given guideline for employees to implement. In that sense, patterns of patterns can help to analyze to what extent, and under what conditions, mathematically calculated optima have a higher change of being adopted and implemented well. For example, it is possible to visualize (mis-)alignment in a team using a so-called dendrogram. A dendrogram is a form of cluster analysis, as shown in Figure 6.1.

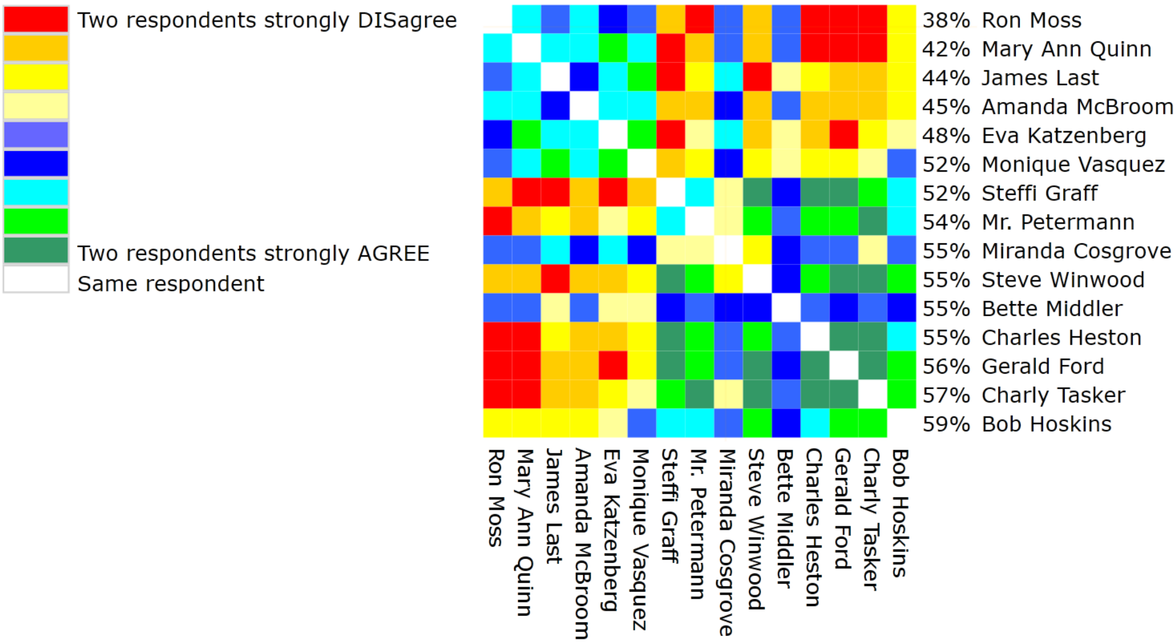

Figure 6.1: An example of a dendrogram to visualize (mis-)alignment

Each respondent in a team is compared on their ambition scores with every other respondent in that team. A green box indicates two respondents are (roughly) planning the same scores for 'In 6 months'. A red box indicates respondents that are maximally misaligned. Shades of orange, yellow and blue indicate intermediate levels of alignment. There are nine (mis-)alignment colors, each representing an alignment percentage from 0% (red) to 100% (dark green) in steps of 12.5%. By replacing the colors by the percentages, it is possible to sort the respondents in terms of alignment with all other team members and calculate the average alignment for the team. Respondent 'Ron Moss' (top row) is the respondent *dis*agreeing most with everyone else. Respondent 'Bob Hoskins' (bottom row) is the respondent most agreeing with everyone else. It is also visible that the team is divided into two camps. The respondents in the upper six rows agree relative well with each other but much less with the other nine respondents. This two-camp situation could be a pattern in many more teams. It is then interesting to see how alignment patterns are correlated with our ambition patterns. For example, it could well be that No Ambition respondents are strongly misaligned about a few topics dead-locking strategic improvements. And it could well be that No Realism respondents are very much aligned while not having a dissent voice to keep the team with both feet on the ground.

In a similar way, it is possible with the modified Guttman scale to visualize who can help whom in the team to improve with what. Respondent #1 has to improve on question A but has already achieved the management target on question B. However, Respondent #2 has achieved the management target on question A but must improve on question B. Logically, these two respondents can share knowledge. With the use of such a form of cluster analysis, it is possible to visualize how many donors (respondents that predominantly give and receive little) and how many receivers (respondents that predominantly receive and give little) there are in a team. A growing database of these visualizations will eventually show knowledge sharing patterns. It is then interesting to see how knowledge sharing is correlated with the ambition patterns. For example, it could well be that No Ambition teams contain only a few donors making the other team members unaware of the possibilities that can be realized. Yet, it could also be that No Ambition teams have very many donors and team members believe that only some have achieved the management target rather than all of them. In either case, by correlating patterns to create patterns of patterns, management has more instruments at hand to support strategic decision-making and subsequent change management.

Ethical issues

Another practical implication to emphasize is the effect of ethical issues. While information technology aspects like encryption and information reduction are well known and statistical approaches to provide individualized privacy have been developed (Esponda, Huerta, & Guerrero, 2016) and legal frameworks – like the American Council of Advisors on Science and Technology (2014) – or company security policies (Hollis, 2007) are in place, these are all defensive measures. These measures could be seen as required – but not sufficient – conditions for respondents to participate. Management wanting to entice employees could use – as discussed in Chapter 4 – incentives (Schneider & Johnson, 1995) as well as warnings (Clifford & Jerit, 2015). Yet, we have noticed while analyzing the knowledge sharing aspect of the projects in our database that – except in just a few projects – no single employee scores that well that they cannot learn from someone else and that no single employee scores that bad that they have nothing to share with another colleague. That said, we assume there is a practical implication for management to focus on the unique contributions of employees within this knowledge sharing setting: give every employee his or her 15 minutes of fame. Then, participation is not just something that is part of the job but an opportunity for career advancement as well. Rewarding of employees would then include reciprocal benefits (knowledge exchange rather than just sharing), knowledge self-efficacy (a type of self-respect from teaching others), enjoyment in helping others and reputation enhancement (Šajeva, 2014). However, these positive arguments must counter the Orwellian 'Big Brother' feelings when respondents might see these surveys as a tight performance control (Lidström & Druzynski, 2010) or when they feel that not participating is not an option (cf. Sarpong, & Rees, 2014).

A positively self-reinforcing cycle

A third practical implication has perhaps the most far-reaching consequences. In Chapter 2 we designed new strategic insights. And by comparing these in data sets we upgraded these insights into patterns and interventions. These patterns and interventions might have a very broad application. As said, we saw in Chapter 5 that 97% of over 48,000 respondents had (potentially) harmful ambition patterns. So, we might postulate that in any next organization that would analyze employees' ambition with regard to the strategic options presented by management, the entity-relationship model (Figure 5.4 in Chapter 5) could give automated advice on what to do for the various teams in that organizations to mitigate the ambition patterns. As mentioned above in the theoretical implications section, we are less sure about the exact mix of the ambition patterns than about the existence of these patterns (the 97%). That means that we would have to further test the reliability of this entity-relationship model. But automated advice would stimulate more organizations to issue questionnaires as described in Chapter 2 to their employees as the costs of automated advice can be much lower than the cost of consultants or in-house specialists that would do interviews or would be busy making sense of statement-driven employee surveys. When advice gets increasingly better and the costs to obtain that advice get increasingly reduced, more and more organizations will be willing to use the approach: there is a scaling effect. All this results in the following positively self-reinforcing cycle, which was depicted in Chapter 1, and upgraded here with the insights gained in Chapters 2 to 5 (Figure 6.2):

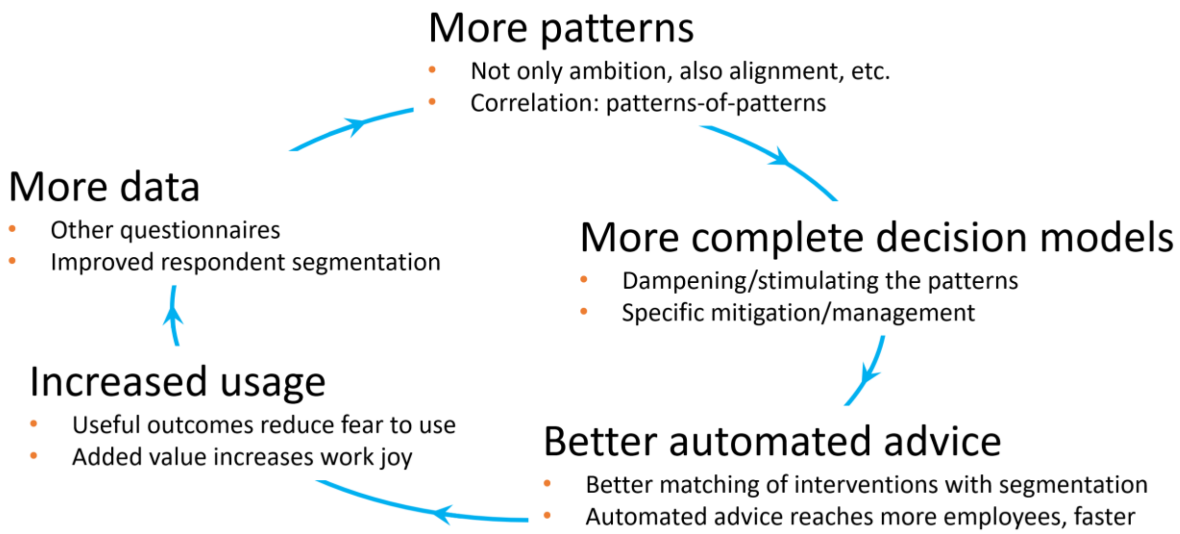

Figure 6.2: An upgraded positively self-reinforcing cycle of automated advice

We covered a part of this cycle (from 'More data' to 'More complete decision models') in this thesis. Learning more about how to deliver automated advice has to do with refining the strategic decision-making models in such a way that the factors why employees would not implement their outcomes as described above in 'theoretical implications' (for example because of fear, beliefs or political interests) could be addressed as well. The step from 'Better automated advice' to 'Increased usage' is more an economic and a commercial aspect: how to reach more organizations and convince them to give it a try. The step from 'Increased usage' to 'More Data' is scientifically interesting as it draws the attention to the underlying data model. What kind of additional data are necessary to fuel the next round of patterns? For example, we described above in 'methodological implications' how we missed data for the further segmentation of teams. And an addition to the data model is not just a question of what would be nice-to-have but should be part of a scientifically underpinned taxonomy or corporate genome (a term coined by Aurik, Jonk, and Willen, 2003). The improving quality of this taxonomy will increase the variety and interdependency of the patterns: the patterns are not merely discovered but increasingly fill in the blanks in an overarching taxonomy.

Given the rise of the ‘Automation of Knowledge work’ as referred to in Chapter 1, it is not to be excluded that after a few spins of the positively self-reinforcing cycle, machine learning will partly or almost completely take over the execution of this cycle. And that is not so far-fetched. Suppose we would add a maturity model to the team effectiveness questionnaire we used in the second study in Chapter 3. That maturity model would indicate on each question’s Guttman scale what answer would link to what maturity level. The levels are then the ideal stations on the organization’s way to the top. Of course, once an organization would score very well on the questionnaire, the first answers would be deleted and new third answers appended: a positively self-reinforcing cycle in itself. A calculation rule could allocate for each team in the organization the best suitable maturity level (the improvement target for the next period) given the actual situation in that team. A pattern-of-pattern calculation rule could calculate the effect on, say, the resulting misalignment and level of knowledge sharing. Another calculation rule could detect the most likely organizational culture out of a standard set of cultures based on the employees’ response patterns. Based on that deducted organizational culture, this calculation rule could autonomously make a choice what alignment and knowledge situation profiles would best match the organizational culture and, by doing so, sort the alternative maturity levels (and other alternative strategies).

It would be a task for managers to come up with a better alternative or accept the best alternative as suggested by the strategic decision-making model. These models are likely to improve much faster than the insight of the average manager. This is partly driven by the feedback loop that the central model managing the calculation rules will absorb any manager’s alternative improvement strategy that outperforms the model, immediately improving that same model by doing so. Similar machine learning scenarios are imaginable for each of the other steps in the positively self-reinforcing cycle in Figure 6.2.

The above scenario might have a high Orwellian ‘Big Brother’ aspect to it, similar to, for example, surveillance data that are also used to lure customers. We plead for a much more positive outlook. There are approximately seven million managers (Occupational Outlook Handbook, 2015) and approximately 600,000 management consultants (Statista, 2015) in the USA. As a smaller group of managers will have large projects consuming many consultants, we can argue that small and medium enterprises (SMEs) will have less or no access to management consultants to help them with strategic issues, even alone because of the costs involved in hiring consultants. For them, a ‘Let’s Google it’ support strategy appears to be the best alternative.

The Worldbank (2015) indicates that globally there are 30 million SME’s with more than 10 employees. We reckon that many SMEs in India, China or sub-Saharan Africa will not have access to a lot of management consultancy. Automated advice that is – certainly in comparison with management consultants’ rates – nearly free may offer management knowledge to a previously unimaginable large audience.

6.6 Suggestions for future research

From a *content* point of view, strategic decision-making goes through a fundamental shake-up as established theories such a Porter’s five-forces model are hardly applicable in modern times where ubiquity trumps scarcity (Choudary, Van Alstyne, & Parker, 2016) and the concept of ‘free’ (business models that thrive on free services like Google does with their search) has overturned many business models (Anderson, 2008). From a *process* point of view, which was the key focus of this thesis, strategic decision-making has always been a combination of mathematics (e.g., risk management), psychology and sociology (e.g., individual and group behavior), economics (e.g., issues of scaling), management and political science (e.g., power and competitive interests) (Buchanan & O'Connell, 2006) and has been in development for at least the last 70 years.

These last 70 years, many advances have been made in quantitatively modelling organizations in order to model human behavior, harness risk and to calculate optima. This started with earliest artificial intelligence, pattern recognition and thinking machines for human behavior analysis and decision-making in the 1950s (Simon, 1955) and 1960s (Minsky, 1969). The 1970s were the era of 'executive information systems' and 'decision support systems' which got extended in the 1980s as 'business Intelligence systems' to serve the whole organization (and not only the board of management). In the 1990s this was further expanded by closely monitoring customers' online clickstreams and after 2000, their buying behavior. In 70 years, from inside the organization to outside; from unstructured- to structured- to semi-structured data. If history would indeed repeat itself, we would be cycling back to modelling unstructured behavioral data but with all the knowledge and techniques we have today. Where human behavior as such can be very complex to model, our approach to simplify strategic choices to options in a questionnaire is a form of data compression knowing that if data cannot be further compressed it is sufficiently specific (cf. Zenil, 2017). We assume that employees have factored everything they hear from customers, see in the corporate administration dashboard, and discuss in their team meetings, etcetera, in their 'In 6 months' ambition scores. Similar to how stock prices reflect everything investors know. A definite area for research is whether our assumption is true and, then, whether we have not 'overcompressed' our data in order to find predictable outcomes. An average company on the NASDAQ gets approximately 650,000 trades daily (NASDAQ, 2017). Our granularity is only a fraction of that. Yet, "although long-range algorithmic prediction models [..] may require infinite computation, locally approximated short-range estimations are possible, thereby demonstrating how small data can deliver important insights into important features of complex 'Big Data'" (Zenil, 2017, p. 1). Lin (2015) discusses controversies around 'the use of Big Data in social sciences' along a difference in objectives: is it about 'better science' (in our thesis, for example, modifying theories on team cognition) or 'better engineering' (in our thesis, supporting management to intervene in harmful patterns)? Further research might explore whether a finer granularity in ambition models truly reflect all that employees know and whether that modelling has to go at the expense of scientific quality.

In Chapter 5, we calculated that the vast majority of respondents showed potentially harmful ambition patterns (all patterns except Focused Change). Future research remains necessary to further verify the general applicability of the ambition patterns and more importantly the likely mix of these patterns. In terms of the pattern recognition process in Chapter 5 – in the paragraph on 'generalization' - the validation data set confirmed the wide occurrence of the patterns (97% scored one of the three harmful patterns) and (to a lesser extent) the mix among the four patterns. Hence, the extent of harmfulness is roughly proved (only very minor percentages in Focused Change), but its composition (the pattern mix) still needs some further investigation. Therefore, a further refinement in the pattern mix is expected when this research will be extended to many more organizations than the roughly 40 organizations covered in Chapters 2 and 3 and when more advanced calculation-/classification methods will be used. It would be then equally interesting to see how the percentage of 'incomplete' respondents would develop. This percentage was rather high in both train and validation data set. Now we understand more about the survey logistics, rewards and incentives, and how to prevent factors leadings to disengagement as discussed in Chapter 4, there is more information how to execute surveys in ways that probably yield better participation from more employees. Yet, there is a need to do additional research on how to further segment response styles and non-response. For example, we have found only a few leads to explain the percentage of 'incomplete' respondents in the validation data set. We discussed in Chapter 4 the limited availability of formal records in organizations' HR departments. We haven't found research on combining strategic organizational aspects and personality questions in one single questionnaire to be able to segment on character and personality. Hence, we expect more from the patterns-of-patterns as discussed above in 'practical implications' and segment on alignment and knowledge sharing and other aspects that can be inferred from using strategic decision-making models.

Other than research on numbers and percentages, there is a need to research the motivation and deliberations of respondents when answering the questionnaires. For example, are planned improvements hypothetical? The respondents' nice-to-have wish list? Highly likely to be implemented? Knowing this gives a feel for the 'hardness' of the Planned scores as this influences the extent of the 'folly of the Crowd'. If the Planned scores are just hypothetical, nice-to-have, improvements, one could ask why the employees did not make any clear choices. Conversely, if the Planned scores were indeed likely to be implemented, management could ask itself why No Focus- and No Realism respondents live on cloud nine, while simultaneously management would be happy with the concrete (albeit limited) choices of the No Ambition respondents. Another reason to research the motivation and deliberations of the 'incomplete' respondents is to understand why they choose one of these incomplete patterns. We haven't found an explanation why a large percentage of respondents went through the trouble of clicking the same answer twice for each of the questions they answered. These percentages are higher than the percentages for respondents who just ignored the Planned score and only indicated the Actual situation.

Then, it is important for future research to understand how the proposed interventions reduce Width and increase Depth. First of all, and as mentioned before in the methodological aspects, there weren't enough Focused Change respondents to truly calculate the factors that reduce Width and increase Depth. More research is needed to verify the suggested interventions with respondents to see how the interventions we calculated would also be accepted. Also, longitudinal research on whether these calculated interventions truly affect the ambition pattern in the direction of Focused Change would be welcomed. We can imagine management doing not one measurement but a series of measurements to track the progress of the strategic decision-making and subsequent implementation and change management over time. Such a measurement series would then shed light whether the proposed interventions result in more 'Focused Change' individual respondents and -teams.

Finally, more research is needed whether management should do just more of one intervention approach or also actively discourage the other approach: there is the need to research what blend of Depth/Width is (un-)favorable for an organization. For example, No Ambition respondents should be stimulated to improve on informal/bottom-up factors. But this thesis hasn't researched whether management should *simultaneously* diminish the formal/top-down aspects of team effectiveness. Should No Realism respondents only work on their formal/top-down team aspects or be actively discouraged from, for example, having a high tolerance for ambiguity?

6.7 Epilogue

In this thesis, the ambition of employees with regard to strategic decision options proposed by the organization's upper management has been modeled into a practical entity-relationship model for a broad application, specifically for the purpose of automated consulting. We have seen that a roughly 200-fold increase in respondents compared to usual literature on team ambition drives innovation in data capturing techniques and pattern recognition. The general applicability of our patterns appears to be perpendicular to certain existing theories. Strategic decision-making modeled in calculation rules to drive automated advice may dramatically improve the maneuverability for management. In summary, this thesis contributes to a fundament for a comprehensive strategic decision-making model library that may become an enormous support to one of the hardest management tasks. Not only in corporations but in small and medium enterprises too. And not in the Western hemisphere alone, but across the globe as well.

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Summary

Summary

Introduction

This thesis is about designing a methodology to model aspects of strategic decision-making into generically applicable calculation rules based on the input from large numbers of employees to support an organization's upper management. When involving the input of large numbers of employees, strategic decision-making is mainly a bottom-up flow of information: the employees become the 'eyes and ears' of upper management. But, when decisions are made and targets are set, it is the subsequent change management where information flows top-down: upper management instructs the rest of the organization what the targets, milestones, budgets and mandates have become. So, when modelling aspects of strategic decision-making, we prefer to apply a modelling technique that would benefit this change management as well and would factor in the probably lesser modelling competencies of lower management and employees.

In organizations, lower management and employees get more and more strategic responsibilities due a reduction of management layers, the increase of autonomous teams and the availability of information technology. Involving employees in strategic decisions is an example of 'the wisdom of the crowd': a group may outsmart the smartest individual given certain conditions. These conditions are that the crowd is diverse, that individual members contribute independently preferably with factual input, that there is decentralization (covering knowledge from many different locations) and that there is a form of aggregation of the members' input. So, the input of all employees in an organization may offer a tremendous insight for the organizations' board of management. But if 'all employees' means involving thousands of employees and when in a rapidly changing world strategic decision have to be made ever faster, the use of automation and, thus, calculation rules, seems logic. Consultancy firm McKinsey rates 'automation of knowledge work' the number two most disruptive technology trend for the coming decade. The employees' ambition to change is the focus of this thesis; modelling that ambition in an entity-relationship model the topic.

It is difficult to obtain the input of all employees regarding strategic decisions just from their 'digital traces' (search terms in their browser, Facebook messages, etc.) they leave behind; we have to ask them. Traditionally, employee surveys do not ask about strategic issues. Plus, these surveys solicit for employees' opinions that may lead to socially acceptable answers and various types of bias. Such an employee input scores low on data quality for feeding calculation rules.

Research questions

The abovementioned deliberations led to the following research questions:

1.) How applicable are the usual employee surveys given data requirements needed for the development of an entity-relationship model based on large-scale employee input gathered on strategic options? If not, would specific survey improvements be necessary? And what would these improvements have to look like?

2.) Can we detect ambition types in the employees' choice out of the strategic options presented by their management? Can these types be meaningfully labelled/interpreted? Will these types differ across strategic issues, industries, and/or countries? Do these ambition types recur as such that we could identify them as patterns?

3.) Are these ambition types manageable (amplify the positive aspects and mitigate the negative aspects) to support or improve the quality of the strategic decision-making process?

4.) How do our research activities compare to the process steps in a formal pattern recognition process as described in scientific pattern recognition literature? Have we left out certain process steps?

Designing a modified Guttman scale

In Chapter 2, we concluded that asking employees to agree on statements or give statements an applicability compared very unfavorably with data requirements from Big Data literature. Hence, we switched to a Guttman scale with an added time dimension, wording that abstains from using adjectives and adverbs and control words ('formal', 'described', etc.) that aid with verifying/auditing the answer. This scale yields reasonably objective input and scores well on data quality. An example:

To what extent are there team objectives?	Now	In 6 months' time
1. We do not have team objectives (yet)	☐	☐
2. We have a general description	☐	☐
3. We have formal, SMART key performance indicators	☐	☐

We tested this Guttman scale in a German energy company where the organization's board of management presented a questionnaire with strategic options out of which lower management and employees could choose. The questionnaire asked per strategic option for a) the actual situation and b) to what extent that actual situation had to improve. Respondents were free to omit questions or skip an answer for either the 'Now'- or 'In 6 months'-options. The respondents' answers were translated into a score from 0 – 10. When analyzing the response, we did not research *what* or *how* respondents wanted to improve. Only by *how much*. That is why we have split ambition, the 'in 6 months' time' score, into two components. 'Width' indicates how many questions a respondent planned to improve. 'Depth' indicates by how much a respondent planned to improve these questions. Example: Respondent XYZ wants to improve in the next 6 months 60% of the questions in the questionnaire with an average of 40% (e.g., from a 4.0 to a 5.6). By combining Width and Depth 4 different ambition patterns emerge. Where 'little' stops and 'a lot' begins is the topic of Chapter 3.

No Ambition: little Width – little Depth
No Focus: a lot of Width – little Depth
No Realism: a lot of Width – a lot of Depth
Focused change: little Width – a lot of Depth

Identifying and mitigating ambition patterns

In Chapter 3, we first studied three different organizations with teams in 32 countries and a cluster of various educational institutions in the Netherlands with an identical strategic problem with in total +/- 2,000 respondents. Based on various scenarios on how to best dissect Width and Depth, the four ambition patterns emerged. Slightly over 40% of respondents scored 'No Ambition'. A similar percentage scored 'No Realism'. Slightly over 10% scored 'No Focus'. Only a few percent of the respondents scored 'Focused Change'. Hence, the vast majority of respondents scored ambition patterns that are (potentially) harmful to their organizations.

In a second study, we analyzed the response to a team effectiveness questionnaire sent to +/- 1.200 respondents in 31 organizations in eight different industries. Comparing the industries, we found that seven of these industries were statistically similar in their variance and distribution of the respondents' answers. We researched how the four ambition patterns scored differently with regard to the various team effectiveness topics. We analyzed what differentiates No Ambition respondents from No Focus respondents (to manage Width) and what differentiates No Realism respondents from No Focus respondents (to manage Depth). There were too few Focused Change respondents to further sharpen those differences. As a rule of thumb, we state that a formal/top-down management approach reduces Width and an informal/bottom-up management approach improves Depth. The respondents only planned ('In 6 months') half of the required interventions to move in the direction of Focused Change.

Zooming in on non-response and Extreme Response Styles

In Chapter 4, we further focused on the database in the second study of Chapter 3. We looked at two important aspects of working with surveys: (1) non-response and (2) 'Extreme Response Styles' (ERS). Our modified Guttman scale eliminated ERS to large extent. Non-response was present and only mildly influenced by age. Part of the non-response could be explained by respondents' disengagement. In this chapter, we also studied respondents that submitted odd responses (the so-called 'incomplete' respondents). An example was respondents who submitted identical answers for the actual situation and in 6 months' time.

Validating the pattern and building the entity-relationship model

Because three of the four ambition patterns (No Ambition, No Focus and No Realism) are potentially harmful for the strategic decision-making process and the subsequent change management, we have researched in Chapter 5 whether we had taken all the necessary steps regarding survey 'logistics' (timing, introduction to the respondents, reminders). That turned out to be adequately handled. We also researched whether we took all the necessary steps to recognize a pattern. Here, we had not covered a crucial step: validating the patterns in a larger validation data set. Hence, a subsequent validation of +/- additional 48,000 respondents in 3,362 teams showed the same four ambition patterns in roughly a similar mix. And only 3% of the respondents in validation data set scored Focused Change. With this validation covered, we then built an entity-relationship model (flow chart) describing the data capture, the calculation logic and the related management interventions.

Main conclusion

Involving relative large groups of employees gives, in line with ‘the wisdom of the crowd’, a refined additional insight which a board of management can include in its strategic decision-making process. The added value of our research is that when employees are asked to make a choice out of strategic options presented by management, the vast majority shows ambition patterns that are potentially harmful to the organization. That harm may be expressed as, for instance, less optimal strategic decision-making, a prolonged implementation time and higher costs. Yet, that harm appears manageable by modifying the style of management (formal/top-down versus informal/bottom-up).

Methodological considerations

In terms of methodology, the modification of the Guttman scale is the basis for our research. We did study some of the disadvantages of employee survey statements but not the (dis-)advantages of other scales. We also were unable to compare our research with large-scale strategic ambition research using such statements. More advanced calculation techniques would perhaps indicate more precisely the borders between the four ambition patterns. More background information would help with further segmentation of respondents and their teams. Next, the, in our opinion, large percentage of ‘incomplete’ respondents is a concern, too. On the one hand, because this collateral damage of unusable response is methodologically not elegant: apparently, a large percentage of respondents was not capable of submitting input. On the other hand, because we were not able to explore explaining factors other than the aspects of team effectiveness we had available. Also, the small number of Focused Change respondents influences the unequivocality with which we can indicate how to manage Width and Depth.

Theoretical considerations

The mix of ambition patterns seems to be at odds with established theories about, for instance ‘groupthink’ and ‘team cognition’. Attention for team cohesion should be reflected in alignment about the strategic direction of the team/organization. It would be statistically very curious if the 3,362 teams in our validation data set all would eschew groupthink and team cohesion. The limited amount of background information regarding the respondents did not allow further respondent segmentation to explain why these patterns exist, despite groupthink and team cohesion.

Practical considerations

In terms of practical aspects, our modified Guttman scale offers new and useful insights that support strategic decision making and subsequent change management. We were able to quantify ambition, alignment, improvement effort and knowledge sharing, detected patterns in ambition and calculated interventions to mitigate potentially harmful ambition patterns. Yet, we haven’t researched whether our calculated situations and interventions (for example, a formal/top-down management style benefits teams with a ‘No Realism’-pattern) will also be automatically executed by respondents. Issues regarding privacy and ethics may inhibit swift adoption. Nevertheless, we foresee a virtuous cycle where more available data leads to more precise ambition patterns, leading to smarter strategic decision-making models giving better advice, leading to an increased usage by organizations yielding again more data.

Suggestions for further research

The most interesting piece of data in our research is the wide occurrence of the three sub-optimal ambition patterns: only 3% of respondents has a Focused Change profile. More research in other organizations could reveal whether this percentage will materially change. In this context, it is also interesting to see how the 'incomplete' response will develop in other organizations. And then it is not just about the percentages but also about the motivation of respondents to 'choose' a certain ambition pattern. Finally, there is more research needed about the effect of the interventions in management style that we have proposed for three of the four ambition patterns.

Samenvatting (in Dutch)

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Samenvatting (in Dutch)

Introductie

Dit proefschrift gaat over het ontwerp van een methodologie ten behoeve van het modelleren van bepaalde aspecten van strategische besluitvorming. Hierbij maken we gebruik van de input van grote aantallen werknemers in een organisatie ter ondersteuning van het hogere management. Het betrekken van grote aantallen werknemers is vooral een 'bottom-up' informatiestroom: de medewerkers als de 'ogen en oren' van het hogere management. Maar wanneer de strategische beslissingen zijn genomen en de doelen zijn gesteld is het tijd voor 'change management' waarbij de informatiestroom 'top-down' is: het hogere management instrueert de rest van organisatie wat de targets, milestones, budgetten en mandaten zijn. Het modelleren van aspecten van strategische besluitvorming is dus gediend met een modelleringsaanpak die ook rekening houdt met change management en met de te verwachten lagere modelleringsvaardigheden van het lagere management en van medewerkers.

In organisaties krijgen het lager management en medewerkers steeds meer strategische verantwoordelijkheden als gevolg van (1) het schrappen van managementlagen, (2) de toename van zelfsturende teams, en (3) de beschikbaarheid van informatietechnologie. Het betrekken van medewerkers in strategische beslissingen is een voorbeeld van 'the wisdom of the crowd': een groep komt onder bepaalde condities tot betere resultaten dan een goed geïnformeerd individu. Deze condities zijn dat de groep divers van opzet is, dat individuele groepsleden hun input onafhankelijk en zo feitelijk mogelijk aanbieden, dat er decentralisatie is (kennis uit veel verschillende locaties omvat) en dat er een vorm van aggregatie is. Daardoor kunnen we stellen dat de input van alle medewerkers van een organisatie een enorm toegevoegd inzicht kan opleveren voor de directie. Maar als 'alle medewerkers' betrekking heeft op (vele) duizenden medewerkers en wanneer in een snel veranderende wereld strategische besluiten steeds sneller genomen moeten worden, ligt automatisering voor de hand. Onderzoeksbureau McKinsey noemt 'het automatiseren van kenniswerk' de op één na belangrijkste technologische trend voor het komende decennium. De veranderambitie van medewerkers is de focus van dit proefschrift; het vastleggen van die ambitie in strategisch besluitvormingsmodel het onderwerp van studie.

De input van alle medewerkers ten aanzien van strategische besluiten kunnen we nog moeilijk aflezen aan de 'digitale sporen' (zoektermen in een browser, Facebook berichten, etcetera) die zij achterlaten. Deze input moeten we nog steeds aan hen vragen. Het overgrote merendeel van de gebruikelijke medewerkeronderzoeken vraagt niet naar strategische onderwerpen. Daar komt bij dat ze meestal vragen naar de (subjectieve) mening van medewerkers. Dit kan leiden tot sociaal-wenselijke antwoorden en allerlei andere vormen van onderzoeksvertekening. Een dergelijke input van medewerkers is vanuit het oogpunt van datakwaliteit maar matig geschikt voor het voeden van algoritmes.

Onderzoeksvragen

De bovenstaande overwegingen hebben in dit proefschrift geleid tot de volgende onderzoeksvragen:

1.) Voldoet een gebruikelijk medewerkersonderzoek aan de data eisen voor het ontwikkelen van een entiteit-relatie model ten behoeve van het verkrijgen van input van grote aantallen medewerkers over de strategische opties van een organisatie? Indien deze surveys niet voldoen, welke verbeteringen zijn noodzakelijk? En hoe zouden die verbeteringen eruit zien?

2.) Kunnen we ambitietypes ontdekken in de keuzes van medewerkers ten aanzien van strategische opties zoals voorgelegd door hun management? Kunnen deze types op zinvolle wijze benoemd/geïnterpreteerd worden? En zijn er verschillen in deze types tussen strategische onderwerpen, industrieën en/of landen? Komen deze ambitietypes dusdanig vaak terug dat we ze als 'patronen' mogen identificeren?

3.) Zijn deze ambitietypes ook te beheersen (in termen van het versterken van de positieve effecten en het indammen van de negatieve effecten) ten behoeve van een beter strategisch besluitvormingsproces?

4.) Hoe sluiten onze onderzoeksactiviteiten aan bij de proces stappen van een formeel patroon herkenningsproces zoals wetenschappelijk beschreven? Hebben we bepaalde proces stappen overgeslagen?

Het ontwerp voor een aangepaste Guttman schaal

In Hoofdstuk 2 hebben we geconcludeerd dat (1) het aan medewerkers vragen om instemming met een stelling of (2) om een stelling een 'toepasbaarheidsscore' te geven niet goed voldoet aan de data eisen zoals beschreven in Big Data literatuur. Daarom hebben wij nieuw onderzoek gedaan op basis van de zogeheten Guttman schaal voorzien van multiple-choice vragen waarbij de antwoorden oplopen in kwaliteit. Deze schaal is uitgebreid met een tijd-dimensie, waarbij het gebruik van bijvoegelijke naamwoorden en bijwoorden wordt vermeden en 'controle woorden' (zoals 'formeel', 'vastgelegd', etcetera) worden toegevoegd. Deze schaal geeft redelijk objectieve input (het minimaliseert cognitief- en emotioneel geladen vragen en antwoorden) en scoort goed qua datakwaliteit. Een voorbeeld van een vraag:

In hoeverre zijn er teamdoelstellingen?	Nu	Over 6 maanden
1. We hebben (nog) geen team doelstellingen	☐	☐
2. We hebben een algemene omschrijving	☐	☐
3. We hebben formele, SMART prestatie indicatoren	☐	☐

Wij hebben deze aangepaste Guttman schaal getest onder medewerkers van een Duits energiebedijf. De directie heeft een bijbehorende vragenlijst met strategische opties voorgelegd aan het lager management en medewerkers. In deze lijst werd per strategische optie gevraagd naar de huidige situatie en in hoeverre die situatie moest worden verbeterd ('Nu' versus 'Over 6 maanden'). Respondenten waren vrij om vragen over te slaan of bij een vraag het 'Nu'- of 'Over 6 maanden'-antwoord over te slaan. De antwoorden van respondenten werden omgezet in een score van 0-10. Door al die verschillende onderwerpen te vergelijken, kijken we niet naar *wat* en *hoe* respondenten wilden veranderen maar uitsluitend naar *hoeveel*. Daarvoor wordt hun ambitie in twee aspecten opgesplitst: 'Breedte' geeft aan hoeveel vragen een respondent wil verbeteren. 'Diepte' geeft aan met welk percentage die vragen moeten worden verbeterd. Voorbeeld: Respondent X wil binnen 6 maanden 60% van de vragen in de vragenlijst met gemiddeld 40% verbeteren (bijvoorbeeld van een score 4,0 naar een score 5,6). Door Breedte en Diepte te combineren ontstaan vier ambitie patronen. Waar 'weinig' ophoudt en 'veel' begint is het onderwerp van Hoofdstuk 3.

Geen Ambitie: weinig Breedte – weinig Diepte
Geen Focus: veel Breedte – weinig Diepte
Geen Realisme: veel Breedte – veel Diepte
Gefocust Veranderen: weinig Breedte – veel Diepte

Het identificeren en managen van ambitie patronen

In Hoofdstuk 3 hebben we drie organisaties met teams in 32 landen en een cluster van een aantal onderwijsinstellingen in Nederland met een identiek strategisch probleem met in totaal +/- 2.000 respondenten bestudeerd. Op basis van een aantal scenario's werd een tweedeling gemaakt voor zowel Breedte als Diepte. De gewijzigde Guttman schaal liet duidelijk de vier ambitie patronen zien. Iets meer dan 40% van de respondenten scoorde 'Geen Ambitie'. Een vergelijkbaar percentage 'Geen Realisme'. Iets meer dan 10% scoorde 'Geen Focus'. Slechts een klein percentage van de respondenten scoorde 'Gefocust Veranderen'. We kunnen hieruit concluderen dat het overgrote deel van de respondenten een ambitiepatroon laat zien dat (potentieel) schadelijk is voor de organisatie. In een tweede studie bestudeerden we de respons van +/- 1.200 respondenten bij 31 organisaties in acht verschillende industrieën op een vragenlijst over team effectiviteit. Een vergelijking tussen de industrieën liet zien dat zeven industrieën statistisch vergelijkbaar waren voor wat betreft de variantie en distributie van de antwoorden van de respondenten. Er is onderzocht hoe de vier ambitiepatronen scoorden op verschillende onderwerpen van team effectiviteit. Geanalyseerd is wat Geen Ambitie respondenten van Geen Focus respondenten onderscheidde (om Breedte te managen) en wat Geen Realisme respondenten van Geen Focus respondenten onderscheidde (om Diepte te managen). Er waren te weinig Gefocust Veranderen respondenten om het onderscheid voor Breedte en Diepte nog scherper te krijgen. Op basis van deze analyse kwamen wij tot de volgende twee vuistregels : (1) een formele/top-down management benadering vermindert de Breedte; en (2) een informele/ bottom-up management benadering vergroot de Diepte. De respondenten planden ('over 6 maanden') slechts de helft van de gewenste interventies om richting Gefocust Veranderen te gaan.

Inzoomen op non-response en 'Extreme Response Styles'

In Hoofdstuk 4 bestudeerden wij twee belangrijke aspecten van het werken met vragenlijsten: (1) non-response en (2) 'extreme responsstijlen ('Extreme Response Styles' - ERS). ERS was nagenoeg afwezig. Non-response was duidelijk aanwezig en werd slechts beperkt beïnvloed door leeftijd, werkervaring en hiërarchische positie van de respondent. Een gedeelte van de non-respons kon verklaard worden door een gebrek aan betrokkenheid van respondenten. In dit hoofdstuk bekeken we ook respondenten die op een onbedoelde manier hun respons gaven (de zogenaamde 'niet-complete respondenten'). Een voorbeeld waren respondenten die op alle vragen identieke antwoorden gaven voor zowel de huidige situatie als de ambitie voor over 6 maanden.

Patroon validatie en het construeren van het entiteit-relatie model

Omdat drie van de vier ambitiepatronen (Geen Ambitie, Geen Focus en Geen Realisme) potentieel schadelijk lijken te zijn voor het strategisch proces en het daaropvolgend verandermanagement, is in Hoofdstuk 5 onderzocht in hoeverre alle noodzakelijk stappen zijn gevolgd aangaande de 'logistiek' rond vragenlijsten (timing, introductie bij de medewerkers, reminders). Dat bleek voldoende in orde. Daarnaast is onderzocht in hoeverre alle noodzakelijke stappen zijn gevolgd voor wat betreft het herkennen van patronen. Bij dit laatste ontbrak één belangrijke stap: het valideren van de patronen in een grotere validatie dataset. Een validatie bij +/- 48.000 respondenten in 3,362 teams laat zien dat dezelfde vier patronen in een ongeveer vergelijkbare verdeling als in onze studie in Hoofdstuk 3 voorkomen. Verder bleek dat slechts 3% van de respondenten Gefocust Veranderen als ambitie patroon heeft. Met deze validatie afgedekt, is vervolgens een entiteit-relatie model (flow chart) samengesteld die het verkrijgen van de data, de berekeningswijze en de bijbehorende interventies beschrijft.

Conclusies

Het betrekken van grote groepen medewerkers geeft een verfijnd, additioneel inzicht waarop een directie van een organisatie zich mede kan baseren bij strategische besluitvorming. De toegevoegde waarde van ons onderzoek is het inzicht dat wanneer aan deze medewerkers wordt gevraagd om een keuze te maken uit strategische opties zoals die door de directie gepresenteerd worden, het overgrote deel van de respondenten een ambitiepatroon laat zien dat potentieel schadelijk is voor de organisatie. Die schade kan bijvoorbeeld bestaan uit niet optimale besluitvorming, vertraagde implementatie en hogere kosten. Maar deze schade lijkt beheersbaar door bovengenoemde aanpassingen in management benadering.

Methodologische aspecten

Qua methodologie is de aanpassing van de Guttman schaal de basis voor het onderzoek. Wij hebben enkele methodologische nadelen van het gebruik van stellingen in medewerkersonderzoeken onderzocht maar niet de voor-/nadelen van andere schalen ten aanzien van datakwaliteit. We hebben ook geen vergelijking gemaakt met grootschalig strategisch ambitie onderzoek onder medewerkers op basis van dergelijke stellingen en/of schalen. Meer geavanceerde berekeningen kunnen wellicht betere grenzen aangeven tussen de vier ambitiepatronen. Ook zou meer achtergrondinformatie over de respondenten kunnen helpen met het verder segmenteren van medewerkers en hun teams. Daarnaast is het relatief grote aantal 'niet complete' antwoorden van respondenten een bron van zorg. Enerzijds omdat we de bijkomende schade van onbruikbare respons methodisch niet elegant vinden: blijkbaar was een groot percentage aan respondenten niet in staat om input te geven. Anderzijds omdat we geen verklarende factoren hiervoor hebben kunnen onderzoeken. Ook is het kleine aantal aan 'Gefocust Veranderen' respondenten van invloed op de eenduidigheid waarmee we kunnen aangeven hoe Breedte en Diepte te managen.

Theoretische aspecten

De ambitie patronen lijken haaks te staan op gevestigde theorieën over bijvoorbeeld 'groupthink' en 'team cognition'. De ontwikkeling die er in teams zou moeten zijn ten aanzien van groupthink of juist team cohesie zou zijn weerslag moeten vinden in overeenstemming ten aanzien van de strategische richting van het team en/of de organisatie. Echter, het zou statistisch bijzonder curieus zijn als de 3,362 teams in de validatie dataset zich geen van allen met groupthink en team cohesie te maken zou hebben gehad In de voor ons beschikbare dataset was weinig achtergrondinformatie voorhanden (zoals Leeftijd en opleiding) die zou kunnen helpen met het verder segmenteren van de respondenten. Deze additionele informatie zou kunnen verklaren waarom, ondanks mogelijke groupthink processen of shared team cognition, toch dergelijke patronen ontstaan.

Praktische aspecten

Vanuit praktisch oogpunt levert onze aangepaste Guttman schaal nieuwe en zinvolle inzichten op ter ondersteuning van strategische besluitvorming en het daaropvolgende verandermanagement. We zijn in staat geweest om ambitie, draagvlak, verbeterinspanning en kennisdeling te kwantificeren. En we hebben ambitiepatronen ontdekt en hebben berekend welke interventies passen bij mogelijke schadelijke ambitiepatronen. Aan de andere kant is niet gezegd dat de berekende interventies (bijvoorbeeld, dat 'Geen Realisme'-teams baat hebben bij een formele/top-down managementstijl) ook automatisch door respondenten worden uitgevoerd. Issues met betrekking tot privacy en ethiek kunnen daar remmend op werken. Desondanks voorzien we een positieve spiraal, waarbij meer data leidt tot betere ambitiepatronen, die op hun beurt leiden tot slimmere strategische besluitvormingsmodellen die beter advies kunnen geven. Hierdoor neemt het gebruik van deze rekenregels toe en komt er weer meer data beschikbaar.

Suggesties voor verder onderzoek

Het interessantste gegeven uit ons onderzoek is de wijde verbreidheid van de drie suboptimale patronen: slechts 3% van de respondenten heeft een Gefocust Veranderen profiel. Meer onderzoek bij andere organisaties kan laten zien in hoeverre dit percentage nog significant zal wijzigen. In het licht daarvan is het ook interessant om te kijken hoe bij andere organisaties de 'niet complete' respons zich ontwikkelt. Daarbij gaat het uiteraard niet alleen om de percentages maar ook om het achterhalen van de motivaties van respondenten om een bepaald patroon te 'kiezen'. Tenslotte is het meer onderzoek nodig naar het effect van de door ons voorgestelde interventies ten aanzien van de meest effectieve managementstijl voor bepaalde ambitiepatronen.

Appendix A
Sample issues/questions

A.1 Sample issues

A modified Guttman scale has been used for assessing a wide variety of issues supporting strategic decision-making and/or the subsequent change management in corporate affairs, human resource management, information technology, marketing & sales and supply chain management.

A sample list of assessments in corporate affairs includes:

- Assess to what extent (not: if) the corporate strategy has truly landed on the work floor.
- Measure how the various business units have set up their innovation.
- Understand where and how to modify behaviour to align with organizational values.

A sample list of assessments in human resource management includes:

- Assess to what extent teams work effectively.
- Monitor how managers develop their leadership styles.
- Assess how an organization handles integrity issues – and violations.
- Capability surveys: are the qualified men/women in the right jobs?
- Employee satisfaction/engagement surveys.
- How does the organization roll-out new ways of working?

A sample list of assessments in information technology includes:

- Does the organization comply with standards in IT (DevOps, ITIL, Agile, Scrum, CMMi, CobIT, ASL, BiSL) and in program-/portfolio management (Prince-II, OPM-3)?
- Understand to what extent processes (testing, requirements- and acceptance management, service management) work as they should.
- Measure to what extent The Business and IT are aligned, and – if not – about what they are misaligned.
- Measure the availability and mix of IT-competencies/skills.
- Compare the application maintenance quality in an IT application landscape.

A sample list of assessments in marketing & sales includes:

- Assess marketing processes, for example, the management of the organization's advertising, creative and media agencies.
- Similar for sales processes, for example: how do sales forces approach their clients?
- How does the social-media approach functions across various brands and business units?

A sample list of assessments in supply chain management includes:

- Assess SCM processes, for example, the management of the organization's contract management processes.
- Perform a spend analysis across operating companies.

- Assess the delivery excellence of suppliers and in order to upgrade from Service Level Agreements (SLA) to Experience Level Agreements (XLA).

A.2 Sample questions

This list below gives an indication how we have tried to stay as close as possible to one of the data requirements borrowed from Big Data literature. One of these requirements is that employee-generated input should preferably be turned into “binary, numerical or categorical representations” (Plewis & Mason, 2007). We have focused on tallying verifiable observations so that the categorical representations in the multiple-choice answers are as binary (in the sense of: hard, verifiable data) as possible. These multiple-choice answers usually have similar patterns. Here is a list of these patterns including examples.

Pattern: **Not yet done / Partly done / Completely done**

To what extent has the business case been signed off?
Not signed off, Signed off by a few stakeholders, By all stakeholders

Have the lessons learned been archived?
No, Only the most important lessons, All lessons

Pattern: **Nothing done / A or B are done / A and B are done**

Do you meet with your manager 1-on-1?
No, We do meet BUT irregularly or unstructured, We formally and periodically meet

Is it clear what staff department XYZ can deliver?
No, There is a formal service catalogue, Same AND a procedure to handle exceptions

Pattern: **Less than x% / Less than y% / More than y%**

How many clients have been invited for our ABC customer evert?
Less than 20%, More than 20%, More than 80%

To what extent have IT-incidents been tracked?
Not done, Only for the Top-20 applications, For (nearly) all applications

Pattern: **Not available / Available for some / Available for all**

To what extent has the new Office 365 version been implemented?
Not happened yet, In 1 or 2 regions only, In all regions

To whom has the new strategy been communicated?
To no one yet, To managers level 1 and 2, To all managers and employees

Pattern: **Not defined / Loosely defined / Precisely defined**

How have the business requirements been defined?
Not done, First indications received, All requirements received and signed off

How have you defined your team objectives?
No objectives (yet), A qualitative description only, Formal SMART objectives.

Pattern: **Not defined / Defined not followed up / Defined AND followed-up**

Do you see possibilities to make our process more client-friendly?
No, I have a few suggestions, I have a concrete plan worked out

Have the lessons learned been archived?
No, Yes, Yes AND in a central database

Pattern: **Not done / Done BUT with caveat / Done and working fine**

Is the help desk functioning as planned?
No, Works for all questions BUT waiting time > 5 mins,
Quick response (5 mins or less) to all questions

Has the strategy been communicated to the work floor?
No, Yes BUT not all feedback has been processed, Yes and all feedback processed

Pattern: **Too little / Too much / Precisely right**

To what extent have suppliers been given a due diligence?
None of the suppliers, All of them, All suppliers that account for 90% of total spend

Have stakeholders signed off on the project?
No, All stakeholders have signed off, All business stakeholders that are affected signed off

Appendix B
Another analytical example using our modified Guttman scale

Another example of analytics using our modified Guttman scale

In the study of the German energy company in Chapter 2, we not only looked at the width and depth of the ambition of the individual respondents. We also calculated with other important aspects of strategic decision-making and change management like alignment and knowledge sharing. We have executed these kinds of analyses for each of the 3,362 teams in our database as well. The resulting outcomes show that the use of our modified Guttman scale and the calculation rules we have built using this scale may help to model and manage organizational change.

We have used the Guttman scale to focus on respondents' ambition, the topic of this theses. In Chapter 6, we described how to visualize alignment using dendrograms. This appendix shows how we constructed the underlying calculation rule.

Step 1. creating a dendrogram

To apply alignment calculations to benefit strategic decision-making we are not only looking how aligned respondents are among themselves but also how aligned these respondents are in relation to the target the upper management had in mind. To achieve alignment output a board of management can work with, we perform 11 different operations in 3 steps.

1. We create per respondent a tabular representation of their scores 'in 6 months'.
2. We compare each pair of respondents and calculate an absolute delta between these two respondents.
3. We convert the absolute delta to a relative delta from 0% to 100%, rounded to the nearest percent (no fractional percentages).
4. We assign the alignment percentages to each of the respondent pairs.
5. We aggregate the percentages in 9 bins with a matching color to achieve the visual representation of a dendrogram. See Figure B.1. A red square means two respondents are not aligned at all with regard to their 'In 6 months'-scores. A green square means two respondents are very much aligned with regard to their 'In 6 months'-scores. Shades of orange, yellow and blue indicate intermediate levels of alignment.

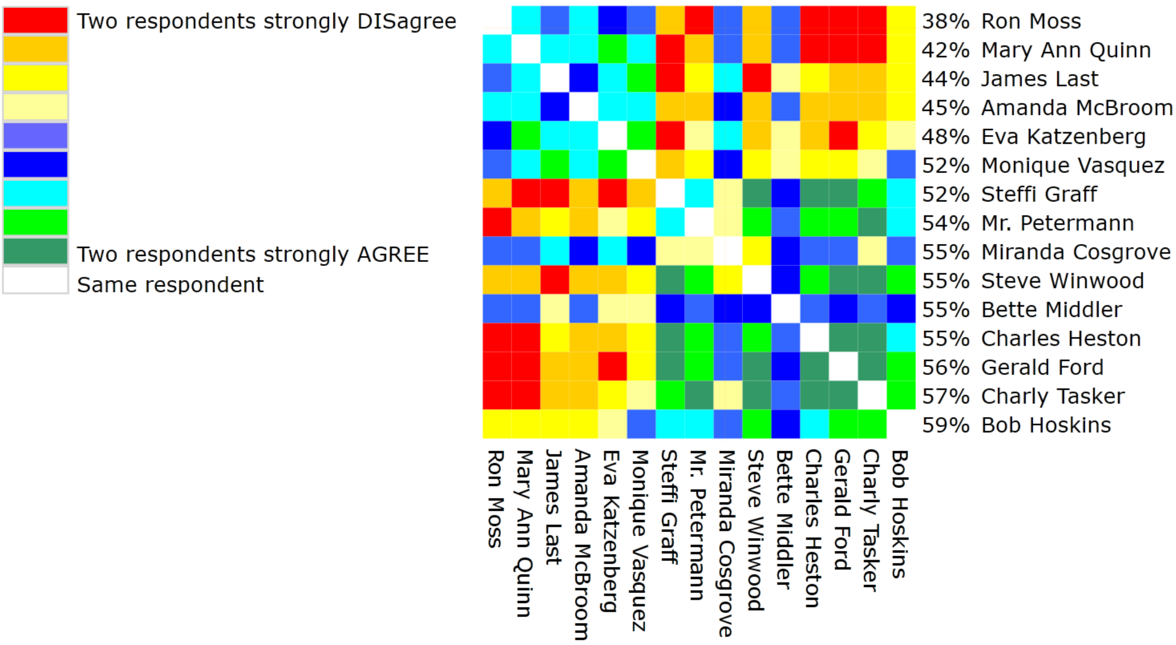

Figure B.1: A dendrogram

Step 2. creating a Change Management Quadrant

6. We calculate the average alignment percentage among all the pairs.
7. We calculate how each respondent pairs with the management target (an additional row and column in the dendrogram).
8. We calculate the average alignment of all respondents with the management target.
9. We combine the output from #7. and #8. into a 'Change Management Quadrant'. In the example below (Figure B.2), we have plotted the results for one team for the three main topics of a questionnaire.

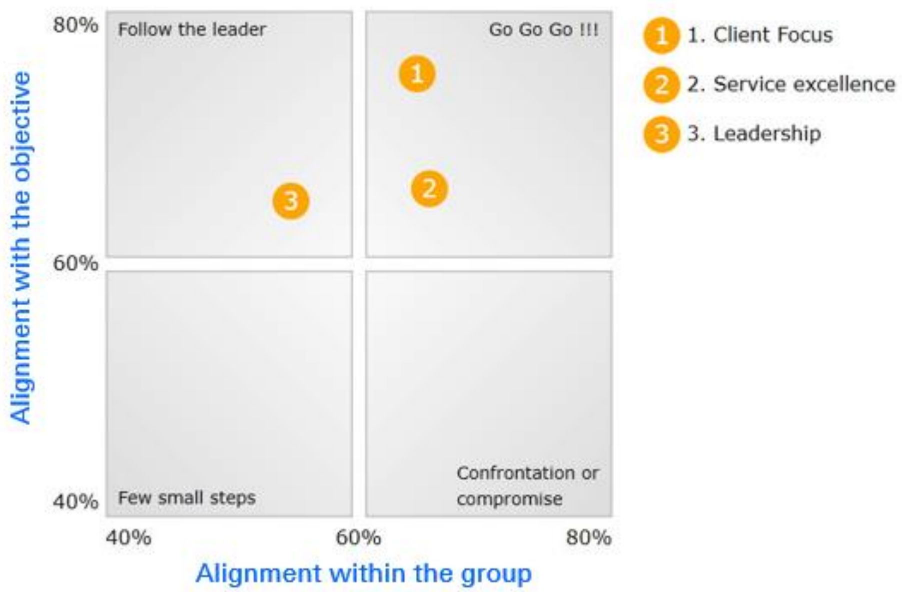

Figure B.2: A Change Management Quadrant

We have divided the Quadrant in four sections each representing a sort of preferred change management style. For example, if the respondents are aligned in their ambition for the next 6 months while simultaneously not being aligned with the management target, the resulting change management style could be referred to as 'Confrontation or compromise'. Either the respondents are confronted with the target because, e.g., there is a non-negotiable government rule that needs to be implemented no matter what. Or management goes into a discussion with the respondents to reach a compromise.

The 3,362 teams scored in this change management quadrant as shown in figure B.3. Of the teams, roughly 40% scored 'Confrontation or compromise', 30% scored 'A few small steps, 20% scored 'Go, go, go!!' and 10% scored 'Follow the leader'. That means that in roughly 70% of teams the respondents are not or insufficiently aligned with their management target.

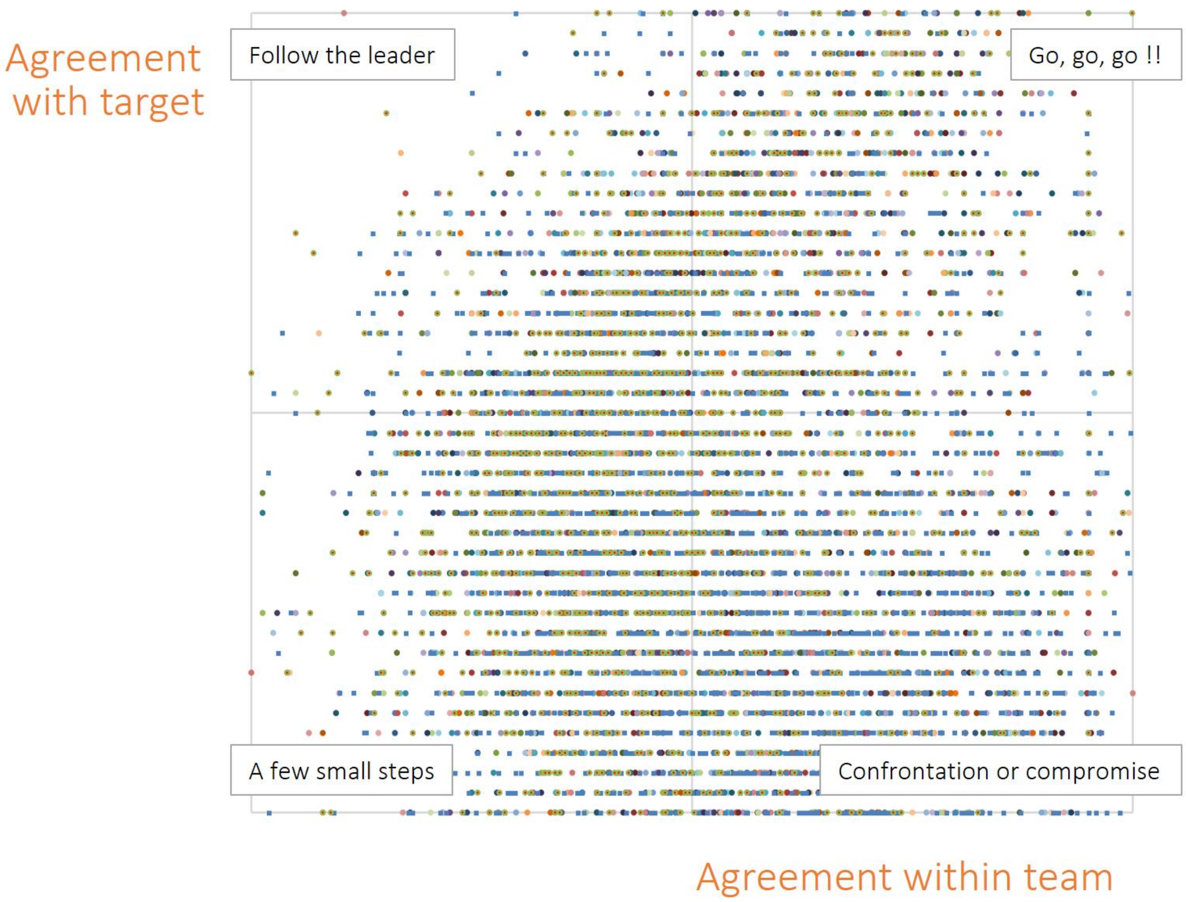

Figure B.3: Mapping the alignment profile of teams (n = 3,362)

Step 3. creating a Weather Map

10. Unfortunately, we have seen the necessity to 'dumb down' this change management quadrant for use by lower management. Usually, managers have trouble interpreting a dendrogram and (to a lesser extent) the change management quadrant. Hence, we dumb down from a numerical to a categorical representation. Therefore, we assign per team and per topic a weather icon representing the change management style. For example, 'Confrontation or compromise' is represented by rain and lightning while 'Go, go go !!' is presented by a full sun. Below are two examples.

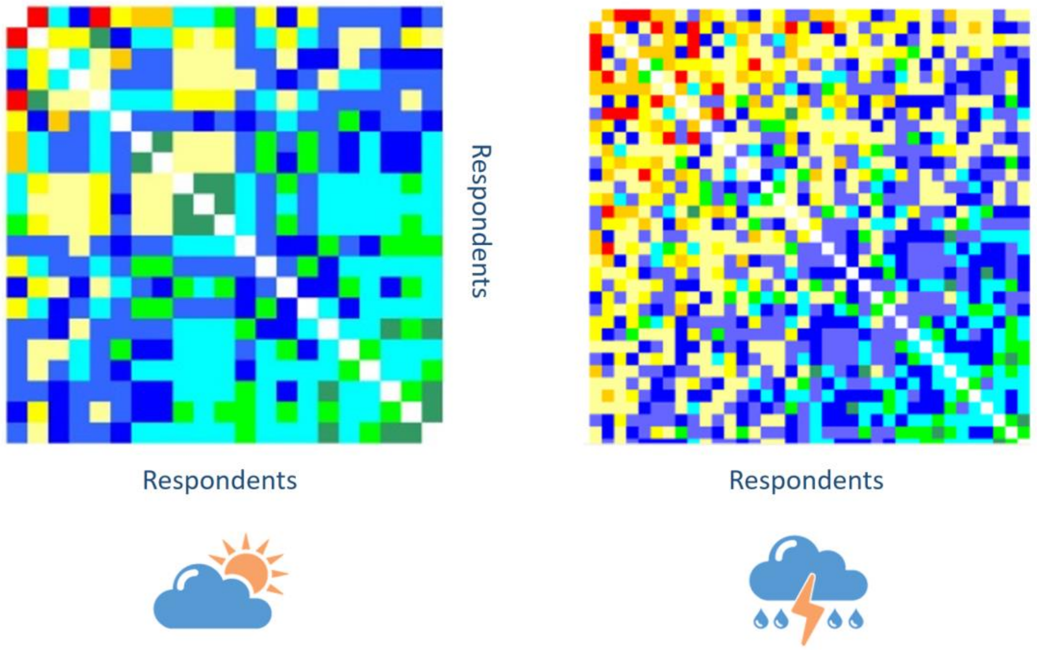

Figure B.4: Two examples of assigned alignment icons

11. Finally, we aggregate the icons in a ‘Weather Map’ as represented in figure B.5. Upper management can now tailor its attention to teams based on their alignment profile. This sample weather map shows for example that the proposed target will not be well received by Team 6. And that the target for Topic 1 might need some further tweaking.

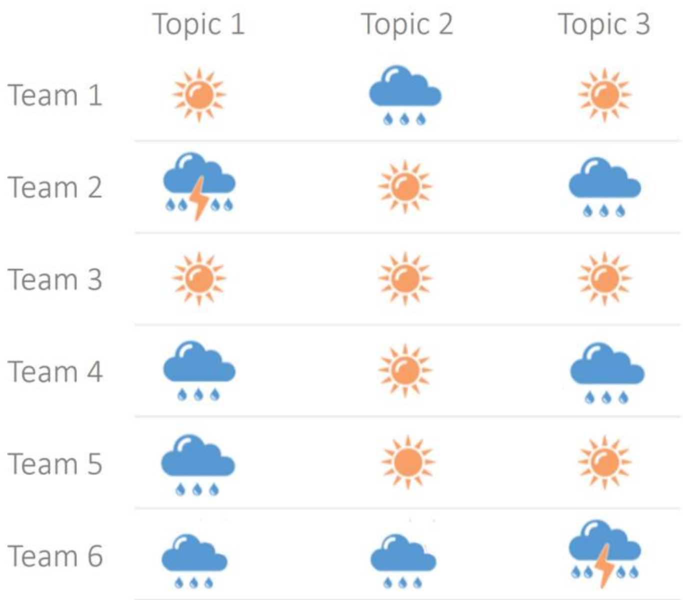

Figure B.5: A Weather Map

Clearly, this approach still requires a lot of scientific validation (hence its relegation to this appendix). For example, the cut-off values of the change management quadrant and the choice of change management styles have been derived from daily practice rather than from a rigorous scientific screening. In terms of data volume, the 5,000 employees answering a 100-item questionnaire as referred to in Chapter 3, would result in dendrogram comparing 250 million answers.

List of Tables, Boxes and Figures

Tables

Boxes

Figures

List of publications

Study 1 (Chapter 2)

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). A new survey scale to capture employee input to support strategic decision making. *Society for Judgment and Decision Making.* Under review.

Study 2 (Chapter 3)

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). A cross-industry research into employee ambition patterns in change management. *Journal of Change Management.* Under review.

Study 3 (Chapter 3)

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). Mitigating employee ambition patterns in change management". *Journal of Organizational Change Management.* Under review.

Study 4 (Chapter 4)

Van de Poll, J.M., De Jonge, J. & Le Blanc, P.M. (2018). Non-response/ERS change appearance in large scale employee surveys based on a modified Guttman scale. *Journal of Business and Psychology.* Under review.

Separate article published in collaboration with the Technical University Delft.

Tax, D. M., Cheplygina, V., Duin, R. P., & van de Poll, J. (2016). The Similarity Between Dissimilarities. In Joint IAPR International Workshops on Statistical Techniques in Pattern Recognition (SPR) and Structural and Syntactic Pattern Recognition (SSPR) (pp. 84-94). Springer International Publishing, Berlin. DOI: 10.1007/978-3-319-49055-7_8

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Curriculum Vitae

Curriculum Vitae

Jan van de Poll was born on January 29th, 1962, in Bilthoven, the Netherlands. In 1987, he graduated as MSc in Business Economics at the Erasmus University, the Netherlands. He worked for 12 years with Philips Electronics in international technology strategy, -marketing, -sales & -management in the Netherlands, Italy, Singapore, Tennessee and Silicon Valley. Consecutively, he worked 8 years as consultant/principal/director at PwC, IBM Global Services and BearingPoint (former KPMG consulting).

In 2008, he founded Transparency Lab, delivering consulting services, -methodologies and -software to consulting firms, system integration companies and selected corporate clients. Transparency Lab serves clients in various European countries and in the USA. The company has its own software development department in Shanghai. Transparency Lab's software has been nominated for the ICT prize of the European Community and Transparency Lab has been named one of the 'New Champions' by the Financieele Dagblad (The Netherlands).