Collaborative decision-making for hierarchical forecasts: a multi-sector perspective

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Abstract

Demand forecasting and planning is never devoid of human judgment. Managers input their opinions at various stages of the organisational decision-making process. The process is generally a combination of statistical forecasts, produced using software packages, and managerial expert judgments. Often this process is broken down into different hierarchies based on product-type, locations, and customer classes. When forecasts are produced in such hierarchical fashion, there is a need to aggregate the forecasts so that consistency is maintained across the organisation. A number of studies have explored how to achieve this forecast consistency using statistical methods. But none of these methods utilise judgmental inputs from managers at different hierarchical levels. Hence, a research gap has been identified to address this topic of hierarchical forecast aggregation using a judgmental reconciliation process.

The research gap is addressed in this study by employing a case study design with 6 case organisations, which are spread across industries, sectors and geographies. Exploratory interviews are conducted with case managers to investigate the current hierarchical forecasting process. Four dominant themes of this process are identified as *information sharing*, *time pressure*, *power*, and *social value*. A strengths, weaknesses, opportunities, and threats (SWOT) analysis on these themes help assess their impacts on the forecast decision-making process. Based on this, a conceptual framework and two theoretical propositions are suggested.

A questionnaire is used to gather wider managerial opinions on the SWOT analysis. Using Multiple Attribute Decision-Making (MADM) methods, the responses are analysed to confirm the impact of each theme. The findings validate the propositions and the suggested framework for decision-making in hierarchical forecasting. Hence, this research demonstrates the need for judgmental reconciliation of demand forecasts when hierarchies are involved. It is shown that a collaborative approach can achieve enhanced decisions with increased employee satisfaction. The thesis concludes with research contributions, limitations and recommendations for future research.

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Let’s celebrate this together, wearing our best kaftans with chucks !!

Table of Contents

Abbreviations

A&E	Accident and Emergency
AHP	Analytical Hierarchy Process
AIJ	Aggregation of Individual Judgments
AIP	Aggregation of Individual Priorities
AM	Arithmetic Mean
ARIMA	Auto Regressive Integrated Moving Average
ATP	Available To Promise
C	Concordance
CEO	Chief Executive Officer
CI	Consistency Index
CP	Communication Provider
CR	Consistency Ratio
D	Discordance
DMA	District Meter Area
DWI	Drinking Water Inspectorate
EA	Environment Agency
EASA	European Aviation Safety Agency
EAST	Emergency Ambulance Service Team
ELECTRE	Elimination Et Choix Traduisant la Realité
EPD	Environmental Product Declaration
ESRC	Economic and Social Research Council
F2SS	Forecasting and Foresight Support System
FAA	Federal Aviation Association
FSS	Forecasting Support System
GP	General Practitioner
HB	Health Board
hts	hierarchical time series
IT	Information Technology
JF	Judgmental Forecast
JIT	Just In Time
KPI	Key Performance Indicator
LA	Local Authority
M	Maintenance
MA	Multi-Attribute
MADM	Multiple Attribute Decision-Making
MBO	Managing By Objectives
MCDM	Multiple Criteria Decision-Making

MD	Managing Director
NA	Not applicable
Ofwat	Water Service Regulating Authority
OM	Operational Manager
ONS	Office for National Statistics
P	Proposition
PCC	Per Capita Consumption
PROMOTHEE	Preference Ranking Organisation METHod for Enrichment Evaluations
RI	Ratio Index
RQ	Research Question
SCM	Supply Chain Management
SF	Statistical Forecast
SKU	Stock Keeping Unit
SODA	Strategic Options Development and Analysis
SOM	Senior Operational Manager
SWOT	Strengths, Weaknesses, Opportunities and Threats
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TV	Television
USA	United States of America
UK	United Kingdom of Great Britain and Northern Ireland
VMU	Vehicle Maintenance Unit
VSM	Virtual Stock Market
WRZ	Water Resources Zones

List of Figures

List of Tables

Preface

Before commencing PhD, I was working as a business associate (analyst) making sales plans for a top US pharmaceutical company. I applied my knowledge from my MSc in Applied Operational Research to forecast and allocate resources (medical representatives) in different zones of the country. During this time, I discovered how one geographical location is broken down into different zones for better planning. Furthermore, the decision-making process involved much more managerial intuition than statistical inputs. This motivated me to do a deep dive into the concept of judgmental forecasting and business decision-making. I accepted this PhD to explore the field of demand forecasting with human interventions.

Chapter 1

1 Introduction

Demand forecasting is a prerequisite for business planning and decision-making. The forecasting process is an attempt to predict the future on the basis of past patterns. Knowing the future helps organisations and individuals prepare for the future and take necessary steps in the present. Managers are able to make operational decisions based on the demand forecasts. These timely decisions are important in the fast-paced and uncertain business world. Hence, these forecasts consist of valuable information that guide the process of management decision-making. This chapter, briefly, outlines the research background, the aim of this research along with the research questions, the research method used to answer these research questions, the main contributions of this study, and the structure of the remainder of this thesis.

1.1 Research background

Forecasting is used in different sectors from energy to logistics. There are different methods on how demand forecasts can be produced. One of the most commonly applied methods is time series forecasting where each demand value is indexed with a time stamp. Statistical methods use the past historical data from the time series to predict the future based on different mathematical models or techniques. A number of software packages are available in the market that can generate such Statistical Forecasts (SFs).

In addition, managers in organisations possess information and knowledge about the future that are not covered by the statistical methods. Instead of depending on numerical values, they use their own judgments to produce forecasts that are reflective of the extra soft information. Such forecasts generated as a result of expert opinions are known as Judgmental Forecasts (JFs). Most of the time, forecasters use a combination of statistics and judgments to make the final forecasts. These forecasts are generally produced for different stock keeping units (SKUs), which are unique numbers that track items within the inventory.

Forecasts are simply numbers, not of any use if not taken forward in the business decision-making process. This decision-making process requires a great amount of planning that have their effects in the future. With the uncertainty of demand within supply chains, the decision-making process is divided into various levels of aggregation. This gives rise to multi-level hierarchies within organisations based on different attributes like product-type, geographical locations, time, or customer type. For effective decisions, information is gathered from the different hierarchical levels within the organisation. Such a process requires collaboration from different departments and various stakeholders.

The after-sales or service industry require a different forecasting approach than other industries. The demand patterns for this industry is intermittent, for example spare parts of a car do not have uniform demand pattern. The service requirements differ for the different parts, hence the need for a separate forecasting approach. The forecasting is also dependent on the contracts signed between different stakeholders like manufacturers and customers. The product life cycle of the different products also influences the approach to forecasting.

From here on, the forecasts described are always demand forecasts. Although literature from other disciplines like psychology and linguistics are used to support arguments.

Another decision point is the storage of spare-parts and allocation of resources as there is a requirement for a minimum of each type of unit. Therefore, for this study the focus is on the after-sales (like spare-parts) and service organisations.

1.2 Research aim, questions and objectives

Research aim: *To develop a framework for collaborative decision-making in hierarchical forecasting.*

The overall aim for this study is the development of a collaborative decision-making framework for demand forecasting when hierarchies are involved. This overarching aim can be broken down into four granular research questions (outlined below). The research objectives corresponding to each of these research questions and how they have been addressed in this thesis is shown in Table 1-1.

RQ1: What is the current practice in business decision-making within the context of hierarchical forecasting?

RQ2: What are the different themes that affect the forecast decision-making process?

RQ3: What impact do these themes have on the forecast decision-making process?

RQ4: How can a conceptual framework incorporating these themes improve the current forecast decision-making process?

Table 1-1: Research questions and research objectives

Research questions	Research objectives	How and where these are addressed
1. What is the current practice in business decision-making within the context of hierarchical forecasting?	To determine the methods and processes being used currently in hierarchical forecast decision-making.	• Literature review • Case stories from interviews with different organisations
2. What are the different themes that affect the forecast decision-making process?	To find out the different attributes (or themes or variables) that effect the hierarchical forecasting process.	• Literature review • Analysis of case study interviews
3. What impact do these themes have on the forecast decision-making process?	To determine the effect of these attributes on the current forecast decision-making process.	• SWOT analysis • MADM via questionnaire
4. How can a conceptual framework incorporating these themes improve the current forecast decision-making process?	To develop and validate a framework that can bring about improvements in the decision-making process.	• Literature review and case stories • Questionnaire responses

Although the research questions (RQs) are mentioned in the first chapter, they were not fully developed at the beginning of this study. These RQs have evolved in an iterative manner through the study, which helped identify the research gaps, design the research methodology for the study, and eventually provide answers to the RQs. This iterative process is described here to understand how the research questions have been developed in this study.

Figure 1-1 shows how each research question is developed and how it is answered within the study. RQ1 starts with a descriptive enquiry into the field of hierarchical forecasting. Previous knowledge from two MSc degrees and work experience is drawn upon to guide this question. To answer RQ1, literature review is conducted along with some empirical data collection from organisations.

During the data collection process and literature review; RQ2 is formulated to explore the themes that are arising from the first RQ1. Similar to RQ1, the second RQ is answered with the support of literature review and empirical data collection. This step results in the identification of research gaps from both the academic literature and the real world; which are discussed in section 3.8.

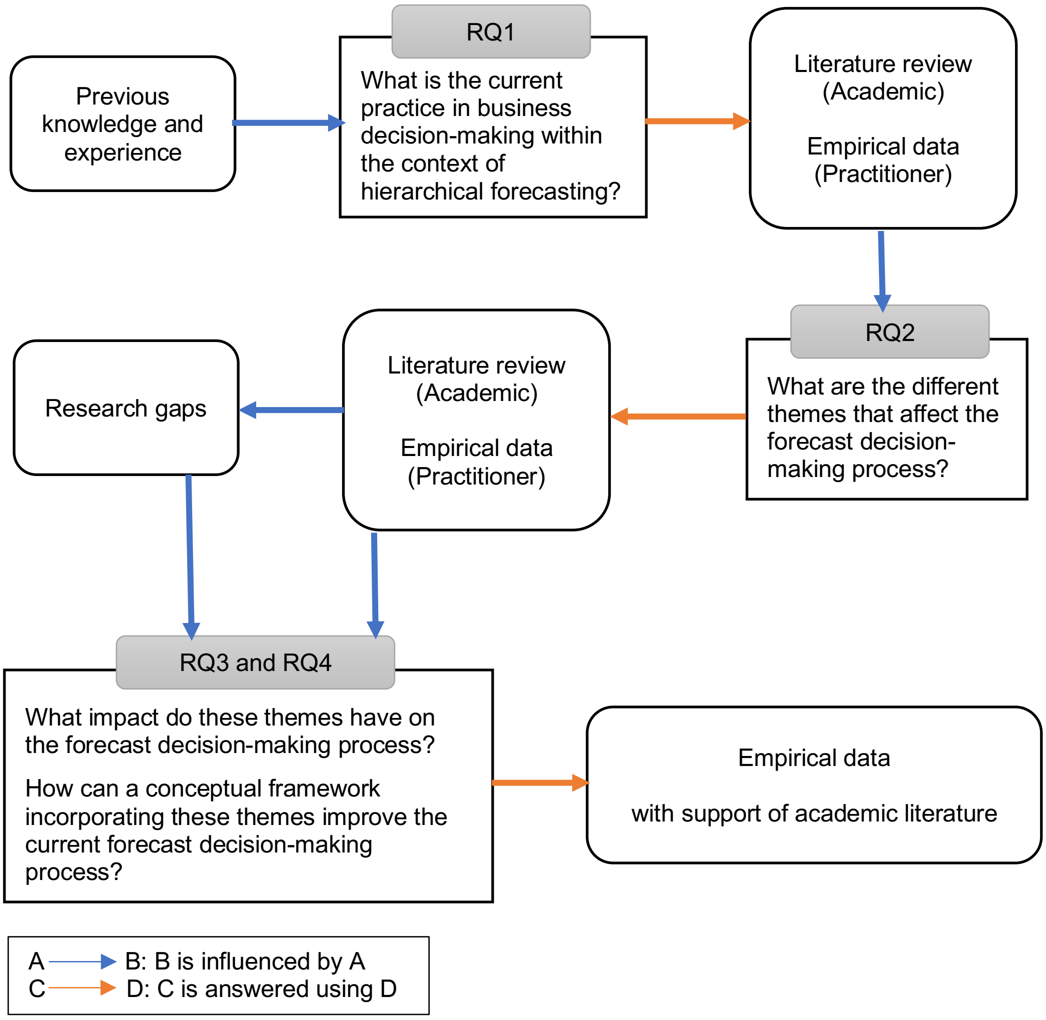

Figure 1-1: Development of research questions

The two main research gaps of judgmentally reconciling hierarchical forecasts and influence of different themes on this process are addressed with the next two RQs. Hence, RQ3 and RQ4 are developed from the literature review and already collected empirical data, influenced by the identified gaps. To answer these two

RQs, wider organisational data is collected from the field. The findings from the data analysis along with the support of academic literature fills the research gaps identified in this study. The next section 1.3 gives a brief idea of the research methodology adopted in this study and how the different stages relate to the four RQs.

1.3 Brief research methodology

With an attempt to answer the research questions (section 1.2), a multiple case study design is adopted in this study. The case study methodology investigates the contemporary phenomenon of hierarchical forecasting within its real-world context. It relies on multiple sources of evidence converging in a triangulation fashion emphasising the reliability and validity of this study.

The study has two stages of data collection: exploratory and explanatory stages. In the exploratory stage, semi-structured interviews are conducted with forecasting team members from the different case organisations. The interviews answer the first two research questions and build a case story for each organisation. These case stories depict the forecasting decision-making processes within the respective organisations. This stage also includes a couple of company visits to these organisations.

The exploratory stage data is analysed using thematic analysis and cognitive maps. The main themes from this stage are carried forward to the next stage of explanations. The explanatory stage answers the next two research questions using the medium of questionnaire to collect wider responses from the cases. The questionnaire assesses the impact of the themes on the forecast decision-making process using Multiple Attribute Decision-Making (MADM) methods. It includes Likert scale questions, pair-wise comparisons, ranking questions, and open-ended questions. Analysing the data from both the stages, a conceptual framework is developed and suggested for better decision-making in hierarchical forecasting. The research methodology is explained in detail in Chapter 4.

1.4 Research contributions

This study has made many contributions that has both theoretical and practical implications. It contributes to the academic literature in several ways. Firstly, it addresses a gap in the literature by exploring the concept of cross-sectional (hierarchical) forecast aggregation from a qualitative lens. Secondly, it is a methodological contribution by conducting an empirical study using multiple case organisations across different sectors.

Thirdly, the study incorporates the concept of the social value of forecast decision-making processes that has never been studied in the field of judgmental forecasting. Finally, it contributes to the literature by suggesting a conceptual framework for collaborative decision-making for hierarchical forecasting. This framework incorporates information from other disciplines like linguistics and psychology. Along with the framework, two propositions (below) are proposed that highlight the main themes of the forecast decision-making.

1. Improving information sharing mechanisms increases the social value within work environments.

2. Time pressure increases dependency on individual judgments in business decision-making.

From a practical outlook, this study adds value to the business decision-making process by considering it from an overall perspective rather than individual teams within the process. It also provides a cross-case comparison between the different organisations that help the case teams to learn and unlearn from each other. The conceptual framework is presented as a good practice document to the organisations that can bring improvements to their forecast decisions.

1.5 Structure of the thesis

Figure 1-2 shows a pictorial description of the whole structure of this thesis. Within this chapter, the four research questions are identified and reported. The findings from RQ1 and RQ2 help formulate the next two research questions RQ3 and RQ4. Different colours have been used in Figure 1-2 to differentiate how the different RQs connect with rest of the thesis. The introduction chapter, the first chapter of the thesis, is followed by a chapter on literature review. RQ1 (orange) is influenced by traditional literature, and it also highlights the need of a structured review. Both these literature reviews along with their findings are reported in the Chapter 2 of this thesis. RQ2 (green) shows the need for an umbrella view of literature in organisational studies, which is reported in Chapter 3. This chapter consists of decision-making in organisations and describes the different approaches in business decision-making. It includes dimensions of decision-making that serve as themes for analysis in the subsequent chapters.

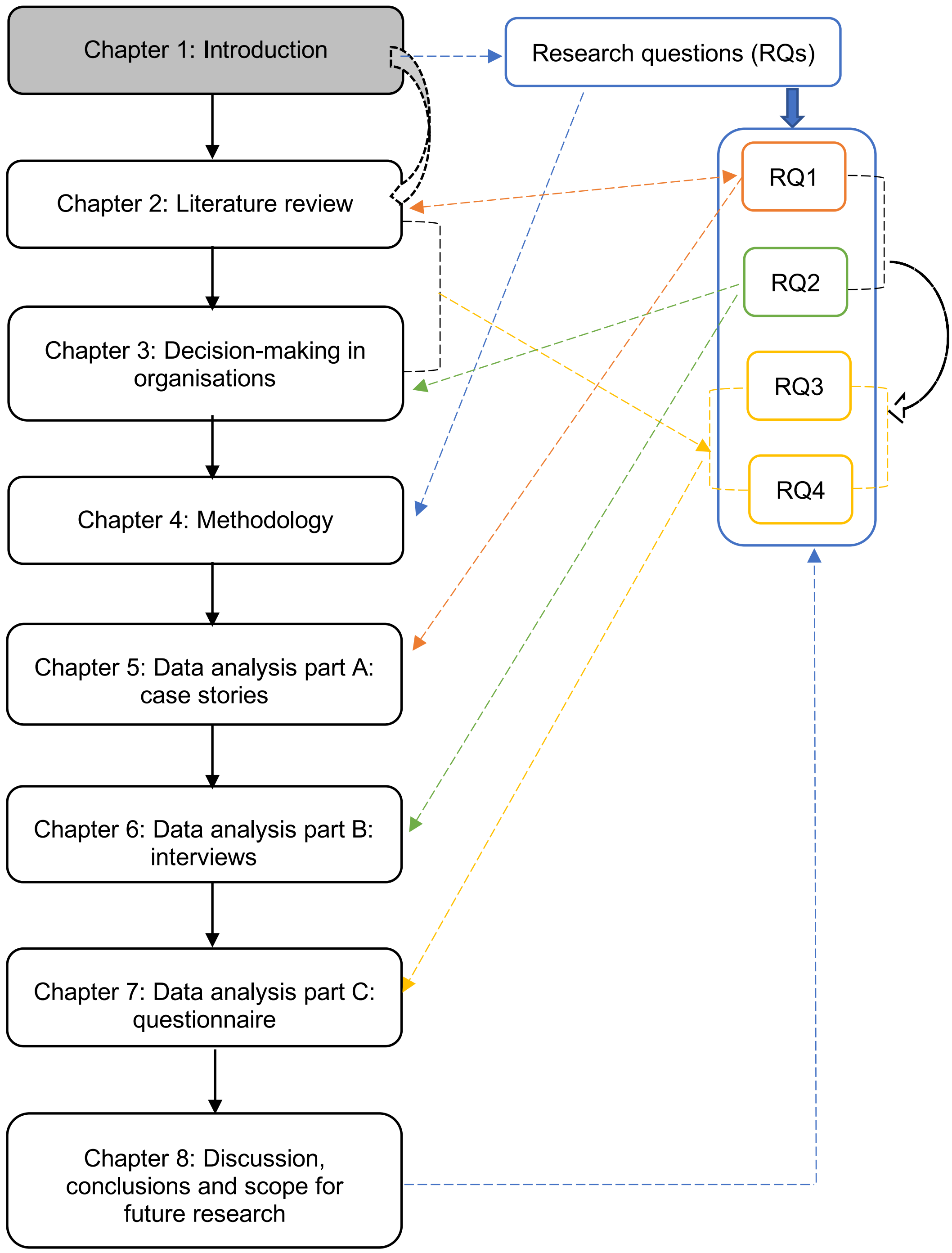

Figure 1-2: Thesis structure (Chapter 1)

The next four chapters are on research methodology and data analysis of the collected information. Chapter 4 illustrates the methodology adopted in this research, from the case study research design to the different data analysis methods. The adopted methodology is influenced by the research questions defined in this first chapter, section 1.2. Chapters 5, 6 and 7 are findings from the data analysis methods describing the case stories, interviews and questionnaire results respectively. Findings from interview data help answer the research questions RQ1 and RQ2 in data analysis parts A (case stories) and B (interview data) respectively. Findings from questionnaire data provide answers for RQ3 and RQ4 in the analysis part C, shown in yellow colour.

Finally, the last chapter is on discussion, conclusions and scope for future research. The discussion brings together the research findings along with the concepts from Chapter 3 to answer the four research questions of this study. The thesis is summarised in the research summary section, including its contributions, limitations, and suggestions for future research. This figure of the thesis structure has been updated after each chapter to provide a visual depiction of one's progress within the thesis.

Chapter 2

2 Literature Review

2.1 Introduction

Forecasting forms an integral part of management decision-making and it helps organisations make timely decisions in the face of uncertainty. The first chapter introduced the different types of forecasts: Statistical Forecasts (SFs), Judgmental Forecasts (JFs) and an integration of SFs with JFs. It also outlined the research aim, the research questions and corresponding objectives for this study. Keeping in line with those research questions, this chapter presents a comprehensive literature review that highlights the research gaps.

In the first section 2.2, the literature on judgmental forecasting is reviewed based on different themes: information available while making judgments, types of JFs, people involved during forecasting, and empirical research versus experimental research. These themes are selected to cover different types of judgmental forecasting present in the literature and the types of research conducted to study this field.

To deal with the effect of demand uncertainty in supply chains, organisations focus on making improved decisions at different levels of aggregation. Time series data can be disaggregated based on different characteristics like product-type, customer-type and geographical locations. This disaggregated data structure forms a hierarchy, enabling aggregation of data from different levels.

Section 2.3 is on hierarchical forecasting that introduces the concept of business hierarchies and how aggregation is an important forecasting approach in today's complex market environment. Out of the two types of hierarchical forecasting, cross-sectional forecasts and temporal forecasts, the former is discussed in detail as it forms the focus of this study.

Combining literature on judgmental forecasting and forecast aggregation, a structured literature review is conducted in section 2.4. This review considers English journal articles (total of 53 papers) using a combination of different keywords that address aggregated expert predictions. This section includes the structured literature review method and its findings. Findings include both descriptive analysis of the papers and categorisation of those papers based on different groupings. This section contributes towards the identification of the research gaps, addressed in this study, in section 3.8. The content of this literature review is referred to in Chapter 8 to make connections between the research findings and the existing body of literature.

The two different types of literature reviews, traditional and structured, have been conducted to increase rigor of the review method. The traditional method has helped define the basic concepts of forecasting and judgmental forecasting. The method provides a broad overview of the research topic, with no clear methodological approach. Some part of the traditional review has also informed the first research question that led to the collection of interview data and its findings. This review also identified the main research gaps of judgmental reconciliation of hierarchical forecasts, which this research has tried to address.

After the traditional review, the structured review is conducted with an aim of finding all existing evidence in an unbiased, transparent and reproducible manner. This review has carried out to answer the first research question of exploring the hierarchical forecasting processes, already covered in the literature. This second review findings show quantitative, in addition to qualitative findings from the first review. The quantitative findings confirm the lack of qualitative studies in this field and hence, a methodological research gap is identified. This gap is addressed by adopting a case study method in this research. The structured review findings have contributed to the knowledge base of latest research studies along with their different methodological approaches. Both the reviews provide recommendations for key questions that need further research.

2.2 Judgmental forecasting

Human judgment is an almost inextricable ingredient of demand forecasting (Pennings et al. 2019). All demand forecasts involve judgment (Goodwin 2002) and there are no objective SFs as even the choice of the statistical method is a judgment call from company managers (Fildes et al. 2009, Arvan et al. 2019). Even in the case of automatic model selection software, there are judgments involved at different phases from deciding on a particular software to purchasing one. Whether they enhance performance or not, qualitative interactions have been established as a key set of tasks in forecasting processes (Fildes and Goodwin 2020). Many studies have been conducted on the value of JFs for more than three decades. This has led to a significant number of developments that have helped reduce the levels of uncertainty that plagues decision-making.

While forecasting is seen as an objective computation, prediction is seen as a subjective estimation requiring management judgment and qualitative information. The accuracy of any judgmental forecasting method is the result of a “*good subjective model*” (Lawrence et al. 2006). A large pool of literature has been accumulated on determining the best forecasting method that helps to incorporate the subjective (human judgment) angle to objective (statistical) methods. The main reason behind incorporating managerial soft information with hard statistical methods is to reflect additional soft information available from the managers. However, it can be seen from literature that there are other reasons as well.

Firstly, managers consider noise as a pattern amongst the time series data and make judgment calls to adjust them in the statistical methods (Goodwin 2002). Secondly, many managers want to gain a sense of ownership of the forecasts because the statistical software is perceived as a black box and they do not understand how the forecasts are being produced. Thus, they intervene with the forecasting process as they perceive to have a better idea about it and make them their own forecasts (Syntetos et al. 2016b).

There are other reasons like when forecasts need to be increased to obtain priority from suppliers. And finally, a number of adjustments take place due to political pressures from other managers to favour a particular outcome (Goodwin 1996). Like managers from service teams, where they are rewarded based on their service performances, want to keep the forecasts low so they can be seen as over-achievers. As making JFs require more effort than simple software forecasts, they are perceived to be more beneficial (Fildes and Goodwin 2020).

Judgment usually comes from forecasting experts in the organisations and hence turn out to be very valuable. However, sometimes experts try to avoid taking any responsibility towards a set of forecasts and hence do not have much to offer in cases involving risk and uncertainty. Taft cited in Armstrong (1980) examine predictions made by both experts and non-experts; and found that non-experts made better predictions about people's behaviour and attitudes. Armstrong (1980) proposed the *seer-sucker theory* on the value of experts. The theory says, "*No matter how much evidence exists the seers do not exist and the suckers will pay for the existence of such seers*". It shows the huge dependency of forecasting teams on experts and why it is important to evaluate how much these experts can improve the forecasted values.

However, there has been a significant change in the results of researches conducted to validate the role of judgment in forecasting. It is now recognised to be an indispensable component of forecasting (Lawrence et al. 2006). Judgment can be very useful and valuable when the forecasting experts have important information that is difficult to capture by the statistical methods (Syntetos et al. 2009b, 2011). It has been found that the combination of human judgment with statistical methods is better than either one of these in isolation (Blattberg and Hoch 1990). Different studies have concluded that incorporation of managerial judgment into SFs leads to improved forecast accuracy (Mathews and Diamantopoulos 1986, 1989, 1990).

In the following sub-sections 2.2.1-2.2.5, the literature on judgmental forecasting is discussed with respect to their different characteristics (Figure 2-1). Based on the type of information available, the literature is divided into two categories: unaided and aided judgmental forecasting. Based on the type of forecasts produced, sub-section 2.2.2 explores the difference between pure JFs and judgmentally adjusted SFs. The next distinction is based on the number of forecasters involved in making the JFs. Finally, the last division is on the type of studies conducted in this field (empirical versus experimental research).

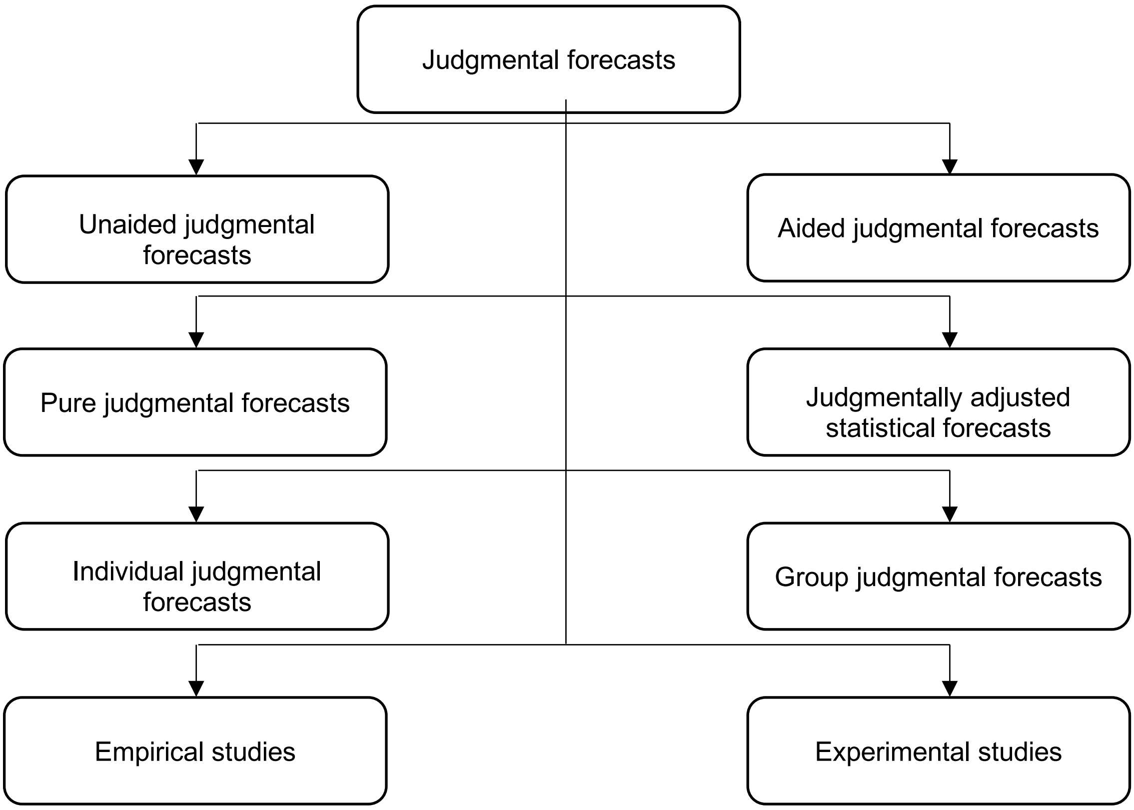

Figure 2-1: Sub-sections of judgmental forecasting

2.2.1 Unaided and aided judgmental forecasting

Based on the information available, judgmental forecasting can be divided into unaided and aided judgmental forecasting. As Lawrence et al. (2006) discussed, the total set of information useful for forecasting can be divided into two classes: historical and contextual data. The first class contains the sales history of a product, and the second class includes all the other kinds of information that can help understanding the past or present, and predicting the future. For example, soft information like market competition, past and future sales promotion data, the impact of the weather, come under the second class of contextual data.

Unaided judgmental forecasting is when demand forecasts are developed without any domain or contextual information. This is not a common situation as it is highly unlikely that the forecaster will not have any information about the future other than the historical data. In this case of unaided judgmental forecasting, the resulting JFs are worse than SFs (Hogarth and Makridakis 1981). This is because the forecasts are adjusted by experts without any additional information but mostly done to gain ownership of the forecasts. In practice, these are cases when managers adjust the forecasts with no additional information other than the time series data, thus resulting in biased less accurate forecasts (Fildes and Goodwin 2020).

In *aided judgmental forecasting*, forecasters use non-time series data (contextual information) to improve the forecasts. When managers are aware of time series historical data, they might also know about other contextual information like special events that have had an effect on the past or might affect the future. Contextual information includes the causal information associated with time series data, that can help improve forecast accuracy. This contextual information is the un-modelled component of the time series data and can contribute significantly to the forecasting process (Lawrence et al. 2006). For example, in the most common scenario, forecasters know about sales promotions that can explain anomalies in the time series data. It has been found that when the SFs are adjusted considering new contextual information, the forecasts improve drastically (Mathews and Diamantopoulos 1986, 1989, 1990, Nikolopolous et al. 2005).

2.2.2 Pure judgmental forecasts versus judgmentally adjusted SFs

Managerial judgment can be used in different ways while forecasting. A common approach is to use only human (managerial) judgment to predict the future and the forecasts produced are known as *pure judgmental forecasts*. In this process, forecasts are produced based on combining qualitative information and subjective beliefs of the managers (Ord and Fildes 2013). Managers often possess expert knowledge and information that are not covered by the statistical methods.

There are many cases when pure JF is the only option available. For example, the case when *i)* there is no historical data available to develop statistical methods, *ii)* historical data is incomplete with missing or incorrect data, *iii)* there is additional information related to new product launches, market competition and promotional events (Hyndman and Athanasopoulos 2018). Additionally, different organisations depend on JFs as they find their forecasting process to be very sophisticated and hence cannot be modelled by statistical softwares (Goodwin 2005).

There are situations where practitioners (forecasting managers) do not understand how the forecasts are being produced and where they are coming from. The statistical models are seen as 'black boxes' which the managers find hard to understand and trust, plus the model forecasts deny them a sense of ownership. The consequence of this is managers predicting JFs which they can treat as their own forecasts. However, these JFs are subject to a number of biases, and the statistical methods usually end up performing better than managerial judgment. For example, managers tend to give more weightage to recent or easily recallable events (Goodwin 2005). In order to reduce these types of biases and increase forecast accuracy, human judgment is combined with the SFs (Trapero et al. 2013).

The incorporation of human judgment into SFs is very common today. And management judgment has been found to play a valuable role in enhancing the SFs (Goodwin 2005, Syntetos et al. 2009b). The forecasts produced this way are referred to as *judgmentally adjusted SFs*. In this process, the first step is to produce SFs by means of using mathematical modelling of the historical (time series) data. Then managerial judgment is used to amend the SFs resulting in adjusted final forecasts which are used for the decision-making purposes.

The adjustment process is informed by both the historical data and the non-historical contextual data (Lawrence et al. 2006). One such example of non-historical contextual data is the information about future promotions or product launches. The advantage of such a combination method is it aids in understanding the cognitive biases in judgments (Goodwin 2000, 2005). Given the inconsistencies and biases in human judgment, one should be careful while incorporating such judgment into their forecasts. Hence, Fildes and Goodwin (2020) recommends using judgments to adjust the SFs only when there is an elaborate explanation of doing so.

Managers should use their judgments sparingly; and only when they have information that is not captured by statistical methods. SFs are not the best when used on their own as they may have ignored some potential extra information, like changes in the forecasting environment, that human judgment can bring to the forecasting process (Goodwin 1996). Blattberg and Hoch (1990) found that statistical methods and human judgment complement each other with different strengths. Their combination has been found to be better than each of them individually.

A number of research studies have been conducted on these combination methods where the SFs are adjusted using human judgment. The size of these adjustments along with their signs (positive adjustments increasing the SFs and negative adjustments decreasing the SFs) during the combination process have been studied. The benefits from large adjustments are more in comparison to that of smaller adjustments (Nikolopolous et al. 2005). Positive adjustments are found to be less effective than negative adjustments as forecasters overestimating the demand is quite common (Fildes et al. 2009, Syntetos et al. 2009b).

The JFs have different effects on the business decisions being made. The judgmental interventions on SFs are found to have adverse effects on the supply chain dynamics if taken unnecessarily (Syntetos et al. 2011). When a forecasting method is used as an input to an inventory system, it is necessary to evaluate the forecast effects on the inventory decisions (stock control) through different accuracy-implication metrics (Syntetos et al. 2010). The implications of judgmentally adjusted SFs on inventory decisions have been examined (Syntetos et al. 2009b, 2010). These adjusted forecasts improving the forecast accuracy translated to substantial inventory reductions, reaping considerable financial returns (Syntetos et al. 2009b, 2010). On the other hand, Syntetos et al. (2011) show the efficiency of inventory systems to be unaffected by demand forecasting performance.

When it comes to demand planning in a supply chain, there can be other kinds of judgmental adjustments as well. Managers often treat forecasts as being an end in their self rather than an input into the decision-making process. Hence, they make adjustments to other decision points in the process. Syntetos et al. (2016a) have looked at value being added when these judgmental adjustments are performed on the forecast decisions rather than the forecasts themselves. It has been found that most of these adjustments are performed because the decisions are mistaken to be forecasts. These adjustments have improved the inventory decisions considering the trade-off between inventory costs and service levels. However, the results are less beneficial than those after adjusting forecasts for the same organisation.

2.2.3 Individual versus group judgmental forecasting

With the increasing complexity in the business world, no one person can adequately deal with decision-making. Business decisions are mostly made within groups, rather than individuals working solely on their own. When individuals make forecasts based on their own decisions solely, it is known as *individual judgmental forecasting*. The behaviour of an individual has an effect on how they have applied their judgment to make the forecasts. And this behaviour is affected by a number of psychological factors like personality, perception and willingness to take risk (Gilligan et al. 1983). Having said that, individual forecasts are faster, and decisions can be allocated directly. Hence, an individual has a significant part to play in the forecasting (decision-making) process within organisations: either acting on their own or within the structure of a group.

Many forecasts and decisions based on these forecasts are made in groups, known as *group judgmental forecasting*. Especially when it comes to judgmental forecasting, it is very frequently performed by groups of people as they require a significant degree of managerial inputs (Fildes and Goodwin 2020). Most managers spend more time (at least 80%) in groups, hence it is important to understand the dynamics of such interactions in cohesive groups (Makridakis and Wheelwright 1989). These group interactions can have an effect to either diminish or exaggerate the individual biases in forecasting (Sniezek 1990). These groups not only have the advantage of gathering a broader range of knowledge and skills, but also make the implementation process easier once the decisions based on the forecasts are made (Gilligan et al. 1983).

Different group techniques can be used for group judgmental forecasting. A group technique is defined as a set of procedures followed to obtain a single judgment forecast from all individuals (Sniezek 1990). Three of the most common ones are: consensus method, nominal method and Delphi method. In the consensus method, group members meet face-to-face to discuss the forecasts and agree on one final forecast. Hence there is an opportunity for the members to discuss the data interpretations and share information amongst them. The nominal method follows three steps: first, each group member produces individual forecasts; second, they meet to further revise their forecasts in an unstructured discussion and finally, the aggregate of the revised forecasts is taken as the final forecast.

The third technique of Delphi do not have any information sharing or communication directly between the group members. Each of the members use a survey to provide their individual forecasts along with their feedback (Nikolopoulos et al. 2015). They are only communicated about the average group forecasts in the form of feedbacks. The process of revising the forecasts and communicating feedback continues till consensus is reached (Sniezek 1990).

As these group techniques aim to achieve consensus, the interactions and communication within the group play an important role. Special care should be taken when such judgments are obtained from groups of people (Goodwin 2005). Because of the greater amount of knowledge and experience, group techniques are found to be superior to individual judgmental forecasting (Gilligan et al. 1983, Nikolopoulos et al. 2015). Although the group techniques are very effective, they can be costly and time-consuming as a number of experts are involved in the process.

In group forecasting, the group members do not share the unique information available to them but instead rely on the same set of information available to all (Pennings et al. 2019). Heterogeneity in the information available to the different members can improve the group performance and increase their commitment to the consensus judgment (Sniezek 1990). Therefore, the choice between individual and group judgmental forecasting depends on the environment within the organisations.

2.2.4 Empirical versus experimental methods

Two principle lines of enquiry can be seen within the literature on judgmental forecasting. The first one looks at JFs from an empirical perspective with data from different organisations. The other investigates the forecasting realm using experimental methods to evaluate the effect of judgment on forecasting. Examples of both lines of enquiry are stated below, with only 5% of the literature in this domain of judgmental forecasting constituting of a case study (Perera et al. 2019).

The first large scale empirical study has been conducted by Mathews and Diamantopoulos (1986). Using data from the same pharmaceutical company, Mathews and Diamantopoulos (1992) have shown that managerial judgment interventions can improve the forecast accuracy, especially when these judgments adjust the statistically derived forecasts. Fildes et al. (2009) have used more than 60,000 forecasts data from four supply-chain companies to analyse strategies designed to enhance the effectiveness of judgmental adjustments. Larger adjustments lead to greater average improvements in accuracy than the smaller ones. Plus, positive adjustments as a result of optimism are much less likely to improve accuracy than the negative adjustments (Fildes et al. 2009, Syntetos et al. 2009b).

An analysis of the judgmental adjustments in the presence of promotions is carried out by Trapero et al. (2013), on case study data from a manufacturing company specialised in household products. The data comprises of shipments, SFs, adjusted forecasts and a binary variable indicating if there is promotion (1) or not (0). In line with previous research, they found that during promotional periods, positive adjustments made the adjusted forecasts less accurate than the statistically derived forecasts.

Syntetos et al. (2009a) consider data from one case company: a Japanese electronics manufacturer for their demand categorisation. Demand categorisation constitutes an essential element of inventory management, facilitating both forecasting and stock control decision-making. Although the categorisation method applied in this study is one of the basic solutions, substantial organisational benefits can be seen. Syntetos et al. (2016b) used data from this same company to evaluate human judgment effects on inventory decisions. The database available had individual demand histories of approximately 1,800 SKUs. Inventory implications of adjusting at forecast levels are more than at the inventory level.

To compare the relative performance of different methods for forecasting special events, Nikolopoulos et al. (2015) have used data from a government body focusing on controlling budgets which aims to accelerate the use of information technology (IT). Group forecasting techniques are found to be the best in terms of forecast accuracy. Eksoz et al. (2019) uses survey data from 105 food manufacturers in Europe and North America, to research the importance of strategic partnerships on forecast satisfaction. They have found group forecasting techniques to be significant for integration in strategic partnerships.

Therefore, it can be seen that a large number of empirical studies focusing on JF accuracy has been conducted, using real data from organisations across sectors.

On the other hand, many others have used experimental setups to study human judgments and evaluate its effect on forecast accuracy. Perara et al. (2019) have found laboratory experiments to be the most popular research method in this domain. Experiments are used as researchers have control of a number of variables while conducting experimental studies. And most of the time, these experiments are conducted with students as they are an easily accessible sample for researchers. Most of them are students in the same university as the researchers and they receive module credits towards their degrees for participating in such experiments.

Goodwin and Fildes (1999) have conducted an experiment to examine how judgmental forecasters make use of statistical time series forecasts, when subject to sporadic special events. They investigated the forecasts under different conditions by varying the complexity of the time series, the level of noise in the series, the presentation and availability of SFs. The availability of the SFs did improve the judgments at times, but the judgmental forecasters' use of these forecasts was far from optimal. They ignored the SFs even when they would have formed an ideal baseline for adjustments.

In another experiment by Lim and O'Connor (1995), forecasters tended to under weigh the SFs even when their attention was drawn to the superior accuracy of SFs. Goodwin (2000) has conducted an experiment where graphical figures of 30 quarterly sales data of a hypothetical product are displayed on a computer screen for the subjects. The sales are occasionally updated with a promotional campaign and presented with bar charts showing the past promotion expenditures. The study concluded that the use of judgment in forecasting is justified when using non-time series information that is difficult to model by the software.

Sniezek (1990) made a comparison of the group judgmental forecasting techniques with a laboratory experiment on 200 undergraduate students. They made individual forecasts first and then got randomly assigned to groups for the next group task. When the task information is shared, group techniques do not have much to offer in terms of JF accuracy. From Soll and Mannes (2011)'s experiment, it is found that people tend to overweigh their own opinions because of egocentric beliefs. Hence participants of these experiments often ignored advice given when revising a forecast.

In another experiment by Syntetos et al. (2010) instead of using forecast accuracy measures, the judgmental forecasters are judged based on the impact of their adjusted forecasts. It was concluded that the implications of judgmentally adjusted forecasts can translate to substantial inventory reductions. Therefore, experiments provide researchers the liberty to control different variables within the same environment that can help generate different types of results, which is not achievable in the case of empirical data.

But the one common thread between both these lines of enquiry is the use of quantitative research methods. Most of the data in all of these studies are quantitative in nature that are further analysed using quantitative analysis methods. Why are qualitative methods not used to carry out such studies? Because JFs are very sensitive data that can reflect any unnecessary managerial interventions to an organisation's future. Hence, organisations are not willing to share such information with academics. As such most research is conducted by quantifying the managerial judgment as adjustments to forecasts.

In few studies, interviews have been conducted to understand the judgmental forecasting method in detail. Fildes and Goodwin (2020) uses semi-structured interviews with direct observations from the forecasting process. However, the interview data is either used in the initial phase to design the experiment, or at later stage to develop better understanding of the quantitative JFs. Hence, this field of judgmental forecasting is prominently dominated by quantitative research where the effects and value of judgments in forecasting processes are evaluated.

Studies using qualitative methods can prove to be advantageous as they can aid in understanding the psychology of judgmental forecasters while making interventions into the forecast process. Such studies help in developing better decision rules for reducing biases in judgments and improving the forecast accuracy for better Supply Chain Management (SCM).

2.2.5 Accuracy of forecasts

With the advent of low-cost easily accessible computing, a number of sophisticated forecasting techniques have been developed (Wood and Fildes 1978). In this field of demand forecasting, performance is measured in terms of forecast accuracy and accuracy metrics (Fildes et al. 2009, Syntetos et al. 2016b). The different measures are defined in Hyndman and Athanasopoulos (2018). These accuracy measures are able to tell how well the forecasting method is able to replicate the data that was used to develop the model in the first place (Mahmoud 1987). A number of studies have used these measures to evaluate the performance of different forecasting methods (Syntetos et al. 2011, Babai et al. 2013, Trapero et al. 2013, Nikolopoulos et al. 2015).

The different measures of forecast accuracy adopted only reflect the ability of the forecasting techniques to replicate the historical data (Wood and Fildes 1978). As forecasting has become a major part of managerial planning in organisations, it is necessary to move from historical accuracy to a more decision-centric evaluation of the forecasts. For example, Syntetos et al. (2010) argue the evaluation of the true utility of JFs as opposed to looking at the accuracy of those forecasts. Hence, organisations should determine the contributions these forecasts can make to effective decision-making, rather than trying to replicate the future (forecast) with past data.

2.3 Hierarchical forecasting

The forecasts are key inputs for many organisational decisions. Demand forecasting should not be just about forecasting techniques, but also forecasting strategies and approaches that can capture the characteristics of the supply chain organisations (Syntetos et al. 2016a). Beer (1978, p. 199) sums up their attitude for business forecast decisions as:

"*You can't do it- until you get the organisation right. It isn't right yet, is it?*"

Demand uncertainty is one of the most important challenges faced by organisations today. The presence of different management structures has encouraged the adoption of sophisticated forecasting methods (Firth 1977). Within these management structures exist different divisions that require different planning decisions. For this reason, the time series data is often segregated according to different attributes like geographical locations, customer classes, product types and stock-keeping units (SKUs). For example, Figure 2-2 shows a three-level hierarchy for a footwear company Clarks based on their product type.

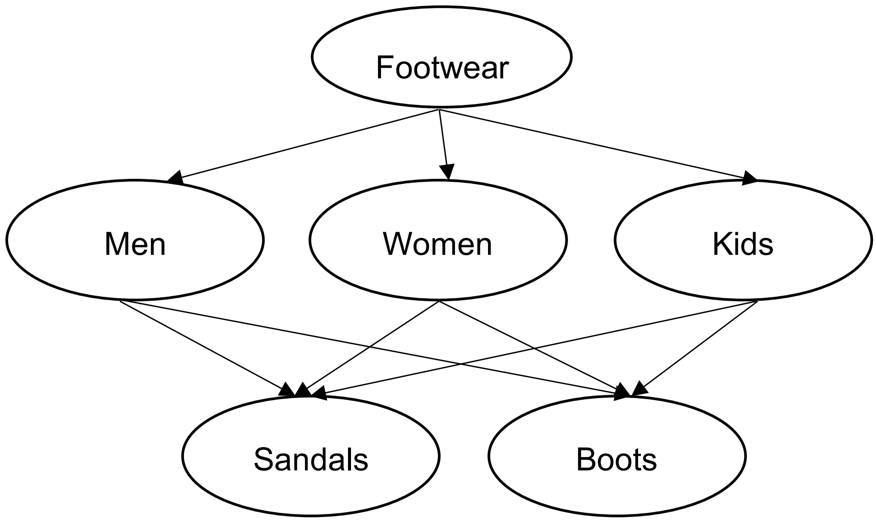

Figure 2-2: Hierarchy of a footwear company
Source: Clarks (2020)

In Figure 2-2, the total sales of Clarks can be divided into three sections depending on the customer classes: men, women and kids. Each of these three nodes (men, women and kids) form the second level and can be further divided into two finer categories (amongst other categories): sandals and boots. These two categories of sandals and boots can either have the total sales for men, women and kids; or can be divided into six categories (sandals for men, sandals for women, sandals for kids, boots for men, boots for women, boots for kids). This results in a hierarchical structure called a hierarchical time series data (Hyndman and Athanasopoulos 2014).

In the practical world, business hierarchies do not exist in isolation based on these different attributes. There are parallel hierarchies that super impose on one another as shown in Figure 2-3. Syntetos et al. (2016a) proposed this cubic structure for superimposed parallel business hierarchies in organisations. There are three dimensions to this hierarchical structure: location, time and product. The total sales of an organisation come from the sale of all products at all locations and at all times. At the most disaggregated level, the sales can be reported for each SKU at each single location for each day.

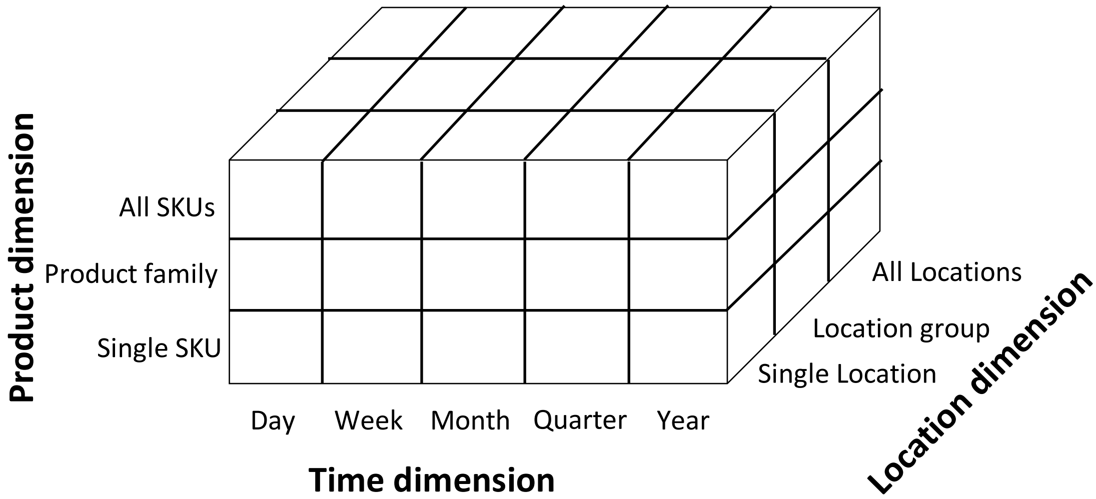

Figure 2-3: Parallel hierarchies superimposing on each other

Source: Syntetos et al. (2016a)

This concept of parallel hierarchy can also be represented in a pyramid structure (Ord and Fildes 2013). Such hierarchical structures dominate the real world and have significant implications on SCM.

2.3.1 Cross-sectional versus temporal aggregation

As seen from the previous section, hierarchical data structures are quite common in the business world where the total sales data can be disaggregated into different categories. To overcome the limitations of traditional forecasting process in utilising the hierarchical information, a number of hierarchical forecasting methods have been proposed (Athanasopoulos et al. 2009, Oliveira and Ramos 2019, Wickramasuriya et al. 2019). Depending on the different dimensions within the hierarchy, different types of aggregations or reconciliations are possible. The two most common types of aggregation are temporal aggregation and cross-sectional aggregation, both discussed below.

When time series data is aggregated with regards to the time dimension (Figure 2-3), it is known as *temporal aggregation*. Here the time series demand in lower frequency time buckets (say quarterly data) are aggregated to higher frequency buckets (say monthly data). Lower frequency time series are derived from higher frequency time series. Forecasts at higher levels of aggregation are generally found to be more accurate than those at lower aggregation levels (Nikolopoulos et al. 2011). However, temporal aggregation results in loss of information as frequency and number of observations are reduced for lower frequency levels (Nikolopoulos et al. 2011). Such aggregation is helpful in case of intermittent demand, as it helps to reduce the number of zeroes in the time series data (Rostami-Tabar et al. 2013).

Another aggregation approach that is very common in the business world and has been discussed in the literature is the *cross-sectional aggregation*. This involves aggregation across the other two dimensions from Figure 2-3, product type and location. In this type of aggregation, the data is reported for the same time periods (Syntetos 2014). This approach helps to extract more useful information from the aggregated series that might not be visible at the SKU level due to shortness of data (Syntetos et al. 2016a). Some researchers (Kourentzes and Athanasopoulos 2019, Spiliotis et al. 2020) have started working on the combination of these two approaches called cross-temporal aggregation.

A number of investigations have been reported in the literature on cross-sectional aggregation of hierarchical forecasts (Hyndman et al. 2007, Hyndman and

Athanasopoulos 2014, Hyndman and Athanasopoulos 2018, Rehman et al. 2019, Yang et al. 2019). All of them look at the best way to aggregate the individual hierarchical forecasts such that the reconciled forecasts are consistent within the structure of the hierarchy. And in this research, this approach of cross-sectional aggregation is considered for further investigation. From here onwards, cross-sectional aggregation of forecasts is referred as forecast aggregation or aggregation of forecasts.

Utilising the hierarchical characteristics of demand data, aggregation approaches can help companies reduce demand uncertainty. In business hierarchies, a large number of managers are involved representing the different nodes making the organisational structure more complex. Managers try to understand and study both the segregated and the aggregated data. Each individual time series is studied for trends and patterns; based on which different forecasting methods are used to generate independent forecasts for each time series.

A diverse set of forecasts is generated across the cubic (or pyramid) hierarchical structure. The demand forecasts need to be aggregated to inform decision-making at a wide range of organisational and functional levels (Syntetos et al. 2016a). For example, in Kourentzes and Athanasopoulos (2018) these sets of forecasts assist in aligning policy decisions for the Australian tourism across the geographical divisions. Reconciliation (aggregation) of the forecasts, such that the lower hierarchical level forecasts add up to give the upper level forecasts, becomes a necessary and challenging exercise. This topic is explored further in Chapter 5, where the cases studies for this study are illustrated.

2.3.2 Different cross-sectional aggregation methods

As mentioned in the previous section, reconciliation of the individual time series forecasts becomes indispensable so that the forecasts are aggregate consistent throughout the hierarchical structure. There have been a number of investigations to find suitable aggregation methods for hierarchical forecasts. The most widely used are: *bottom-up* and *top-down* methods (Hyndman et al. 2011, Spiliotis et al. 2020).

A number of researchers compared both these methods to come up with the best method. Some of them favour the *bottom-up* method (Dangerfield and Morris 1992, Zellner and Tobias 2000), while others think the *top-down* is the better one (Fliedner 1999, Athanasopoulos et al. 2009). More straight forward decisions are assumed to be taken at the lower levels of the organisations (Gilligan et al. 1983) and hence bottom-up makes more sense to decision makers. However, the bottom-up method requires the forecaster to collect much more data and takes longer time (Hughes 1987). On the other hand, the break-down method tends to be less expensive as one needs to forecast less.

There is another method called the *middle-out*, which combines both the top-down and bottom-up methods. Additionally, Hyndman et al. (2007) proposed the *optimal reconciliation* method that uses a regression model to optimally combine the individual forecasts from each individual time series. These methods have been described in Appendix D, with mathematical derivations for the top-down and optimal reconciliation methods.

2.3.2.1 Bottom-up method

The most commonly used forecast aggregation method is the bottom-up method (Dangerfield and Morris 1992). In this method, independent forecasts are generated at the lowest hierarchical level and added up towards the top of the hierarchical structure (Hyndman and Athanasopoulos 2014). The forecasts at the top hierarchical level is an aggregation (summation) of the lower level forecasts. The advantage of this method is it helps to capture the dynamics of the individual series (Athanasopoulos et al. 2009) and hence there is no loss of information from the bottom hierarchical level. The disadvantage is the forecaster needs to forecast each individual time-series that depends on the number of nodes at the bottom level.

2.3.2.2 Top-down method

This method follows a reverse direction to bottom-up; here the forecasts of the top-most hierarchical level are produced and then disaggregated to get forecasts of the lower levels. The advantage of this method is the simplicity to apply: only one set of forecasts are to be produced and it is faster than the previous method. However, as data from lower hierarchical levels are not considered there is a huge amount of information loss in this method.

The disaggregation of the top-level forecasts can be done in three ways based on different proportions (Hyndman and Athanasopoulos 2018). The first approach is based on average historical data proportions. In the second one, the disaggregation is based on proportions of historical averages. The third approach improves the historical and static nature of the proportions in the first two approaches. Here individual base forecasts are produced for all individual series in the hierarchy. Taking one level at a time, the proportion of each base forecast relative to the aggregate of all the base forecasts of that level is calculated. Based on these forecasted proportions, the top-level forecasts are disaggregated to get the revised lower level forecasts. Whatever approach is chosen, it is repeated for each level from top to bottom of the hierarchy.

2.3.2.3 Middle-out method

This method combines both the bottom-up and top-down methods. A middle or intermediate level within the hierarchical structure is chosen. Base forecasts for all the nodes in this level are generated. For forecasts above this intermediate level, forecasts are produced using the bottom-up method i.e. just added to get forecasts of the higher hierarchical levels. For forecasts below this intermediate level, top-down method is used to get revised forecasts by disaggregating the forecasts from each node within this level. Hence, this method is a further extension of the bottom-up and top-down methods.

2.3.2.4 Optimal reconciliation method

The above three methods have been the traditional methods for ensuring that forecasts across the hierarchy added up appropriately (Hyndman and Athanasopoulos 2014). Then Hyndman et al. (2007) suggested a method for handling hierarchical time series through an optimal reconciliation process. At first, independent base forecasts are generated using a linear regression model for all the nodes in the hierarchy. Based on the error of the regression model, a reconciliation approach is used to adjust the independent forecasts. This results in revised forecasts that are aggregated consistently within the hierarchical structure. The revised forecast for each node is a weighted average of the forecasts from all nodes (Hyndman and Athanasopoulos 2014).

This method utilises information across all the levels within the hierarchy and allows interactions between series within the same hierarchical level (Hyndman et al. 2011). This method has been found to produce more accurate forecasts than the other three methods: bottom-up, top-down and middle-out (Hyndman and Athanasopoulos 2014). These methods for hierarchical time series (hts) forecasting is implemented in the *hts* package with R programming language (R core team 2019).

2.3.3 Using judgment in reconciliation of hierarchical forecasts

In hierarchical forecasting, various forecasting methods can be used to forecast independently the various time series representing the different products or geographies or even customer classes within the company hierarchy. This has the undesirable consequence of the top-level hierarchical forecasts not being equal to the sum of the lower level forecasts (Hyndman et al. 2011). Consequently, some adhoc methods are used to reconcile or aggregate these forecasts to ensure that they add up appropriately. The previous section (2.3.2) described different statistical methods to reconcile the hierarchical forecasts from the literature. These methods produce the individual forecasts independently and then use mathematical models and techniques to make them aggregate consistent.

These statistical methods exploit the past information (historical time series data) available and thus, may not capture the contextual knowledge that managers at different hierarchical levels might possess (Syntetos et al. 2016b). These managers can use judgment to forecast the individual time series at different levels depending on the chosen forecasting method. For example, in the bottom-up method judgment inputs from the bottom level is considered while top hierarchy's judgment does not get reflected in the forecasting process. On the other hand, top-down method does not consider judgment from the bottom level nodes.

Even though the optimal reconciliation method might take into account the judgment from different hierarchical levels while generating the forecasts, the final revised forecasts may not reflect it as the regression model follows one pre-determined format every time. Hence, the revised forecasts as a result of the statistical aggregation methods may not be acceptable by the managers from different hierarchies. Another reason to favour such statistical aggregation methods is because most software packages already support such cross-sectional aggregation of data (Nikolopoulos et al. 2011, Rostami-Tabar et al. 2013).

Different levels within a business hierarchy have different forecast information requirements. Forecast information inputs vary with different managers representing different hierarchical levels and functions within an organisation (Fliedner 2001). None of the statistical aggregation methods utilise the information from the different hierarchical levels such that the forecasts are acceptable to all managers. This issue of linking judgmental interventions with hierarchical forecasting has been mentioned by a number of researchers in the literature (Spithourakis et al. 2015, Syntetos et al. 2016a). It can be achieved by judgmental decision-making methods that enable communication and collaboration between managers of the forecasting team, or even from other hierarchical echelons within the same organisation. This concept of judgmental reconciliation of hierarchical forecasts is being addressed in this study.

2.4 Structured literature review

From the previous section 2.3, it is seen that managerial judgments play a pivotal role in the aggregation of hierarchical forecasts. With that in mind, a structured literature review is conducted under the broad topic of judgmental forecasting. To avoid the negative consequences of the growing amount of scholarly literature and to benefit from the increasing knowledge base, a literature review of the primary studies is necessary (Hochrein and Glock 2012). There is a large amount of literature in this field, hence the search is narrowed down to papers only addressing the issue of forecast aggregation.

There are two main objectives of this review: firstly, to summarise the existing research by identifying trends, patterns and issues; and secondly to identify the contextual content of the field to contribute to theory development (Seuring and Müller 2008). From the traditional (narrative) review, it can be seen that there is no research done in the topic of judgmental reconciliation/aggregation of hierarchical forecasts. But to make sure that no literature is missing as the traditional literature review is known to be biased (Tranfield et al. 2003), this structured literature review is conducted. Traditional reviews do not stick to a structured paper selection and evaluation process (Hochrein and Glock 2012), thus frequently lacking thoroughness and rigour (Tranfield et al. 2003).

With the aim of exploring and understanding the use of judgment in forecast aggregation, the structured literature review is divided into three main stages: planning the review, conducting the review, and reporting and dissemination. The review method is described in the next sub-section 2.4.1. This is followed by the review findings in section 2.4.2 which includes descriptive analysis of the resultant papers (2.4.2.1) with some other major results portrayed in the section 2.4.2.2. The literature is discussed with respect to different dimensions of forecast aggregation in 2.4.2.3. A short discussion is provided in section 2.4.3 to summarise the review.

2.4.1 Review method

Every discipline has its own characteristics and so there is no 'correct' way to conduct a literature review (Hochrein and Glock 2012). The search for related publications is mainly conducted as a structured keyword search. English journal articles have been collected as a result of keyword searches from three different databases: *Scopus*, *Proquest ABIInform* and *EBSCO*. Major databases are chosen in such a way that most journals from the field of judgmental forecasting are reflected in the search.

The structured review process is shown stepwise in Figure 2-4. The keyword search starts with different variations of the words: 'judgment', 'forecast', 'predict', 'expert' and 'manager' in the title, abstract and keyword sections. As expected, the keyword search results in a huge number (4,044) of papers in these databases. To reflect the aggregation aspect of forecasting, the search is narrowed down using further keyword filters for 'reconcile'/'reconciliation' or 'aggregate'/'aggregation' to 535 results.

The number of journal articles satisfying both these keyword searches in the English language is 267. These articles are scrutinised individually after a quick content check, to remove duplicates and irrelevant articles, which further reduces the number to 38. These are reviewed with a full citation search both prospectively and retrospectively, finding a total of 53 relevant articles. To improve the reliability of the research, the databases and individual papers are checked by a second researcher.

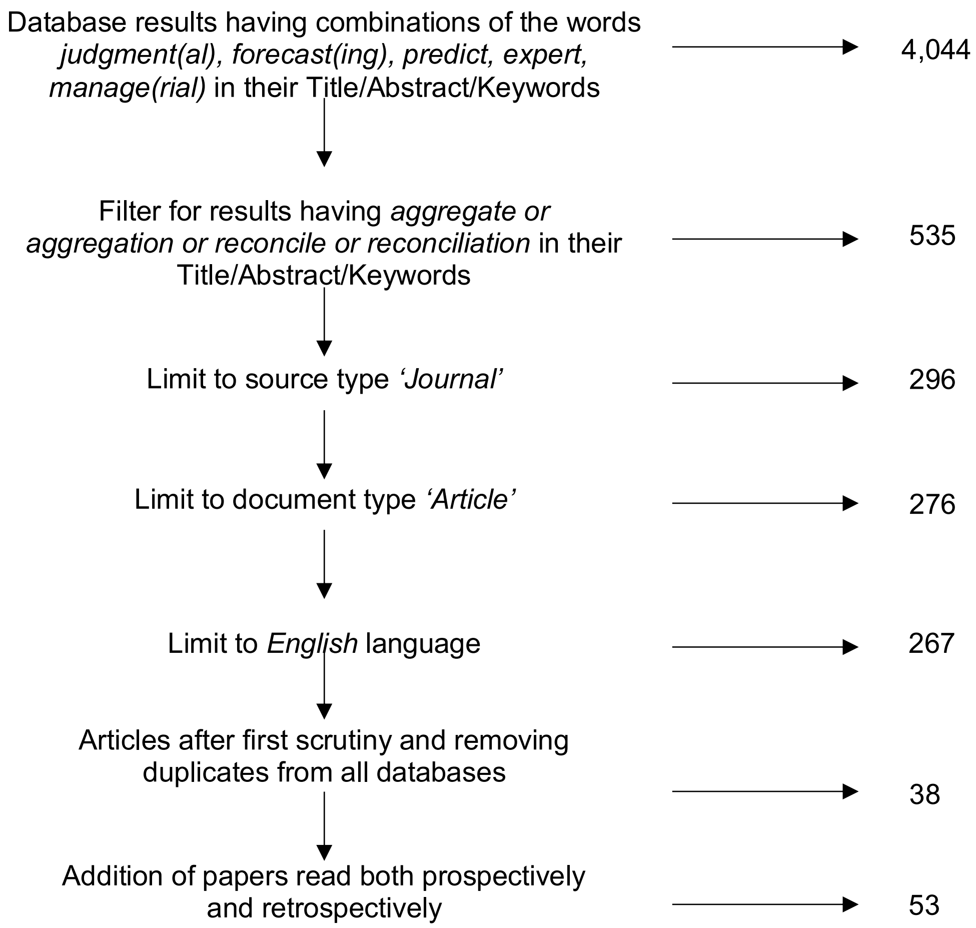

Figure 2-4: Structured literature review process

The review method follows a content analysis process proposed by Mayring (2003) cited in Seuring and Müller (2008) consisting of four steps: *material collection*, *descriptive evaluation*, *category selection* and *material evaluation*.

(a) Material collection: In this first step, the material to be collected is defined and delimited. English journal articles considering forecasting aggregation in the field of judgmental forecasting are reviewed. The search strategy is described and documented to enable the reader to replicate and/or to extend the search (Hochrein and Glock 2012).

(b) Descriptive evaluation: The formal aspects of these articles are assessed providing the background for subsequent analysis. The descriptive findings provide insightful knowledge on how the methodological approaches have developed with time.

(c) Category selection: The articles are categorised across time, industry and different methodological approaches. The selection of categories is based on the existing literature in a deductive fashion before the articles are analysed. However, a few other categories are developed from the material and added inductively after reading these articles.

(d) Material evaluation: In the final step, the articles are analysed based on the previously mentioned categories. This allows identification of relevant issues and interpretation of the results. These findings should clearly be related to the theoretical knowledge base and practical requirements, if any (Hochrein and Glock 2012).

2.4.2 Review findings

In this section, the results and findings from the structured literature review are presented. In the first step, descriptive dimensions are used to classify the articles. Each of the 53 articles are read and segregated based on their research methodologies along with the dominating research field. The descriptive analysis based on the publication time, research methodology and research field are presented in the next subsections. Along with the descriptive analysis, the articles are also characterised based on three different dimensions: amount of judgment in the study, whether group forecasting is involved, and the aggregation method applied. There are nine (9) reviews papers within these 53 papers and they have been discussed separately towards the end of this section.

To gather an idea about how the review has been conducted, consider the example of the paper by Spithourakis et al. (2015). This paper presents a Forecasting and Foresight Support System (F2SS) that combines features from a business forecasting system. A simulation exercise is carried out with students from a forecasting background, which clearly categorises under the *experiment* research methodology. As it does not specify any particular industry apart from the fact that this system is for business forecasting, it is placed in the business category of research field.

The participants are asked to make forecasts based on both quantitative and qualitative data, so judgment is involved in this research, but the amount is categorised as *low*. It's group forecasting exercise is a group activity, hence encouraging the participants to communicate with other team members. Additionally, in the third week of the experiment, they use different statistical hierarchical aggregation methods to combine the forecasts. As these methods (top-down and bottom-down) use basic arithmetic knowledge of summation and division, the aggregation method for this study is chosen to be mathematics. This is the process followed for all the other articles, and the findings from the review are discussed below.

2.4.2.1 Distribution across time and research field

The basic body of this structured literature consists of 53 articles (until March 2020). The allocation of the publications over time is shown in Figure 2-5. The first paper is by Grinnell et al. (1971) on Bayesian predictions by faculty members that are combined to observe conservatism in prediction aggregation. Highest number of publications (7) are seen in the year 2019, with three review papers by Arvan et al. (2019), Perera et al. (2019) and Song et al. (2019). All three review papers cover group forecasting which shows that an extensive literature on this topic exists for authors to conduct reviews on them. Since 2011, there has been a substantial number of articles published on aggregation of (judgmental) forecasts.

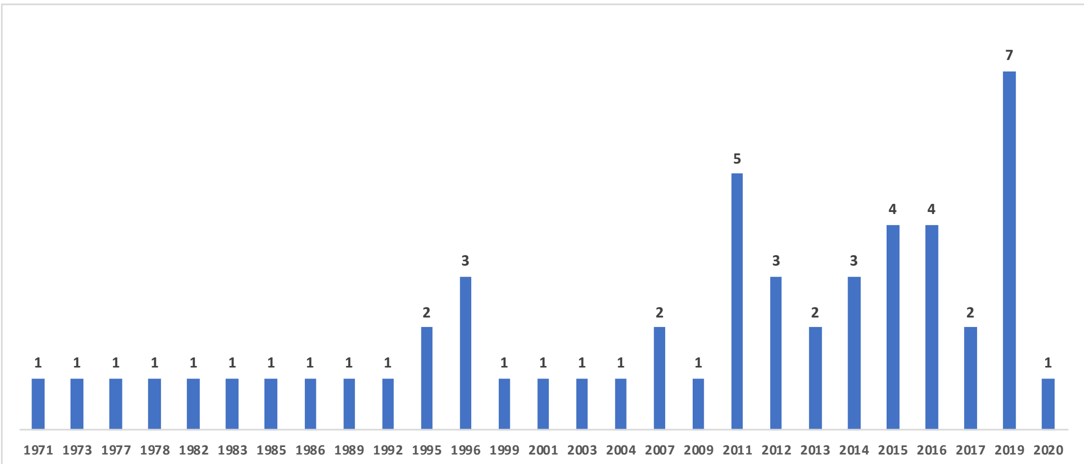

Figure 2-5: Distribution of publications over time

When there are publications or studies on a particular topic across different research fields, it can be seen as an active topic in several fields. Within the body of literature for this structured review, ten different research fields have been found (Figure 2-6). Researchers have tried to address the issue of forecast aggregation across different domains: from computer science to transportation. The highest number of publications are in the field of forecasting where authors do not mention any specific industry as the target. Forecasts are generated or evaluated that can be applied across different industries from business to election polling.

For example, the study by Major and Ragsdale (2001) looks at the processing of information (expert predictions) coming from remote locations over the internet. They introduce a new component viz. transaction manager that can combine the various pieces of information coming from remote internet sources. This has been categorised as a study within the computer science research field.

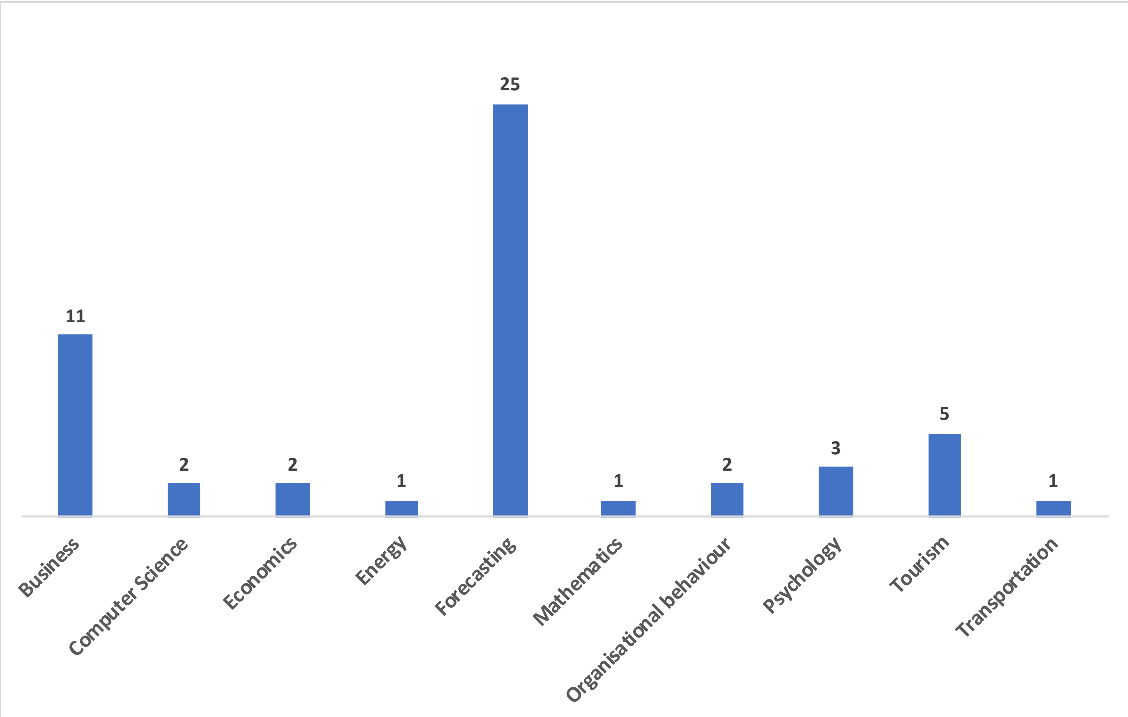

Figure 2-6: Distribution of publications based on research field

A cross-comparison is made for the distribution of publications across both time and research field as shown in Table 2-1. The years have been grouped into five groups: 1971-1980, 1981-1990, 1991-2000, 2001-2010, 2011-2020. The table shows how interest in the topic of forecast aggregation has increased exponentially for the last decade of 2011-2020.

Additionally, the topic has gained interest within new research fields like organisational behaviour, energy and tourism, where there are no publications before 2011. Interest has also increased in the general topic of forecasting with 14 publications in the last decade.

Table 2-1: Distribution of publications over time and by research field

Research Fields	Year groups					
	1971-1980	1981-1990	1991-2000	2001-2010	2011-2020	Total
Business	1	1	1	2	6	11
Computer Science				1	1	2
Economics		1		1		2
Energy					1	1
Forecasting	2	2	6	1	14	25
Mathematics					1	1
Organisational behaviour					2	2
Psychology	1	1			1	3
Tourism				1	4	5
Transportation					1	1
Total	4	5	7	6	31	53

2.4.2.2 Research methodologies employed

Six research methodologies are differentiated within this review: (1) Analytical, (2) Case Study, (3) Experiment, (4) Survey and (5) Theory papers. Figure 2-7 shows the assignment of the publications to the different research methodologies. Certain papers can fall under more than one category, such as there are papers which have experiments but use data from a case company. In such cases, the methodology mentioned within the article is taken as the research design category. For example, Wang et al. (2011), Kaczmarek-Majer and Hryniewicz (2019) and Lin (2019) are experimental studies but with data set from different organisations.

Within the theory category, nine out of the ten articles are literature review papers that review existing literature on a topic associated with forecasting and put forward some observations.

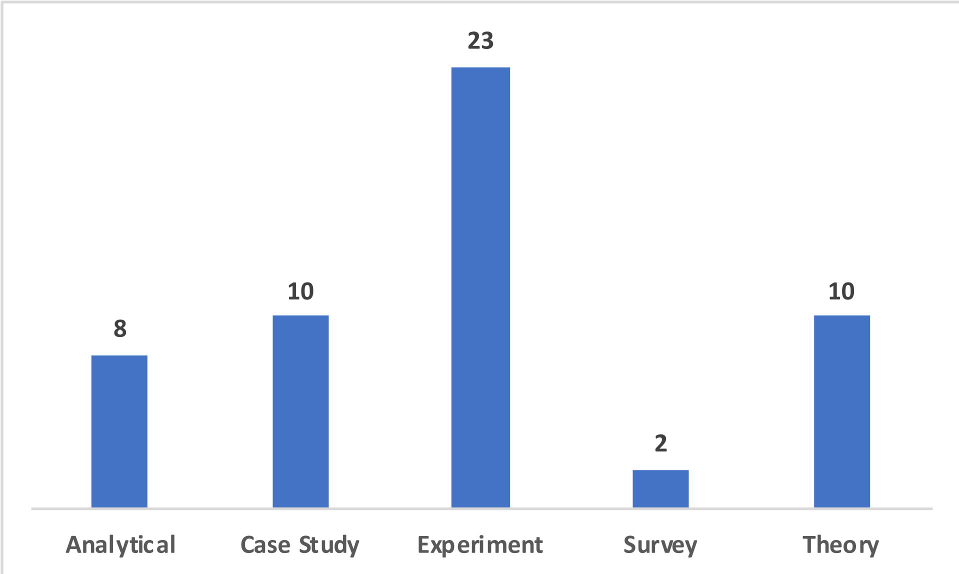

Figure 2-7: Distribution of publications based on research methodology

Experimental studies account for almost 44% of the publications, being the most common research method to be employed. The second most favourable methodology with 10 studies is that of case study where the authors have access to data from one or more case organisations on which they perform their analysis. There are eight studies that use analytical methods to develop forecast combinations for expert predictions. A number of principles like Bayesian aggregation, maximum entropy and fuzzy model for collaborative forecasting can be seen within this body of literature.

Additionally, from Table 2-2 it is evident that most of these (6 out of 8) analytical studies are in the field of general forecasting. Similarly, when it comes to experimental studies almost 50% of them are in this field of forecasting, whereas five of them address more specific cases of business forecasting. When it comes to the tourism and transportation fields, only two research methods (case study and experiments) can been seen with one review paper. As mathematical rigour of the papers has not been assessed, no particular methodology can be qualified as better or other publications be disqualified in any of the categories.

Table 2-2: Distribution of publications across research field and research methodologies

Research field	Research methodologies					
	Analytical	Case study	Experiment	Survey	Theory	Total
Business	1	2	5		3	11
Computer Science			2			2
Economics	1			1		2
Energy				1		1
Forecasting	6	4	11		4	25
Mathematics			1			1
Organisational behaviour		1			1	2
Psychology			2		1	3
Tourism		2	2		1	5
Transportation		1				1
Total	8	10	23	2	10	53

2.4.2.3 Dimensions in forecast aggregation

Depending on the three dimensions of judgment, group forecasting and aggregation method, the publications have been characterised into different categories. Within the dimension of judgment, the publications are segregated based on how much human judgment is actually taken into consideration while forecasting or aggregating. There are three categories within this dimension: high, low and none (if no judgment is involved).

For the second characteristic, the publications are recorded based on whether they consider group forecasting within their study or not. And for the third characteristic, the aggregation methods within these publications are divided into different categories, each of which are explained below in subsection C. Finally, a fourth dimension of review papers is added towards the end of this section. Figure 2-8 shows the four dimensions for categorisation in this review.

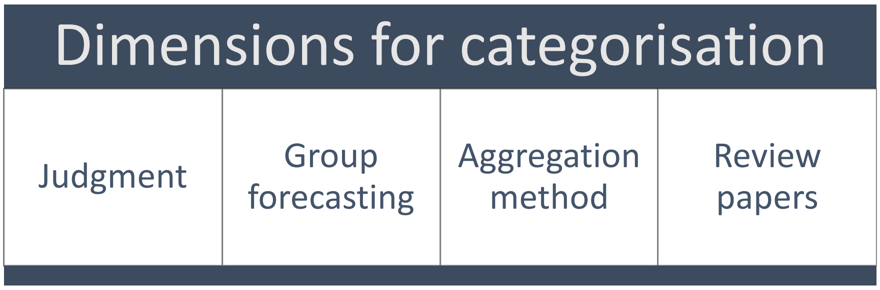

Figure 2-8: Dimensions for categorisation

A. Judgment involved

Since keywords relating to judgment is the first criterion for this literature review search, it included a number of studies with "expert prediction" in their title/abstract/keywords. Yet it is surprising to see that 21 (including 9 review articles) out of these 53 publications have no element of judgment within their study. What these studies refer as JFs or expert predictions are input data used for developing the aggregation methods. There is no element of human judgment involved within the aggregation process.

Like Morris (1977) and Ernst et al. (2016) use Bayesian approach to aggregate more than one expert opinion or forecast, but these are purely quantitative mathematical models. Similarly, maximum entropy based aggregation techniques are used by few authors (Myung et al. 1996, Major and Ragsdale 2001, Moreno and López 2007) to find ways to combine experts' predictions. Verstraete et al. (2020) mentions about expert prediction in their abstract but has not used any judgment within their study.

On the other hand, there are 32 publications that integrate some degree of human judgment in their study. Few authors have low amount of judgment like Hyndman et al. (2011) where a statistical model for optimal reconciliation of hierarchical forecasts is developed. But the input forecasts for this method can be both statistical or judgmental according to the authors in the article. Jouini and Clemen (1996) use Bayesian aggregation for the decision makers but the decision makers must use subjective judgments as a basis for constructing the aggregation model. The participants of the Spithourakis et al. (2015) are encouraged to use their own judgments to make the forecasts. Baecke et al. (2017) investigates the integration of human judgments into statistical forecasting systems using JFs from a case company.

In the category of high judgment involvement, subjective JFs by knowledgeable persons are used to obtain the aggregated forecasts. Staelin and Turner (1973) developed a behavioural model to aggregate JFs that depends on the forecast level within a business hierarchy of an organisation.

In the study conducted by Fischer and Harvey (1999), participants are asked to judgmentally combine four “experts” opinions provided to them during the experiment. They challenged the idea that combinations of separate forecasts produced by judgments are inferior to those produced by simple averaging. When participants are provided with the information of their previous period forecast error, it helped to combine the forecasts in such a way that outperform the simple averaging method. Seifert and Hadida (2013) do not combine forecasts but look at integrating with SFs derived from a model. Zhou et al. (2019) uses a range of experts from academics, government and industry to produce energy predictions for crude oil and natural gas.

Hence it can be concluded that even when judgment is mentioned in the keyword search, a number of papers do not actually have expert judgment involved in their research studies. Most of them are quantitative procedures for aggregating diverse subjective forecasts (in the form of numbers) optimally.

B. Group forecasting

This dimension of group forecasting is defined as when a number of people forecast together. Since the second search criterion is on forecast reconciliation or aggregation, one way of categorising the publications is based on whether they consider groups while forecasting or aggregating the forecasts. Only 14 out of the 53 publications have considered group forecasting in their research. Out of these 14 publications, six of them are review papers where the authors review previous literature on group forecasting. Hill (1982)'s review paper compares whether groups perform better than individual forecasters, from the literature.

Few papers have included groups while forecasting or aggregating the forecasts in their studies. In the Good Judgment Project by Ungar et al. (2012), different modes of information sharing are considered: individual predictions in isolation, individual predictions seeing what others predict, a prediction market and team predictions. Teams of forecasters work in groups of 15-20 and they have to provide the basis of their forecasts to each other. Team conditions are found to be better than the others, and the teams even benefitted from trainings. But the authors do note that these collaborations between the team members are conducted over an online environment, hence a number of effects from real-world team collaborations are missing from this experiment.

Most of the studies are on aggregation of forecasts produced by different individuals separately or several forecasts produced by the same individual. Hence, there is no concept of group forecasting in these studies, a few examples of which have been cited here. Nelson and Bessler (1992) conducted five experiments where subjects produce one-step ahead forecasts of a variable generated by a Monte-Carlo process. The performance of aggregates of the subjects' forecasts are compared with an ARIMA model to show that the model can serve as substitute for aggregating expectations. The results are based on simple averages of the means of the individual distributions.

Chen and Rakha (2016) develops an agent-based modelling approach to predict multi-step ahead expected travel times using both real-time data and historical data. Each agent is considered as an expert in decision-making at the microscopic level, consequently providing a recommendation each on the future experienced travel time. The aggregation of these experts' forecasts (with individual weights) provides the predicted travel-time distribution. This research has been considered under the field of transportation.

Satopää et al. (2015) introduces a novel modelling framework for prediction polls using data from two real-world prediction polls. The framework is for partial information aggregation, it down-weighs sets of forecasters that share similar information and up-weighs ones that have unique information. Pennings et al. (2019) considers group forecasting between the software and the experiment participant who form a pair with alternating roles of operations manager and sales manager. They have found such group interactions stimulated cooperation, reducing participants' biases.

C. Aggregation method

This category directly fits with the second search criterion keyword: aggregation or reconciliation. For this dimension, the aggregation method applied in each of the publications is used to categorise them. Four main categories are used: mathematics (e.g., simple average or statistical probabilities), mathematical models (e.g., Bayesian approach models, fuzzy models), judgmental, and no aggregation method (NA for review papers). There are four papers where the aggregation method is not very clear, like in Spann and Skiera (2003) an internet-based Virtual Stock Market (VSM) approach carries out the forecast aggregation. It is not clear how this aggregation is calculated within the VSM approach.

13 publications come under the last category of either no aggregation method or NA (9 review papers). The four papers with no aggregation methods are Hogarth (1978), Lim and O'Connor (1996), Harvey and Harries (2004) and Lin (2019). Hogarth's (1978) note on aggregating experts is about the number of experts to be combined and the selection of these experts, no such forecast aggregation method. In Lim and O'Connor (1996), information from multiple sources are aggregated to produce the forecast. It helped to understand how people select and use multiple pieces of information during preparation of the forecasts. In Harvey and Harries (2004), the participants (experts) simply combine the forecasts by assigning different weights. Lin (2019) uses Delphi method to collect and combine the expert predictions, but no aggregation method has been used.

Only one paper used a judgmental approach to aggregating forecasts from this collection of 53 publications. In Fischer and Harvey (1999), three experiments are conducted to check under what conditions judgmental combinations of individual forecasts can be better than simply averaging the forecasts. The participants play the role of a managing director of a consumer products firm. They are provided with four individual forecasts from four senior staff members and they have to combine them to provide a final estimate for the next month's sales. The aggregation method is judgmental as it depends on the participants completely. When outcome feedback is provided, the judgmental combinations are found to be better than the simple average method.

The rest of the publications are on quantitative aggregation methods: either using mathematics like averaging, summation and statistics; or different mathematical models based on Bayesian approach, maximum entropy and others. Ashton and Ashton (1985) study the impact of aggregating subjective forecasts for five aggregation methods (with different weights while averaging) on forecast accuracy. Aggregates of the subjective forecasts are found to be more accurate that the individual forecasts themselves. Regardless of the aggregation method, the gain in accuracy is because of the combination of a small number of forecasts.

Chen (2012) presents fuzzy collaborative forecasting models based on fuzzy linear regression to forecast the unit cost of a product. The experts' forecasts differ in these models and consequently need to be aggregated through collaboration. The results show improvement in the forecast effectiveness through collaborations. Athanasopoulos et al. (2009) combine hierarchical forecasts from an Australian domestic tourism market for several levels of aggregation. They calculate bottom-up, three variations of top-down, and optimal reconciliation of the hierarchical forecasts; and compare the forecast accuracies for each of these methods. Top-down based on forecast proportions and the optimal reconciliation method are found to best for tourism hierarchies.

Baecke et al. (2017) uses two models of restrictive judgment and integrative judgment to compare the properties of judgmental adjustments. They use a data set from a European publishing company that consists of the SFs, judgmental adjustments, and actual outcomes. They combine the human judgment with the SFs using the two types of judgmental models. The integrative model has a beneficial effect over the restrictive model and basic SFs.

D. Review papers

There are nine review papers within this set of 53 publications with the first one being Hill (1982). Most of them review literature on group forecasting, two of them on forecast combination/aggregation, two of them on human judgment in forecasting, Syntetos et al. (2016a) reviews general literature on supply chain forecasting with sections on forecast aggregation, and Song et al. (2019) reviews tourism demand forecasting.

Hill (1982) has made experimental comparisons to check whether groups perform better than individuals on four dimensions of task, process, individual differences and methodology. The review has shown that group performance is generally superior to that of an average individual. Two other papers by Straus et al. (2011) and Wright and Rowe (2011) review literature on group-level phenomena. When team members in a group withhold unshared information, they fail to introduce disconfirming evidence into the discussion (Straus et al. 2011). They are more likely to share common information that has been shared with all group members and this shared information tends to dominate decisions made by the groups.

Groups have the power to change the attitudes and judgments of individual members. Consequently, groups have been found to exert social pressure on individuals threatening the group consensus (Straus et al. 2011). This heterogeneity in group memberships and its impact on opinions is studied by Wright and Rowe (2011). It concludes that group forecasting includes both factual knowledge that forecasters try to support their forecasts with, and also expertise knowledge that they use to persuade other group members.

Clemen (1989) reviews the extensive literature that had accumulated on the combination of forecasts. The principal conclusion is the accuracy of forecasts can be substantially improved with combinations of multiple individual forecasts. Forecasting combinations can help individuals understand the underlying processes better, thus making better individual models. A wide spread use of the applicability of forecast combination is illustrated with examples from different areas: meteorology, economics, environmental, tourism, sports (football game) amongst others.

The review paper by Clemen (1989) is extended by Mancuso and Werner (2013), by reviewing several more papers with new methods and applications. The review included studies of combining forecasts using objective or subjective mechanisms. Objective methods combine more than one forecast by assigning different weights to these forecasts. Contrarily, subjective methods use intuition and acquired knowledge to combine forecasts while reaching consensus within a group like the Delphi method.

The review by Syntetos et al. (2016a) aims to bridge the gap between theory and practice. The paper discusses how forecasts may be required at different aggregate levels than those at which they are produced. Forecasts are required at some higher or lower level than the demand input level based on the decisions to be made from those forecasts. Hence, importance of forecast aggregation is highlighted and there is a call for more academic literature on this topic of studying the effects of different forms of aggregation to different decision-making levels.

In 2019, there are three review papers by Arvan et al. (2019), Perera et al. (2019) and Song et al. (2019). Song et al. (2019) reviews 211 key papers on how demand forecasting has evolved over time in the field of tourism. They found that evolution of forecasting methods is still ongoing with different combinations of models. Perera et al. (2019) conducts a systematic review of human judgment in forecasting focusing on key features that impacts supply chain decisions. They call for more research studying the effects of such human interventions in forecasting with the rest of the supply chain.

On the other hand, Arvan et al. (2019) is a systematic review of judgmental forecasting with an emphasis on integrating methods. They suggest building a conceptual framework to develop a behavioural informed Forecasting Support System (FSS) with dynamic feedback mechanism. Table 2-3 shows the 53 publications with their categorisations for this review.

Table 2-3: Categorisation of the publications

Publication(s)	Judgment involved	Group forecasting	Aggregation method	Review paper
Grinnell et al. (1971)	High	×	Mathematical model	
Staelin and Turner (1973)	High	×	Mathematics	
Morris (1977)	×	×	Mathematical model	
Hogarth (1978)	×	×	None	
Hill (1982)	--	√	NA	√
Figlewski and Urich (1983)	Low	×	Mathematics	
Ashton and Ashton (1985)	High	×	Mathematics	
Little (1986)	Low	×	Not very clear	
Clemen (1989)	--	×	NA	√
Nelson and Bessler (1992)	High	×	Mathematics	
Salo and Bunn (1995)	High	×	Mathematics	
Jouini and Clemen (1996)	Low	×	Mathematics	
Lim and O'Connor (1996)	High	×	None	
Maines (1996)	High	×	Mathematics	
Myung et al. (1996)	×	×	Mathematical model	
Fischer and Harvey (1999)	High	×	Judgmental	
Major and Ragsdale (2001)	×	√	Mathematical model	
Spann and Skiera (2003)	High	×	Not very clear	
Harvey and Harries (2004)	High	×	None	
Moreno and López (2007)	×	×	Mathematics	
Tziralis and Tatsiopoulos (2007)	×	×	Mathematical model	
Athanasopoulos et al. (2009)	×	×	Mathematics	
Hyndman et al. (2011)	Low	×	Mathematics	
Soll and Mannes (2011)	High	√	Mathematics	
Straus et al. (2011)	--	√	NA	√
Wang et al. (2011)	High	×	Mathematics	

Wright and Rowe (2011)	--	√	NA	√
Chen (2012)	Low	√	Mathematical model	
Ungar et al. (2012)	High	√	Mathematics	
Karvetski et al. (2013)	Low	×	Mathematics	
Mancuso and Werner (2013)	--	×	NA	√
Seifert and Hadida (2013)	High	×	Mathematical model	
Graefe et al. (2014)	Low	×	Mathematics	
Satopää et al. (2014a)	Low	×	Mathematical model	
Satopää et al. (2014b)	High	×	Mathematical model	
Budescu and Chen (2015)	Low	×	Mathematical model	
Pathak et al. (2015)	Low	×	Not very clear	
Satopää et al. (2015)	×	×	Mathematics	
Spithourakis et al. (2015)	Low	√	Mathematics	
Chen and Rakha (2016)	×	×	Not very clear	
Croce et al. (2016)	×	×	Mathematics	
Ernst et al. (2016)	×	×	Mathematical model	
Syntetos et al. (2016a)	--	×	NA	√
Alvarado-Valencia et al. (2017)	High	√	Mathematics	
Baecke et al. (2017)	Low	×	Mathematical model	
Arvan et al. (2019)	--	√	NA	√
Kaczmarek-Majer and Hryniewicz (2019)	Low	×	Mathematical model	
Lin (2019)	High	√	None	
Pennings et al. (2019)	High	√	Mathematics	
Perera et al. (2019)	--	√	NA	√
Song et al. (2019)	--	√	NA	√
Zhou et al. (2019)	High	×	Mathematics	
Verstraete et al. (2020)	×	×	Mathematics	

2.4.3 Discussion

A structured literature review is conducted on forecast aggregation within the field of judgmental forecasting. This review presents classification and analysis of the 53 publications collected on this subject, describing their main characteristics. A brief descriptive analysis of the publications with respect to publication time, research field and research methodology employed is presented. The articles are classified along three dimensions: human judgment involved in the forecasting process, group forecasting, and forecast aggregation method.

Because of the unknown future and market complexity, single forecasts may not always be sufficient for decision-making. Forecast aggregation is suggested by a number of authors, be it in a group or otherwise. Aggregation does not require additional input data beyond that ordinarily used, nor does it require that forecasting models be employed (Ashton and Ashton 1985). The most obvious shortcoming of this present body of literature on forecast aggregation is that of subjective methods of aggregating forecasts through collaborations. A number of authors have called for further research on this line of research (Hill 1982, Clemen 1989, Syntetos et al. 2016a).

Structured literature reviews have been argued to lie within the 'pragmatic' management research with aims to serve both the academic and practitioner community (Tranfield et al. 2003). The structured and systematic approach helps to ensure the objectivity of the review process (Seuring and Müller 2008). The validity of the process is ensured by presenting this work at different seminars and an international conference, where other researchers and practitioners had the opportunity to comment on it.

Reliability is addressed by having all steps of the formal analysis conducted by two researchers. This structured literature review has different advantages depending on the audience. For academics, the reviewing process increases methodological rigour. On the other hand, it helps to develop a reliable knowledge base for practitioners, by accumulating knowledge from a wide range of studies.

2.5 Summary

Forecasting is a crucial aspect of the planning process in any organisation. This chapter presents a literature review on demand forecasting with special reference to the business sector. The chapter starts with an introduction on judgmental forecasting, that is then divided into different types based on a number of factors.

(a) Based on information available during forecasting, the section on judgmental forecasting is divided into unaided and aided.

(b) Based on ways how judgment is used for forecasting, this section is divided into pure JFs and judgmentally adjusted SFs.

(c) Based on number of people involved during judgmental forecasting, individual and group forecasting literature are discussed.

(d) The literature is reviewed within two principal lines of enquiry where researchers use empirical and experimental research methods.

The next section 2.3 introduced the concept of hierarchical forecasting and the different (hierarchical) forecast aggregation methods: cross-sectional and temporal aggregation. The following section 2.4 is a structured literature combining the two previous sections on judgmental forecasting and forecast aggregation/combination. A total of 53 publications are reviewed, classified and analysed under different categories such as judgment, group forecasting and aggregation method. Description of the review method and review findings (descriptive analysis and categorisations) are included in this section.

The structured literature review has increased the rigour of this research by making sure no academic articles are missed. The review has added value by streamlining the process of literature search, for assessing the current state of research in judgmental forecasting. This has helped develop a knowledge base on which one could rely upon to decide the course of this research. The descriptive analysis of this review provides quantitative analysis of previous studies. It shows how active this research topic is today and hence, the relevance of this research study. The different dimensions have guided the identification of areas that require further investigation within the field of judgmental forecasting. This has allowed key research gaps to be identified. These gaps are then addressed through this research (see, in particular, section 3.8 below).

The next Chapter 3 provides a general discussion on organisational decision-making. This follows from the findings of RQ1 and the traditional review that highlight the need for literature in organisational studies. The findings from this chapter (both structured and traditional reviews) highlights the research gaps in the next chapter. Findings from the structured review also guides the adoption of case study methodology in this research. The findings from this chapter are used to answer the research questions in the discussion chapter, in combination with empirical data results. Figure 2-9 is a pictorial description of the thesis structure showing progress until now, highlighting the links of this chapter with other chapters.

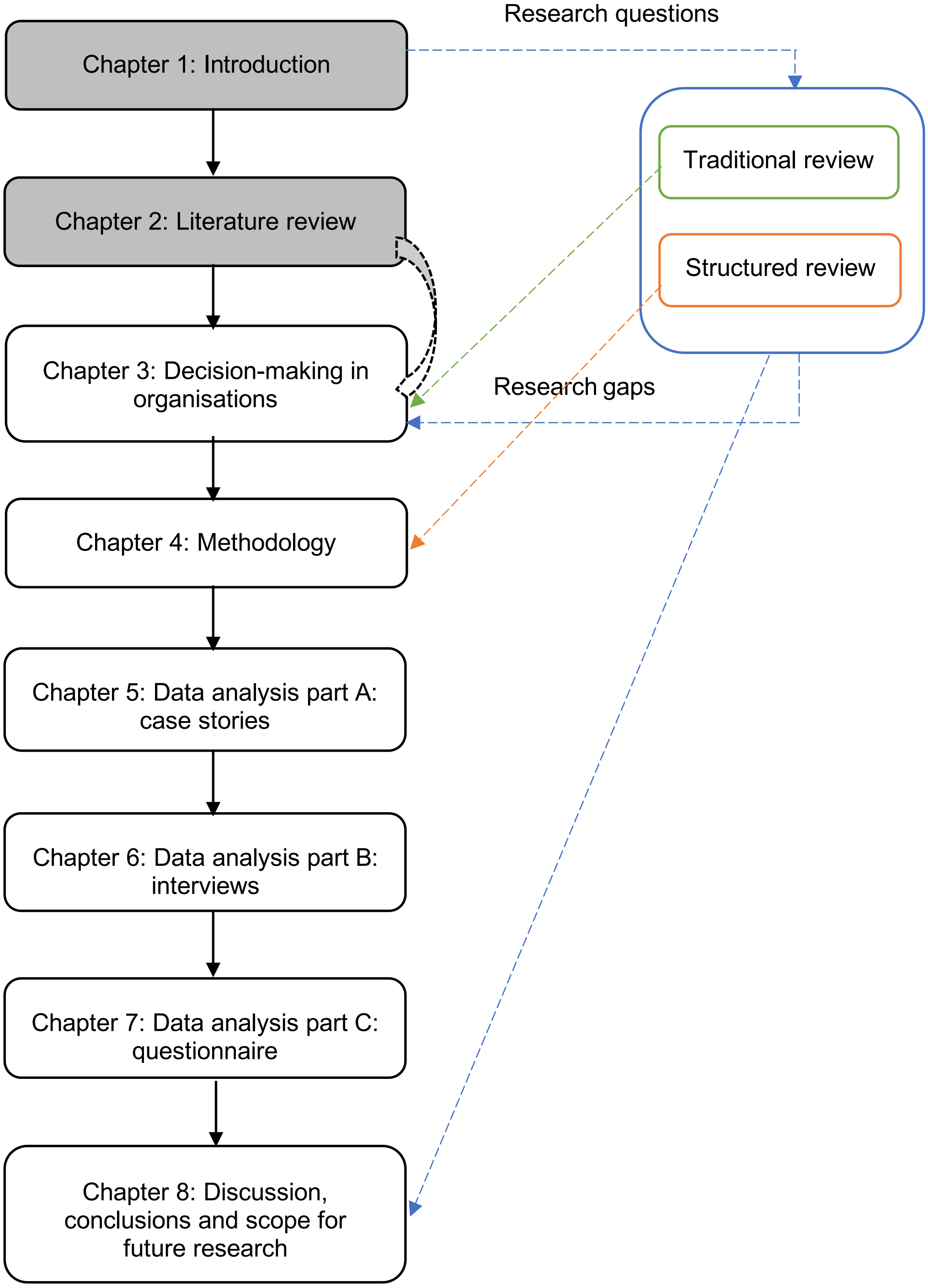

Figure 2-9: Thesis structure (Chapter 2)

Chapter 3

3 Decision-making in organisations

3.1 Introduction

Forecasts are not of much value in themselves; it is the decisions based on these forecasts that are important. Different organisational decisions are taken based on these forecasts like inventory management, stock-replenishment and service levels (Fildes and Goodwin 2020). The literature in this chapter has been conducted after the first two research questions are answered. From these two RQs, it is evident that an umbrella view of organisations decision-making process outside of the field of business forecasting is needed. With that in mind, different organisational decision-making models are studied and reported here. This chapter addresses general organisational decision-making; it includes the Strategic Options Development and Analysis (SODA) method, a collaborative decision-making model, and a consensus decision-making model from linguistic literature. One of these models help develop the conceptual framework for this research.

This research is iterative in nature as seen from section 1.2, during the development of the RQs. Because of this a number of literature reviews are conducted throughout the study. When the four main dimensions of judgmental hierarchical forecasting process are identified from the interview data, a literature search is conducted for each of these themes. Section 3.7 describes these four dimensions of business decision-making: information sharing, time pressure, power struggle and social value; along with the literature corresponding to each of these dimensions.

In the second phase of data collection, a questionnaire is designed to gather wider opinions on the four dimensions of forecast decision-making. The questionnaire data is analysed using SWOT analysis and MADM methods. The literature review of these two data analysis methods are also reported in this chapter in sections 3.5 and 3.6. These sections show how these methods have been applied to forecasting research previously and are still used for different decision-making studies. Bringing together the literature from the above sections and the previous Chapter 2, the final section 3.8 highlights the two research gaps that this study aims to address. These gaps connect directly to the research questions in section 1.2. This chapter helps design the study's research instrument - to be discussed in the methodology Chapter 4.

Decision-making is a process of choosing courses of action among different alternatives for the purpose of attaining a goal (Turban 1995). The decision-making practices in business studies generally assume knowledge to be objective and believe there are straight forward techniques to problem solving. However, with increasingly complex business environments, there is a greater element of judgment involved that has suggested the need for a broader perspective of decision-making (Gilligan et al. 1983). Often there is much confusion between the terms of decision-making and problem solving. One way to distinguish is that decision-making ends with recommendations whereas problem solving additionally includes implementation of those recommendations (Turban 1995).

There are two different kinds of views of the decision cycle: *open* and *closed systems*. In the continuum reflecting the independence of systems, open and closed systems represent the two extreme ends. An *open system* makes decisions considering the organisation's environment, whereas *a closed system* is totally independent of the environment (Turban 1995). The open system approach attempts to develop a more realistic understanding of the organisation and its individuals. On the other side, the closed system presumes the organisation to be isolated and that everyone is trying to achieve a clear and unambiguous set of goals.

However, in the real world of constantly changing and competitive environment, there exists a high degree of ambiguity in the explicit set of goals which most members of the organisation may not accept (Gilligan et al. 1983). This research takes into consideration case organisations as open systems which has been discussed below (Figure 3-1).

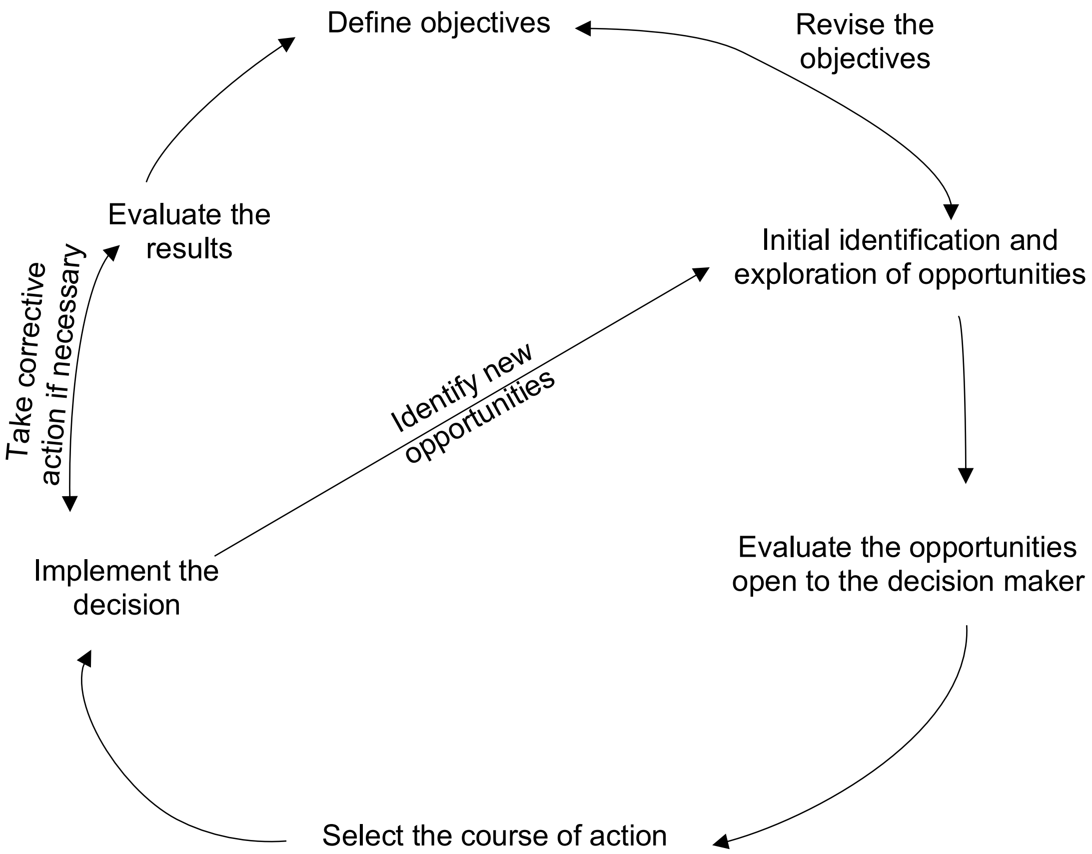

Figure 3-1: The decision cycle
Source: Gilligan et al. (1983)

This open system approach to the decision-making cycle is described as found in Gilligan et al. (1983). The fundamental element of this approach is the dismissal of perfect information and clearly stated economic objectives. The emphasis here is placed upon "*feedback, learning and adaptation, together with the effect of this upon ends and means*" (Gilligan et al. 1983, p. 8).

The first step in the decision cycle is to set organisational objectives with an estimation of the performance level that is likely to be accepted within the organisation. From here, the decision maker moves to identification and evaluation of the different opportunities (courses of actions) that are available to them (Turban 1995). Based on the evaluation of these opportunities against the performance level set in the first step, they select the best amongst them. Once the proposed course of action is selected, it is time to implement it and evaluate the results of the decisions being made. These results can then be used as a source of information while taking the next decision.

The essence of the open system is that judgmental issues play a significant role in its dynamic approach. The decision cycle described above explains what a typical decision maker *does* rather than what they *should do* when faced with the need to make a decision (Gilligan et al. 1983). Plus, a decision maker may not need to go through all the steps of the decision cycle. It depends on the circumstances and the type of decisions being made.

For example, while deciding on the number of spare parts to order, the decision maker will already have decided on a supplier and the quality of the spare parts required during the first decision-making cycle. They only need to forecast and reorder the quantity required in every cycle, while periodically reviewing the decision-making process for improvements. On the other hand, in case of product launches and new investments, the decision makers make use of the full decision cycle as there is a considerable amount of uncertainty involved in such circumstances (Gilligan et al. 1983).

3.2 Strategic Options Development and Analysis (SODA)

An organisation can be viewed in different ways when it comes to their decision-making processes. One of the views is to consider organisations to be composed of individuals who may or may not hold similar views on what is happening around them (Pidd 2003). With such a view, another technique of organisation decision-making, SODA, has been developed by Colin Eden and colleagues for strategic thinking and planning.

The aim of this SODA method is to enable groups of people to commit themselves to a joint agreement by taking into consideration all the possibilities they envisage (Pidd 2003). It uses interviews and cognitive maps to explore people’s perceptions and views regarding a specific problem. The idea behind the cognitive mapping technique is to draw on these individual views and perceptions. Group maps are constructed from the individual cognitive maps that are used for negotiations to arrive at a common commitment for action. This early (above) version of the technique is referred to as SODA 1.

There is another version SODA 2, which dispenses the individual cognitive maps but instead builds causal maps with the group directly via group decision support technology (Pidd 2003). However, both these versions rely on a facilitator to draw the maps and direct the groups toward joint agreement. The choice between

SODA 1 and SODA 2 depends on the circumstances but when time is short, the latter is preferred.

SODA 1 is useful when a group of employees have their own views but need to be blended into an effective decision-making team (Pidd 2003). It starts with personal interviews with each individual, later developing cognitive maps for each one. These individual maps reflect the perceptions and desires regarding the problem the team needs to address. A skilled facilitator merges these individual maps into one strategic map that is used for discussion and negotiation with all team members.

On the other side, SODA 2 is organised directly with the team rather than starting with individuals. A group map is developed with the use of a software that is linked to each of the individuals' personal computers. This map reflects the team's concerns and opinions regarding the problem. With the help of a facilitator (like SODA 1), this map helps the team to reach a joint agreement on what to do.

Both these techniques, SODA 1 and SODA 2, recognise the presence of conflict and disagreement within organisations, and how people with different mixed agendas choose to co-operate (Pidd 2003). They appreciate individuality and subjectivity as the basis for problem definitions in organisational decision-making.

3.3 Collaborative Decision-Making

Decisions in organisations are mostly made by a group of managers, there are very few situations when one single person has to make a decision on their own. When it comes to groups making decision, there can be three different types of decision processes depending on the number of people involved: *autocratic*, *collaborative* and *consensus* decision-making styles. Warner (2012)'s model (Figure 3-2) for collaborative decision-making is used to explain these three different styles.

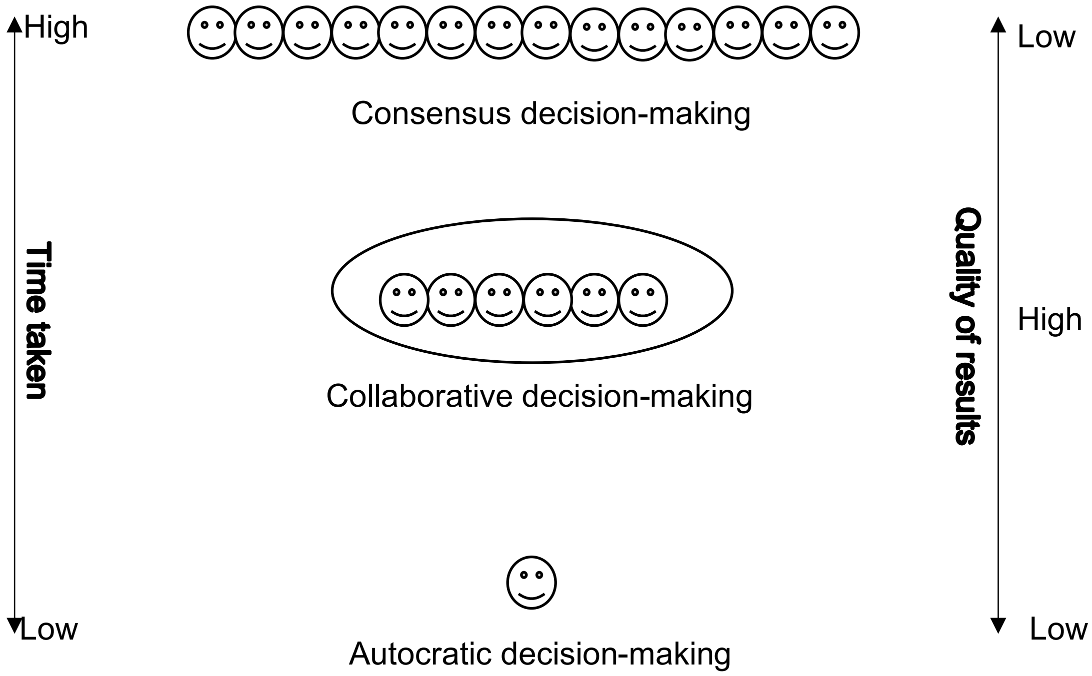

Figure 3-2: Consensus decision-making
Source: Warner (2012)

Autocratic decisions are made by one single person on behalf of others, especially when time is short. At the other extreme is consensus decision-making, when opinions are collected from everyone who will be affected by the decision made. In the middle of these two styles is the collaborative one which is the integrative behaviour that requires sharing of information and listening to what others have to offer. There is usually confusion between the consensus and collaboration styles. Consensus decisions involve general agreement although it may not be the ideal solution. Whereas in collaborative style individuals know that their ideas may not prevail but through their contribution they become part of an important decision being made.

In Warner (2012)'s model, there are two other dimensions distinguishing the three styles: *time taken* and *quality of results*. The most critical dimension to keep in mind while making any kind of decision is that of time availability and how one might have to adjust depending on it. The time taken for autocratic decisions is low and that for consensus style is quite high. For the collaborative style, the time taken is in between the two extremes. This is the most common situation where managers usually know when decisions should be made so that there is no last-minute hurry and also, they never have the luxury of weeks or months to make one decision.

The other dimension on results' quality reflects the outcome of the decisions made using the different styles. A single person cannot make the best decision for and on behalf of others. Equally, when many managers are engaged a consensus decision might be achieved but it will not be the ideal one. The collaborative style lies in the centre of this dimension that has the sweet spot when a few carefully chosen people provides inputs and participates in the process. Even if these people may not agree with the final decision, they appreciate the investment made in obtaining their inputs.

Collaborative decision-making is about aggregating the understandings of decision makers, rather than compromising. Owen (2015) developed a framework for collaborative decision process based on decision analysis. It explicitly performs aggregation of individuals' understanding of the decision to be made, the alternatives available and finally, the reason for the resulting decision choice. This framework does not strive for an optimal or compromising solution. But this solution is one in which each of the individuals feels ownership and agrees to implement it.

The idea behind this collaborative process is that each individual can never have a complete idea of how the business works. Only with the knowledge of other colleagues who have different experiences, even when these might result in conflict with each other, a unified understanding of the problem is developed (Owen 2015). There are reports that show collaborative decisions to be of better quality and the commitment to its implementation is much higher, making this style the best for decision-making in organisations (Warner 2012).

3.4 Decision-making using linguistics

Real-world decision-making processes involve more than one actor (managers) to make decisions in groups. Group decision-making is when more than one expert who are characterised with their own ideas, motives, experience and knowledge try to achieve a common solution (Herrera-Viedma et al. 2005). When the experts' opinions are considered with the same intensity, it is called *homogeneous group decision making* and otherwise it is *heterogeneous group decision making* (Herrera et al. 1997).

However, there is limitation to incorporating the expert decisions into quantitative models. The best solution can be achieved when the experts can express their opinions in numerical values, but that is not always the case. There are cases when experts deal with vague information or have to express in qualitative aspects (like good, medium or bad) that cannot be assessed with quantitative values (Herrera-Viedma et al. 2005).

In such scenarios when information is assessed through qualitative values rather than quantitative ones, linguistic decision-making is found to be useful. Linguistic decision-making is based on the use of a linguistic approach and for solving problems under linguistic information (Herrera and Herrera-Viedma 2000). The linguistic approach is an approximation technique representing the qualitative aspects in experts' opinions as linguistic values by means of linguistic variables (Herrera and Herrera-Viedma 2000). These variables do not have numerical values but words or sentences in a natural or an artificial language.

Herrera et al. (1997) developed a rational consensus model (Figure 3-3) in a linguistic framework for heterogeneous group decision-making problems. This model allows more soft information consistency to be incorporated into the decision-making process. Here the group decision-making process is made up of two processes: *consensus process* and *selection process*. The first process is to achieve maximum degree of consensus among the experts on a set of alternatives. The second one is to select the solution set that all experts agree upon.

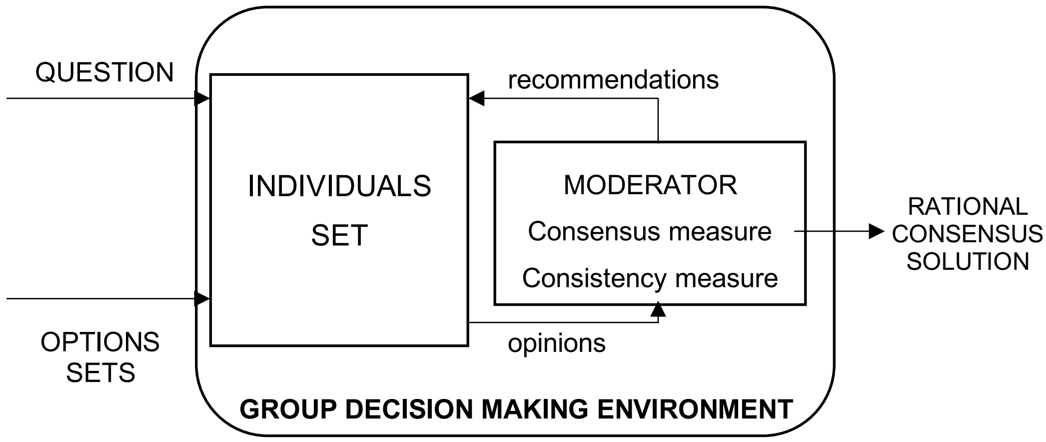

Figure 3-3: Consensus reaching process
Source: Herrera et al. (1997)

Herrera-Viedma et al. (2005, p. 644) says "*it is preferable that the set of experts reach a high degree of consensus before applying the selection process*". A moderator is present who coordinates between the different experts via exchange of information and arguments, to alter and bring their opinions closer. Measures are used by the moderator to analyse, control and monitor the consensus reaching problem.

In this approach, the burden of quantifying a qualitative concept is eliminated (Herrera and Herrera-Viedma 2000). Additionally, the model allows less distorted (more rational) consensus solutions that can rise due to the inconsistencies in the experts' opinions (Herrera et al. 1997). The applicability and usefulness of these linguistic decision models can be extended to different decision frameworks. It can be used to model qualitative information in different real-world scenarios involving decision-making. Hence, this model developed by Herrera et al. (1997) is adapted to develop a conceptual framework for hierarchical forecasting in section 6.4.

3.5 SWOT

SWOT is the acronym for Strengths, Weaknesses, Opportunities and Threats, and it is an environment analysis tool for business decision-making. Analysis of an organisation's resources and environment is central to strategic planning for business development and growth. In contrast to the common belief of viewing business planning as a systematic, sequential and rational process, in reality it is found to be a "*somewhat more incremental, non-rational and irregular; more organic than mechanic process*" (Pickton and Wright 1998, pp. 101-102).

SWOT provides an analytical framework for categorising the different environmental factors, both internal and external to the organisations. It helps to gain a better insight into an organisation while making strategic plans and decisions (Phadermrod et al. 2019). In business settings, SWOT analysis is undertaken via interview techniques or brainstorming (Rocha and Caldeira-Pires 2019).

Figure 3-4 provides a visual representation of the SWOT factors and its process. By identifying the SWOT factors, different strategic plans for business growth and improvement are developed. These strategic plans propose policies connecting the different strengths and opportunities, while compensating for weaknesses and neutralising the threats (Rocha and Caldeira-Pires 2019). SWOT has also been used for analysis in different forecasting studies (Chang et al. 2002, Markovska et al. 2009).

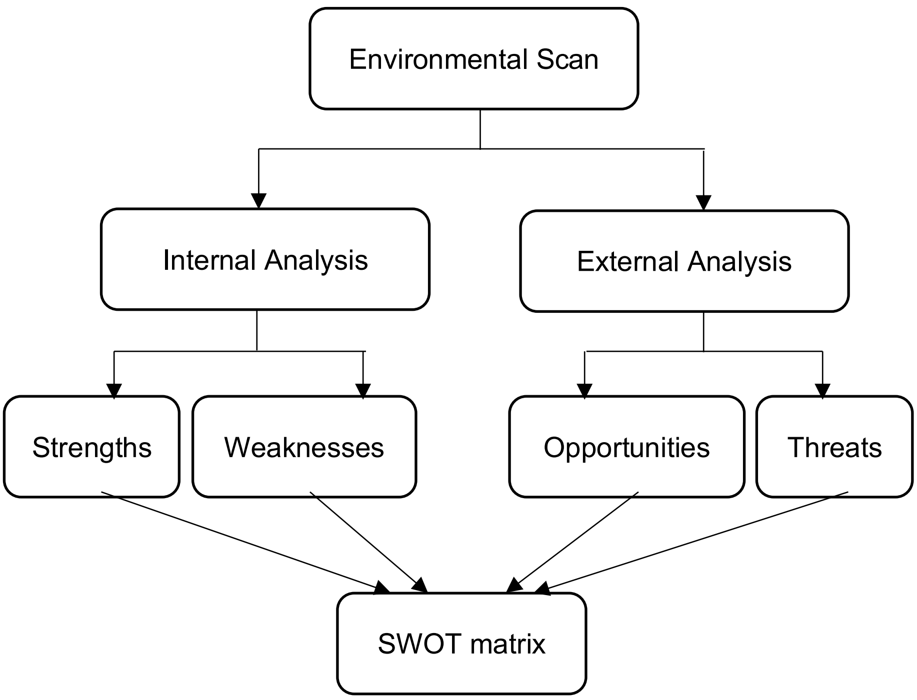

Figure 3-4: SWOT analysis framework
Source: Görener et al. (2012)

Chang et al. (2002) uses the qualitative method of Delphi to forecast the future potential products of Taiwan's machinery industry. The forecasting method is preceded by the SWOT analysis on Taiwan's machinery industry, to guide the Delphi experts' opinions. Markovska et al. (2009)'s study combines primary data from stakeholders' insights with secondary data of documents and statistics. They use SWOT analysis to stretch future actions towards sustainable development for the Macedonian energy sector.

The big advantage of using SWOT is that it provides a better and improved understanding of the work environment, including managerial and inter-departmental points of view along with prejudices (Pickton and Wright 1998). SWOT provides a practical tool to be used by professionals and academics, and it is mostly preferred because of its simplicity. It has been adopted and used widely, generally accepted uncritically. It is still used today for analysing internal and external environments for suggesting different business strategic plans. For example, Rocha and Caldeira-Pires (2019) undertakes a study based on SWOT analysis of interviews with different stakeholders for Environmental Product Declaration (EPD) in Brazil.

SWOT is mainly used for its simplicity, but it can lead to strategic errors if used naively (Pickton and Wright 1998). The limitations of the use of SWOT are the three major points: inadequate definition of factors, absence of factor prioritization, and excessive subjectivity from the complier while generating the factors (Pickton and Wright 1998, Rocha and Caldeira-Pires 2019). To overcome these points, many authors (Görener et al. 2012, Büyüközkan and Ilicak 2019, Phadermrod et al. 2019) have used it along with quantitative tools like Multiple Criteria Decision-Making (MCDM) methods (explained in the next section 3.6). It has been suggested by Pickton and Wright (1998, p. 101) that "[SWOT] *should* *be used as a dynamic part of the management and business development process*", rather than an output generating tool for strategic business planning.

3.6 Multiple Criteria/Attribute Decision-Making (MCDM/MADM) methods

MCDM/MADM is referred to as the study of identifying and selecting alternatives based on the values, opinions and preferences of the decision maker (Gavade 2014). Businesses have different goals and objectives; and their decision-making processes identify different activities that help achieve those. In general terms, a decision-making process consists of eight steps as defined in Sabaei et al. (2015) and presented here in Figure 3-5. To achieve the goals and objectives, there are different MCDM methods that organisations can choose from. These MCDM methods are used for sorting, ranking and/or quantifying alternatives based on Pareto optimal selection (Hodgett 2016).

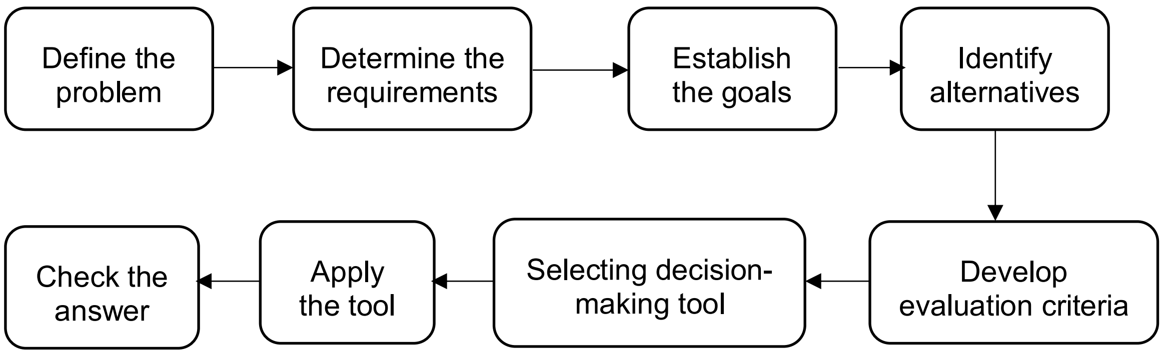

Figure 3-5: General decision-making process
Source: Sabaei et al. (2015)

Hodgett (2016) divides these MCDM methods under two distinct categories of multi-attribute (MA) methods and outranking methods. The first category methods allocate a numerical value to each of the alternatives, that maximises the decision problem function. Weighted sum, Analytical Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) come under this category. The other category uses outranking methods for pairwise comparisons between alternatives to sort the best one out. Examples of such methods are Elimination Et Choix Traduisant la Realité (ELECTRE) and Preference Ranking Organisation METHod for Enrichment Evaluations (PROMOTHEE).

Weighted sum is the simplest of all methods and it uses normalisation to evaluate the value of each alternative. The overall value of every alternative is equivalent to the products' total sum (Kolios et al. 2016). AHP is a prioritised ranking of the decision alternatives based on the overall preferences provided by the decision makers (Anderson et al. 2017). It is the most common method to be used by researchers and practitioners. On the other hand, the idea behind the TOPSIS method is the optimal solution must be as close as possible to an ideal solution and as far as possible from any given negative ideal solution (Kolios et al. 2016).

There are different variations of the ELECTRE method like ELECTRE I, II, III, IV, IS and TRI. The philosophy behind this method is it generates a system of binary outranking relations among the alternatives (Kolios et al. 2016). On the other hand, PROMOTHEE instead of eliminating any alternative based on pair-wise comparisons, puts them in an order based on the decision maker preference (Sabaei et al. 2015).

Table 3-1 comparing the three most common methods of AHP, ELECTRE and PROMOTHEE has been suggested by Sabaei et al. (2015). As it can be seen, AHP can be considered as an outranking method with pair-wise comparisons. Plus, AHP and ELECTRE can handle both quantitative and qualitative data types criteria, whereas PROMOTHEE is only for quantitative data.

Table 3-1: Comparison of AHP, PROMOTHEE and ELECTRE

	Outranking method	**Data type**
AHP	Pairwise comparison	Qualitative/ Quantitative
PROMOTHEE	Partial/complete pre-order	Quantitative
ELECTRE	Partial aggregation	Qualitative/Quantitative

Source: Sabaei et al. (2015)

Even though different authors (Velasquez and Hester 2013, Sabaei et al. 2015, Hodgett 2016, Kolios et al. 2016) have tried to compare these methods to find the best and most accurate amongst them, the results cannot be generalised. The decision to adopt any MCDM method depends on the nature of the problem, its data collection and analysis; hence it varies based on what "*fits* [best] *each individual method and application*" (Kolios et al. 2016, p. 17).

As the thesis is progressed, the rationale behind the choice of AHP and ELECTRE as the two methods for this study becomes clear. In brief, it is because both of these methods, AHP and ELECTRE, are found to be particularly relevant when the criteria are qualitative in nature and they fit the research problem in this study perfectly. AHP has been found to be suitable for dealing with future aspects of a decision problem that are not well known (Kolios et al. 2016).

Both these methods are still being used by researchers for various types of decision problems. Hodgett (2016) compares AHP and ELECTRE for equipment selection, and developed a new multi-attribute evaluation method, Multi-Attribute Range Evaluations (MARE) that reflects the decision maker's preference better. Uysal and Yavuz (2014) has used ELECTRE for determining the appropriate facility location in Turkey. Görener (2012) uses a combination of SWOT with AHP for selecting significant strategic decision factors for cooker hoods in a manufacturing firm. Similarly, Brunnhofer et al. (2020) is a three-phase Delphi study using a combination of SWOT and AHP to assess strategic factors that affect the biorefinery concept in European pulp and paper industry.

3.7 Dimensions in business decision-making

In this section, the literature of different dimensions (or key elements) of group decision-making environments in business organisations are presented. These four dimensions, shown in Figure 3-6, are *information sharing*, *time pressure*, *power struggles* and *social value* aspects of organisational decisions. They have been found as a result of thematic analysis (section 6.2) of exploratory interviews from forecasting managers of different case companies. The process of solving a decision problem can be seen as the following stages: perceiving the existence of the problem, acquiring information, considering the alternative possibilities, and evaluating the information (Ben Zur and Breznitz 1981). These different stages show how the four dimensions impact the decision-making process.

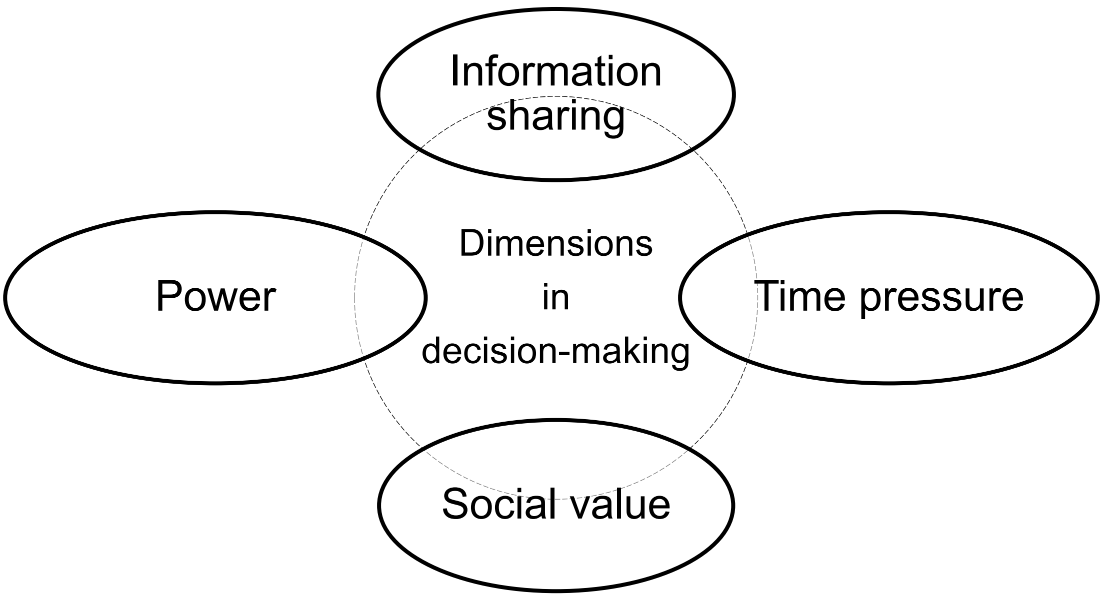

Figure 3-6: Dimensions in business decision-making

Information sharing is how different team members or managers from different hierarchical levels share data amongst themselves for various group tasks. The second dimension is that of time pressure which highly impacts any kind of decisions being taken in day-to-day businesses. People often need to make decisions within limited available time and hence, time pressure can sometimes reduce the quality of decisions taken both individually and in interactive environments (Kocher and Sutter 2006).

Another dimension is that of power struggles between managers in an organisation. Especially when hierarchies are involved, managers from the top hierarchy have a major influence on the opinions and actions of managers from the lower hierarchies. The last dimension is the concept of social value as a shared value in businesses in addition to the economic value of decision-making. Social value is the degree of importance that employees in an organisation put on their experiences within the work environment. These four dimensions are explored further in the next four sub-sections with the help of relevant literature from different fields of study.

3.7.1 Information sharing

The first dimension of information sharing is the most vital dimension in today's ever-expanding global economy, but the management of information has been mostly neglected. With more available information in business decision-making, the uncertainties in the future can be reduced (Ali et al. 2017) resulting in better annual profits (Khan et al. 2016). Dynamic business environments demand decision makers to decide on the selection and integration of information, keeping in mind the time constraints (Kerstholt 1994).

Along with time, there are a number of other constraints for information sharing in a business; like information quality, trust and confidentiality between teams (Ali et al. 2017) and social motivation to do so (Bălău and Utz 2017). Because of such constraints, information sharing leads to conflicts when there are differences in opinions or disagreements in decisions. Such conflicts can sometimes lead to more information or data being shared. Hence, these conflicts can act as stimuli for richer discussion and a better decision-making process.

Moye and Langfred (2007) investigates the role of task and relationships conflict on the relationship between information sharing and group performance. They have found that information sharing has a direct effect on group decision-making performance, explained by two distinct mechanisms: more efficient group process and better decision-making. The group process improves with more information sharing as it leads to better coordination between team members. With regards to decision-making, when members share more information better decisions will be made improving the performance of the team. Sharing information over a course of time, group members become more efficient at problem solving with better coordination and responsibility allocation for the task.

There is an extensive literature on information sharing in the supply chain sector but all of them look at information being shared between partners in a supply chain (Lee et al. 2000, Zhao et al. 2002, Byrne and Heavey 2006, Zhang and Chen 2013, Ganesh et al. 2014, Khan et al. 2016, Ali et al. 2017, Yang and Zhang 2019). Supply chain companies have become aware of the importance of information sharing that aids in creating a collaborative environment (Ali et al. 2017).

The performances of supply chains depend on their levels of coordination among different stakeholders (Khan et al. 2016). Sharing the sales and demand information between different partners in a supply chain is a major strategy to mitigate "*bullwhip effect*" (Lee et al. 2000, Zhang and Chen 2013, Ganesh et al. 2014, Khan et al. 2016). But to the best of our knowledge, none of this research looks at information shared between vertical hierarchical levels, something this study is addressing.

Ali et al. (2017, p. 991) suggests that "*supply chains should always strive to share information in order to be most effective*". Information sharing and coordination are found to be beneficial for potential savings and better performances of supply chains (Zhao et al. 2002, Byrne and Heavey 2006, Khan et al. 2016). When there is an inter-dependency of different group members within the task, information sharing can lower the negative relationship between information sharing and task conflict (Moye and Langfred 2007). However, under time pressure individuals give priority to the information perceived as most important while making decisions (Ben Zur and Breztinz 1981). Hence time pressure is the next dimension of decision processes that has been discussed in the following sub-section.

3.7.2 Time pressure

The goal of any decision maker is to make decisions without much cognitive strain or stress (Young et al. 2012). But most of the occasions when managers have to make decisions, be it economic decisions or deciding about business strategies, are under severe time pressures (Kocher and Sutter 2006, Paola and Gioia

2016). These managers tend to take risky decision choices under time stress in haste (Sadiq and Chan 2015).

There is an extensive range of literature that has found that time pressure does have an effect on decision-making (Kahneman and Tversky 1979, Ben Zur and Breztinz 1981, Kerstholt 1994, Young et al. 2012, Sadiq and Chan 2015, Paola and Gioia 2016). The decisive aspect of time pressure is that there is always a tight time limit to make decisions with monetary consequences (Kocher and Sutter 2006). Bălău and Utz (2017) have found that rushed decisions are made under time pressure, avoiding information sharing which might prolong the decision-making process.

As time pressure highlights uncertainties and doubts, people prefer to avoid the negative outcomes (Kahneman and Tversky 1979, Ben Zur and Breztinz 1981). One of the reasons why a number of forecasting managers may choose to go for SFs rather than judgmental ones. The judgments in decision problems come with huge amounts of responsibility, conflicts and a number of negative consequences (Ben Zur and Breztinz 1981). With tight time constraints, managers are aversive of ambiguity and uncertainty.

Performance in such jobs is affected by the stress and pressure of having to make the best decision within the time constraints (Paola and Gioia 2016). Increased anxiety is a feature of time-pressured situations as imposition of a deadline places an extra demand on the decision makers (Maule et al. 2000). As multiple number of cognitive processes are involved in decision-making, they may all be differentially influenced by time pressure (Young et al. 2012). When it comes to individual decision-making tasks, time pressure impacts the information processing capacity and the consistency of decisions (Kocher and Sutter 2006).

On the other hand, Young et al. (2012) have found that an individual's perceptions on risk attractiveness increases when they have to make decisions under time stress. Individuals seem to allocate more time in processing more general information about the problem with the imposition of a deadline (Maule et al. 2000). Greater priority is given to understanding the decision problem in hand rather than evaluating the alternatives and outcomes.

Organisations need to implement procedures that limit the changes made to decisions being taken under time pressure (Sadiq and Chan 2015). Managers have to take steps to remain consistent in their decisions. Plus, they need to be aware of how decisions can deviate from the usual; and this shall provide them with a greater understanding of the decision-making process (Sadiq and Chan 2015). In the fast-changing present scenario, decision makers have to make changes to the decision strategies to achieve the best outcome within the limited time (Kerstholt 1994). Taken together, the literature shows that when time is limited it has a great amount of effect on the decision makers, and on the outcomes and processes (strategies) underlying the judgment in decision-making.

3.7.3 Power

In organisational settings, managers may not be truthful about their forecasts because of social and hierarchical pressures (Zhou et al. 2019). The third key dimension of business decision-making is that of managerial power. Power has a broad spectrum of definitions depending on different scenarios. For the scope of this study, its definition has been restricted to managers' characteristics that can give rise to power struggles within business decision-making processes. The three elements considered within this definition are: experience, product expertise (knowledge) and authoritative position (formal position in the business hierarchy).

Plus, these three elements may be interweaving into one another. For example, one in a higher authoritative position can be with more experience and/or more expertise. These three elements result in creating power struggles amongst managers that has an impact on their forecast and planning process.

Experience is an important determinant of managerial decision-making. It manifests into the manager's choice of soft information, use of this information and the decisions themselves (Perkins and Rao 1990). With experience, managers become experts in determining information valuation for decision-making. Experienced managers can understand the uncertainties and consequences of their decisions more than their unexperienced counterparts (Perkins and Rao 1990). Especially when it comes to new product decisions, experienced managers give more weightage to soft information in their decisions.

This highlights how experience can act as a power determinant and impact the decisions being made in hierarchical forecasting. It manifests into the very first step of group forecasting where information is acquired and processed. However, experience can sometimes also be a proxy for expertise as some amount of knowledge gets accrued with continuous usage of a product (Raju et al. 1995).

Product expertise (knowledge) is another key concept for business decision-making processes. Product experts seek more information sharing than novices when making decisions (Selnes and Howell 1999). While there can be different types of knowledge, the definition of product expertise provided by Raju et al. (1995) is adopted here. It has two parts: objective knowledge (amount of knowledge stored in memory) and subjective knowledge (feeling of knowing something).

Product experts develop cognitive skills making them reliant on intrinsic information cues while making decisions. But this dependency of managers on intrinsic versus extrinsic information is subject to the ambiguity of information. With more involvement with a product category, managerial judgments lead to better forecast accuracy (Belvedere and Goodwin 2017). Like experience, product expertise can influence the entire decision-making process from searching information to decision outcomes (Raju et al. 1995). Although there might be some correlation between product knowledge and experience, the effects of the latter on decision-making can be separate from that of product knowledge.

There exists a real interplay between managers' positions within the business hierarchy and their decisions. A manager's hierarchical position defines how much power they can assert on the business decisions and this gives rise to intra-team power struggles. Power has been linked to demeaning behaviour and at times, even aggressive tendencies that can destroy relationships and impede goodwill (Fast et al. 2012). Managers in more powerful positions are given control over decisions and allowed to direct other managers' actions, whereas lower position managers are expected to keep their opinions to themselves (Anderson and Brown 2010).

Greer et al. (2017) have conducted a literature review of how power impacts team outcomes. Although there are a number of research studies with conflicting results, they found power struggles to negatively impact team-level outcomes with heightened conflicts within power-dispersed teams. Dynamics of power dispersions in intra-team hierarchies result in conflicts, preventing team learning and information sharing, with weakened interpersonal relationships corrupting social interactions within teams. On the other hand, social psychology literature points that when a team prefers to have a hierarchy it helps in clarifying information and interactions, thus enhancing team coordination.

With more hierarchical levels involved, a group is found to perform worse as the managers at higher positions are corrupted by the power the group affords them (Anderson and Brown 2010). This results in a break down in intra-group communication and coordination. When decisions help to achieve goals, power should lead to actions that can help achieve those goals (Fast et al. 2012) and not otherwise. Although Charles Darwin argued over 170 years ago that hierarchies are necessary for groups to succeed, researchers have found that hierarchies pervade social groups and have a profound impact on group decisions (Anderson and Brown 2010).

3.7.4 Social value

Very little focus has been given to the social dimension of group decision-making in any business setting. From the previous three dimensions, it is clear how much the work environment can influence the decision-making process and the decisions themselves. This social dimension is actually a result of the decision-making process when different values (economic, social and environmental) are created within organisations. The economic value is given the highest priority by businesses as its evaluation helps to appreciate their monetary gains. Supply chain organisations have constantly tried to reengineer their efforts to better match supply with demand so as to reduce inventory and stock outs with great economic savings (Lee et al. 2000).

The Social Value UK (2020) organisation defines social value as the measure of relative importance that individuals place on their life experiences. This value is measured from the perspective of those affected by the organisation's work, from employees to end customers. Fischer (2014, p. 3) quotes "... *understanding social values requires a reflection on evolving social needs within broader development processes..."*. Unlike economic values, evaluating social values can be difficult in practice as they cannot be monetised or compared with money-metric values (Fischer 2014).

However, the social value of employees must be cultivated within organisations for their socio-economic developments. Considering their employees' social values, Nike (footwear manufacturing company) has improved the working conditions for their workers in its supply chain (Khan et al. 2016). Their reengineering efforts have improved the efficiency of supply chains resulting in greater coordination and cooperation through information sharing (Khan et al. 2016). Such coordination, cooperation and participation by different team members generate positive effects on the work culture and increases the social value of an organisation (Le Var 1998).

Social values are inherently subjective, derived from the sense of dignity that employees perceive from particular social settings (Fischer 2014). These social values get corrupted by individuals at higher positions during team interactions in the organisation. Greer et al. (2017) have cited the example of the epic power struggle between Apple' founder Steve Jobs and Apple's CEO John Scuelly that had detrimental consequences for the organisation.

With devolution of power within the decision-making process, more managers can participate and contribute to their optimal capacity (Le Var 1998). Hence, organisations need to focus on conditions that can develop a sustained perception of social value cultivated within the employment settings (Fischer 2014). Despite knowing the benefit of social value in organisational decision-making, there has been no research in the field of judgmental forecasting to evaluate its effect. With more light on this topic, decision-making processes in organisations can be redesigned to incorporate more information sharing within limited time and less power struggles, to increase their social values.

3.8 Research gaps

As discussed in section 2.2, incorporating human judgment with the statistical or model forecasts results in improved forecast accuracy. Experts tend to incorporate the soft market information into the forecasting process, that is generally not captured by the quantitative models. Section 2.3 shows that due to the constantly changing market environment, decision makers have to make decisions for different levels of the business hierarchy.

This calls for forecasting at different business hierarchical levels and these forecasts may need to be aggregated or disaggregated depending on the level for which decisions are to be made. Combination of forecasts are seen to be a safer option than individual forecasting methods (Hibon and Evgeniou 2005). And these combination methods can range from statistical methods to using judgment to decide how to combine the forecasts.

Management judgment can help reduce the differences between the forecasts from the different combination methods (Scharzkopf et al. 1988). To incorporate such managerial judgment coming from different hierarchical levels, judgmental reconciliation of the forecasts becomes a challenging task. Given the frequency at which judgmental forecasting adjustments are made by managers and the value of such managerial interventions, development of such facilities can be a big merit for organisations (Syntetos et al. 2009b).

A number of studies have been conducted on forecast aggregation/combination in hierarchical forecasting (Rostami-Tabar et al. 2015, Hyndman and Athanasopoulos 2018, Hartmann et al. 2019, Rehman et al. 2019, Yang et al. 2019), but none of these studies use subjective methods of aggregation for hierarchical forecasts. This has been deduced from the structured literature review in section 2.4. Hence, judgmental reconciliation of hierarchical forecasts has been identified as a research gap by few authors (Fliedner 2001, Petropoulos 2014, Spithourakis et al. 2015, Syntetos et al. 2016a).

As seen from the structured literature review (section 2.4), group processes need to be examined further for variables or factors that can affect the group forecasting process (Hill 1982). There is scope of development for Forecasting

Support Systems (FSSs) that can allow managers to feed independent estimates of required adjustments into the system (Fildes et al. 2009). Syntetos et al. (2010, p. 140) says “*investments in intelligent judgmental adjustments may reap considerable financial returns*”. But such developments will not be effective if forecasters do not make use of such facilities because of cultural or political reasons. Arvan et al. (2019) have suggested development of a conceptual framework as a first step towards building behaviourally informed FSS.

The interview analysis presented in Chapter 6 suggests that the four dimensions that impact the organisational decision-making process are information sharing, time pressure, power struggle within groups and social values. But there is a lack of research in the field of forecasting that studies the analysis of such organisational factors (Fildes and Goodwin 2020). The implementation of effective company forecasting processes depend on both the individual making the forecasts and also the interactions between managers within organisational context (Fildes et al. 2009). Hoberg et al. (2020) has raised a research opportunity on the human factor in supply chains by studying how organisations behave with diverse team structures.

The benefits of information sharing in supply chain forecasting need to be assessed (Fildes et al. 2009). Few researchers look at time pressure in business environments. Psychology has a number of studies, but they are mostly concentrated on individual decision-making and lacks an interactive environment central to economic decision-making (Kocher and Sutter 2006). Hierarchies are very important and persuasive in both groups and organisations. Very little literature exists on actually how the hierarchy steepness can impact the entire collective organisational levels (Anderson and Brown 2010). There is a call for future research on different industry characteristics such as information sharing, time pressure, and power struggles in organisations (Bălău and Utz 2017) and on collaborative forecasting (Eksoz et al. 2014).

Additionally, there is huge dependency on quantitative (positivists) research methods, like laboratory or field experiments, that do not cover the intricacies of judgmental forecasting processes. There is a gap in terms of interpretive research methods to establish the values and beliefs of managers engaged in forecasting at a deeper level (Fildes et al. 2009). Eksoz et al. (2019) has called for multi-method research work on coordination and collaboration in judgmental hierarchical forecasting; especially with diverse set of products from across industries. Many authors have highlighted the limited case-study based research in the field of forecasting (Arvan et al. 2019, Perera et al. 2019, Fildes and Goodwin 2020). This study addresses these research gaps with a mixed-method case study approach to hierarchical forecast decision-making.

3.9 Summary

This chapter has provided a more general discussion on decision-making in organisations. The structured review from Chapter 2 along with findings from first two research questions has showed the need for a wider literature search on business decision-making. From a broader literature search, SODA method, a collaborative decision-making model and a consensus decision-making model from linguistic literature are discussed in this chapter.

Literature on the data analysis methods of SWOT analysis and MADM methods are presented in sections 3.5 and 3.6. These data analysis methods are influenced from the analysis of data in Chapters 6 and 7. Section 3.7 presents literature on the four fundamental dimensions of decision-making: information sharing, time pressure, power struggles and social value of decisions. These four dimensions have been determined from the second research question via interview data, reported as case stories in the Chapter 5.

The final section shows the research gaps that have been identified from the body of literature presented in Chapters 2 and 3. Two main research gaps of judgmental reconciliation of hierarchical forecasts, and a call for more interpretive research to understand the organisational decision-making are discussed. The research method used to address both these gaps is explained in Chapter 4. Figure 3-7 shows the present progress of this study within the overall thesis structure, along with the links of this chapter with other chapters.

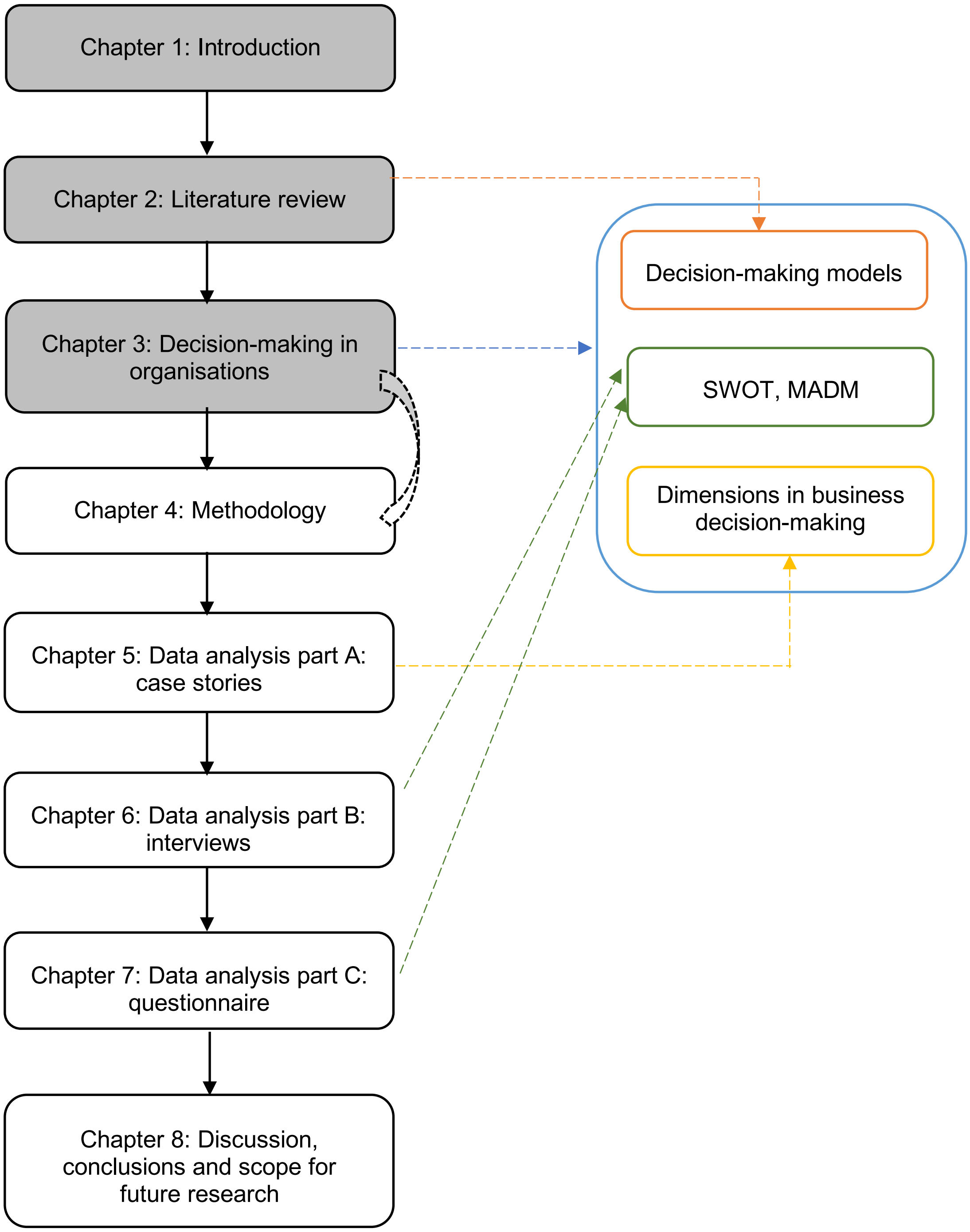

Figure 3-7: Thesis structure (Chapter 3)

Chapter 4

4 Methodology

4.1 Introduction

The purpose of this chapter is to provide a detailed description of the methodology used in this study. Methodological principles allow us to solve the research problem of interest and hence this chapter illustrates the methodological assumptions underpinning the study. The critical review of the literature conducted in the previous chapters enabled the identification of the research gaps considered in this study. The structured literature review helped to understand the lack of qualitative research within this field and hence elucidated another research gap. The methodology employed to address those research gaps is explained here along with the philosophical stance adopted while conducting the study.

The chapter starts with a general discussion on research approaches, namely deduction, induction and abduction. The philosophical position underpinning the research is discussed with the different epistemologies adopted by social scientists in business and management. The epistemologies in the field of forecasting are explored to justify the particular choices made for the purposes of this study. In the next part of the chapter, the overall research design is discussed, followed by the case study research design developed in this study. This research is abductive in nature, which is reflected in the data collection methods for both primary and secondary data.

The first stage of data collection involved exploratory interviews with senior managers from the case organisations to explore the forecasting methods employed by them. The data collected in the first stage helped design the second stage of this research: a questionnaire. This stage is an explanatory one: results from which help explain different themes found in the exploratory (first) stage. Towards the end of the chapter, reliability and validity related issues are considered along with a discussion of how those issues have been addressed. The ethical considerations considered while collecting data for this study are explained. The chapter ends with a brief conclusion while demonstrating its position within the overall thesis structure.

4.2 Research approaches

In this section, the three research approaches: deduction, induction and abduction, are discussed based on definitions provided by Saunders et al. (2012), also shown in Table 4-1. If a researcher starts with a theory (usually found from the literature readings) and they design a strategy to test the theory, then they are using a deductive approach. Conversely, if the research starts with data collection to explore a phenomenon and then the researcher generates or builds a theory (in the form of a conceptual framework) then they are using the inductive approach.

There is a third approach called abduction, according to which data are collected to explore a phenomenon, study patterns and identify themes, to generate a new or modify an existing theory which the researcher subsequently tests through additional data collection.

Table 4-1: Research approaches: Deduction, Induction and Abduction

	Deduction	**Induction**	**Abduction**
Logic	When the premises are true, the conclusions must be true.	Known premises are used to generate untested conclusions.	Known premises are used to generate testable conclusions.
Generalisability	From the general to the specific.	From the specific to the general.	From the interactions between the specific and the general.
Data collected	Data are collected to evaluate propositions or hypotheses related to an existing theory.	Data is collected to explore a phenomenon, identify themes and patterns to create a conceptual framework.	Data is collected to study a phenomenon, identify themes and pattern, locate these in a conceptual framework and test this through subsequent data collection and so forth.
Theory	Theory falsification or verification.	Theory generation and building.	Theory generation or modification; incorporating existing theory where appropriate, to build new theory or modify existing theory.

Source: Saunders et al. (2012)

Abduction combines both components of deduction (moving from theory to data) and induction (moving from data to theory) in a back and forth fashion. Deduction and induction complement each other in abduction for testing plausible theories or propositions. An abductive approach leads to new insights of an existing phenomenon by investigating it from a new perspective (Kovács and Spens 2005).

In this study, an abductive approach is applied to explore the phenomenon of forecast reconciliation when business hierarchies are involved, and identify factors having an effect on such forecasting decisions. Explanations from such factors are integrated into a conceptual framework of collaborative decision-making in hierarchical forecasting.

The research approach determines the research design and methodologies that helps the researcher to adapt the method catering to different constraints. A number of constraints are encountered during research, such as having limited access to data or lack of prior knowledge of the research topic. Hence, it is an important decision to make before starting any research project. And most researchers start with a plan to answer particular research question(s) that needs to be solved.

Similarly, in this study the research approach has helped to decide on the research design and the kind of evidence (data) required to answer the research questions. Taking into consideration the different constraints, the data collection and analysis methods are decided. These subsequent layers of the research methodology (as shown in Figure 4-1): epistemology, research design, data collection and analysis methods are explained in the following sections.

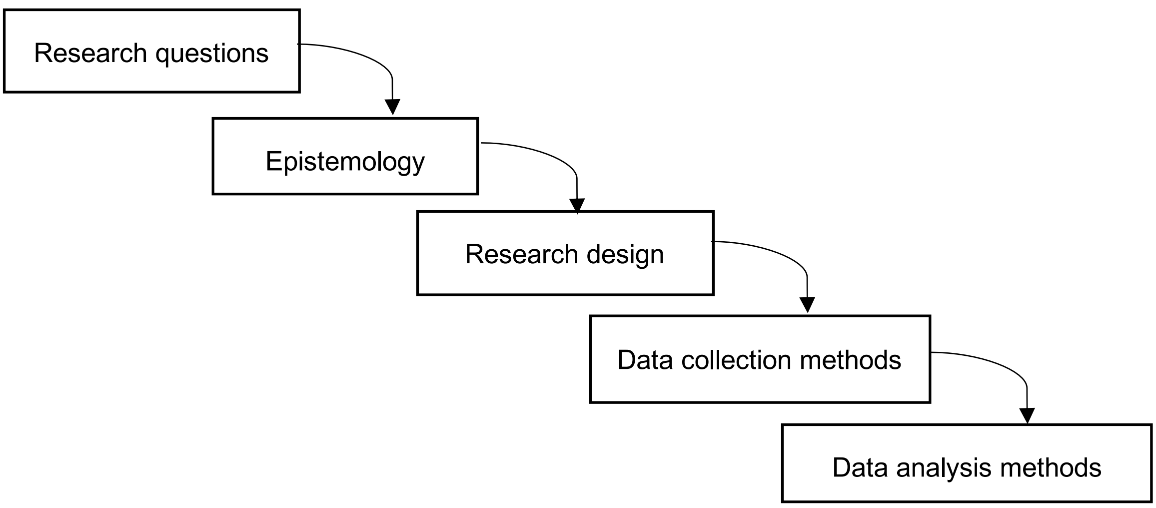

Figure 4-1: Research methodology flow

4.3 Epistemology

Epistemology is to answer important questions, like 'What is the relationship between the researcher and the context being researched?' and 'What do we know about the context being researched?' An epistemological paradigm asks what is being regarded as acceptable knowledge (Bryman 2012). It refers to the development of knowledge along with the nature of it. The paradigms are general sets of assumptions about the best ways of enquiring into how things work (Easterby-Smith et al. 2012). These assumptions shape how one understands the research questions, the methods to use and how one interprets the research findings (Saunders et al. 2012).

4.3.1 Positivism

The two main epistemological paradigms in business and management are the 'Positivistic' and 'Interpretivist' ones. The doctrine of positivism is quite ambiguous as it is defined in different ways by different authors. It is quite broad as some authors describe it as a descriptive paradigm whereas others use it to define crude and superficial data collection (Bryman 2012). The research is said to be value-free where a sharp distinction is drawn between the researcher and the research. Positivists view the natural world to be independent of the social world. Hence this paradigm is mainly considered to be objective and concepts are defined in such a way that quantitative methodologies can be used to identify and measure them (Guba and Lincoln 2005).

Researchers emphasise quantifiable observations and perform statistical analysis on these observations. Within this philosophical positioning, human behaviour is explained in terms of cause and effect relationships (May 2001). For example, data from a single company is used to study and improve the forecast accuracy (Mathews and Diamantopoulos 1994, Kourentzes and Athanasopoulos 2019).

4.3.2 Interpretivism

Interpretivism (also referred to as social constructionism or social constructivism), on the other hand, 'respects' the differences between the natural and social world (Bryman 2012). Social reality is considered to be a product of different interpretations that people can associate with, and researchers are required to grasp the subjective meaning of the social action. This paradigm mostly relates to research work referring to humans rather than processes.

Denzin and Lincoln (2005, p. 22) argue that "*All research is interpretive; it is guided by the researcher's set of beliefs and feelings about the world and how it should be understood and studied*." The challenge here is to enter the world of social actors and attempt to understand this world from people's point of view. The interpretivist position employs qualitative methods to gather data from which ideas are induced (Easterby-Smith et al. 2012).

For example, a person-to-person interview will involve the researchers' feelings while framing the questions to ask and the interpretations they bring to the participants' responses. It is not possible that the interviewer will ask the same questions to all the participants in the same manner and interpret the responses in an objective manner like a computer software. However, a large extent of objectivity should be maintained while conducting the research, so that it can be replicated by future researchers.

The fact remains that the paradigm adopted also depends on the research problem in hand. Positivists believe that the researcher and context being researched are independent, while interpretivists consider them to be inseparable (Teddlie and Tashakkori 2009).

4.3.3 Strengths and weaknesses of the two paradigms

The strengths and weakness of both paradigms, positivism and interpretivism, are fairly complementary (Table 4-2). The positivist researchers have the advantage of being independent observers within their research settings, whereas researchers in the other paradigm (interpretivism) are part of what is being observed and this sometimes introduces subjectivity into their research findings.

Table 4-2: Strengths and weaknesses of Positivism and Interpretivism

	Positivism	**Interpretivism**
Strengths	Potentially fast and economical to implement; easier to provide justification of policies; value-free research.	Accepts value from multiple data sources; enables generalisations beyond the present sample.
Weaknesses	Not good for social process, meanings or theory generations.	Access can be difficult; problems reconciling discrepant information.

When it comes to interpretivism, getting access to participants can be difficult and data analysis is usually very time consuming. As the researcher is involved within the research, interpretations can differ and sometimes do not gain credibility from others. The weak spot of positivism is when it comes to studies of social processes. This is where interpretivism has an edge over positivism, as interpretivists accept value from multiple data sources making the data collection less artificial. This helps interpretivists to make generalisations beyond the present sample.

4.3.4 Pragmatism paradigm

There has been an on-going debate for researchers to choose a particular epistemological paradigm. Although epistemologies are generally presented in their pure form, their research applications demand some compromise. There have been suggestions that researchers consider their philosophical stance as a *"multi-dimensional set of continua rather than separate positions"* (Saunders et al. 2012, p. 129). With that view in mind, one should adopt the position related to 'pragmatism' when they do not accept that there are predetermined theories or frameworks that shape one's knowledge, nor do they accept the fact that people can construct the truth out of nothing (Easterby-Smith et al. 2015).

The pragmatist view suggests that it is perfectly possible to work with different epistemological positions together, viewing the world through different lenses. This paradigm helps in employing multiple methods, which can be advantageous in answering different research questions (Teddlie and Tashakkori 2009). As a pragmatist, one is only concerned about the practical consequences of a study.

Pragmatism suggests that there are no predefined theories that can shape the knowledge or understanding (Easterby-Smith et al. 2008). The research question itself drives the selection of multiple or mixed methods that help to advance the research. It is not necessary for pragmatists to use any particular method(s) (compatible with a single paradigm), but rather use method(s) that enable the collection of credible and reliable data that can help answer the research question. It combines both inductive and deductive research logics as abductive logic (as described in the second section 4.2 of this chapter). Table 4-3 summarises the contrast between the three epistemological paradigms discussed: positivism, interpretivism and pragmatism.

Table 4-3: Paradigm contrast

Dimensions of Contrast	***Interpretivism***	***Positivism***	***Pragmatism***
Methods	Qualitative	Quantitative	Both qualitative and quantitative; researchers answer questions using best methods
Logic	Inductive	Deductive	Both inductive and deductive
Epistemology (researcher/participant relationship)	Subjective point of view; reality co- constructed with participants	Objective point of view	Both objective and subjective points of view, depending on the stage of the research cycle
Possibility of causal linkages	Impossible to distinguish causes from effects; credibility of descriptions important	Real causes temporally precedent to or simultaneous with effects	Causal relations, but they are transitory and hard to identify; both internal validity and credibility important

Source: adapted from Teddlie and Tashakkori (2009)

In pragmatism, the social entities are believed to exist both objectively and subjectively through inter-subjectivity. One can use quantitative data to understand the phenomenon under study objectively without any human intervention. On the other hand, qualitative data can be used to understand the phenomenon subjectively with interpretations from the subjects and researchers involved.

4.3.5 Paradigms in forecasting

The positivist paradigm dominates the field of statistical (demand) forecasting where most of the work done is quantitative in nature. Researchers use the deductive approach of collecting data to assess the validity and utility of already established hypotheses (or forecasting models). Different combinations of constructs as causal relationships are tested that can help generate better forecast accuracy. Under these circumstances, the researcher is value neutral and the relevant studies may be perceived as purely objective. These observations reinforce the positivist stance of forecasting researchers. As Perera et al. (2019) explained, forecasters use mostly secondary data from laboratory (Petropoulos et al. 2017, Pennings et al. 2019) or field experiments (Önkal et al. 2008, Legerstee and Frances 2014) to derive insights from them that help them in testing their proposed hypotheses or models.

However, when it comes to judgmental forecasting, qualitative methods along with quantitative ones are used to study the impact of judgment on forecast accuracy. Data on human judgment are considered to be very sensitive and hence, companies are often unwilling to share it with academic researchers. This makes it difficult for the researchers to collect such JFs data from the field (primary data) where they can interact with the forecasting managers directly. Most of the time they are forced to work with secondary data (collected by someone else in the company and given to the researchers) in the form of numbers and figures. But there have been a few cases when studies involved interviews with case companies (Asimakopoulos et al. 2011, Fildes and Goodwin 2020). Fildes and Goodwin (2002) adopted an interpretivist approach to study the use of a forecasting system in a pharmaceutical company.

To conclude, there can be different epistemological positions adopted by forecasting researchers depending on the specific research question(s) being investigated. But mostly, it is a positivist position using a deductive approach with quantitative data on demand forecasting.

4.3.6 Epistemology adopted in this research

This study is a blend of both positivism and interpretivism paradigms, i.e. I embrace the pragmatist position. The key aim of this study is to develop a framework for collaborative decision-making in hierarchical forecasting. To achieve that, a combination of deductive and inductive approaches is applied. The structured literature review points to a pragmatic research approach (section 2.4.3). To address the research questions, a multiple method strategy has been employed where data is collected in two different stages. This is because sometimes one single point of view is not enough to describe the entire picture.

Exploratory interviews are conducted with managers from forecasting units within the case organisations. This inductive nature of the research points to an interpretivist epistemological position where a social process is interpreted by a researcher in a subjective manner. The analysis of interview data shows four major themes for hierarchical forecast decision-making. Insights generated from the themes along with the literature review help create a conceptual framework.

In the explanatory stage, a questionnaire is designed with the aim of assessing the validity of the proposed framework. The questionnaire is able to capture managerial perceptions through quantitative scales and open-ended questions. In this method, a deductive approach is followed where the themes and a conceptual framework, generated from the interview observations, is validated through different types of questions. This deductive aspect of the research points to a positivist direction.

Therefore, it is a multiple method abductive study where a pragmatic paradigm is employed to understand the logic and to theorise observations. This aligns with Saunders et al. (2012, pp. 128-129) who argue that

> "*The important issue is not so much whether our research should be philosophically informed, but how well we are able to reflect upon our philosophical choices and defend them in relation to the alternatives we could have adopted.*"

4.4 Research Design

The research design is a blueprint or framework of the overall plan for data collection, measurement and analysis that facilitates answering the research question(s) (Cooper and Schindler 2006). The choice of a research design depends on the overarching aim of the research and its associated research questions. Designing research includes all the activities that help in collecting data in order to achieve the research aim. The design explains the sources from where data will be collected, how will it be analysed, and the ethical issues related to it. In addition to the above, there is also the role the researcher plays in the study under concern that guides the choice of the research design to be adopted.

As discussed in the previous section 4.3, research is influenced by the researcher's view of the world which leads to the research philosophy adopted within that research. The assumptions made for the research philosophy underpin the research design and the data collection methods used to address the research questions. There are two ways (shown in Table 4-4) researchers can engage with the research environment. One where researchers strive to be independent or be 'detached' from the people and processes they are studying; and in the other, the researcher gets engaged in an 'involved' nature while studying social systems, like complex organisations, as there are added values to being closer to such systems. Hence, quadrants A and D are positivist research designs whereas B and C are interpretivist designs.

Table 4-4: Epistemology and research style

Engagement of researcher / Epistemology	**Detached**	**Involved**
Positivist	A	D
Interpretivist	B	C

Source: adapted from Easterby-Smith et al. (2012)

The research designs under positivist epistemology are the *experimental design* and the *survey design*; both look at patterns and causal relationships. From the interpretivist angle, the researchers try to construct the truth and reality from everyday life. This covers a wide range of designs like *action research* (develop solutions to real organisational problems through a participative and collaborative approach), *archival research* (use administrative and historical records as principle source of data), *ethnography* (interactive approach to study groups who interact with each other), and *narrative research* designs (involve participants' personal accounts of any event or experience). However, there are designs that bridge the epistemological divide, notably the *case study design* and *grounded theory design*. And as discussed in section 4.3, the epistemological position that bridges this divide is pragmatism.

There exists another type of classification for research designs (exploratory, explanatory and descriptive) where the problem structure or nature of the research drives the formation of the relevant categories. Here the three different types are explained based on definition from Ghauri and Grønhaug (2002). In the *exploratory design*, the problem is unstructured or less structured. The researcher often has to observe, gain insights and construct justifications about a topic of interest. There are a number of ways of doing this: by conducting in-depth individual interviews, experts' interviews or focus group interviews.

The second category of research design is the *explanatory design* where the problem under scrutiny is structured. Generally, the problem within this design studies the effect of causal relationships between variables. The researcher intends to isolate the cause(s) and explain to what extent it can have an effect on the variables.

The last category is the *descriptive design* when the problem is structured and well defined. The objective here is to understand an accurate profile of events, persons or situations. It can be an extension or forerunner for an exploratory research or part of an explanatory research. It is mostly regarded as "*a means to end rather than an end in itself*" (Saunders et al. 2012, p. 171).

A combination of both exploratory and explanatory designs is used to address the particular research problem in this study. Both of these types are explained in the case study design in the following sections. The next section starts with a general discussion on case study design and how it fits within this study. It is followed by the case study design adopted in this study, detailing the different types of data collection methods and the analysis methods.

4.4.1 Case study design

A case study design as defined by Yin (2014, p. 16):

> *A case study is an empirical inquiry that*
>
> - *investigates a contemporary phenomenon (the "case") in depth and within its real-life context, especially when*
> - *the boundaries between the phenomenon and context are not clearly evident.*

The essence of case study design is to illuminate why and how decision(s) are being made, and what are the effects of such decision-making processes. The rationale behind this design is to study social relations rather than individuals (Silverman 2013). When the aim is to obtain some in-depth description of the phenomenon of interest, the case study becomes more relevant than other research designs. While most of the case studies are pre-defined in focus and scope, some of them can be emerging and self-defining (Buchanan 2012). A thorough analysis of a particular phenomenon requires the researchers' personal observations that result from their intervention or participation in the actual process to be examined (Gummesson 1991).

Yin (2014) distinguishes between four different types of designs based upon two dimensions within case study:

- single case versus multiple cases;
- holistic case versus embedded case

A *single* case is used when this represents an extreme critical or unique case, or a case of particular interest. This type of case study is useful when the case presents itself as a rare opportunity that has not been studied before (Saunders et al. 2012). In this type of design, the researcher(s) seeks to arrive at specific conclusions based on a single case company (Gummesson 1991). One example could be part-time students conducting research for the organisations they work for.

One may also consider *multiple* (or collective) cases with the assumption that similar findings can be replicated across cases. In this type of design, the researcher replicates the procedure for each case. By doing so, different perspectives on the same phenomenon (or issue) can originate. This type of design helps to derive general conclusions from a multiple (more than one) number of cases.

Yin's second dimension of *holistic* versus *embedded* refers to the unit of analysis in the research. A researcher might study an organisation as one unit with a holistic approach or they can consider a number of units within the organisation as embedded units. Another type of distinguishing the cases are based on the data analysis method: *within-case* analysis and *cross-case* analysis. The former is to provide a detailed description of each case and themes within each case, while the latter looks for similarities and differences across the cases (Creswell 2007).

The case study design can embrace different epistemological paradigms. It is mainly considered to be a positivist dominant design. However, it can also be devised in ways consistent with the interpretivist philosophy (Easterby-Smith et al. 2012). Single case study research employs an interpretivist philosophical position, whereas advocates of multiple (more than one) case study design are on the positivist side.

A case study examines the underlying processes in organisations that can spot the novel, the unusual, the interesting- the black swan that challenges the theory of all swans being white (Buchanan 2012). When multiple sources of information are used, alternating philosophical stances between positivism and interpretivism are adopted by the researcher(s). This points towards the pragmatism epistemology as discussed in the section 4.3.4.

In business and management science, most studies are about understanding and/or improving the performance of an organisation (Gummesson 1991). Researchers try to give recommendations on the solutions of specific problems for a specific type of organisation. Hence, the use of the case study design is becoming increasingly accepted as a scientific tool in management research.

As explained towards the end of the previous section (4.1), research designs can be exploratory, explanatory and descriptive. Case study research in management studies is more inclined towards the exploratory use, where the case study is used as a pilot that can lead to the formulation of hypotheses or more precise research questions (Gummesson 1991). A case organisation is used to explore the topic of interest when much information is not available regarding that topic. This helps gathering empirical evidence based on which, the hypotheses or propositions are developed. These are further validated through other sources of information that can help generalise the results beyond the scope of the case organisation.

4.4.2 Advantages and disadvantages of case study design

Case studies enable researchers to utilise a wide variety of tools to capture the richness of information associated with case companies. Hence, this research design is of particular interest to management researchers. They can use qualitative data and/or quantitative data within this research design. As the emphasis is upon intensive examination of a setting (Bryman 2012), a multi-method approach helps to use many sources of evidence to produce more accurate accounts (Buchanan 2012). It helps the researchers retain a real-world perspective in studying small group behaviours, and organisational and managerial processes (Yin 2014).

This design is of particular interest when the participants are managers that implement findings. Alloway (1977), cited by Gummesson (1991, p. 76), argues that "*the familiarity of a managerial audience with the language, data format and analyses used in case research is, alone, a major advantage*". Additionally, the richness of the data helps the researcher(s) to assess the applicability of the findings to particular circumstances outside the studied cases.

Case researchers seek to obtain a holistic view of a specific phenomenon. This is a time-consuming task and it is generally not possible to carry out more than one or a very limited number of in-depth case studies in a research project (Gummesson 1991). However, it does enable the researchers to study more than one aspect in isolation and in relation with each other, within its total environment.

In comparison to other research designs, case studies provide a platform to study a phenomenon and its context in detail. Experimental designs deliberately separate a phenomenon from its context by controlling different variables. Surveys can help to deal with this complexity between phenomenon and context, but their ability to investigate the context is very limited (Yin 2014). That said, there can be many disadvantages of using case study research.

The most common critique for case study research is to be inferior to methods that are based on random statistical samples with a large number of observations (Gummesson 1991). The case study design can be used to generate hypotheses but not to test them. Hence, generalisations cannot be made based on case study research. Also, case studies are, typically, associated with a lack of statistical validity.

4.4.3 Case study design employed

The 'phenomenon' in the definition of case study (section 4.4.1) can cover a range of possibilities. For this research, the forecasting decision-making process in each organisation is considered as the case. Case studies of decision-making processes constitute a useful method when the research topic is relatively less explored (Ghauri and Grønhaug 2002). As discussed in the literature review chapter, this topic of judgmental reconciliation of cross-sectional forecast has received limited attention.

The choice of case study methodology is determined by the research gaps and the research questions (as shown in section 1.2). It has been identified from the literature review that case studies are not a widely used methodology in the field of judgmental forecasting, and there have been calls for organisational insight driven methodologies in this field. With the exploratory research questions, case studies provide settings required for the intensive examination of the forecast environment. This methodology also aligns with the pragmatic epistemology of this research, with multiple levels of data collections.

The other methodologies considered for this research are the experimental design and survey design. With the experimental design, the phenomenon of hierarchical judgmental forecasting would have to be separated from its real-world context by controlling different variables. The survey methodology would deal with this phenomenon in the context of after-sales industry but with very limited ability to investigate the practical world context. Since the research aim is to carry out in-depth understanding of the phenomenon within the real-world context, case study methodology is adopted.

This study adopts a multiple case study design with a holistic approach within the pragmatic philosophical position. The unit of analysis is the 'case' within the selected organisations in after-sales or service industry. The case is defined as the sales/demand planning unit in each of the organisations that make forecasting decisions at a hierarchical level. This unit of analysis of forecasting planning units are analysed as an entity in this research. The boundaries of the case have been restricted to organisations with after-sales (spare parts and customer service) forecasting.

The case selection followed a purposive sampling, rather than random sampling, using cases (organisations) where the processes being studied are most likely to occur (Silverman 2013). Hence, the sampling strategy is selected in such a way that it fits the purpose of the study, the research objectives, the resources available and the constraints faced. Emmel (2013, p. 141) mentions that *"Cases are chosen because they contribute to creatively solving the puzzle under investigation and present as convincing a case as can be mustered with the resources to hand."* Keeping that in mind the cases are chosen such that they allow interpretation and explanation of the process on judgmental reconciliation of demand forecasts.

Easterby-Smith et al. (2012) recommends the number of cases to be between four and 10 for a case study design employing a combination of the positivist and interpretivist epistemologies. Having more than two cases in one study can strengthen the findings even further (Yin 2014). But the ability of a researcher to carry out work on a project is intimately tied up with the availability of data and information that can provide a basis for analysis and conclusions (Gummesson 1991). Also, the selection of the cases is made based on their forecasting processes and whether they have hierarchies within the organisation that reflects their forecasts. This ensures that the unit of analysis exists for all selected cases.

As this study adopts an abductive approach, a small number of cases are found to be more appropriate than a large number. This allows research time for gathering in-depth data from each case. Therefore, a total of six (6) cases are selected in the after-sales industry for this research. These cases are spread across geographical locations and sectors. Accessibility to different organisations has been a major factor while selecting these cases and the number of cases. There have been a few other cases that were selected but did not get included in this research for access issues. The different cases are explained in the next chapter along with their forecasting processes.

At the very beginning, a case study protocol (Figure 4-2) is prepared in line with the method outlined in Yin (2014). It has four sections: overview of the case study, data collection procedures, data collection questions, and guide for the case study report. The overview of the case study (section A) covers the aim and research objectives of the case study, description of the cases and relevant readings from the topic under investigation.

The second section (B), on data collection procedures, details the different methods of collecting data from the field with a reminder to protect the human subjects (ethics). Section C, on data collection questions, helps the researcher remember what is the information that needs to be collected. The last section (D) is a guide for the case study report with the outcomes, presentation of collected data, bibliographical information and other presentations to be made for the case organisations.

A. Overview of the case study

1. Aim: To develop a framework for collaborative decision-making in hierarchical forecasting.

2. Answer the four research questions of this study:

- What is the current practice in business decision-making within the context of hierarchical forecasting?
- What are the different themes that affect the forecast decision-making process?
- What impact do these themes have on the forecast decision-making process?
- How can a conceptual framework incorporating these themes improve the current forecast decision-making process?

3. Cases: Forecasting decision-making units in after sales organisations.

4. Number of cases: 6

5. Readings: Literature on hierarchical forecasting, MADMs, SWOT, group decision-making

C. Data collection questions

1. Exploratory interviews:

- What are the demand forecasting methods within the cases?
- Explore the judgmental aspects of these forecasting methods.
- How hierarchical forecasting is conducted in the organisations?
- How forecasts are reconciled when hierarchies are involved?

2. Questionnaire:

- Section A: Demographics of the respondents
- Section B: Questions on the different attributes (themes)
- Section C: Reflective questions on the attributes and the framework

B. Data collection procedures

1. Documentation: Official documents available on company websites and those provided during the interviews.

2. Interviews:

- Face to face interviews with managers from these organisations, about one hour in length.
- The data collected from interviews try to address the first two research questions of this study.

3. Questionnaire:

- An electronic version of questionnaire is prepared to gather data from the managers.
- With different sections, it tries to answer the last two research questions of the study.

4. Ethical considerations.

D. Case study report

1. Outcome of the case study.

2. Aim and research questions.

3. Presentation of data collected to case organisations and other researchers.

4. Analysis of the data.

5. Findings from both data collection phases.

6. Best practice document for case organisations.

7. Bibliographical information.

8. Presentations may be made in front of the case organisations.

Figure 4-2: Case study protocol

This study employs a strategy of working the data from “ground up” (Yin 2014) within the case study research design. Instead of thinking about any theoretical propositions or hypotheses before the contact with managers in a deductive fashion, this research starts pouring into the data and building concepts and ideas from it in an inductive way. This inductive strategy can yield appreciable benefits as it helps to cover the behaviour and events that the case is trying to explain. This information can feed into the next stages of the research and help collect more data.

The case study has been designed in two different phases (or compartments) as shown in Figure 4-3.

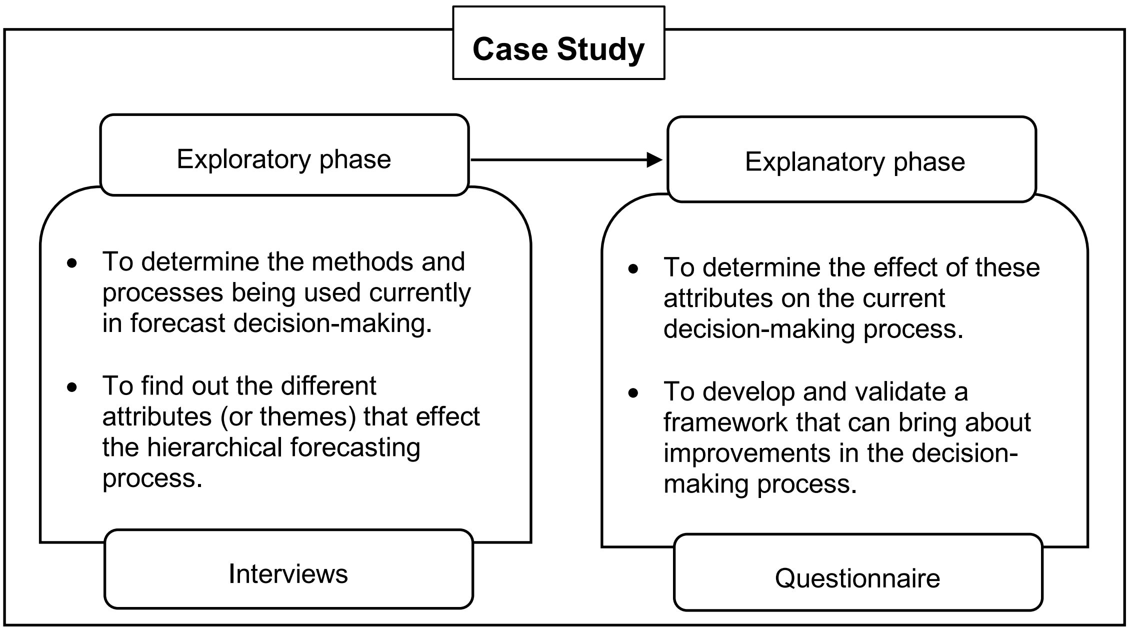

Figure 4-3: Case study design with research objectives

A. **Exploratory phase:** The first phase is exploratory in nature addressing the first two of the four research objectives as illustrated in Chapter 1. The purpose of this stage is to identify the forecasting processes in these organisations along with the different latent attributes that have an effect on these processes. The data collection methods used in this phase are the interviews, company websites and documentations made available during or after the interviews. The analysis method used in this phase is explanation building, where attributes, propositions and a conceptual framework are developed for further investigation in the next phase.

B. **Explanatory phase:** This phase of the case study explains the effect of the latent attributes on the forecasting processes studied. These latent attributes are the factors found in the exploratory phase: *information sharing*, *time pressure*, *power*, and *social value*. It also provides explanations regarding how the proposed framework can help improve the current forecasting processes. Questionnaires are used in this phase to collect data from the cases with respect to the last two research objectives. Multiple attribute decision-making (MADM) method is used as the analysis method here to compare and aggregate results from each individual case and across the cases.

The data collection methods for both the exploratory and explanatory phases are described in detail in the next section 4.5. The combination of methods in these phases emerged and developed during the research process rather than being clearly defined in the research design phase. Both cross case and within case methods of data analysis have been employed to address the research questions. The study borrows theories from other disciplines (like linguistics, psychology) to inform the case study design. During the analysis of exploratory interviews, literature from other organisational studies (not restricted to the field of forecasting) have helped to understand the dimensions (attributes) of business decision-making processes. For the framework, linguistic literature on group decision-making has been included to develop the framework for hierarchical forecasting. This helps generalise the results beyond the setting of the specific case of hierarchical forecasting in the after-sales industry.

4.5 Data collection methods

The data collection methods in a research design depend on three conditions: (a) the type of research question(s), (b) the extent of researchers' control on behavioural events, and (c) the degree of focus on contemporary rather than historical events (Yin 2014). As this research is about theory generation rather than theory testing, qualitative case study research is applied (Ghauri and Grønhaug 2002; Bryman 2012).

Soft qualitative methods are useful when the concern is not about how to deal with an issue but what should be done (Pidd 2003). The work of a qualitative researcher is to find ways of extracting information from the qualitative material as it contains human responses in its full richness. The strategy is to emphasise on words rather than quantification of data (Bryman 2012). Thus, this has been regarded as a powerful tool for business and management research (Gummesson 1991).

For this study, data have been collected in two different phases where the results from the first phase informs the second phase. The first phase of data collection corresponds to an exploratory stage of the case study design and the second phase to an explanatory one (Figure 4-4).

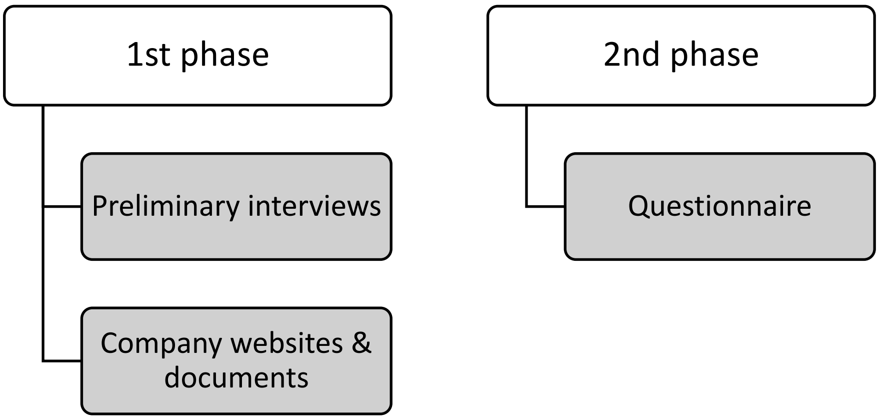

Figure 4-4: Two-phase data collection

This combination of data collection methods have emerged as a response needed during the research process. As there have been very few empirical studies in the area of hierarchical forecasting, the first phase of conducting in-depth interviews had to be undertaken. It is important to recognise that, this phase of data collection through in-depth interviews is constructed as a response to the difficulties faced in understanding the current practices of hierarchical forecasting in organisations. It has also helped in generating access for further data collection from these cases organisations.

Preliminary interviews are conducted in the first phase to explore (pre-understand) the forecasting processes in the various types of organisations. This concept of *preunderstanding* refers to people's insights into a specific problem and social environment before they start a research program; it serves as the input for the next research steps (Gummesson 1991). To supplement the in-depth interviews, secondary data from the organisations' websites and documents (whenever made available) have been collected to interpret the cases. These documents are private company presentations showing the forecast decision-making process within the cases.

The data obtained from the interviews compliment the literature review and facilitate the development of attributes (themes), propositions and a conceptual framework. In the second phase, a questionnaire is designed to collect data that validates the results from the first phase. In the questionnaire, there are both quantitative and qualitative (open-ended) questions. Both these phases of data collection are explained in the following sections 4.5.1 and 4.5.2.

4.5.1 Exploratory case study: Interviews

When the research questions require collecting information from organisational members like managers, the best method to achieve this is through in-depth interviews. This managerial qualitative information is often referred to as the "*natural language data*" (Easterby-Smith et al. 2012, p. 126). Interviews demand real interactions, face-to-face or telephonic, between the researcher and the manager (Ghauri and Grønhaug 2002).

The exploratory part of this multiple case study design uses preliminary in-depth interviews with managers from the different cases to gather a preunderstanding of the empirical situation. This method is mostly used to elicit the views, perceptions and opinions of the individual managers regarding the forecast decision-making process within their organisations.

The sampling strategy for the interview data collection stage is influenced by the first research question and chosen research design. To answer the first research question, the participants have to be forecasting and planning managers from the case organisations. To ensure this, a purposive (or selective) sampling strategy is adopted to study particular characteristics of a population of interest that best enables to answer the research question. This strategy is also influenced by the two other sampling strategies of convenience (easy to access managers within these organisations) and snowballing (existing participants are asked to nominate further participants from their organisations).

To gather an accurate and clear picture of the respondents' behaviour, the interviews are designed as semi-structured in-depth interviews rather than structured ones. This is because the managers are free to answer the open-ended questions in their own thinking. On the contrary, there is also the possibility of the interviewee simply constructing a narrative and not speaking about their actual experience (Silverman 2013). Therefore, the interviewer has been careful as to not divert too much from the topic while at the same time allow the respondents to answer the questions openly without any prompts or hindrance.

An interpretivist philosophical position is employed while conducting the interviews and analysing the data. The interviews have been conducted in a semi-structured manner offering the interviewees a great deal of leeway in how to reply (Bryman 2012). Four broad questions (below) have been asked to each manager while the semi-structured nature of the interview provided the flexibility of asking them in any order.

1. What (demand) forecasting methods are used in your organisation? Can you describe it briefly?

2. How much judgment is involved in that process? Do you follow any particular method of incorporating judgment into your forecasting process?

3. Are hierarchies (based on product type or geographies in your organisational structure) involved in your decision-making process (demand forecasting)? If yes, how do you forecast the different nodes of the hierarchy? Is the same forecasting method used for all nodes or does it differ?

4. How do you handle differences of opinion in your judgment process? In other words, how do you reach a consensus decision, when managers' opinions (on hierarchical forecasts) differ?

Additionally, questions not included in the schedule were also asked when the interviewer picked up on things said by the managers. As permissions have been granted, the interviews are audio-recorded. Later on, the interviews are transcribed to help with the analysis. The transcribed interview data are analysed in the next chapter using two steps: cognitive maps and thematic analysis.

The cognitive maps address the first research objective of the study (to determine the methods and processes being used currently in forecast decision-making). The maps result in process diagrams for the different case organisations showing how hierarchical forecasting takes places in each of them. Thematic analysis addresses the second research objective of determining the different attributes that impact the hierarchical forecasting process. Both these analysis methods along with the findings are presented in Chapters 5 and 6.

4.5.2 Explanatory case study: Questionnaire

The data collected in the first phase through exploratory interviews are analysed with the help of cognitive maps. These maps help to develop process flowcharts for each of the cases studied. Additionally, from the interview data different themes are generated on what attributes have an effect on the forecasting process as described by the company managers. To further explain these themes from the perspective of managers at different hierarchical levels, a questionnaire is designed. The purpose of the questionnaire is to confirm the data collected from the first stage by having opinions from a wider audience.

In this second phase of data collection, a questionnaire is used to gather information for the explanatory stage of the case study. Questionnaires enable multiple factors to be identified simultaneously and hence potential underlying relationships to be examined with large samples (Easterby-Smith et al. 2012). The sampling procedure for this stage follows the same strategy to that of the first exploratory stage. Here the strategy is guided by the research questions 3 and 4. With a purposive sampling strategy, managers in forecasting and planning teams within the cases are invited to participate in the questionnaire. To gather wider participation than the interview stage, snowballing strategy is used to reach more managers within the cases. The combination of two sampling strategies helps to reduce biases in the selected population.

The questionnaire is designed according to the method described in Churchill and Iacobucci (2002), shown below in Figure 4-5.

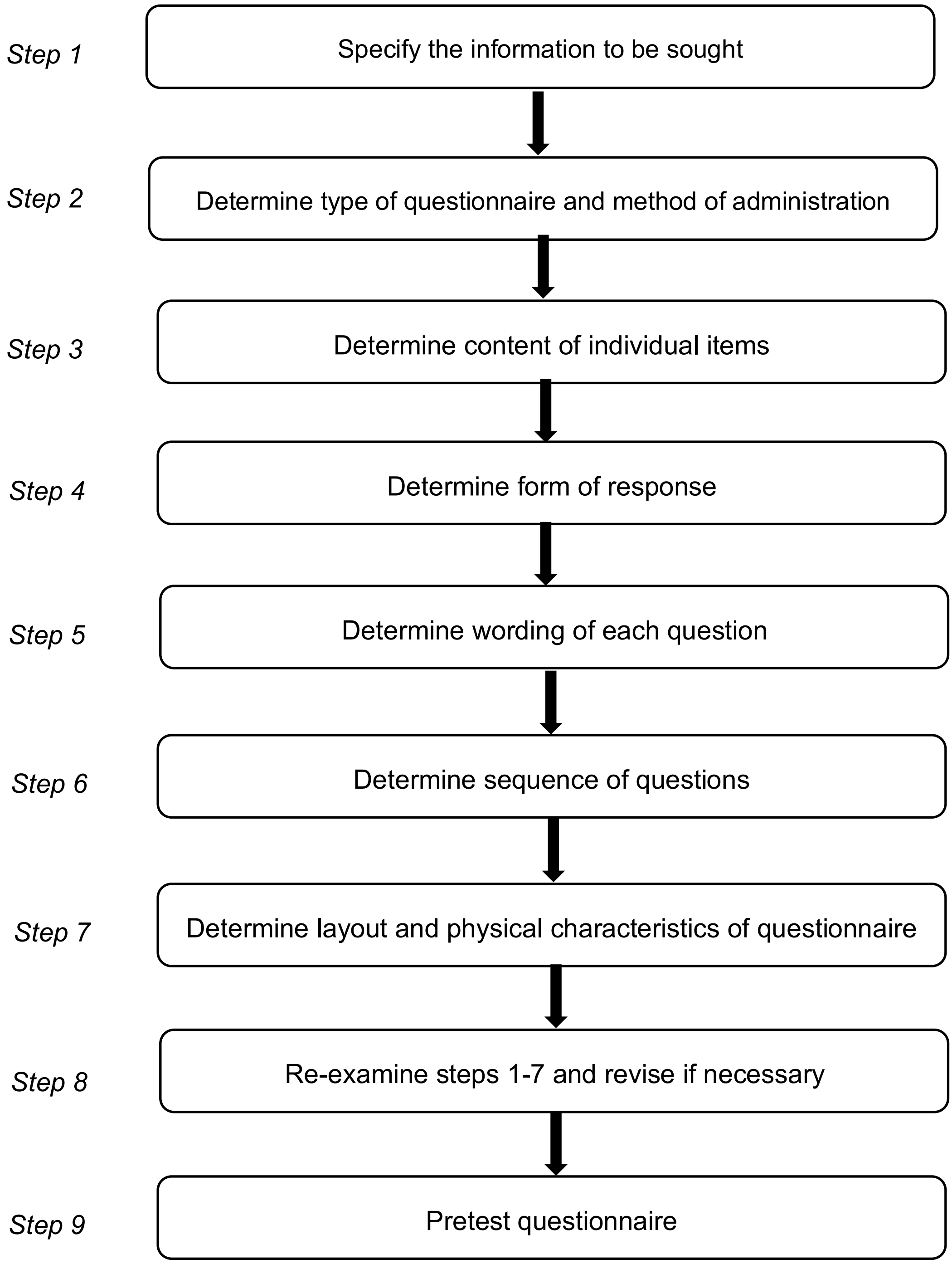

Figure 4-5: Questionnaire development process

Source: Churchill and Iacobucci (2002)

Participant consent is collected before starting the questionnaire on the introductory page and they are informed about the anonymity of the data collected. The introduction page also gives a brief summary on what the research is about. A pilot study is conducted with 12 respondents compromising of other researchers, managers in companies and students. This is done to pre-test the questionnaire and the final questionnaire is edited based on the recommendations of the respondents. Moreover, this helps the researcher to check whether the responses align with the analysis method(s).

The questionnaire is designed in three parts as shown in Figure 4-6: section A includes demographics questions, section B has questions from the themes (concepts) developed, and section C has reflective questions on the themes and the framework. Section A gives an idea about the background of respondents, their age, gender, job profile, educational background and work experience. These questions can be used to compare and contrast the responses between managers from different hierarchical levels, power positions, educational background and even gender.

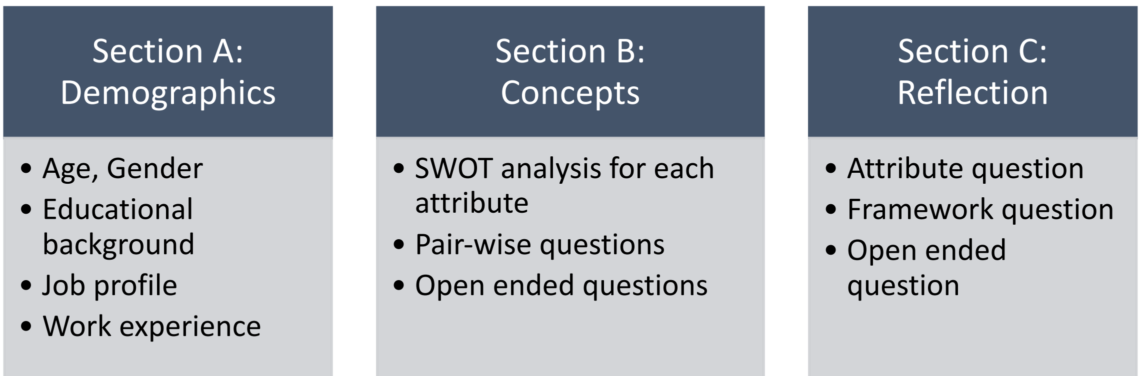

Figure 4-6: Different sections of the questionnaire

Section B includes questions on the SWOT analysis of concepts or themes. The thematic analysis gives four major themes (or concepts) for decision-making in forecasting: information sharing, time pressure, power and social value (explained in detail in Chapter 6). Definitions of each theme is provided in the questionnaire to avoid any confusion from participants regarding the description of the themes. This provides consistency between participants' understanding of the themes before attempting the questions.

The strength, weakness, opportunity and threat of each theme is compared pair-wise and also ranked to gather participants' opinions on these themes. These SWOT analysis questions are later analysed using different MADM methods (AHP and ELECTRE) that feed into the framework for collaborative decision-making. There is an open-ended question at the end of each section for participants to highlight their experience or give examples for each theme.

From the process maps, the thematic analysis and literature review, a conceptual framework is suggested for collaborative decision-making in the data analysis Chapter 6. Section C collects reflective responses from the participants on these themes (concepts) and the framework. The concept question is a pair-wise comparison between the themes and the responses to this feed into the MADM analysis. The framework question is asking participants whether they think a collaborative framework for decision-making will be useful for their company.

The questionnaire ends with an open-ended question where the participants are asked to highlight anything they would like to say about the study in general. A copy of the questionnaire is attached in Appendix B. The analysis methods for the questionnaire is discussed in Chapter 7, data analysis part C.

Advantages and disadvantages of using questionnaire

One advantage of using questionnaires is data from a larger sample can be collected in comparison to other qualitative methods. One of the questions that was asked to the interviewees was regarding further access in their organisations. Most of them could not provide further access in the form of interviews as it turned out to be quite time-consuming for them. But they were willing to complete online questionnaires as it was more convenient for them. Plus, questionnaires are quicker to administer, and they can be sent out in large quantities at the same time. The interviewer effect is not present as the questionnaires are self-completion, hence reducing interviewer biases.

On the other hand, there can be a few limitations to the data collected when it comes to questionnaires. Firstly, there is no prompting and so if a participant is having difficultly answering a question there is no one to help them. Hence, a good amount of attention must be paid to ensure that the questionnaire is easy to complete. Secondly, it is impossible to check whether the right person answered the questionnaire (Bryman and Bell 2011). There is no control over the intrusion of a non-respondent in answering the questions. Thirdly and most importantly, there is no way to collect additional data based on the respondents' answers which is an option with data collected via interviews.

4.5.3 Complete research plan

Figure 4-7 shows the complete research plan of this study indicating the inductive and deductive stages. It is shown as a four-stage study, from the start of the literature review to the presentation of the research to the case organisations. The four stages are as follows:

Stage 1: The literature review and the first phase of data collection are carried out simultaneously. The literature review as described in the previous chapter consists of traditional literature review, structured literature review, and literature borrowed from other disciplines like psychology and linguistics. The first phase of data collection is the semi-structured interviews conducted with the case managers.

Stage 2: In stage 2, data analysis of the interview data is carried out using cognitive maps and thematic analysis. A conceptual framework, along with propositions, are developed that can improve the decision-making process in hierarchical forecasting. The framework is deduced from the literature review in stage 1. Also, findings from the interview data analysis guide the design of the framework.

Stage 3: Second phase of data collection in the form of online questionnaires is carried out in this stage. The questionnaire is designed in three sections: A, B and C. Section A includes demographics of respondents, section B includes questions on the SWOT analysis of the themes, and C is a reflective section on questions on the themes and a general question on the framework.

Stage 4: The final stage is where the questionnaire data is analysed using MADM methods. The findings validate the effect of the themes, propositions and the framework for collaborative decision-making in organisations with hierarchical forecasting.

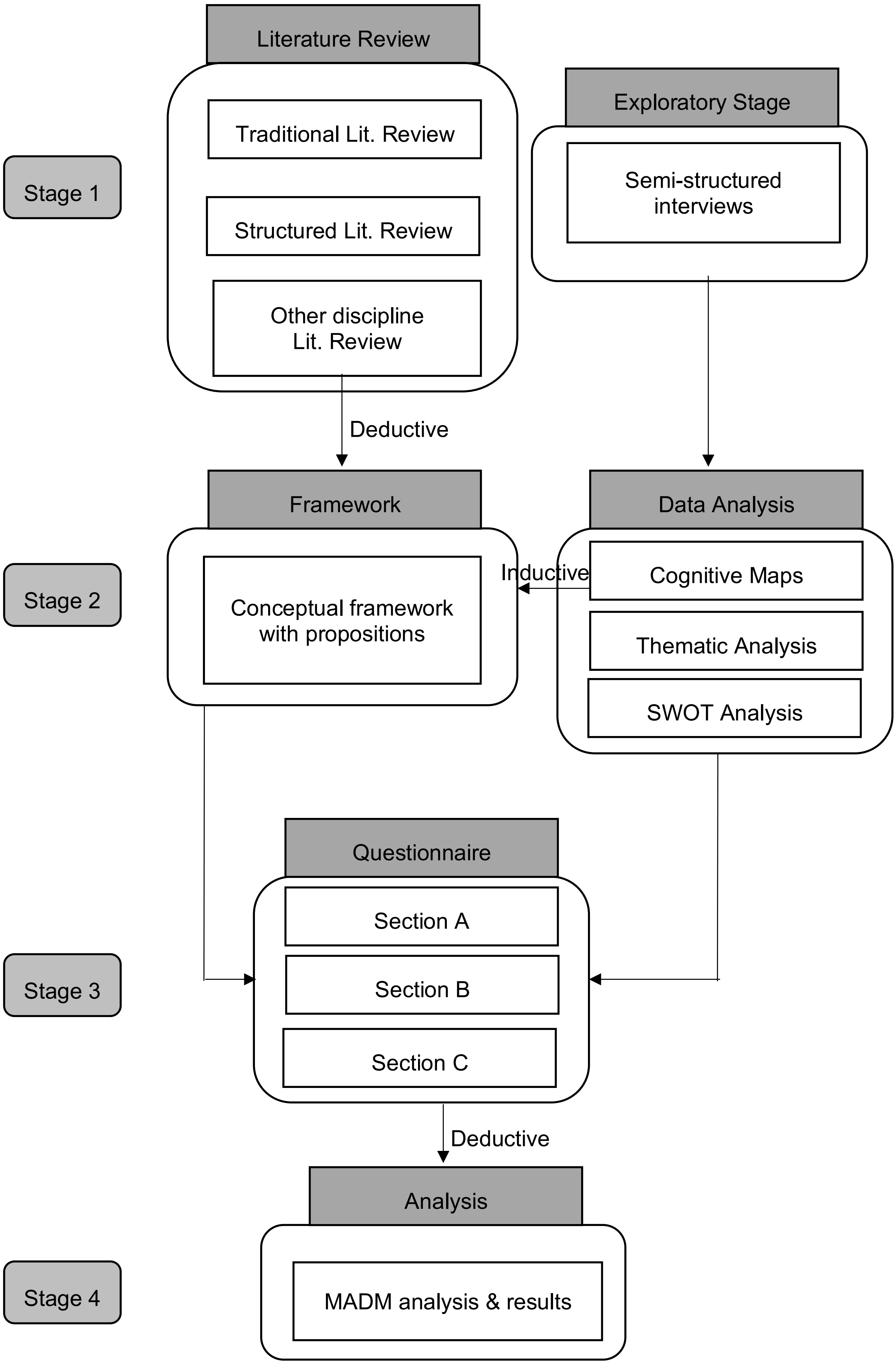

Figure 4-7: Research plan

4.5.4 Triangulation

Triangulation is the combination of two or more methods to study a social phenomenon. The approach of single source of evidence is not recommended for case study research (Yin 2014). As case studies usually involve more than one source of information, they help triangulate facts to develop converging lines of inquiry to produce more accurate facts (Buchanan 2012). This acts as a major strength for case study research as it increases the overall quality of the study, enabling the researchers to address a broader range of behavioural issues.

When the case study is on behaviours within organisations, the accounts of those involved might vary and even compete with each other. This happens as the managers' viewpoints are impacted (and sometimes even silenced) by a number of factors like experiences, political pressures, power structures within the organisation and relationships with other managers. Therefore, it is useful to expose this 'polyphonic, polysemic' nature of organisations with many and different voices and meanings (Buchanan 2012). It is the role of the researcher to give these voices expression and it can be achieved by collecting data from more than one source of evidence.

In this study, there are two types of triangulation taking place: one is *data triangulation* where data is collected from multiple sources and the other is that of *methodological triangulation* where different methods are being combined. Data triangulation means to collect information from multiple sources but aimed at corroborating the same findings. In methodological triangulation, different methods are combined to support the findings of the overall study. Figure 4-8 shows the convergence and non-convergence of the multiple sources of evidence for this study.

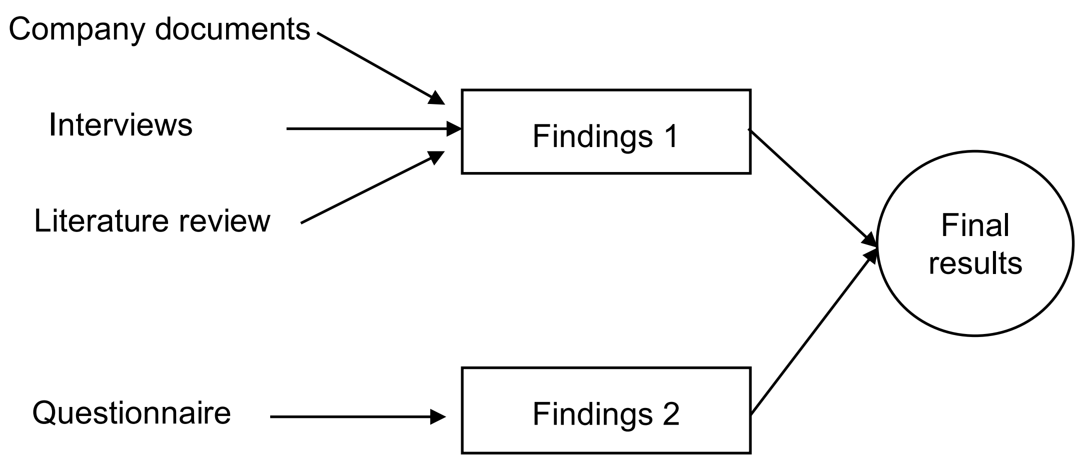

Figure 4-8: Convergence and non-convergence of multiple sources of evidence

Within each phase of data collection, there is convergence of evidence as the findings of each phase is supported by more than one source of information. Like data collected via interviews, company websites and literature review help to come up with the conceptual framework. Similarly, qualitative and quantitative data collected in the second phase via questionnaire help to improve and validate the framework for better decision-making at hierarchical forecasts.

However, both these phases of data collection are analysed separately, and the results are comparable from both the procedures, but no data triangulation occurs between them. Again, within the overall picture of the case study design, both these methods support the final findings of the study, thus triangulating different methods for the same findings.

The mixture of different kinds of methods help to integrate the quantitative and psychological aspects of decision-making (Goodwin and Wright 2014). The findings from one source of evidence can be cross-checked against those from other sources (Bryman 2012). Mixed method "*enables researchers to simultaneously ask confirmatory and exploratory questions, thus verifying and generating theory in the same study*" (Teddlie and Tashakkori 2009, p. 152). Based on different sources of information, the findings of a case study research are likely to be more accurate and convincing (Yin 2014).

4.6 Reliability and Validity

One should be able to judge the quality of a research design as it is a set of logical statements. Reliability and validity are two prominent criteria for evaluating social science research designs (Bryman 2012). Singleton and Straits (2010, p. 131) try to distinguish the two terms as "*Reliability is synonymous with "consistency"; validity is synonymous with "accuracy". A valid measure is necessarily reliable, but a reliable measure may or may not be valid.*"

4.6.1 Reliability

Reliability refers to the question of whether the results of the study are repeatable (Yin 2014). It is fundamentally concerned with the consistency and stability of the measures employed (Singleton and Straits 2010). It is of more concern to quantitative researchers, as they have to demonstrate that the same results can be obtained when later researchers repeat the same data collection procedures. This issue of reproducibility for management mathematics has been highlighted in an editorial by Boylan (2016).

In this study, if other researchers follow the same procedure of conducting exploratory interviews and questionnaire with the same case organisations, they should arrive at the same findings and conclusions. However, it should be noted that there might be some subjectivity within the findings as it involves human bias in coding the themes.

Using case study protocol and documenting every step of the research reinforces the *external reliability* of this study. Additionally, members of the supervisory team agree about the findings and observations. This strengthens *the internal reliability* or sometimes called inter-observer consistency (Bryman 2012).

4.6.2 Validity

Validity is concerned with the integrity of the conclusions of a research (Bryman 2012). For a case study research, there are three different types of validity: *construct validity*, *internal validity,* and *external validity;* as defined in Yin (2014). *Construct validity* is about identifying correct operational measures for the concept being studied. To increase the construct validity of a case study research, one can use three different tactics: multiple sources of evidence, chain of evidence and composition. This study has used different types of data sources like secondary data from company websites, and primary data from interviews and questionnaires. In addition to each case being described in the following Chapter 5, a data analysis report will be documented as evidence (if required by the companies). This allows an external observer (supervisor) to follow the derivation of any evidence from the initial observations to the final case study conclusions. Along with these steps, the data triangulation with convergent evidence strengthens the construct validity of this study.

Internal validity is defined for explanatory or causal studies only and not for exploratory or descriptive studies. For case study research, it has a broader sense where the researcher must be careful of inferring an event from some earlier occurrences. It has been avoided in the exploratory stage of this study by using explanation building as the analysis method for this stage.

On the other hand, *external validity* defines the domain to which the study's results can be generalised beyond the immediate study, regardless of the research method(s) used. As case companies cannot be used as sampling units (due to their small number) for a population, it is wrong to consider statistical generalisations from case study work. Analytical generalisations have to be considered for findings that go beyond the setting of the specific cases. As this study generates analytical generalisations rather than statistical ones, it helps strive its external validity. This study uses replication logic within multiple cases that helps to address the question of external validity.

4.6.3 Relevance

Some also propose that *relevance* of the research as equally important. Relevance refers to the importance of a research topic within its substantive field or the contribution it makes to the literature of the field (Bryman 2012). In this study, the *relevance* can be ascertained from the previous literature review Chapters 2 and 3. This research addresses research gaps that have been identified by a review of the judgmental forecasting literature. Table 4-5 shows how this study has succeeded in addressing the different tests with regards to its quality.

Table 4-5: Tactics for design tests

Tests	Case study tactic	Research phase in which the tactic occurs
Reliability	Case study protocol Chain of evidence	Data collection Data analysis
Construct validity	Multiple sources of evidence Data triangulation Supervisors review draft of case study report	Data collection Data collection Discussion
Internal validity	Explanation building	Data analysis
External validity	Analytical generalisations Replication logic in multiple-case studies	Research design Research design
Relevance	Address research gap	Literature review

4.7 Ethical considerations

Research ethics is the application of norms or standards of behaviour that guide moral choices to scientific research. Ethics are the moral values or principles that influence the way researchers carry out their research activities (Ghauri and Grønhaug 2002). The ESRC Framework of Research (2010, p. 3) cited in Bryman (2012, p. 144) states "*Research should be designed, reviewed and undertaken to ensure integrity, quality and transparency*". As researchers, it is important to check the rightness or wrongness of the study being conducted. It may be with respect to the participants or the sponsor of the work or even to other research colleagues (Miles and Huberman 1994).

Researchers should avoid treating ethical dilemmas as afterthoughts, so that it does not turn out to be a topic of concern in the later stage of research. They have a moral responsibility to find answers to their research questions honestly and accurately (Ghauri and Grønhaug 2002). Ethical responsibility of a researcher starts with the formulation of the research questions. And it is best to gather approval of these ethical issues at an early stage of the research process.

For this study, ethical approvals have been obtained from the Ethics committee of Cardiff Business School. For the data collected through exploratory interviews, informed consent forms are sent to the participants. Additionally, participation consent has been collected from the participants in a fully voluntary and uncoerced manner. The approved Ethics form is attached in Appendix A. For the second stage of the research, again the same procedure has been followed and ethics approval has been obtained before collecting data via questionnaire. Also, all information collected has been stored according to the guidelines of the current Data Protection Act. Whenever requested, non-disclosure agreements have been signed with the case companies. To maintain anonymity, some names have been changed and pseudo names used for confidentiality.

4.8 Summary

Decision-making is one of the most recurrent of human activities (Hogarth 1980). Human judgment plays a major role in the decision-making process in organisations. This chapter describes the methodology behind this study to understand the hierarchical decision-making process in after-sales forecasting. The methodology is reflective of the research questions (Chapter 1) and the need of the research to address the research gaps from literature (Chapters 2 and 3). The key thing to note is the iterative nature of the methodology applied in this research. The Research Questions have evolved as the research kept progressing, as highlighted in section 1.2 in Chapter 1. This also changed the need for different types of literature reviews required for this research, as seen in the two previous Chapters 2 and 3.

Starting with a general discussion of research approaches in this chapter, the rationale behind the choice of a pragmatic epistemological position has been illustrated. The concept of research design along with its applications in business and management is explained by contrasting two different epistemological positions: positivism and interpretivism. A multiple case study design is employed in this study with two phases of data collection. Both the phases of data collection are guided by the research gaps mentioned in the last Chapter 3.

For the first phase, in-depth interviews are conducted with managers from the case organisations to appreciate their perceptions about hierarchical decision-making. This is supplemented by secondary data sources from the online websites of these organisations and other documents made available to the interviewer. The data collected from this stage is analysed in the next two data analysis chapter parts A and B. Tools like cognitive maps, thematic analysis, and SWOT analysis are used to analyse this data.

For the second phase, a questionnaire is used to capture the subjectivity views of the managers using quantitative scales. The questionnaire design is influenced by the findings from the first phase of data collection. The questionnaire data is analysed using two different MADM methods: AHP and ELECTRE in Chapter 7 (Data Analysis Part C). The analysed data guide the propositions and the conceptual framework suggested to the case organisations towards the end of the study.

Data triangulation and method triangulation are explained after the data collection methods in this chapter, to show the convergence of evidence collected from various sources. Additionally, the reliability and validity of the research method used in this study have been discussed. The chapter is concluded with the ethical considerations carried out during the research. Figure 4-9 is a pictorial description of the thesis structure showing how much has been covered until now and also outlines the next chapters in the thesis.

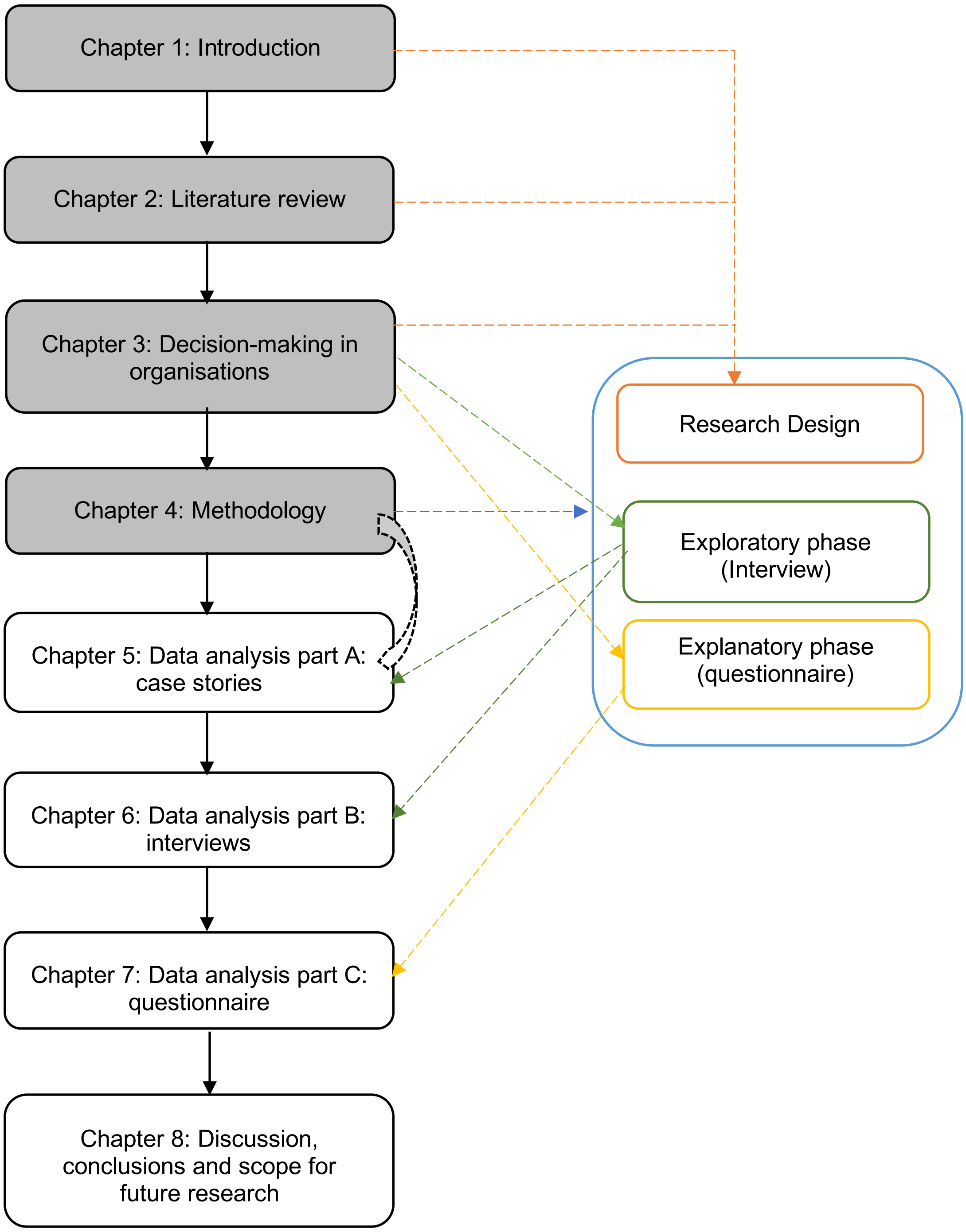

Figure 4-9: Thesis structure (Chapter 4)

Chapter 5

5 Data analysis part A: case stories

5.1 Introduction

This chapter presents the case stories of the six (6) different companies/organisations that participated in this research. The case stories have been generated from data analysis of the exploratory interviews. Such qualitative data from the interviews helps to go beyond initial concepts and generate or revise conceptual frameworks (Miles and Huberman 1994). The words have been moulded into stories with a vivid and meaningful flavour.

The interview data collection method along with its philosophical assumptions have been explained in the previous chapter. The analysed findings from this chapter and the next, help to design the explanatory phase (second phase) of the research methodology. The data collected through interviews are answers to semi-structured questions, allowing the interviewees the liberty to provide their own subjective interpretations.

The interviewees are selected on the basis of their involvement within the forecasting decision-making process in the case organisations. Managers from different hierarchical levels have been interviewed to capture the process dynamics from different perspectives. Although it cannot be denied that this selection is also driven by convenience and availability of managers.

The interview data have been transcribed and presented for each case, along with the information found on their respective company websites. It also includes information from the company visits that were conducted for two of the cases (D and E). In addition, some companies shared relevant documents with us that helped to understand their organisational structure.

The first section of the chapter provides a brief description of the cases before starting each individual case story. Each case story is organised into four sub-sections starting with their forecasting process, judgmental forecasting, forecast reconciliation, and finishing with a cognitive map depicting their respective forecasting process. The cognitive maps show how forecasting varies in these organisations and at which stage different factors impact their forecasting processes.

These factors are categorised into different themes in the next Chapter 6, along with a conceptual framework for collaborative forecasts. Section 5.10 provides a comparison across the 6 cases with a focus on points of similarity and points of differences from their respective cognitive maps. Finally, this chapter concludes with a short summary on the case stories, along with a brief discussion on how this chapter is positioned within the thesis structure.

5.2 Case description

This research follows a case study design with an aim to obtain a holistic view of a specific phenomenon: the reconciliation of forecasts in organisations. The boundaries of the case study have been restricted to organisations with after-sales (service) forecasting. The case has been defined as *sales/demand* *planning units in different organisations that use forecasting at a hierarchical level*.

Six cases are considered for this research keeping in line with the number of cases suggested for a pragmatism case study research. With six different organisations, the researcher is able to analyse the data both within and across cases. These cases collectively represent a wide range of companies and industries with locations in different parts of the world; hence is deemed to be sufficient.

The six cases as shown in Table 5-1, have different characteristics that collectively offer a broad view of the organisational decision-making process. The companies represent different types of industry with their headquarters spread across the globe. Forecasting at each organisation involves some hierarchies: either product-type or geographical locations or customer-based categories.

Table 5-1: Characteristics of the cases

Cases	Industry (Sector)	Headquarters	Number of interviews	Hierarchies
Case A	Tele-communication (Private sector)	England	2	Yes
Case B	Airline (Private sector)	Chile	2	Yes
Case C	Emergency (Public sector)	Wales	3 (1 group interview)	Yes
Case D	Online retail (Private sector)	England	3 (1 company visit)	Yes
Case E	Automobile (Private sector)	Sweden	2 (1 company visit)	Yes
Case F	Water utility (Private sector)	England	2	Yes

Managers from each of the cases are invited to participate in this research. Ethics approval for the interview process has been obtained from the ethics committee of Cardiff Business School (Appendix A). Once access is granted, exploratory interviews are conducted with the managers from the cases (forecasting units within these companies).

The interviews are semi-structured, allowing the interviewees to provide a non-invasive commentary on the forecasting methods used in their respective companies. The interviews last from 45 to 90 minutes, depending on how much information the interviewees want to share. However, effort has been made to gather some basic amount of information that answers the four interview questions in each session.

We have, also, tried to gain access to more than one interview for each case, to reduce the amount of respondent bias in the data collected. The audio-recordings of the interviews are transcribed and analysed along with other information found on the companies' websites, and documentation on their organisational structure.

In this case study research, the first step is to develop a case story where each case is explained with general information about their organisations. In addition to that, the forecasting process in each case organisation is described. This is a useful step as it helps to explore the data without the clutter of referencing or the systematic analysis (Buchanan 2012). This can help find the black swan from the pack of white swans that is the case that stands out from the rest (Buchanan 2012). This shall highlight how each case use the different dimensions of forecast decision-making within their processes.

Hence, the next sections in this chapter contain a case story for each organisation with their cognitive maps. The idea is to sketch out a map of the forecasting process in each case from the interviewees' words. The assumption behind this is that individuals sometimes work cooperatively and sometimes not. But to be effective team members, they need to appreciate each other's thinking for a joint commitment (Pidd 2003). And a cognitive map helps to display such group dynamics in a flowchart format.

The cognitive map is a two-dimensional representation of the concepts that the managers have expressed during the interviews and how these concepts are linked together for each case. These maps consist of nodes (concepts) and arrows. The concepts are ideas, issues and factors that have meaning for the forecasting managers and are expressed in words by them. The arrows represent causal linkage between the concepts. These cognitive maps facilitate the development of a conceptual framework in the next Chapter 6.

5.3 Case A

The first company is one of the world's leading communications service providers with various products like fixed-line services, broadband, mobile and TV products and services along with networked IT services. They sell their products and services in the UK and worldwide to consumers, small and medium enterprises and even the public sector.

For this research, the company's provisions service division has been considered as case A. Two interviews have been conducted: one with a principal researcher (A1) who works closely with their forecasting and analysis team. The second interviewee (A2) is the Director of Customer Forecasting and Analysis division. Their organisational chart is shown in Figure 5-1, provided by the company which helps display their hierarchical structure.

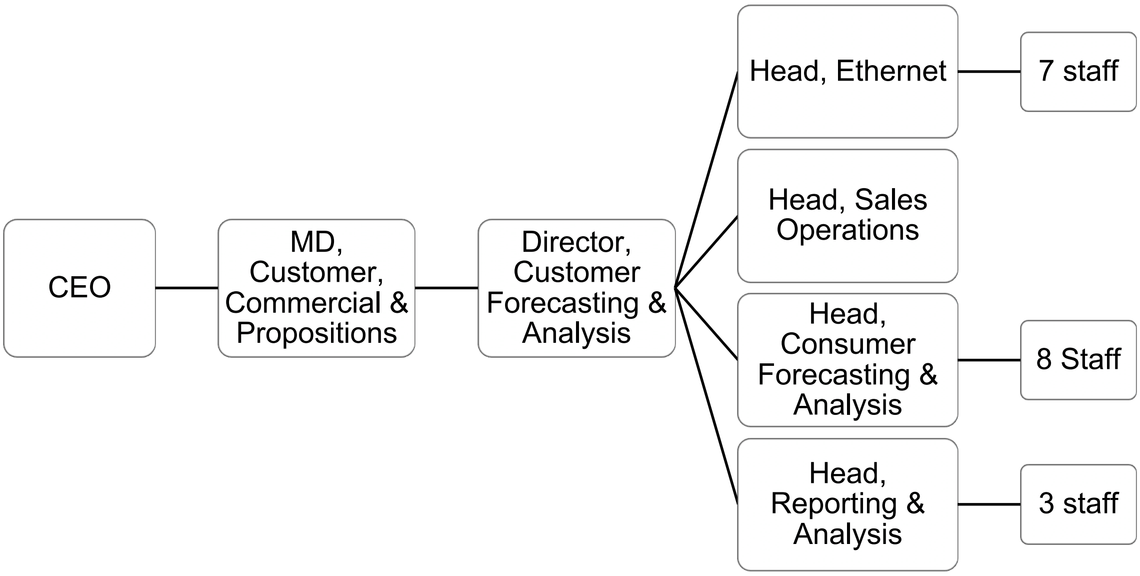

Figure 5-1: Organisational chart for case A company

Along with the different products, this company also provides repair services to customers within the division of Reachout (pseudonym name to maintain anonymity), which provides after-sales repair services to customers. Reachout provides access to network and services to customers (along with repairing). The supply chain relationship is customer-consumer-Reachout. Within the branch of Reachout, there are hierarchies based on both product-type and geographies as explained in the next sub-section.

5.3.1 Forecasting process

In the product hierarchy Figure 5-2, Reachout is divided in to two main divisions: Provisions and Repairs. Under Provisions comes the Customer Forecasting and

Analytics team which as the name suggests is the customer forecasting team for this case. The second interviewee A2 is the head (Director) of this team.

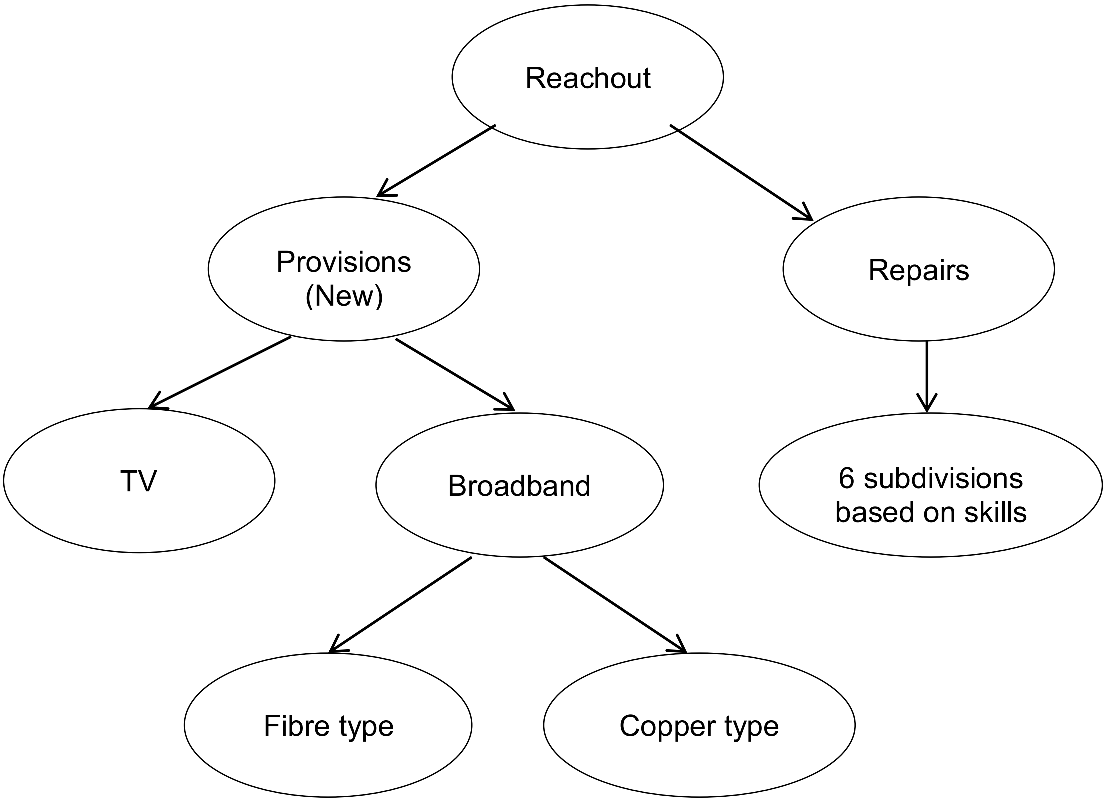

Figure 5-2: Case A company hierarchy based on product type

The forecasting for Provisions (new connections) is made on a monthly basis. The demand for new connections is relatively stable with a lead time of 7-8 working days. The forecasting method used is moving average at the Provisions hierarchy level. Once the SFs are ready, other members of the team get involved in the process. The communication provider(s) looks at the SFs and the accounts' manager makes judgmental adjustments to these forecasts.

While forecasting, the case team considers different hierarchy nodes as separate markets. For example, *Broadband* and *Ethernet* services act as different markets and hence different forecasting methods are used for each of them. Even though

Fibre and *Copper* are part of the same Broadband market, they are again considered to be separate markets while forecasting.

This is because the *Fibre* market demand is driven by different factors than the rest of *Broadband* market. The *Broadband* market demand is driven by factors like penetration of market and the dynamics of it. On the other hand, the drivers for *Fibre* market demand are fast speed and other strategies. Hence, it is better to visualise the forecasting process of this case from a market viewpoint (Figure 5-3), rather than their product or geography hierarchy.

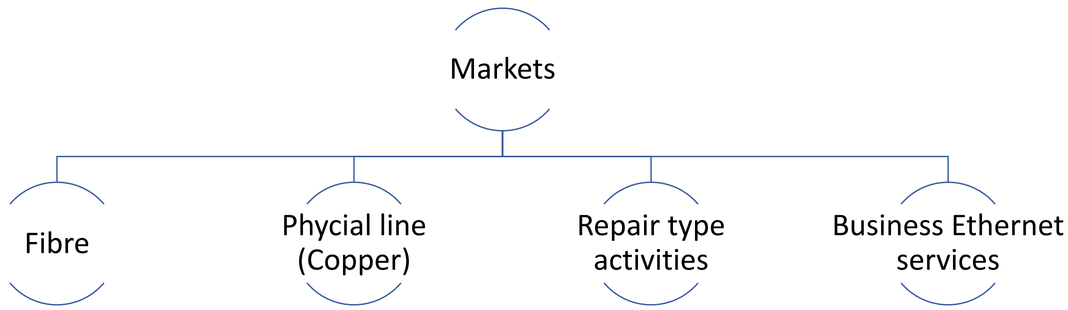

Figure 5-3: Case A company hierarchy based on market

Apart from markets, the case team also considers customer provider information while forecasting. These customers are not the end customer of their supply chain but the customers to whom the company provides services, who are then service providers for the general public: end customers. This is important to remember while forecasting because no matter how much demand is there at the end customer level, if their customer providers decide not to provide competitive prices it will have an effect on their entire market forecast.

From the market point of view, this case forecasts for four different sectors namely, *Fibre*, *Copper*, *Repair* and *Ethernet*. To forecast these four sectors, the team maintains a balance between statistical forecasting methods used and human judgment needed. However, this combination of statistical methods and judgments varies depending on the sector as some are easier to predict than others.

Repair market

For the *Repair* market, it is on one side of the combination scale with an analytical regression model at geographical level. Forecasts are produced for the lowest geographical level and then a bottom-up approach is used to aggregate them. For the main forecasting model, different weather inputs like amount of rain, wind and storm are considered. As there is never a good long-term forecast for weather, the team considers historical trends for past 10 years and adjust the trend accordingly for each geography as and when needed. Then a regression model is used to provide the baseline SFs.

While forecasting for the *Repair* market, they do gather information from other levels of hierarchy. They talk to people from operations (lower in the business hierarchy) since these people know more about repairs (which are result of operational failures). This helps them to gather an idea of how much they can save against the baseline forecasts. Hence, forecasting for the *Repair* market is very analytical in nature but there is, still, a small element of judgment involved.

Ethernet market

At the opposite end of the combination scale is the *Ethernet* market, whose forecasting process is very judgmental with little amount of statistical data involved. The statistical data steps involved include looking at long-term historical data to check for any trends in the market. In this scenario, although the lower hierarchical level may have more information about the market, the upper hierarchy makes most of the forecasting. The upper hierarchy is considered to have a better understanding of the long-term trend from a broader perspective.

Much of the information for this *Ethernet* market comes from the communication providers (CPs). An assessment is carried out to see how the CPs are doing, what they are saying, what their strategies are and what their future strategies will be. Hence, forecasting is very judgmental for *Ethernet* and a top-down approach is used to break down their forecasts using historical averages for each geography.

Copper and Fibre market

For the *Copper* market, the forecasting is a combination of trends and qualitative information. There is no sophisticated statistical method within this market. The demand for *Copper* does not change much, except when new projects come in then big differences are expected in the numbers. For the *Fibre* market, the forecasting is much like *Ethernet* as it depends what the customer providers are doing with the market. Therefore, forecasting for *Copper* market is more trend based, whereas *Fibre* market is more qualitative information based.

Geography hierarchy

In addition to product-type hierarchy, the case also has a geography-based hierarchy (Figure 5-4). In this hierarchy, forecasting is performed at the lowest level: Senior Operational Managers (SOMs) level. Bottom-up approach is used to aggregate the forecasts and obtain forecasts for the levels higher in the hierarchy. A1 says forecasting is most accurate at the highest hierarchical level (UK level).

But because of ease of deploying, the team prefers to forecast at the lowest level (SOM).

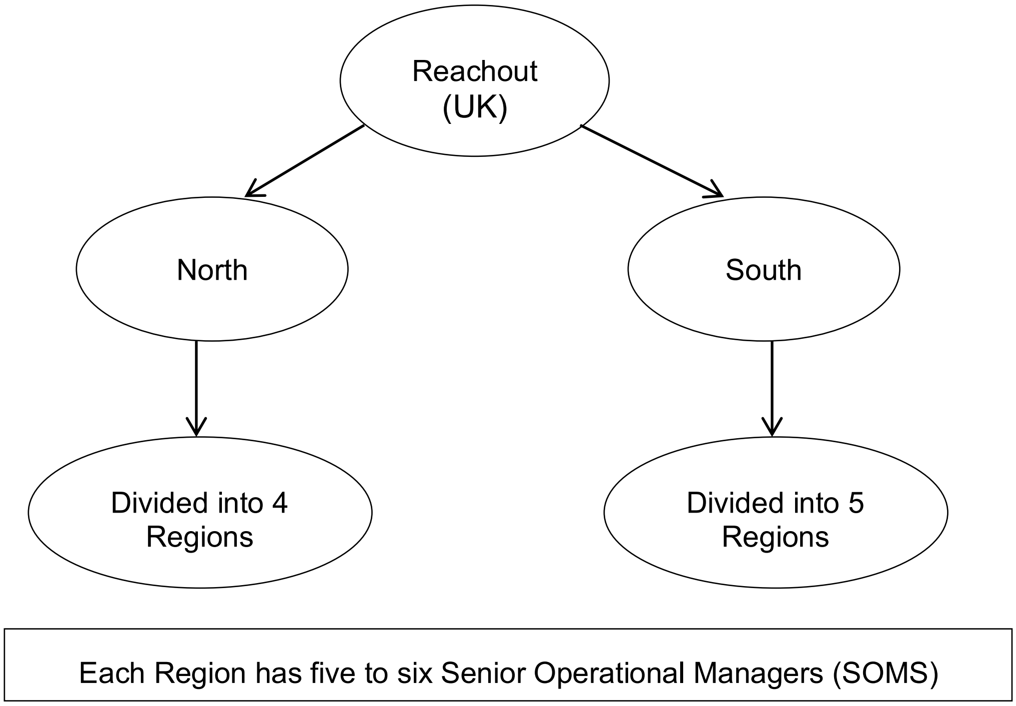

Figure 5-4: Case A company hierarchy based on geography

As seen for the *Repair* market, the demand is very unstable and hence forecasting is done at a combination of both product and geographical hierarchies. A sophisticated tool for demand forecasting is used for each SOM patch. Then managers' use their own judgments to check whether the system forecast needs any adjustment. Few years ago, this forecasting process was solely based on managerial judgment. But then it got changed to a statistical plus judgmental forecasting process.

The demand forecasting process is carried out in one SOM location to derive the SFs. This SOM patch is further divided into six different operational patches, each managed by Operational Managers (OMs) or the planners. The planners interpret the SFs to see if they can move around the resources (engineers) for the repairs.

The planners forward their forecasts to the SOMs and it moves up the hierarchy following a bottom-up method. The planners carry out the forecasting exercise one month in advance, then have two-weeks' time to refine, and one week just before the forecasts are locked down.

5.3.2 Judgmental forecasting

A2 agrees that there exist substantive biases in their judgmental forecasting, mostly because the team has to make a lot of assumptions, pre-empting some decisions that are being made as a result of the forecasts. For example, while deciding on how many engineers to employ for repairs, forecasters usually decide to go for a higher forecast as it is easier to reduce resources than to increase them. This may be a result of unconscious judgments; as they prefer to over-forecast rather than under-forecast from an operational perspective.

At the same time, there are pressures from within the organisations (upper hierarchies) to not overcall the revenue as it adds additional risk to the company. In such scenarios, the team increases their forecasts with a pessimistic attitude. Plus, there are pressures from the lower hierarchical level (operational team) to reduce the forecast as they may not be able to meet their targets.

An example cited by A2 is how a few years ago there was pressure on the team to support a big growth in revenue and hence deliver optimistic forecasts. But now the table has turned, and the pressure is not to do anything that can overcall the revenue and to be on the pessimistic side. There are times when the two optimistic and pessimistic judgment calls compete with each other. And forecast judgments are very much dependent on the decisions being made as a result of the forecasts.

Both the interviewees agree on existence of human biases when it comes to hierarchical forecasting. When it comes to the upper hierarchy, the managers see the bigger, broader picture whereas managers at lower hierarchical levels have more first-hand experiences. But there are also other "illogical biases" (A2) in the forecasts that effect the decision-making process.

A2 says the main focus for their boss (upper level) is to drive additional revenue. And the focus of their team (lower level) is to produce a good forecast after talking to the lower hierarchical levels (operational team). And A2 agrees that this leads to psychological bias as for operational team it is more about meeting their targets. Therefore, there are the vertical biases where one person knows more than the other. And illogical biases where people in lower levels are in pressure from other people and this does enter into their forecasting decisions.

For example, *Ethernet* market, which is very judgmental, the forecasting team spends a lot of time talking to the sales people. The sales team wants the forecasting team to keep the forecasts low. On the other hand, there are pressures from the top to not under-forecast as it has effect on revenue. Hence, hierarchical forecasting is present for this case and the competing pressures for involving judgments come from different levels based on product or geography.

5.3.3 Forecast reconciliation

For forecast reconciliation in this case, different hierarchies are involved, and it usually depends on the decisions being made from the forecasts. Generally, the forecasts are developed at the lowest levels and are reported to the higher levels (like for the *Repair* market). But if there are any tipping (qualitative) information then the higher levels get involved. Depending on the impact of the forecast decisions, the higher up the hierarchy it goes.

Like for example, in one particular year one of the CPs made an aggressive increase in their forecast considering their expansion. To incorporate this decision into the forecasts, managers from different hierarchies had to get involved. Hence, it can be clearly seen that there is a hierarchical decision-making process present in this case company.

A2 gives examples when there are cases like deciding on new investments that require budget plans, the decision-making involvement process will go up to the highest level (Board of Directors). The decisions about how much to invest and what will be the returns will be made by Reachout team, but the decision whether to include the investment plan or not will be done by the Board. Depending on how big the decision is it can go all the way up in the hierarchy.

5.3.4 Cognitive map

From the description of the forecasting process for this case, the below cognitive map (Figure 5-5) is developed. This map follows a vertical structure where the process starts from historical data and ends with aggregation of forecasted data. It shows how information flows from different hierarchical levels and also how judgment is involved. The different nodes demonstrate the influences of various departmental and overall factors on this process.

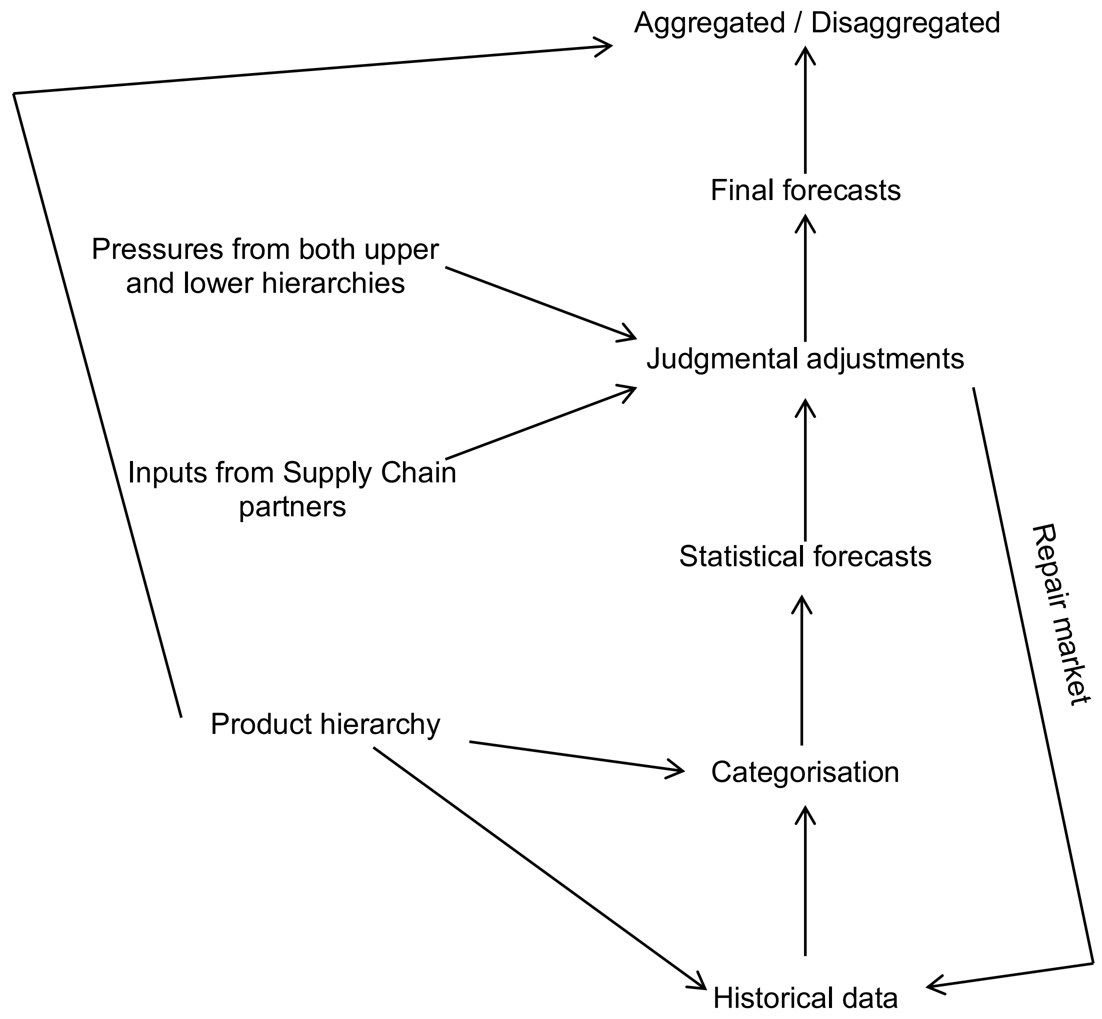

Figure 5-5: Cognitive map for case A

In this case, inputs are gathered from different teams from operational levels to even customer providers in the supply chain. Depending on the type of market, the combination of SFs and human judgments in the decision-making process varies. Aggregation/disaggregation of forecasts take place for each product type, depending on the information used in the forecasting process. And the different hierarchies involved in the forecast reconciliation process is contingent on the gravity of that forecast decision(s).

5.4 Case B

The second case company is one of the largest airlines in South America, with new aircrafts and a relatively new fleet. It is a multinational company with most operations in South America. Their maintenance division that handles the inventory management of spare parts, is included in this research as case B. Two interviews have been conducted with two demand planners (B1 and B2). A presentation has been made available that explains their demand planning process. Figure 5-6 shows their hierarchy based on type of maintenance carried out at different airports.

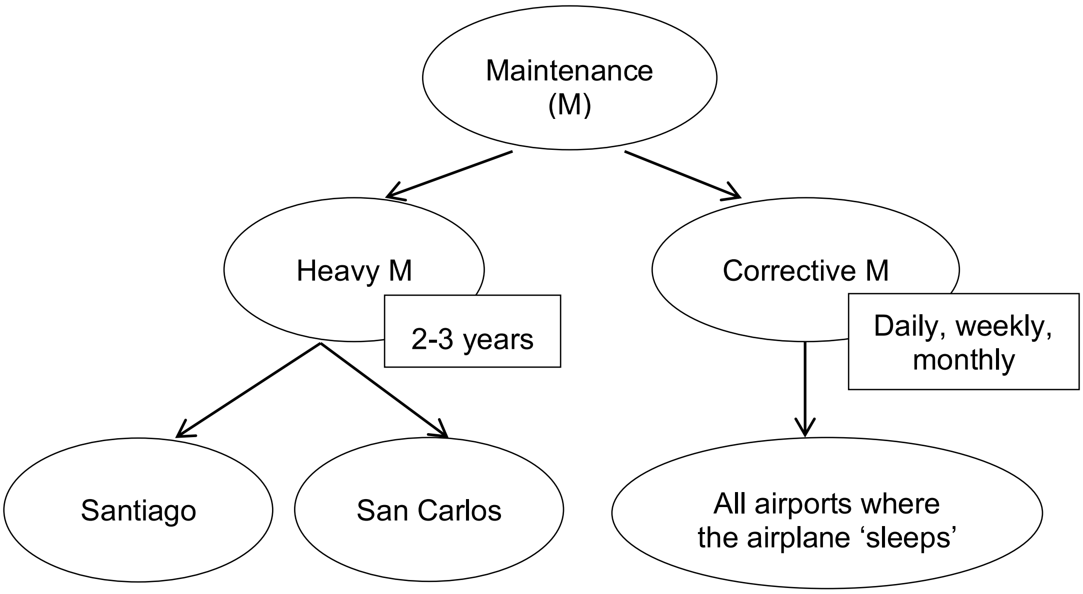

Figure 5-6: Case B company hierarchy based on maintenance type

The company executes all major maintenance themselves viz. *heavy maintenance* (large planned checks every 2-3 years when an aircraft is 2-3 weeks on the ground for maintenance execution) and *corrective maintenance* (daily, weekly or monthly checks which are executed typically at night when the aircraft is not flying). All heavy maintenance, however complex, is carried out in two of their locations: one in Santiago (Chile) and Sao Carlos (near Sao Paulo, Brazil).

Rest of the maintenance work is carried out in all the airports across the globe wherever their aircrafts are *sleeping* (not flying) during the night.

The demand planning team's job is to make sure all types of materials required for different kinds of maintenances are available at all (~200) locations. Basically, they manage the inventory for different locations across the globe for both heavy and corrective maintenance. Hence, the company has inventories in all the locations where the aircraft is *sleeping* (not flying) and also where the aircraft lands in case there is an issue with any of its parts (like wings).

When it comes to maintaining an aircraft, there are a range of materials with different types and varied prices. Some of these are very expensive, which makes forecasting very important and crucial for this industry. Case B company has different kinds of fleets from Boeing to Airbus; along with several combinations of motors that give them a wider spectrum of materials. And its common characteristic with any other after-sales industry, is the relatively low demand (on average one or two per year) of the products. There is an exception for the chemical parts used for cleaning aircrafts, which are relatively fast-movers (products that are used frequently).

There are thousands (between 50K-100K types of items, 400K are kept in stock) of different items (SKUs) from bolts and nuts; whose worth varies from 1$ bolts to computers worth 0.5 million$. Hence, as an airline company they have to maintain inventory in quite a few airports (about 200 locations in South America), with relatively far away suppliers from United States of America (USA) and Europe.

From a supply chain perspective, this case is quite complex making its forecasting and planning more important and crucial. The case team's objective is to achieve good service level for their clients (maintenance) with relatively low investment in inventory. As explained, both product and geographical types of hierarchies are present in this case scenario. Their product and geographical hierarches are interlinked making forecasting even more interesting.

5.4.1 Forecasting process

The planning team considers the following two types of maintenance for forecasting:

1. *Preventive maintenance* follows a dependent demand model: The demand planning team works together with the maintenance team (which is placed lower in their business hierarchy). The maintenance team provides them with a task planning document detailing what tasks need to be done. For example, a part is not working properly or a part may have worn after X number of years. Along with the task planning document and the historical data for each task, the demand planners make a so-called "dependent demand plan" (B2).

2. *Corrective maintenance* follows an independent demand plan: It is when something has failed and needs a change. This part is planned based on historical demand and many different extrapolations.

In addition to the two kinds of maintenance required, this case company has a product hierarchy with different types of materials (Figure 5-7): *consumables* (things installed in the aircraft but are never repaired but replaced) and *components* (things that are repairable, internally or externally). For example, when bolts need maintenance, these are thrown away and not repaired as they are pretty low cost. However, when a port computer fails, they try to repair these computers as they cost a lot to the company.

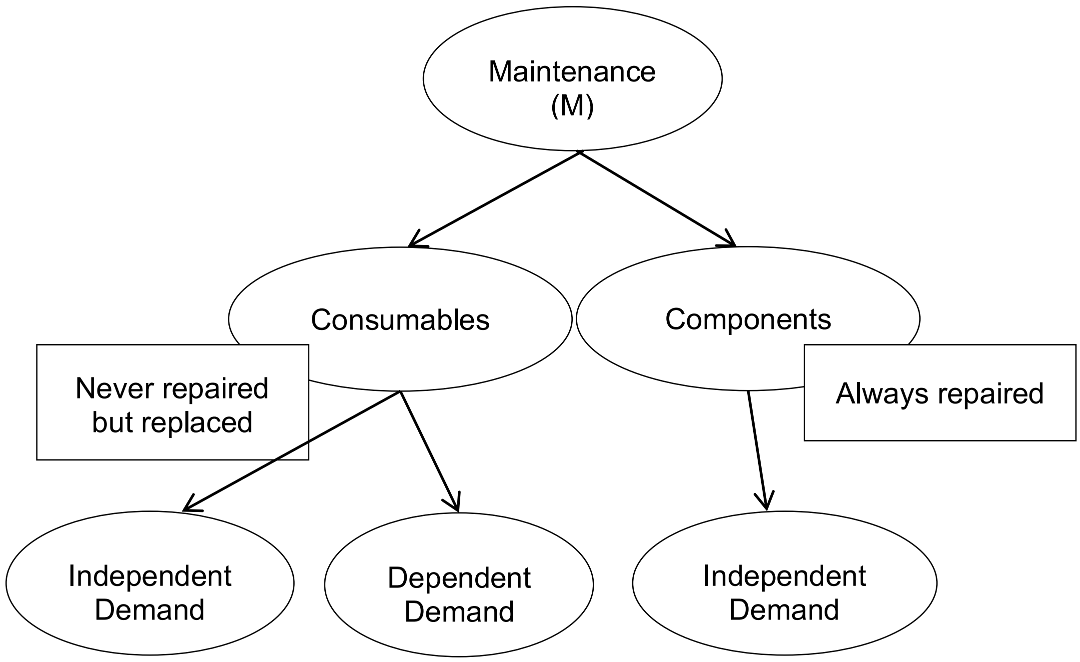

Figure 5-7: Case B company hierarchy based on material type

Accordingly, forecasting methods (Figure 5-7) are different for both types with methods being defined at different levels, with the aim of achieving the highest accuracy. Demand can be either dependent or independent based on whether it is subjected to soft information coming from “junior department” (B2) on a maintenance task. This information is provided in the form of documents by different clients. Independent demand is forecasted through statistical methods using time series data. Only 30% of the total demand is dependent, the rest is independent demand. But the parts with dependent demand are the most expensive.

There is another additional layer of essentiality to the demand of products (both component and consumable): *Go* part (an aircraft can fly without it, it is not so important), *No-go* part (an aircraft cannot fly without that part) and *Go-with* part (it depends, for example an aircraft can fly without a component but only for five days).

Components

As *components* have to be repaired once failed, their forecasting follows an independent demand path. However, there are few special scenarios when there is a dependent and intermittent demand based on historical data. In such scenarios, the case team forecasts at the highest hierarchical level as it results in best accuracy. Forecasting at lowest hierarchical levels gives high coefficient of variance with no additional information. Accuracy is defined from a forecasting accuracy point of view that is lower cost and lower inventory.

Therefore, for *components* forecasting a top-down method is followed where forecasts are produced at the highest level and then divided to get forecasts for lower levels. The forecasts are divided statistically based on historical proportions. However, there has been cases when judgment has been involved to divide the upper level forecasts. An example cited by B1 was when the forecasts for a large aircraft are divided from the upper hierarchy (based on locations) to the lower level.

From the historical data, models can suggest that Lima (Peru) does not need to get a spare for a particular part. But the customs in Peru is very complex and if it is a spare part without which the aircraft cannot move, the decision is made to stock it in Peru. Because the cost of not having the spare part will result in the aircraft not being able to fly for 3-4 days, which will turn out to be very costly for the company.

Consumables

For *consumables*, there are both independent and dependent demand plans. Dependent demand incorporates a huge amount of soft information and hence, forecasting is carried out at a lower aggregate level. There is a lot more specific information about the locations at the lower level. Like for example, an X part needs to be removed from Y location on Z date. These are then calculated out at country level for Spanish speaking countries with one hub in each country where the aircraft *sleeps* and all heavy maintenance happens there.

But for Brazil (which is the majority of the company's business), the forecasting is done for 4-5 major hubs where the aircraft *sleeps*. These forecasts are added up for upper levels following a bottom-up approach. At the end, all forecasts (irrespective of material type) are aggregated to get one demand planning solution for the company. These aggregated level forecasts help to negotiate with suppliers.

5.4.2 Judgmental forecasting

There are several elements of judgment in the decision-making processes for this case. One example is when they have to work with (internal) clients from maintenance (the engineer) to leaders from other countries. The information for the clients also includes information for aviation agencies like the Federal Aviation Association (FAA) and European Aviation Safety Agency (EASA). All the clients are allowed to provide recommendations to the planning team; like “I think the forecast for this part will be etc. in the upcoming year” (B1). The maintenance department gives such soft information about parts needing change, “what and when” (B2). The demand planning team then uses such recommendations as minimum forecast levels.

An example cited by B1, is that of the rainy season in the north of Chile when the surfaces of aircrafts get impacted. This point is discussed in the client meeting and a person from the airport in North Chile might say what is needed to prevent the surface of an aircraft from being worn out. This type of soft information cannot be deduced from typical forecast graphs and figures. Hence, the method used to adjust the forecasts is: if the statistical model forecast is higher than the recommended forecast then it is not changed; but when the model forecast turns out to be lower, the recommendation is applied as the minimum forecast and the model forecast is adjusted.

B2 says the “engineering [maintenance] department is the law” as they know how each and every part work in an aircraft. Additionally, the case team do include an expiry date for each of the client recommendations after which date they start trusting their statistical models again. This system of including an expiry date was introduced when the team realised that there was excess inventory that is not being used, as a result of the increased recommended forecasts.

Another type of judgment involved in this case’s forecasting process is something that a demand planner faces almost every day: the outliers. These are the numbers that do not fit in with the other numbers within the set. In such a scenario, the planners remove the outliers from the models. Additionally, the team has to make other judgment calls when it comes to initial provisions (new products) when no historical data is available. For example, when a new model aircraft is purchased, the recommended forecast for spare parts comes from the manufacturer. These forecasts are pure judgment numbers, as no one knows what is going to fail in the new aircraft.

The case team tries to combine this information with data from similar aircraft models. Like for an aircraft of model A350, they combine it with A340 (the earlier version). They use time series models on data from similar other products; but at the end, managerial judgment is applied especially when it comes to the most expensive parts. B1 gives an example when the manufacturer suggested buying three spare parts for one item in A350, a part that never failed in A340. Eventually, the team decided not to buy three units but instead with a judgment call to buy one and increase the forecast as and when the part starts failing.

5.4.3 Forecast reconciliation

There are two types of parallel hierarchies in this company: hierarchies based on how a planning team works and hierarchy at which level to forecast. With the respect to the first part (Figure 5-8), the company has planning teams in three different locations (because their main clients are in these three locations): *Line maintenance* (for Spanish speaking countries, i.e. all countries except Brazil in South America, in Santiago), *Line maintenance* (for Brazil in Sao Paulo) and *Heavy maintenance* (one plan but divided again in two locations i.e. Santiago which is the same as for Line maintenance, and Sao Carlos).

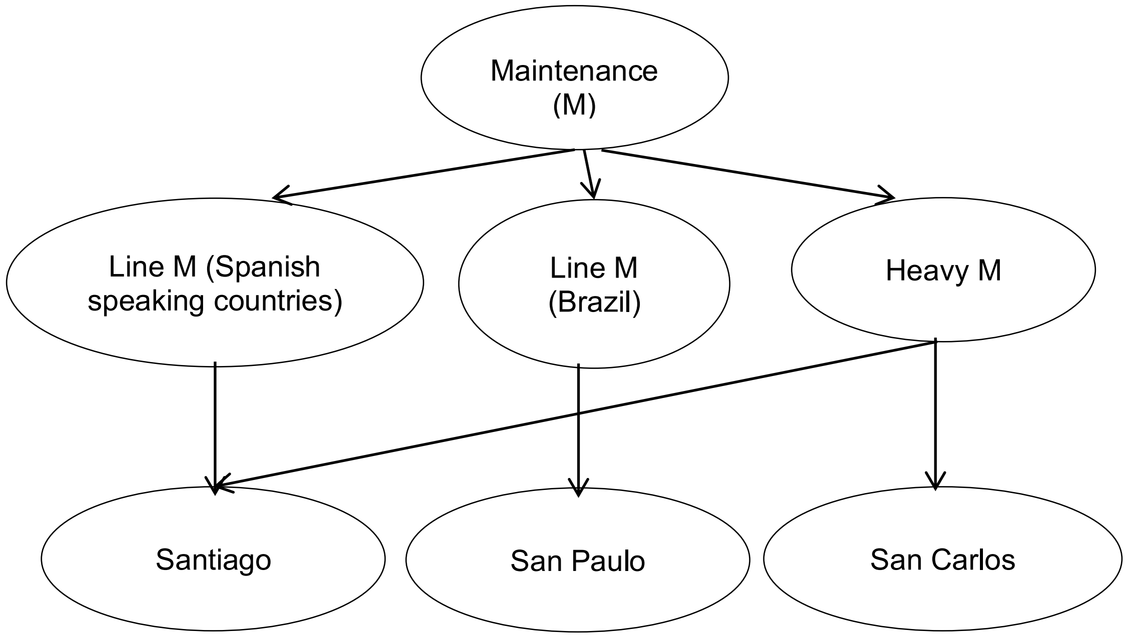

Figure 5-8: Case B company hierarchy based on team duties

Forecasting is carried out at SKU level using middle-out method of aggregation, where it is aggregated and disaggregated for top and bottom levels respectively using weights (based on airline usage at that location). The head of the demand planning team sits in the head office, whom the demand planners from the three locations (Santiago, Sao Carlos and Sao Paulo) report in a hierarchical matrix. The above hierarchy becomes even more complex as there is a further distinction based on material type: *consumables* and *components* (as explained earlier).

There is a negotiating team within the organisation that talks to the maintenance department (as this department gives the highest amount of soft information for forecasting). They speak to managers about their opinions, and questions those that suggest adjustments based on personal views. This is required because as B2 says “money is not (focus) for them but for us it is (a) focus”. In doing so, they also incorporate information coming from other locations into their forecasting process.

B1 says that forecasts should be made at the hierarchical level that gives the best accuracy. And with the needs of the clients, these may be aggregated or disaggregated. For different purposes, different aggregation level forecasts are used. For price negotiation, forecasts aggregated for Brazil and Spanish-speaking country levels are used. But for warehouses that are local, lowest level forecasts are used.

Teams from different hierarchical levels like the maintenance team, and engineers are involved in the decision-making process. However, they do not have much say in the process. They are allowed to give recommendations with a valid reason why they want something and how much of it is going to be used. But the final decision on the forecasts is made by the demand planning team. B1 does mention that the lowest level does not have the expertise to perform the forecasting task. But they do agree that the meetings with those teams are very beneficial as both the sides can communicate and prioritise the work.

5.4.4 Cognitive map

Considering the different scenarios for forecasting in this case, the following cognitive map is developed (Figure 5-9). In most cases, different statistical models (depending on the product-type) are used to generate forecasts from historical data. These forecasts are adjusted depending on the available information, either as recommendations from maintenance team, or additional data provided by supply chain partners, or judgment calls from the experienced demand planning team.

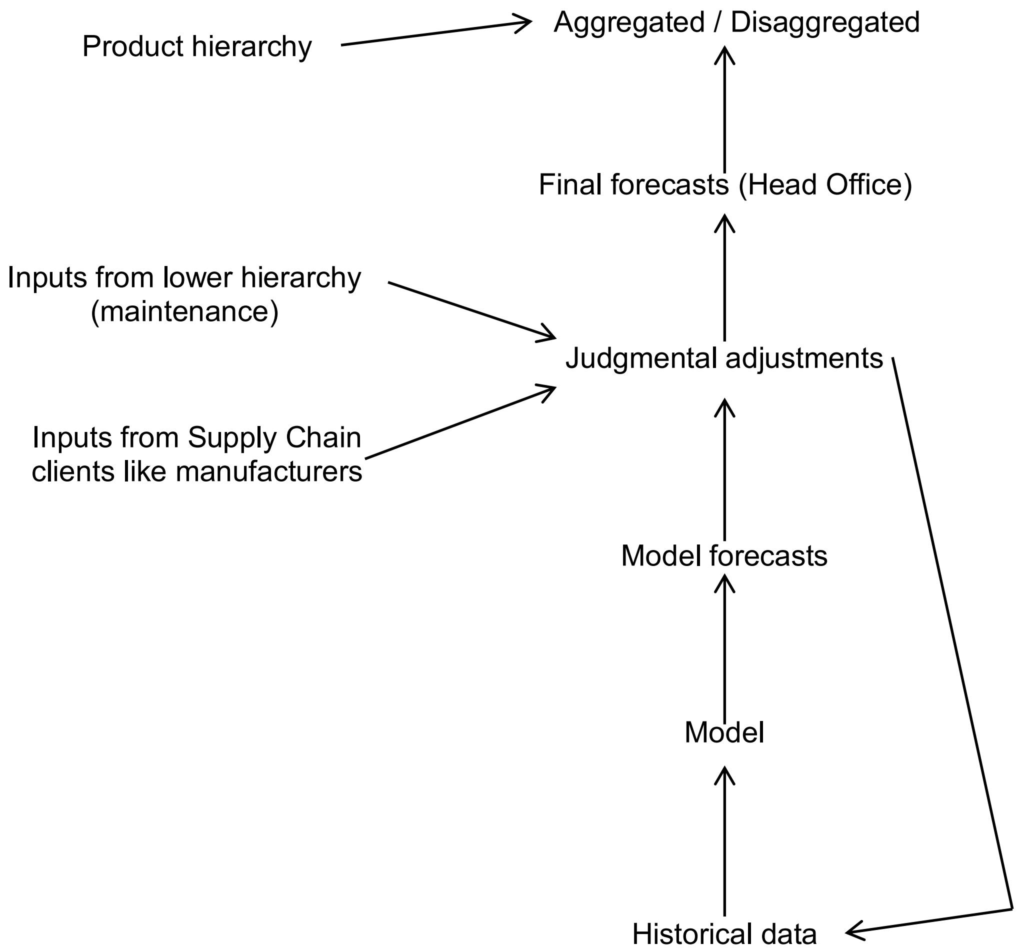

Figure 5-9: Cognitive map for case B

The forecasts are sent higher up the organisational business hierarchy to the head office. Depending on the product type (material type), aggregation or disaggregation of the forecasts taken place in bottom-up or top-down fashion. Decisions from the forecasts are made at different aggregation levels, depending on the different aspect of decision-making from price negotiations with suppliers to inventory management in warehouses.

5.5 Case C

This is one of the public-sector emergency health services in the UK. They are spread across the seven health boards in Wales, as shown in Figure 5-10 (only for contextualing purpose). They operate from a combination of contact centres, regional offices and ambulance stations. They attend more than 250,000 service calls every year, which includes urgent calls and also transporting non-emergency patients across locations. They have about 3,200 staff, out of which 85% comes under the operations team. The planning team of this organisation is taken as case C.

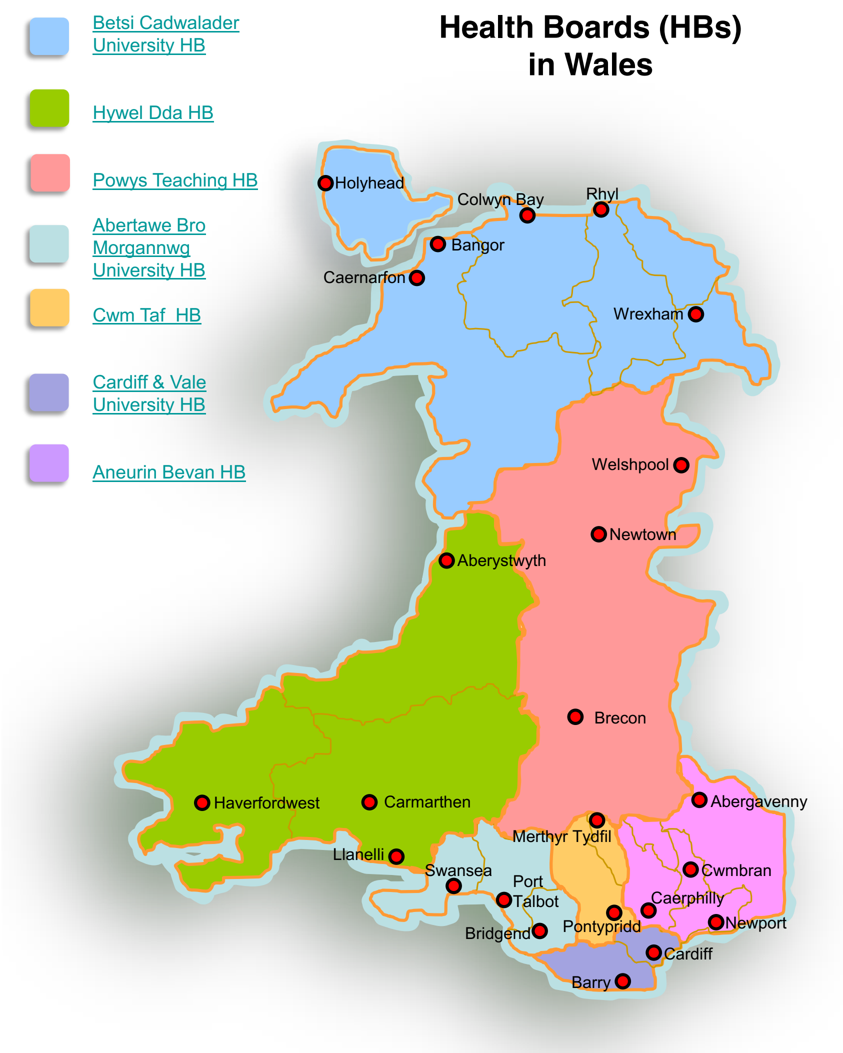

Figure 5-10: Geographical distribution for case C

Three interviews are conducted for this case, one of which is a group interview with two consultants. Interviewee C1 is the assistant director for commissioning and performance who runs a small team of four people along with another four in planning and performance. But they also work in cross-corporate groups like the operational directorate.

Interviewees C2 and C3 are two consultants who are hired by this case organisation to provide a demand and capacity review plan for the next 4-5 years. The consultancy ABC specialises in resource planning for emergency services and public sector, broadly. They were commissioned by the case team to carry out a demand and capacity review: this involved collecting data, data analysis, understand how they were currently operating, build up the simulation models, calculate impact in terms of performance and workload and on different scenarios given by the case team. Part of this project was to create a demand projection for next 4-5 years and how would that impact their performance, to come up with a set of recommendations for resource increase to meet the demand increase along with some other efficiency measures (like reduce time spent in hospitals and others).

Interviewee C4 is the assistant director of operations for this team, who has previously held a high position in Cardiff Police. Their current role is to bring in intelligent ways of working productively, to become leaner and create opportunities to save money. Along with the interviews, a number of documents with the map of different health boards, organisational chart, and demand planning reports from consultants are made available to the researcher.

From an operational perspective, forecast decisions need to be made for the next six weeks ahead for all seven health boards based on skills of each individual resource (as some are better with heart attacks while other might be better with elderly people). The tools used to make these decisions are based on the number of resources, events happening in the near future along with the demand. This gives an accumulative figure minus the resources who are sick or on training courses or not available for other reasons.

Case C makes use of best practices and is not just limited to demand forecasting (provided by the consultant) but also includes having the right units at the right places at the right times; looking at how the team can be supported externally as well to reduce the demand. There are different internal and external collaborations that are required to fulfil the demand. Hence, it is not just about pure science (statistics) for them.

Whenever there are forecast decisions to make, one wants to minimise the risks. For a private company, the aim is to maximise profit. For an emergency service, it is better to over-supply the service and not miss any call. Hence forecasting teams overestimate the demand and the number of resources, rather than underestimate it.

From an organisation structure perspective, Figure 5-11 shows the different players in hierarchical layers within the company. When organisational decisions are made, these players have power struggles because of this hierarchical structure. Being a public sector company, there are other external teams (health boards, Welsh Government) as well influencing their decision-making process.

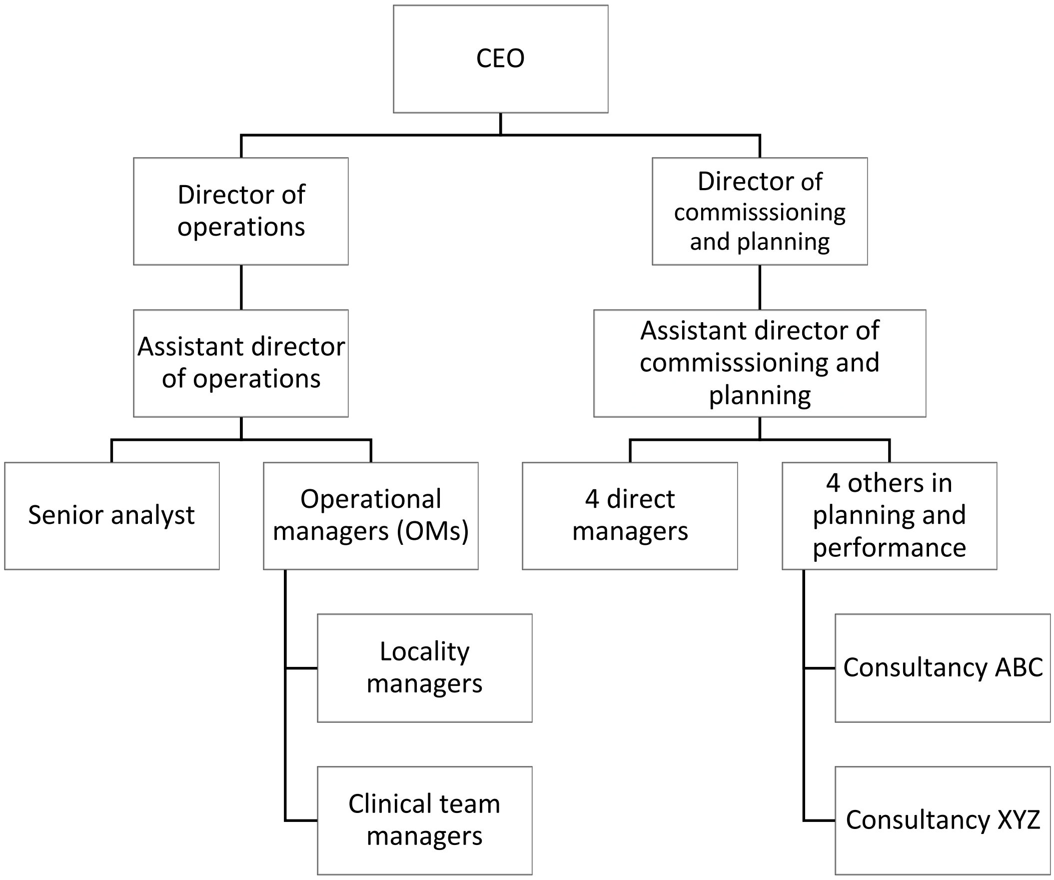

Figure 5-11: Organisational chart for case C company

5.5.1 Forecasting process

Demand for this team can be divided into different types as shown in Figure 5-12. There are about 400,000 incidents a year which divides the incident demand into instant demand and phoned demand. For example, there might be five phone calls reporting one motorway incident. So, phoned (called) demand outgrows the incident demand. Based on acuity, incident demand is categorised as red (life threatening), amber (serious but not life threatening) and green (the rest of the calls). There is another distinction between failure demand (calling for an emergency because there are no GP services) and value demand (emergency call for say cardiac arrest).

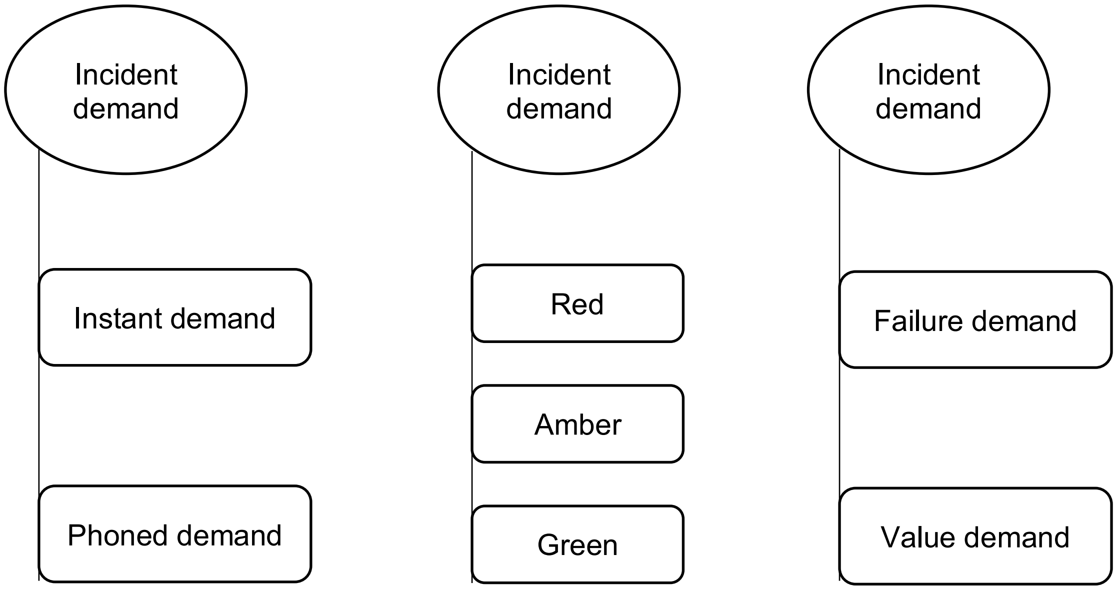

Figure 5-12: Case C demand hierarchy

The main forecasting for this case is outsourced to a couple of consultancy companies as “there isn’t an in-house capacity” (C1). The forecasting process used by ABC (consultancy) is based on population and demand rate for per head of population. They collect the age and gender of patients that case C had responded to each year over the last 4-5 years. And they combine that with the population count from the Office for National Statistics (ONS). This is done for each of the local health boards, like the way case C is structured with business operating units in these areas of the health boards.

For each year, for each age and gender group, they calculate the population and the demand rate per person. For each category (age-gender-health board), they look at the trends of how the demand rate has been increasing and apply simple linear trend on it. This linear trend is used to forecast the future. Once the predicted demand rates are generated, it is combined with the population projections from the ONS to calculate the demand levels for each local health board. In this way they able to capture both the growing and the aging population.

There are 5 steps of patient flow in the health system and in this way the patients enter the emergency department, as shown in Figure 5-13. Once a patient chooses the emergency department, the case team will receive the call, speak to the patient about the situation, and decide whether to displace an ambulance service. There is a very strict target of the ambulance reaching to the patient within eight minutes of the call. The next step is whether the paramedic may treat the patient on scene, or access and find a hospital pathway for them. The last step is to convey them to an emergency department.

Figure 5-13: Case C's five steps of emergency care pathway

However, patients do not follow this exact flow and actually the reverse happens by taking the ambulance to hospital as first step. For case C, the earlier a patient is treated, the cheaper the treatment is. Because there will be no need to send an ambulance (so it can be used for more severe cases) or take the patient to a hospital (as ambulances get stuck waiting outside hospitals). There are also non-emergency routine appointments that make use of the ambulance service. This makes demand planning more complicated for the case team.

In the health scenario, there are different hospitals, emergency services like the ambulance and others, local health boards and every department have their own objectives to meet. In reality, "patients flow through the unscheduled care system" (C1). And this unscheduled care system is made up of the ambulances, doctors and the emergency departments of hospitals. Underneath these lies the different care pathways. Once a patient leaves the ambulance care pathway, they enter the emergency department, and are discharged to enter the non-emergency patient transport service.

The patient is flowing through different lateral divisions and hence that “should” (C1) define the planning and decision-making process (Figure 5-14). “The reality is patients do not flow through vertical. They are lateral, and they flow across organisations” (C1). And each of the different departments in the health system have their own different objectives for quality and workforce. They base their individual planning processes on the style of Managing By Objectives (MBO).

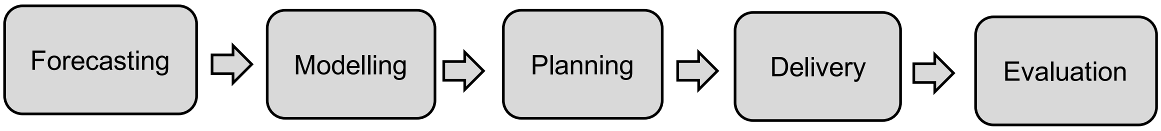

Figure 5-14: Case C’s decision-making process

The departments in this health system spend most times deciding and planning the delivery (operations). These departments make effective operational decisions by reacting to difficult scenarios, but do not send such information upstream in the decision-making process. There is a human behaviour aspect where “there is a propensity for action” (C1). According to C1, everyone just wants to do stuff but does not take a step back and think what is happening in the other steps of the process. The above five steps of the decision process should be followed but it is not, at the moment.

C1 explains one situation when they went to meet other emergency departments. They said, “What was fascinating is they couldn’t even describe the five steps…

how do you manage?” It is surprising as managers within the organisation make their schedules and rosters without knowing the entire process. There is no team within the ambulance emergency department to look after their forecasting process. Hence, there is no agreed ways of forecasting whether it is strategic or tactical or operational forecasts. The department is highly dependent on consultancies to do this job for them.

The strategic part of forecasting is done by the consultancy company ABC, who looks at 4-5 previous years of incident data by age and gender cohort. At the other end is the operational part of forecasting which is the rostering. The rosters have a demand profile next to it which is decided on a rolling three years average. C1 thinks this operational part needs to be “more sophisticated”. And the tactical plan in the middle is still open to debate.

However, the operational assistant director C4 says the performance of the team has improved drastically lately. The team worked to find out why and where they were having a lot of unpredictable demand. “Instead of identifying the symptoms, what are the root causes of those problems. And how even looking outside the organisation you could react to it” (C4). For example, they worked with hospitals to make their services better. Like taking a pregnant lady straight to maternity, removing the bottlenecks of the accident and emergency (A&E) department. That frees the ambulance sooner to be available for the next call.

5.5.2 Judgmental forecasting

The strategic forecasts from consultancy ABC is accepted as it is, because they were hired to do so. If their forecasts turn out to be wrong over time, the case could sue them. “That’s their responsibility and that’s why we are employing them” (C1). “We are fairly reliant on the contractors, ABC, being capable of [doing the forecasting]. It is their responsibility … to do an accurate forecasting” (C1). There is no internal assurance process to check the consultant forecasts. Because the case has the view that it is the responsibility of the contractors to check everything.

This highlights a gap between public sector and private sector in terms of forecasting. “I have a suspicion that there may sometimes be a desire not to forecast and model because people might be afraid of the results” (C1). This is a political system and there is the provision of information request. If there is a report on the increase of demand and how much more resources are needed, “that may not be welcomed by senior decision makers and politicians because it causes them a problem as the opposition will pick it up” (C1). If the performance is lower and was predicted, sometimes the decision makers prefer not to know it. Because if there is an enquiry then it will come out that they actually knew that.

What went wrong with ABC’s consultancy review was; C1 says “Whilst we took as an ambulance service some decisions off the back of it, we didn’t engage properly with the system. And actually, didn’t really see the light of day.” The funders and commissioners were not engaged and hence the project failed. Therefore, the next time proper permission was taken for funding and the steering project team included the commissioner on it. In the words of C1; “it is all very well that [forecasters] might sit in a darken room and just do numbers, but actually they also need to learn how to work with an organisation.”

C4 gives an example to understand how statistics can go wrong. The consultants from ABC provided them with a map of where the ambulances should be place within the different regions of Wales. ABC gave them locations in coastal areas where they could attend calls from the different directions of these rural areas. But the location points could not reach any place in eight minutes as it was in the middle of everything.

For example: in Monmouth which is a politically sensitive area and expensive area, ABC recommended to move two ambulances and resources from there to Cardiff. But there are practical reasons why the case team cannot do so. It is 1.5 hours away from Cardiff and if there is an emergency call there, the patient might die before the ambulance arrives. Hence, it can be seen why human judgment needs to be applied for such predictions instead of depending on statistical matrices working on better utilisation of resources.

Additionally, the demand for ambulance service is seasonal. The seasonal demand comes in different months: like December is very busy with all bars and restaurants being filled up. January is comparatively quiet. Also, because Wales is surrounded by coasts, some of the areas' population increases by 300% during summer months. On a daily basis, there is massive difference in forecasts: the busiest time for ambulance service starts on a Sunday and goes onto 10 am on Monday morning.

"The consultancy… is only predicting against normality... they are predicting we are not going to have any hospital delays, we could have like we are today. We had the worse hospital delay in my 7 years. Yesterday we had a 12 hour. An ambulance comes in and has its blue lights on sirens and wait outside the hospital for 12 hours before they take the patient off" (C4). "What [ABC] said is because they weren't contracted to look at that, they didn't. But they also didn't look at seasonal demand" (C4). "[The prediction] was exactly whatever we asked them for and we asked them for the wrong things" (C4).

If this case wants to use their judgment in the forecasting and planning process, it has to be backed up by some supporting arguments. "In order for someone to have an opinion, what is it corroborated by" (C4). Only experience cannot be used as a supporting argument to increase the forecast. "You got to give me some sort of evidence to prove that. Then I can look at statistics to balance that, to understand statistics against common sense" (C4).

5.5.3 Forecast reconciliation

There are different types of hierarchies; one incident demand hierarchy (red, amber and green), geography hierarchy (locality to health board to region to Pan Wales), governance decision-making hierarchy (the steering group running the project, executive management team: directors with chief executives, board for ambulance service, the Welsh Government). The forecasting process is similar to all categories of incident demand and all geographies. Because there is a decision-making hierarchy, the decisions might differ and eventually the forecasts.

Traditionally, the evaluation for the case stops at the five steps of the ambulance care pathway. But there is a problem with amber calls, the waits outside hospitals are "far too long" (C1). With data linking from different departments, there is a relationship seen between these amber call patients and the rate of them being discharged from the hospital, and this correlation is quite high.

With information sharing between different players within the health system, the case looked back into their own process of five steps, especially the 'give me treatment' step. This led to actions being taken to train paramedics to be allowed to give the treatment that provide less conveyance to hospitals. This is being done using demand information to how the paramedics are being trained. And this is something that the team wants to look at in the future to shift left on this 5-step process (Figure 5-13) and improve the process. This can be looked as a series of inter-locking steps rather than individual ones.

C1 says everyone needs to start thinking of the value generated in the entire system and not just one department. They give the example of "… the cost of not conveying [any information to the hospital] is X… the value or cost if the person is in hospital, so the system cost. So, you start thinking about the whole system values and cost, not just your bit" (C1).

Internal collaborations

The case team needs to collaborate with healthcare professionals (doctors, clinics) to manage the demand. If the doctors give too many of not-so-serious calls to the ambulance service, the team can focus on attending the serious calls. C4 says "some doctors are very stubborn and will give you the patients no matter what. Others will be very sensible and not send so many into you or into the hospital if they know we are really busy." So, understanding the demand really helps the decision-making process.

By collaborating with a senior clinician, the team changed the operating style of paramedics. They introduced a program for advanced paramedics who train for five years and can treat people in their own homes. This way the paramedics spend more time working with patients rather than just conveying them to hospitals. “The demand that you reduce here on the holistic picture of demand there is huge” (C4).

“One of the massive investments that we have met is making sure that we train the right people to work at the right time of day in the right places to support [the] other people” (C4). Rescheduling roster timings for community first responders’ volunteers help increase their productivity from 74 calls (2015) to 820 calls (2016); same number of volunteers in both years. For example, moving volunteering shifts from Friday evening (there are already a lot of ambulances scheduled for that time) to Monday morning (busiest time).

“Demand projections are part of a bigger puzzle” (C3). There are many other things going on and there are representatives from different parts from medical leaders to union leaders. “It is not just trying to satisfy a number of customers. There are many different facets to the quality of an ambulance service that is provided” (C3). “I would say it is important to engage with people from different levels, but you do have to be careful about anecdotal evidence. Similarly, you don’t want to just rely on data, the data can mislead you. The anecdotal evidence can mislead you as well” (C2).

The consultants talk to the steering project group comprising operations leaders and managers from the client. The project team in case C also included medical directors to make sure the recommendations are safe from medical perspective, and union leaders who wanted to make sure any changes made to shift timings would be agreeable to the workforce. This is the same group that is looped into the feedback mechanism where the consultancy project team explains their process and results.

Case C have bought a software from another consultancy XYZ to do the ambulance forecasting. This requires information from different teams like the operations, ambulance responses, clinical contact centres and even the clinicians. Hence, “you must put a team around that and it is not purely [a] statistician that is forecasting and a statistician that is modelling. So, you are bringing that potential judgment and feel from the people that is actually out there doing it. I am conscious of that but we don’t do that at the moment” (C1). “I would not want to facilitate this work without people who are steeped in field operations…” (C1).

The operations team, here, work with adverse conditions sometimes not reaching patients on time to conveying cancer patients to hospitals. After talking to the team about how they were feeling about such situations and if they know any way round it, the idea of using bus lanes by ambulances was suggested. The council allowed only blue siren ambulances to use the bus lanes. With strategic meetings with the leaders of local authority, C4 negotiated to be allowed to use the bus lanes all the time. This way the ambulance service saved a lot of time and could fulfil most of their demand.

C4 says “I steered the ship but didn’t row the boat.” Hence, taking inputs from the ground staff is highly appreciated in this case. “Who gets the glory, they do. They feel better. They think of more ideas because they got kudos. So, is it about the staff? Yeah it is, they have seen things on the front line and it is vital that you listen to them and understand” (C4). One can always listen to them and allow them the exposure to understand their options. But there needs to be back-up on how the suggested option will work.

“No, I do not have the final say, I am more of a… consciousness adviser… could I have the final say, yes because of my level in the organisation but I tend not to. If someone can convince me that their method is worth trying, I would must prefer to let them try it and learn by mistakes and then go to other methods. Then just stream roll them in to what I say… But I am not autocratic, if they want to try something and they are really passionate about doing it…” (C4).

External collaborations

There is a collaborative initiative called the Tri-Service Intelligence Hub created by C4 between Fire & Rescue, Police and Ambulance. Finding areas of communality between the teams so one team can attend it rather than all the three teams going for it. Like 80% of fires are deliberate and 50% of those are related to mental health. By addressing such a point together will reduce calls for both teams and work better for the community.

For Rugby international games, the demands for the fire, police and ambulance spikes. This helps to understand “where we are best use to each other but best use to ourselves as well” (C4). With information sharing, the ambulance team is able to help Police and Fire especially during days like Halloween, Bonfire's night and New Years' Day, when the demand for ambulance is relatively low.

One interesting thing C4 shares is how Tesco's sickness level is one of the lowest with only 2-3%. When C4 asked Tesco how they achieved it, the answer was by treating people fairly and making sure there is a de-brief process in place when someone comes back. "What could we learn from others, not only ambulance services, health boards, but also the likes of John Lewis... you know other industries as far as where they have reduced sickness or contributed towards performance." (C4).

5.5.4 Cognitive map

From the above discussion, the following cognitive map is designed for case C (Figure 5-15). The initial forecasting is carried out by the consultancy ABC who considers historical incident demand data with population growth. And this is based on different age cohorts, health boards and demand types. Following this there are different judgmental inputs that come in from different players in the planning team. This step has pressure from the upper hierarchy with a number of players in the public sector. But also, these adjustments come as suggestion from the ground staff who are on the field. There are different types of collaborations both externally and internally to address the root causes of demand spikes.

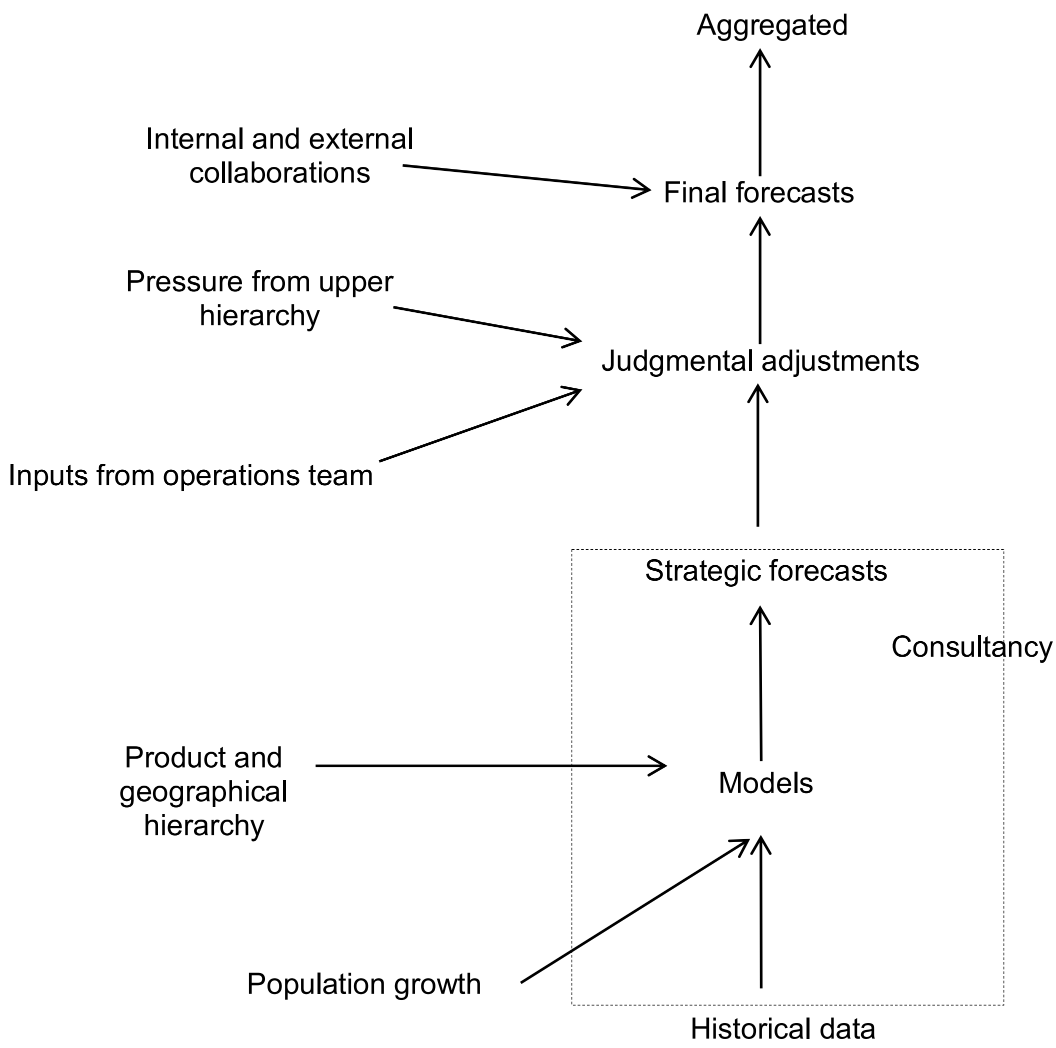

Figure 5-15: Cognitive map for case C

5.6 Case D

This case is an online retail company, being one of the world's largest online supermarkets. They have more than 300K products from different suppliers and serves about a quarter of a million customers across the UK. The forecasting is done for each item (SKU) every day for every location (warehouse) and forecast for the next 100 days on a daily basis. For one location, the company has 30K plus items, with a total of 30K*100 forecasts.

The demand planning team for this company is considered as case D for this study. Figure 5-16 shows the organisational chart for this team and its hierarchy. There are senior demand managers on top of these demand managers, who report to an operational manager who comes directly under the head of supply chain.

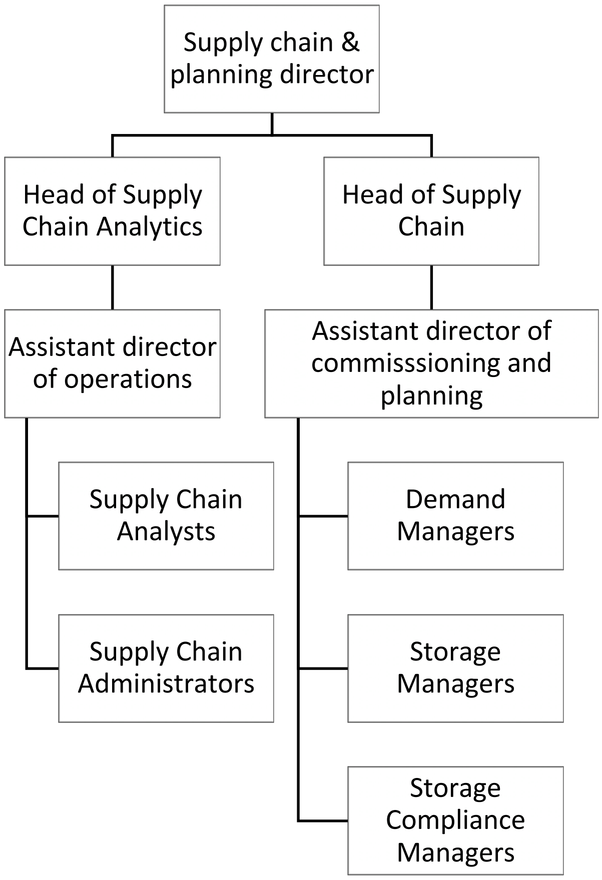

Figure 5-16: Organisational chart for case D company

For this case, three interviews have been conducted with a company visit. The interviews are with managers from (a) different teams and (b) different levels within the organisational hierarchy. Interviewee D1 is the head of supply chain analytics. Interviewee D2 is the demand manager responsible for Dairy and Tins supply forecasting. Interviewee D3 is a senior data scientist from the data science team.

The unique characteristic of this case is its Available-To-Promise (ATP) business function. ATP means based on available resources; the company is able to provide answers to customer orders. The company sells 80% of what they order before it is delivered to the warehouse. Whatever is ordered today to the supplier as a result of forecast decisions, was what the customers already had on their baskets two days ago.

This is the difference with other supermarkets, the service is provided in a different way: the company allows the customer to purchase a product (say milk) even before it is delivered by the supplier to the warehouse. This requires their forecasting to be even more accurate and time-constrained.

5.6.1 Forecasting process

The sales demand of products is forecasted in a “completely” (D1) systematic manner using a combination of different forecasting algorithms or techniques. These forecasting engines predict the demand skewed by each location and each day for the next 100 days. There are about 20 of such engines, some of them very simple (like using average forecast for the last few weeks) through to very complex (machine learning, neural network driven) algorithms.

These algorithms consider internal factors like past sales data, past promotional data, other product sales data in similar categories. The data science team is currently working on including other external factors like weather into the neural network forecasting algorithms. These are hosted both in premises-based Oracle databases, and also in the Cloud storage from Amazon and Google.

There are regression-based algorithms which are used for forecasting. Plus, data from previous seasonal events, example cited by D1 is how to forecast for Christmas season they use previous Christmas data from the past years. These are called “traditional” (D1) seasonality, including Christmas, Easter and Halloween. But there is also something referred to as “Monthly seasonality” (D1), the day after pay-day customers behave differently to a week before pay-day. Additionally, there is weekly seasonality, changes in certain products throughout the week. A good example (cited by D1) is that of whole roast chicken. It is sold a lot more on the build-up to the weekend, rather than a Tuesday. As it can be seen, some products are heavily weighted on seasonality while others less so.

The algorithms forecast for all products, then the best one is chosen by demand managers to make decisions on replenishment. The decision is made on how the algorithm performed in the past. The algorithms are within a software package Olive (pseudo name) that does all the needed forecasting for the team (D2). The demand managers do overwrite things when they see seasonality and other soft information not covered by the statistical software (D2). D2 said they are not sure about how Olive runs in the background, and the data science team will know about it. The demand managers only know what is shown on the display screen of the software.

There are inputs from the promotional team that has information on the different marketing and promotions approved by the buyers and sellers. The statistical software is seen as good for day-to-day running but not for special day occasions. D2 cited the example of Pancake day sales which is not recognised by the software as a special event and the managers need to amend the forecasts for that day.

This case company has a different element to its forecasting process. Every item has something called the order penetration number. To explain this concept, D1 gives the example of strawberries. If the sales for strawberries yesterday was 100, using Naïve method the next forecast for it should be 100. But this is not how the forecast is calculated. They compare the sales of strawberries to the total number of orders yesterday. Say out of 1000 orders, 100 had strawberries: 10% of the orders included strawberries. This is the order penetration number for strawberries. So, the system will generate the next forecast as the 10% number. Separately in the business, the team forecasts how many orders are to be delivered tomorrow. If that number is 2000 orders, the forecast for strawberries will be 200 (10% of 2000 orders). This is how the order penetration number is inherently important for their forecasting process.

The team forecasts both the order penetration number and the number of deliveries (orders) per location. The product of these two numbers gives the forecasts for each SKU per location per day. The first number comes from the software, adjusted by demand managers. And the second number comes from the upper hierarchy (business team) who makes decisions on it. The process of forecasting this number is explained in the next section 5.6.2 as there is much more human judgment involved.

The data science team (along with a team of software developers) does the forecasting (produce forecasts on a daily basis). And the demand planning team looks at these generated forecasts and make judgmental calls on whether to adjust them or not. The data science team is responsible for the algorithms (models) that the developers embed into a software. D3 gives more information on this technical aspect of forecasting.

There are two sides to the software: firstly, Olive was built about 10 years ago; and secondly, New Demand forecasting which is an upgraded technological branch. Olive has its own forecasting engine using old technologies, like linear regression. New Demand forecasting uses a lot of newer technologies, with different libraries in machine learning such as neural networks. The idea behind the two sides is to have different models performing under various possibilities to generate different levels of forecast accuracies.

5.6.2 Judgmental forecasting

This case uses the 'exception' method to include managerial judgment. Vast majority of the replenishment and ordering decisions come from the system forecasting software. Managers overwrite very little of these forecasts generated by the system, because "we believe our system generates accurate forecasts inherently" (D1).

To forecast the number of orders per day per location, the business team takes into consideration a number of soft information factors like weather, capacity of the business to deliver, and customs. The system does some part of this order forecasting, but it is more judgmental. Because the system might think the business will grow and can deliver every week every month every year. "The system is not very intelligent to understand that our business is going to be constrained by x or y or z …" (D1). There is a hard limit on the total number of outbound orders that is allowed which is decided by upper hierarchy (OM level).

The system SKU level demand forecasts do not consider seasonality properly, like when customers go on holiday during the summer or that Christmas being very busy. This is when managerial judgment comes into play. This is the SKU level overwrite judgment by the demand planners and demand managers. And there is the business level sales forecasting (order forecasts) which is based on judgments too. The product of both these numbers gives the overall SKU level daily forecast.

The big challenge for the company is to spot forecasts that require manual intervention from the managers. There are data analysts within the planning team and also data scientists that are working to spot these systematic forecasts that they believe are inherently inaccurate. These interventions are done for two main reasons: (a) to see if managers can improve the algorithm to make it more accurate; and (b) how to change the forecast "to something that [the managers] have more confidence in" (D1).

During the company visit, D2 presented how the software front end looks like for their products. There are three colour codes for the judgmental amendments of managers: what they thought was going to happen (green), what did happen (red) and what they think will happen next (yellow). D2 agrees that the software is like a black box for them and they only make amendments to the numbers according to their judgments. D2 says they forecast daily for three weeks that are sent to the suppliers.

The demand managers overwrite the forecasts on a daily basis and they can place the order to suppliers on the same day. Unless there is known promotion well ahead of time, the demand managers will not change anything for the future except the daily forecast. D2 says Olive will not change any overwritten forecast or at least it should not change. They said “[they] never really questioned [how the software actually worked]” (D2).

The judgment calls for overwriting the forecasts are “completely on the demand managers” (D2). The demand managers have access to previous history data that they consider while making those decisions. Once these decisions of forecast amendments are made, the demand managers speak to the suppliers to check whether they can meet those numbers.

D3 says “our models at the end, they need to be judged or monitored by a KPI”. This key performance indicator (KPI) is how much is the system prediction deviating from the actual sales. The business also looks at two other KPIs while making forecasting decisions, purge and ATP. This means the forecast decisions are such that there is not too much purge in the warehouses, but also that there is enough product available for the customers. These things are taken care by the demand managers judgmentally adjusting the system generated forecasts.

“So that judgment is not really easy to store into the models” (D3). There is a certain amount of data available for the models and rest of the information is not stable enough to incorporate them into the models. There are occasional meetings when the demand managers speak to the data science team about the forecast performance. And “anecdotally” (D3) the data science team can look into the process but there is no direct way of converting the judgments into numbers to include in the model.

Another type of judgment applied is when the data science team uses their own judgments to make decisions on model choices. “The business is not so concerned which model we are using as long as the predictions are good” (D3). The team checks new models using past data and decide whether it should be included in the kit of models for demand forecasting.

5.6.3 Forecast reconciliation

There are both product hierarchies and geographical hierarchies present for this case. They have different product types and different delivery (warehouse) locations. But all forecasts are generated out at the most granular level of each SKU, per day and per location. Because of the order penetration number for every SKU, it cannot be calculated at an upper hierarchical level or category level. The sum of all the order penetration numbers will be one (the total number of SKUs sold will be the total number of orders sold).

Within the organisational structure, the demand managers look after certain different product ranges, like dairy, poultry and soft drinks. One manager in the supply chain team is responsible for one SKU across all the locations. So, each manager has the final say for their own SKU, whether they want to use the system forecast or they want to overwrite it. “They essentially own that, they are the final decision maker” (D1).

These managers sometimes “need a bit of extra information to help them make good decisions” (D1). For example, the system does not have knowledge of the media (TV adverts, bake off) or promotions attached to certain products. There are marketing and merchandise teams within the business who can help demand managers to access that information. In this way, D1 thinks “there is less bureaucracy in coming up with your final forecast.”

A lot of information comes from the promotional team as they change promotions every month. This has an impact on the forecasts and the demand managers have to collaborate with the promotional team to discuss the future. The promotions for this case are not just seasonal, it is very much dependent on the external factors (buyer-supplier). Hence, there will always be a need for human judgment to make the forecast adjustments. Since the demand managers work closely with the promotional team, there are times of conflict between them. Both these teams have to agree on what they think will be the forecasts and reach a consensus decision. As there is no overlap or cross-over on product lines between the demand managers, there is less issue between them.

“If [a product] is thrown in the bin, it is my fault; if it is out of stock, it is my fault” (D2). Although there are external factors that impact the forecast decisions. For example, one type of cheese that takes 8 weeks to produce, there is a chance of going out of stock for this product because the supplier is unable to supply it. “That is not my fault. I will still get judged on that, it will go into my numbers. But I have to explain that” (D2).

When any product goes out of stock, the information goes higher up the hierarchy and the demand managers have to answer their decisions behind the forecasts for that product. This is something beyond control for the managers, but it is part of their role to manage the suppliers. With proper information sharing and time management, out of stock situations can be handled better. And this reflects on the customer service level of the case organisation.

The “collaborative forecast where different people with different opinions all come in together to form a consensus forecast” (D1) happens at the higher-level of business team forecasts. This process has different teams and managers involved with all having an input on the decisions made. Some of the people involved are the warehouse capacity team, delivery (drivers and vans) team, marketing team, merchandise team, customer insight team (to see if customers are shopping as the business had predicted or not) and the sales team. This decision-making process drives the absolute number of order penetrations which feed into the final forecasts of every SKU.

Because of many different stakeholders, the decision-making process provides challenges to reach consensus amongst them. The hierarchy and structure of the organisation along with the ownership of each position play a big role here. And the formalisation of this process is seen as a big challenge especially with the strict time frame. Because of the reactive environment, “these [forecast] decisions need to be made promptly and quickly and efficiently” (D1).

The data science team and the demand manager team have very few contacts between them. The data science team do not seem to care about the changes made by the demand managers. They compare their accuracy with their own numbers generated by the system model and not what is the final output of the forecasting process. D3 does not think that will happen in the future because even though the demand managers make necessary changes to few forecasted values, incorporating these into the models will prove detrimental to the model's accuracy. D3 agrees that it will be good if demand managers knew what the models are taking into account while forecasting as seasonality is already covered by these models. D3 says they "would like to do sharing of information". Also "for [the data science team] it will be beneficial to know how [demand managers] are using our predictions in more details" (D3).

D1 agrees that collaborations between the different teams (vertical) is important for their business. They also talk about horizontal collaborations with suppliers that drive the demand forecasting process. There are areas where there is conflict of work culture between the different hierarchical levels and teams. But one cannot simply tell the demand managers that they are not needed any more as the models are good enough, this could affect the social value within the teams. As an upper level manager, D1 agrees there is scope for more collaborations across the different teams.

5.6.4 Cognitive map

Based on the information provided by the interviewees, the following cognitive map (Figure 5-17) is designed for this case. There are the systematic forecasts generated by the software with the help of data science team. These forecasts are adjusted by the demand managers, with inputs from the promotional team, to provide the SKU level penetration number. Then there are the business level forecasts for order number decided by the upper hierarchy. These multiplied by the order penetration number with total number of orders give the SKU level daily forecasts. This forecast information is then sent to supplier portals for further decisions on orders and replenishments.

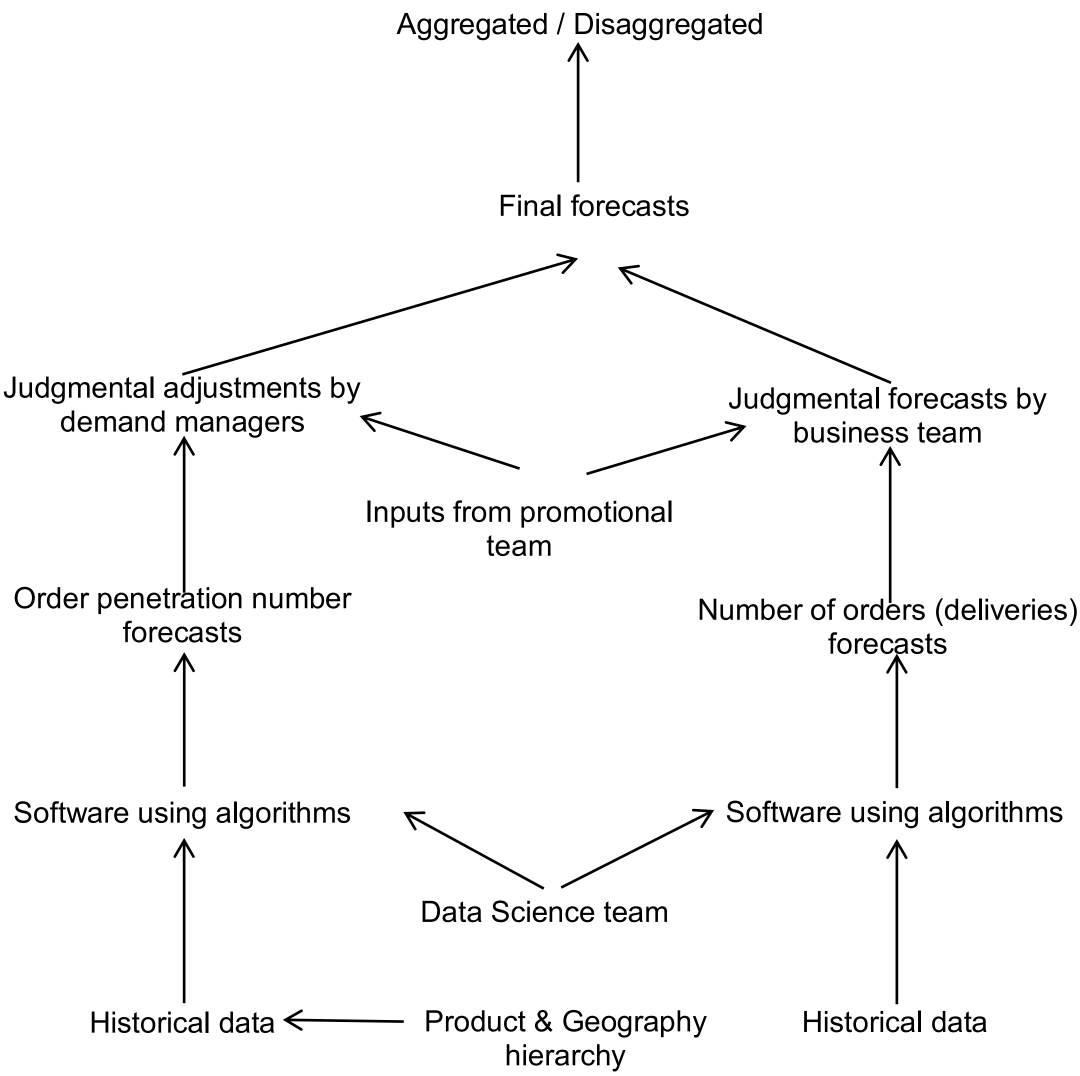

Figure 5-17: Cognitive map for case D

5.7 Case E

The fifth company is a global manufacturing company with presence in more than 100 countries. They provide sales of commercial vehicles, their parts and products; along with services to their customers. They have different parts based on frequency: sold at higher versus lower frequency. But also, parts of different values: parts of £1 and parts of £30,000 per unit. Figure 5-18 shows the geographical spread of the different dealers (standard) and Vehicle Maintenance Units (VMUs) for specific customers across the UK.

Figure 5-18: Geographical distribution for case E

For this study, the spare part forecasting team for their manufacturing parts is considered as case E. Since their forecasting team is constantly collaborating with their retailers (dealers), one of their biggest European dealers is also included within this case. Two interviews and a company visit are conducted to gather information at the first phase for this case. Interviewee E1 is area manager parts (sales) within the UK. There are two managers in the forecasting team who look at the same set of data. They report to a general manager of parts (operations) who then reports to a Service Director.

This case is different from the rest as it includes an interview with a regional general parts manager (E2) from the Cardiff dealer. Figure 5-19 shows the organisation hierarchy for this case. This further shows the importance of collaboration between different teams in a company; and sometimes these can be different players in the supply chain.

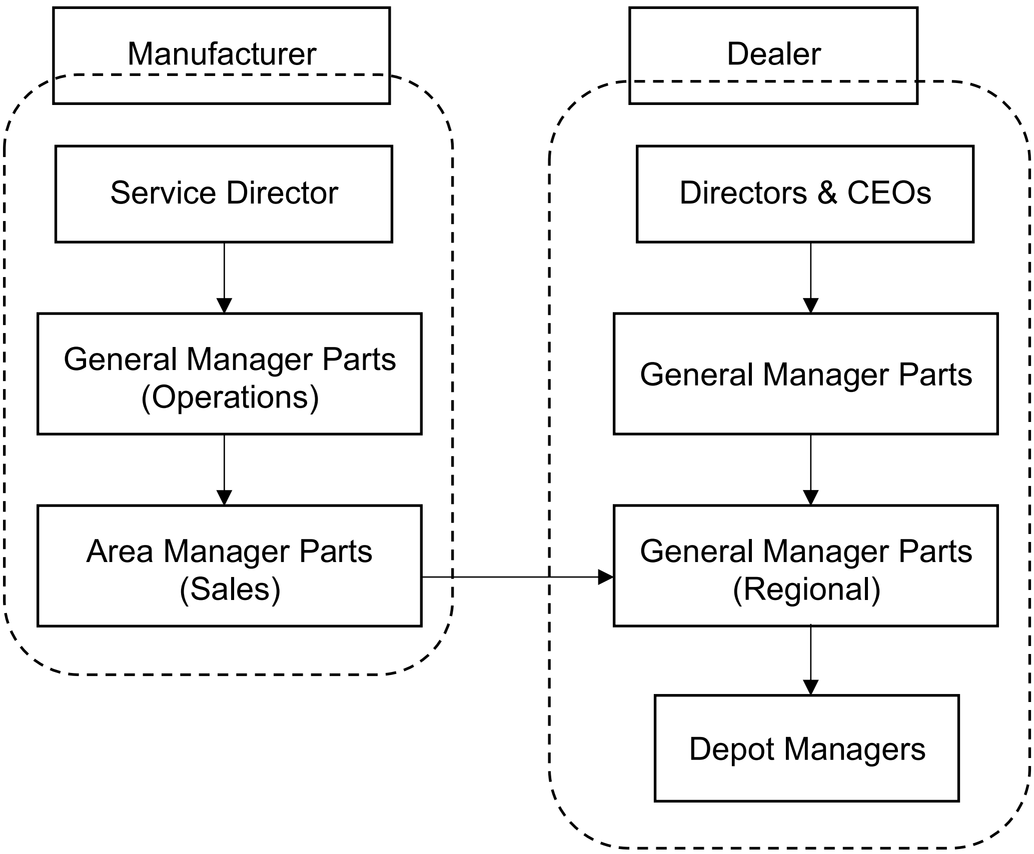

Figure 5-19: Organisational chart for case E company

As this dealership is not owned by the manufacturer directly, they have their own forecasting system in place. The dealers that are directly under the manufacturer have to follow the system forecasts, resulting in obsolete stock with a huge amount of money tied up with that.

During the company visit, the forecasting software system is presented and how it operates from the dealer's end. Also, emails sharing information from depot managers to the forecasting team are shown. These emails say what items they have sold and also what items cannot be stored because of capacity issues. This process helps to build trust amongst the different team members. Because of time pressure, sometimes the forecasting team do not have time to go through the stock of each and every item (SKU). Then they can rely on the depot managers' inputs and place the orders.

From the dealership end, there are directors and CEO of the organisation that get the daily reports on forecasts. But the higher authority people do not get involved unless something unusual is seen at the financial stock market side. The upper hierarchical level tends to have a "helicopter view" (E2) of the organisation.

5.7.1 Forecasting process

The forecasting process is called 'after-sales' forecasting, mainly for spare parts for the vehicles (like batteries, light bulbs). There are two main methods to do the forecasting for this case: exponential smoothing method and moving average method. These methods are the same as defined by general forecasting books (Appendix D). The entire forecasting process is statistically driven and gives rise to statistical (model) forecasts. These forecasts lead to order decisions to keep stocks available when needed, known as safety stock.

As part of the franchise agreement with the manufacturer, the dealer has to keep a certain number of parts in stock at all times. About 400 lines of parts from the manufacturer must be kept on the shelf for vehicles that break down in that area.

The forecasts are based on demand in a system that is setup by the manufacturing company. This system uses past sales history information of parts over the last few months and year. And there is a recommendation from the manufacturer to the dealers: "… if you sell a part at least 3 times a year, then you keep it in your stock …" (E2). With this dealer's organisation, the E2 says "we actually manipulate this [forecasting] system".

There are three forecasting team members within the dealership organisation. They look at the forecasts on a weekly basis monitoring the movement of all parts. They consider the ordering recommendations that have come from the main company (manufacturer). With such information, they adjust the forecast according to each geographical branch (19 branches across the network with four in Wales and rest in Midlands). They look at each part, the demand for sales, the worth of the part before making the decision to stock it. From the dealer's perspective they look at four or more movements (sales) of each part, before placing an order. With three movements (recommended from the manufacturer), it is considered to be "not a big deal" (E2) for the dealer.

They make these process adjustments because if the dealer orders a part and cannot sell it, the manufacturer may not take it back as part of the agreement. This results in that part becoming obsolete which costs a write down value. A write down value is calculated as 25% (if the item is not sold for 12-18 months), 50% (18-24 months) and 100% (for anything more than 24 months old). The part that is most concerning for the dealer is when they fail to sell any part for more than 24 months (when the write down value is 100%).

Other types of forecasting adjustments made by the dealer is for items that are sold out. For example, if both items of one part are sold then E2 will place an immediate order to can receive it within the lead time of three days. E2 says they have tried talking to the manufacturer about the differences in forecasts at both ends, but in vain. Because the manufacturer forecasts at a higher level looking at European market sales, they do not exactly know what is going on at the granular levels.

There is another leverage here in the relationship of manufacturer-dealer relationship in case of forecasting. The manufacturer offers four opportunities during a year where if the dealer had ordered any part but could not sell it, the manufacturer will take it back from them. This gives the dealer some confidence in their forecasting adjustments with the thought that if it is not sold, it will be taken back.

The forecasts for the parts are decided based on the stock movement point of view and the importance of the item. For example (cited by E2), the starter motor, the batteries, mirror glasses: even though these parts are not sold much, they have to be kept on shelf. And if these are not sold after 12 months, the manufacturer will take them off anyway.

5.7.2 Judgmental forecasting

There are different elements of human judgment that are involved throughout the forecasting process. Firstly, the physical storage size of warehouses requires adjusting the systematic forecasts (seen during the company visit). There are times when the forecasting process predicts a number of units for storage, but the physical space may not be available. An example cited by E1 is truck tires, they can be huge in size for big trucks. "… if they forecast 50, then you have nowhere to put it and you cannot keep so many ..." (E1).

Secondly, there is a seasonality effect that involves human interventions into the statistical forecasting process. For example, forecast of batteries needs to be adjusted during winter as their consumption differs from the rest of the year. Thirdly, package size also determines the forecasting adjustment process. Even though forecasting is done at each SKU level individually, one particular item cannot be ordered just by itself but has to be ordered in packs. This is because the supplier(s) will send the order in packs and not by individual units.

The human (managerial) judgment is incorporated into the forecasting process based on experience and sometimes recommendations. As E1 quotes, "… basically there are no rules and it is based on experience only…". On a weekly basis, the manager scans through the stocks and look for units that needs adjustment. They do not look for every individual unit but the most expensive ones amongst those orders. Hence, this is also based on the value of the parts.

E2 talks within their depot site, they look after 6 branches (depots). They say it is difficult to keep track of each part sold on a daily basis. So, when the manufacturer's recommendations (forecasts) arrive, they go back to the depots for "local knowledge" (E2) on which parts need to be ordered and what changes are required. Also, the forecasting team visits each depot to talk about the orders and forecasts, this way the value created within the organisation is maintained. The physical presence of the general managers helps to build the team culture between the different teams.

An example cited by E2 on why depot level information is necessary is that of a part sold 18 times in a year, based on which the forecasts are generated. But the local depot knows that it was a one-time order for a customer and actually it is not sold as frequently. Using such information sharing methods from depots, the forecast team at dealer level adjusts the forecasts accordingly. It is shown how in the online (software) system for one part that was sold only once in last year, the system still forecasts to stock four such parts in one location. E2 highlights this is the problem with the system forecasts and why the manufacturer system does not work well with their dealer system.

One clear example how the forecasting statistical system fails is noted during safety campaigns. Since all vehicles within that campaign request for that part change, it is recorded as sales by the statistical software. And this then impacts the next forecasts as the system does not know that this was part of a safety campaign. This kind of information is spotted by human interventions and then, necessary adjustments are taken to not order that part next time. Also, the system only sees the sales data and forecasts for every item that is showing past sales figures. But the software does not know what type of part it is, what type of space is needed to store it, and if there is storage available to do so.

E2 says their past experience of working in different industries before joining the present organisation, helps in making those judgment calls on the forecasts. Depending on the importance of a particular part, either it is kept in stock or it can be ordered from some other location to be delivered the next day. This is something that the forecast software does not take into consideration while running the statistical method, hence human intervention is important in this case.

5.7.3 Forecast reconciliation

In the auto industry, there are many brands that have different product hierarchies based on different generations of spare parts. But in the case of this company, such hierarchies are not seen as they follow a “common module built” (E1). So, the same parts are used in vehicles from at least three different generations and the life cycle of one generation is about 5-7 years.

From a geographical perspective, there are different branches in the UK that carry out their own forecasting processes. This is because the different locations have different service requirements at their depots and hence their forecasting process is catered accordingly. But this is at a dealer level where each dealer has a different franchisee statement with the case company.

There is also a distributor warehouse which is the aggregate of all 90 branches within the UK. Each country distributor sends their forecast numbers to the global warehouse which aggregates them to get the global forecast numbers. Hence, the forecast reconciliation process follows a bottom-up approach, where forecasting is carried out at the lowest geographical level of depot locations. And it has to follow this approach because “… the forecast is demand driven ...” (E1).

“The higher the hierarchy, the least they depend on experience” (E1). This is because the forecast is driven by the demand stated by the dealer. And the upper hierarchy do not have much say in the forecast reconciliation process. They do make some changes on seasonality but not much as higher the level, the managers do not see the granular information. Each individual branch makes their forecasts independently and then aggregates them at regional level. And a similar process is followed for the rest of the upper hierarchies.

When asked about this hierarchical process, E1 says “oh, this is very complicated”. To make them aggregate consistently across geographies, the demand is divided based on two criteria: (a) based on frequency; and (b) based on goods value. For higher frequency, there is higher safety stock. For lower frequency, there is less safety stock, risking not having it. For high value and low frequency, they will definitely not stock it. For low value and low frequency, they might have it.

For the different categories based on value and frequency, the team forecasts for each category and decide on how to adjust forecasts for each of them. There is a volume planning department that reviews these forecasts that come at factory level. The factory level teams also forecast for the distributor levels.

For the dealer, there is a hierarchy based on depot locations with 19 branches in total. And the same forecasting process is used for all the branches. The three members of the dealer’s forecasting team covers 6-7 branches each. Each one of them work different days in the week so they can keep track of the ordering system. There is a general manager on the top of these three forecasting managers who looks after all the parts in all the branches.

The managers rely on the guys on the “ground floor” (E2) as these people know what parts are being sold, number of vehicles in that area, what stocking area (warehouse size) is available. However, the forecasting manager (E2) has the final call to say what to order for each depot. This is needed in order for the forecasting team to keep a track of orders from depot supervisors to avoid over-ordering.

5.7.4 Cognitive map

From the above discussion, the cognitive map for this case E has been designed as below (Figure 5-20). The forecasts are produced by a company software using statistical methods. These are further adjusted by the forecasting team to adjust for seasonality and other information. When this data reaches the dealers, they use their own judgment to adjust the forecasts to fit their own business. These adjustments are impacted by the product hierarchy (value and importance of the part) and also the franchise agreement between the manufacturer and dealer.

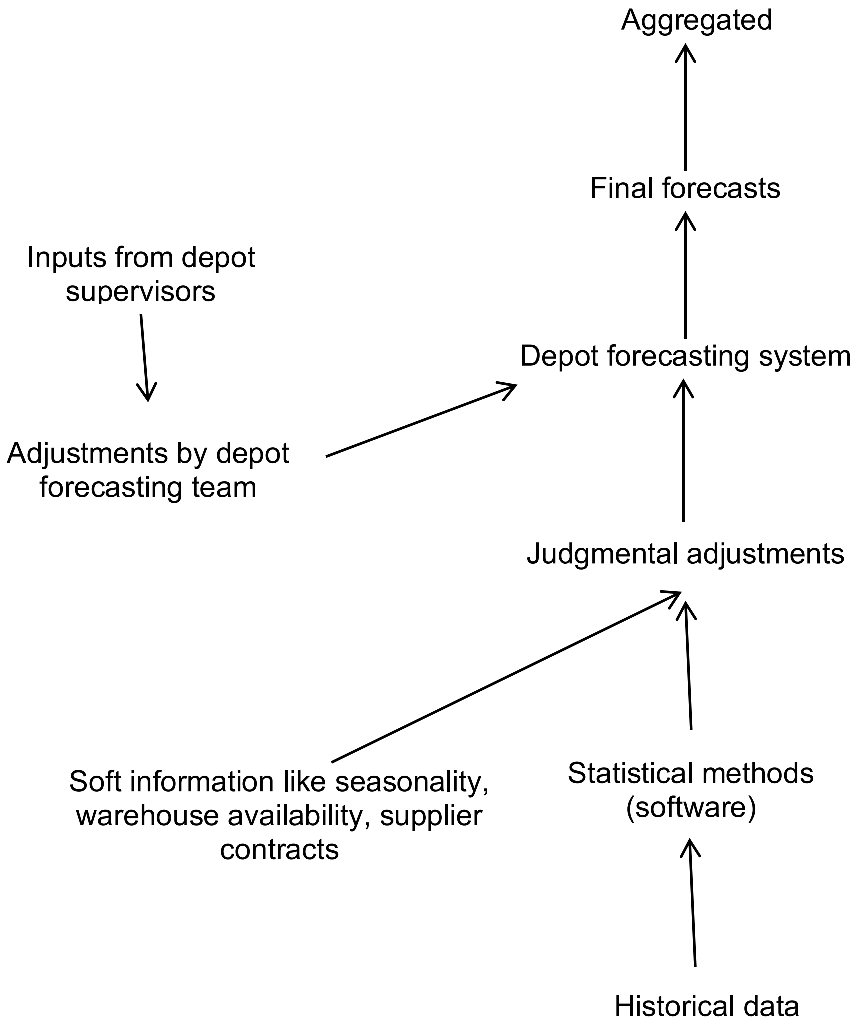

Figure 5-20: Cognitive map for case E

5.8 Case F

Case F is a private utility company providing water services in the South of England. It is one of the nine water companies in that region. Their operations cover a wide area of more than 10K square kilometres. Case F is the demand forecasting and planning unit within this water company.

Two interviews were conducted with this case, one with the technical director (F1) and the other with the demand strategy manager (F2). For this case F, the strategic demand planning team including the forecasting team members is considered. Below is the organisational chart for the case F in Figure 5-21.

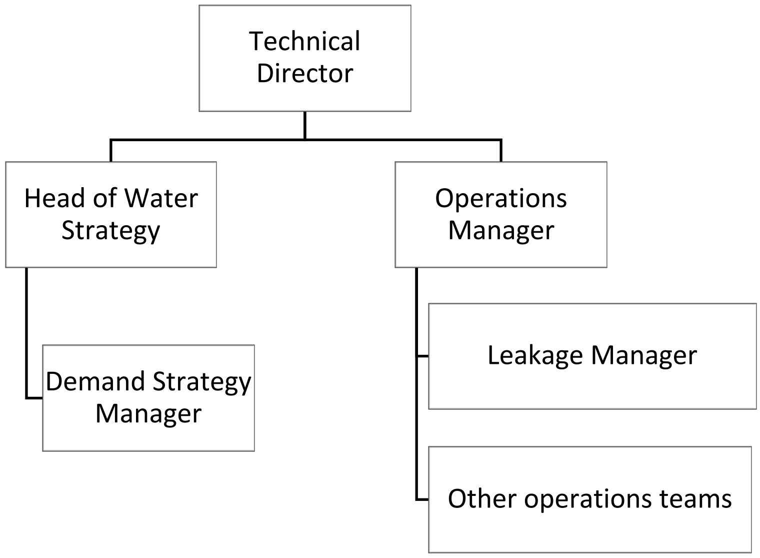

Figure 5-21: Organisational chart for case F company

Unlike other businesses who can decide on their product prices depending on the customer market, water companies cannot do so and are not allowed to do so. As water is a basic necessity for living, the water industry is regulated by a number of agencies. There are different UK and European legislations in place to govern the running of this company.

The Water Service Regulating Authority (Ofwat) in England and Wales looks into the investment and revenue forecasts, regulating the economic side of the water industry. They explore how much it costs to run a water company, how much investments are required for the next five years and then suggests to the water company on how “much you can charge for your water” (F1). Plus, there is the Environment Agency (EA), which regulates the interaction of the water industry with the environment. And the Drinking Water Inspectorate (DWI) regulates the public health aspect of the industry, i.e., the quality of water being supplied.

The other aspect of this industry that no other utility company has is the "statutory duty to supply" (F1), which means no customer in their region can be denied from water. Other utilities like power, gas, telecom companies do not have this statutory duty supply. They do have to supply and meet the demand, but they are not bound to do so. If things go wrong then these utility companies have a way out, unlike the water industry. Because of this and the number of different regulators, a considerable amount of time is spent on the forecasting process. The different regulators along with various teams within the company have to agree on the forecasts. This puts additional pressure on the demand teams, who have to make sure that the forecasts are correct.

5.8.1 Forecasting process

This case team generates two types of forecasts depending on the time-frame (Figure 5-22): *operational* (productions) and *strategic* forecasts. The operations team forecasts for the next week ahead according to climatic factors, what the current demand levels are, the time of the year (demands are expected to go up during summer), and other elements like number of dry days. This does not involve too many teams within the company, it is just the operational side who calculates the forecasts. However, this operational forecasting process is quite critical as it works in Just-In-Time (JIT) delivery system. The accuracy of the forecast depends on how much water is in store. This again makes this company distinct from the other cases in this study.

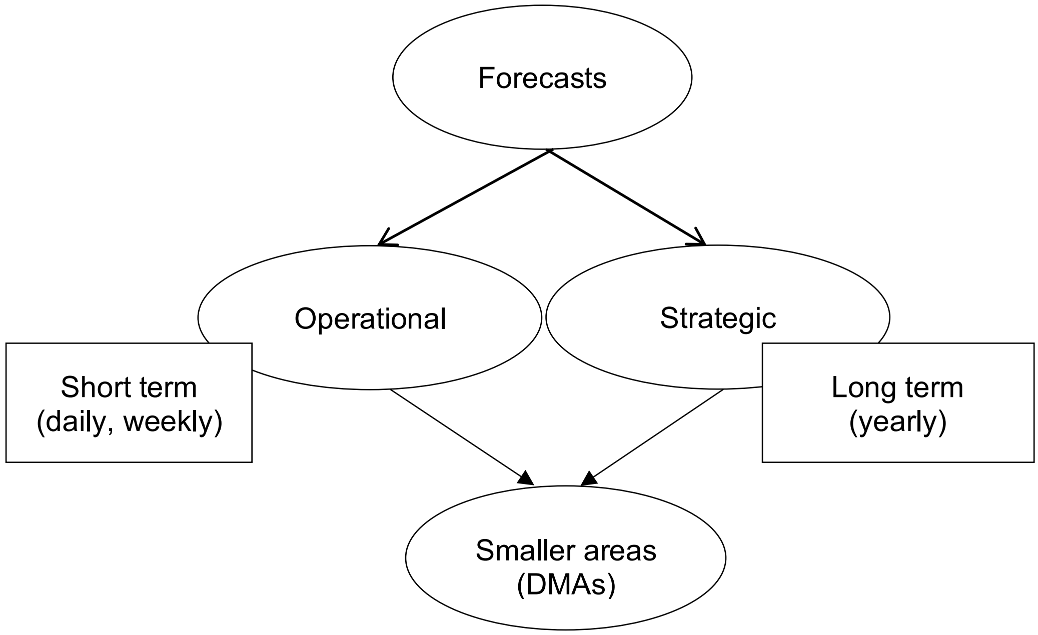

Figure 5-22: Case F hierarchy based on time-frame

The strategic side of forecasting has a “more wider” (F1) role within the company as it is long-term planning. This type of forecasting works around population growth, housing growth, climate change impacts, and present customer demand, to predict how much the current demand will increase in the future. This is also impacted by soft information coming from different company policies (universal metering, water efficiency campaigns, rate targeted within the region). With that forecast information, the company builds strategies how to deal with the demand over the next few years.

For strategy forecasting of households’ demand, micro-component analysis is applied. The demand is broken down into sub-components like clothes washing, personal washing, toilet flushing, etc. The consumption associated with each of these components is estimated. This is added up using bottom-up approach to get PCC (per capita consumption). This is done on yearly basis and for each year there is a new PCC that goes forward.

An external company is hired to provide population growth forecasts for the entire region, which consult 6 other water companies within that region. This is usually based on the ONS forecasts. The other job for this external company is to liaise with all local authorities to check for housing building projects. F1 quotes "this is where some of the difference start to build up". The reason behind the difference in numbers is: the housing growth forecast provided by the local authorities is for another 5, 10 or 15 years. There is already a myriad of different time lengths of forecasts going forward. In addition to that, there is also another government aspiration target on number of houses being built in this region for the near future. And that target deviates from the local authority (LA) plans, as some of the government plans usually require constant updating.

Plus, there is an annual revenue correction factor given by Ofwat, when companies are over or under forecasting. The revenue is huge, about 100 million £s for the water industry, and even if the forecast is fairly accurate with the difference being in decimals, it still creates a huge impact of 20-30 million £s. Hence this correction factor helps to take away some risk from the company. This factor is used in the following way:

(i) If the actual < forecast, the company have collected more than expected, customers can pay less the following year.

(ii) If the actual > forecast, the company can charge more to the customers next year to compensate for the loss.

5.8.2 Judgmental forecasting

In the bigger picture of forecasting for this case, there are a number of areas when expert opinions are required. One major area is deciding on the housing growth forecast number in the decision-making process. As mentioned earlier, there is a government housing growth aspiration target, and a trend based (typically) lower forecast from the external company for the same housing factor. This is when the expertise and judgment are involved and incorporated into the forecasting process.

The experts in this field, people with experience or agile analytics, give a sense of (a) the most likely forecast and (b) most importantly, understanding the uncertainty in the forecast. Including expert judgment in forecasting "… is where the industry has shifted to in the last 10 years…" (F1). These experts also help to finalise the long-term strategic forecasts, incorporating the revenue correction factor from Ofwat. Then these experts have meetings with the finance team about the forecasts and the rationale behind them. "So, they can both agree on what will be the final set of forecasts going into business plan submissions" (F1).

The forecasting is based on some assumptions like replacement rate of devices such as washing machines, dish washers, behaviour change, and climate change. For these assumptions, "… there is a bit of judgment involved but it is evidence based…" (F2). For example, customer surveys would show how old the machines in the service area are and then this will impact the forecast. Hence, there is subjectivity in the assumptions, and it is backed up by evidence.

There is a considerable amount of time pressure during this entire process of forecasting using expert knowledge. The “real” (F1) time pressure is faced mostly by the planning team who is in the forefront, generating the forecasts and “socialising” (F1) with other teams. Because the deadline is upon this team, other teams do not seem to pay much attention. And quite often, this aspect “catalyses” (F1) the decision-making process for business planning.

There is also the regulatory and government culture, where the agencies dictate the water company to plan according to their housing aspiration target (which can be very different from what is actually happening). This is “…regardless of whether authorities are building houses at a slower rate or a higher rate, they are still saying…” (F1) the company should focus on the government target. F1 says this builds tension within the teams because if the houses are being built at a different rate then it has an impact on the infrastructure and eventually, their water demand.

5.8.3 Forecast reconciliation

Case F has a single product, water, and they only supply one quality of water. In terms of geography, their entire network is segregated for better forecasting. Their area within the UK is divided into three regions of water supply: eastern, western and central. This is further divided into 14 water resources zones (WRZ). A WRZ is defined as an area where the risk of failure is uniform across the patch. This means properties within this area have the same requirement of water. Figure 5-23 shows this geographical hierarchy of case F.

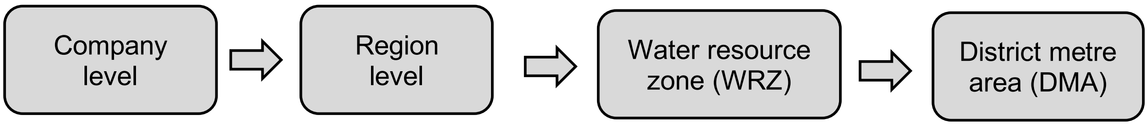

Figure 5-23: Case F hierarchy based on geographical divide

Strategic forecasting is done at the WRZ level and the forecasting method used is the same for each WRZ. A bottom-up approach is used to aggregate upwards. There is another component of the WRZ: district meter areas (DMAs). It has over 960 small DMAs, which has approximately 1000 properties per DMA. This helps to measure how much water goes into each DMA to be used on a daily basis, and hence feeding directly into the operational forecasts. This information, then, goes into deciding how much water is to be pumped and stored in the reservoirs. This generates the daily *water balance* for the operational team.

The operational and strategic teams overlap over this concept of *water balance*. The operational team uses this information to make sure there is no leakage, and that right amount of water is being stored to be delivered. Whereas, the strategic planners take the water balance information and make sure their long-term forecasts are within the acceptable range, adjusting for climate changes (like dry summer). With an exchange of emails, the two teams: strategy and operational discuss the volumes, which is included in the total demand forecast. And F2 says, "… it is a fairly collaborative process…"

"The data onus for each length of data are the ones who eventually make the decisions" (F2). For example, the leakage strategy manager will make decisions on the leakage forecasts. They will decide on the policies that can help reduce the leakage amount by x amount in the next y years. And the other teams would not change that number as the leakage manager is accountable for that number. Therefore, different teams make decisions and share them as inputs to the strategy forecasting manager, who then incorporates it into their total forecasts. Or vice versa, F2 can suggest that they can reduce the total demand by reducing leakage by this amount.

There are also interactions with the other water companies in the region. Depending on the operational demand of the case company and those of the neighbouring companies within the same region, this affects the amount of effluent that comes back to the sewer treatment works. These interactions between different companies are better managed with the fact of having a common independent company. This external company generates the population growth and property (housing) forecasts for the entire region. F1 says at least the companies tend to agree on these numbers, if not on rest of the forecasts.

The third-party company has expertise in generating regional and sub-regional forecasts; and a collaborative system on how to liaise with the local authorities. Hence, this information provided from the external company is incorporated into each water company’s own demand forecasting models. The ultimate prediction of volume of water required in the future is derived in the company itself. This is because, F1 believes, the expertise to generate forecasts at a company level lies within the company.

Therefore, for this case F there exists a hierarchy of teams who makes the decisions on the forecasts. When it comes to including judgmental inputs, F2 says "yes, I do make the assumptions, but I will still need to get them approved or signed off at some level". It is managers at upper hierarchy positions, like interviewee F1, who make the final decisions. The senior managers look at the forecasts and send them to the managers in the upper hierarchy. This is referred to as a "bottom-up type" (F1) forecasting approach, where one looks at all the components and make a consensus decision on it.

The upper hierarchy, then, cross-refer these forecasts with other teams, like the revenue team. There are a number of checks and challenges in place to make sure the forecasts are in the best position and not the result of individual managerial judgments. But, ultimately, it is the strategic planning team that will sign off on the forecasts and is accountable for those going forward.

5.8.4 Cognitive map

For this case, the forecasting process follows a slightly unique flow (Figure 5-24). Two types of forecasts are generated using different types of inputs: operational and strategic forecasts. Historical data along with climate forecast data is used for both these forecasts. Information from the operational forecasts also feed into the strategic forecasting process via the water balance concept.

The external team provides the population growth number along with the housing growth from local authorities. These forecasts are then judgmentally adjusted based on recommendations from the different regulators, inputs from other companies in the same region and also, government pressure. Once the strategic team finalises the forecasts, it is sent up the hierarchy to cross-check with other teams like the revenue team. These are then aggregated using a bottom-up approach.

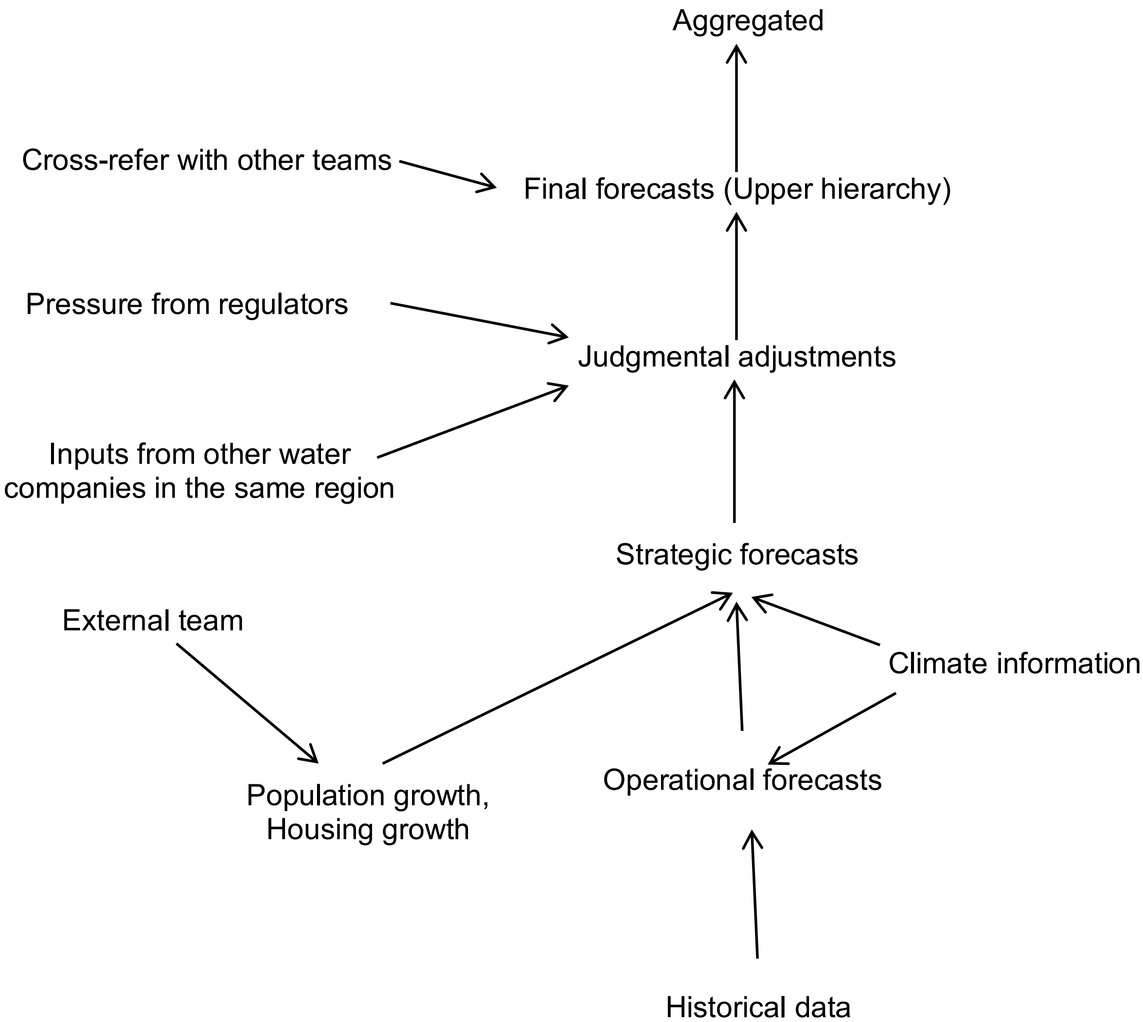

Figure 5-24: Cognitive map for case F

5.9 Other cases not included

Additional interviews were conducted with other companies during the course of this study. These companies are spread across other industries like oil and gas, electronics, logistics and defence. But because of restricted access to interviews and data, these cases are not included in this study. However, it can be seen from those very few interviews that this area of collaborative forecast is regarded as important by different managers. This area has not been explored much both in academic and professional arenas.

5.10 Comparison across cases (cognitive maps)

From the cognitive maps of the six cases, it can be seen that the overall hierarchical forecasting process follows a similar pattern. A combined process map is shown (Figure 5-25) for forecast reconciliation within different hierarchies. The first two interview questions show that the forecasting methods vary with different cases, most of the time it varies for different products and services. The other two interview questions tell us about their hierarchical forecasting. Whether these cases have hierarchies within their organisations, whether they consider hierarchical forecasting, and how they reconcile (aggregate) their forecasts for different levels. Like their forecasting methods, their forecast reconciliation methods also have a combination of both statistics and judgments.

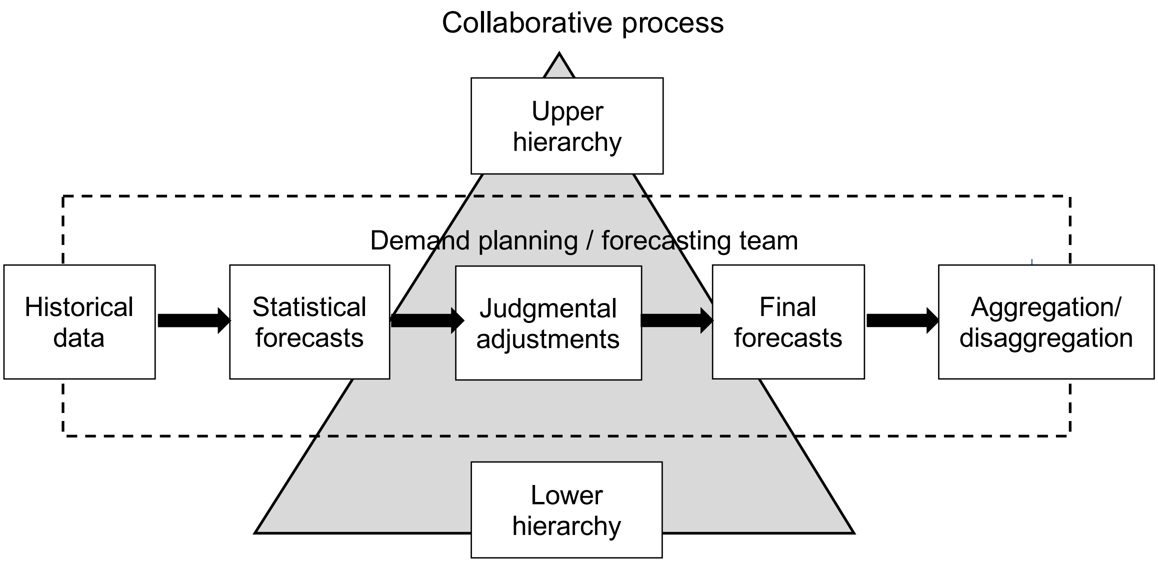

Figure 5-25: Decision-making process in hierarchical forecasting

The differences across the cases would be the forecast reconciliation methods used, which are either top-down (the base forecasts for the top level of the hierarchy are generated and then disaggregated to produce the lower level forecasts of the hierarchy) or bottom-up (forecasts are produced at the lower levels of the hierarchy and they are aggregated upwards in order to obtain upper level forecasts). And their decision-making steps within the reconciliation is a collaborative process that includes managers from different hierarchies. Like ground level maintenance staff (with first-hand experience with products and services) to top level management (with a broader umbrella view of the business). Another point of difference are the stakeholders involved in the decision-making process, like for cases C and F the regulators and government in itself. Whereas for other cases A, B, D and E, the stakeholders are mostly internal teams with directors and mangers involved for risky decisions.

5.11 Summary

A case study research method was discussed in Chapter 4 that addresses research questions on forecasting in the after-sales (service) industry. This chapter presented the case stories from the six different organisations that participated in this study. It includes their forecasting process, judgmental forecasting, forecast reconciliation, and a cognitive map representing their forecasting process.

The interview data, from the first stage of data collection, is analysed in this chapter to present the case stories. Wherever available, the organisational charts of these companies have been included. The presence of hierarchical forecasting can be seen in different organisations; either in product types or geographical locations or customer-based demand categories. The forecasting processes of the cases have been analysed using cognitive maps, which help in developing flow diagrams for each of them.

This chapter answers the first research question of this study, to explore the forecasting process in different organisations. This has been identified as a research gap in section 3.8 of Chapter 3. The case stories are thematically analysed, in next chapter of data analysis B, to identify different factors that impact the hierarchical decision-making process. These factors are categorised into different themes that are explained in the next Chapter 6. The findings from this chapter along with Chapter 6 help design the second stage of data collection: an explanatory stage with mixed method questionnaire.

Next Chapter 6 also includes a SWOT analysis of the identified themes with evidences from the case stories in this chapter. The SWOT analysis statements are used for the design of the questionnaire to collect more empirical data from the cases. The cognitive maps from this chapter, along with Figure 5-25, influence the development of a conceptual framework in the next chapter. Finally, this chapter along with the next two chapters on data analysis are discussed in Chapter 8, with the help of literature from Chapters 2 and 3, to answer the four research questions of this thesis. Finally, Figure 5-26 shows the positioning of this chapter within the entire thesis.

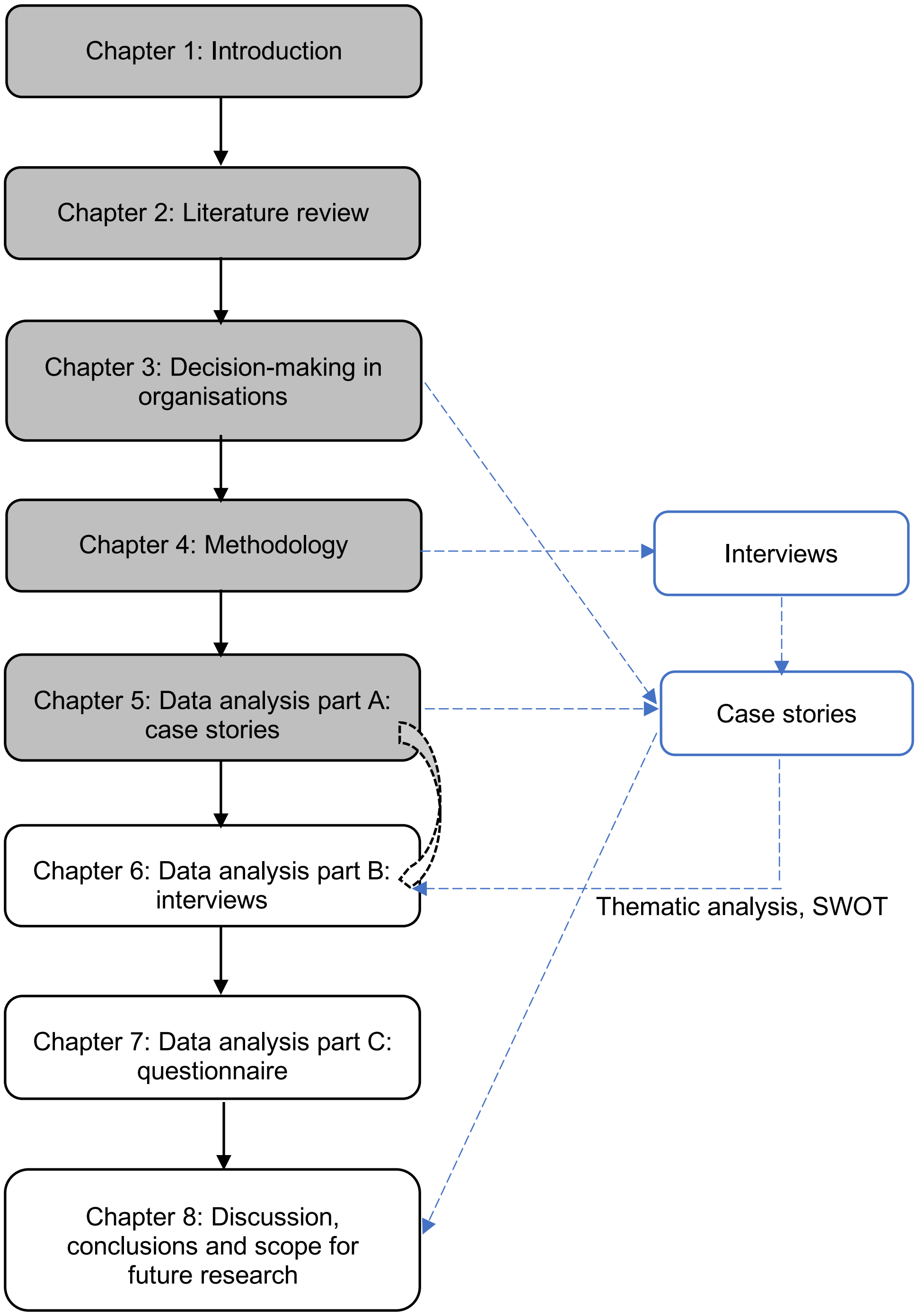

Figure 5-26: Thesis structure (Chapter 5)

Chapter 6

6 Data analysis part B: interviews

6.1 Introduction

This chapter covers the second part of data analysis methods for the first phase of data collection; the exploratory interviews. It follows from the previous chapter Data Analysis Part A with the six case stories and their respective cognitive maps. A thematic analysis of the case stories is conducted to find common and emerging categories (themes) from the case descriptions. Four themes are generated: *information sharing*, *time pressure*, *power* and *social value*. In the first section of this chapter, these four themes are illustrated with examples from the six cases.

In the second section, SWOT analysis is applied on the four themes for decision planning. SWOT analysis aids in narrowing down the themes to their main strength, weakness, opportunity and threat. Since a multi-attribute decision-making model is used for analysing the second stage of data collection, these SWOTs help in designing the instrument for it. These SWOT statements are used in the questionnaire to gather wider participation views on the four themes.

In the final section of this chapter, the cognitive maps from case stories (part A analysis) help develop a conceptual framework from the linguistic literature. This framework is suggested for collaborative decision-making process in hierarchical forecasting. The development of the framework is outlined in the third section, reflecting the themes from section 6.2. The framework along with the SWOTs for the four themes are used in proposing two theoretical propositions for this research. The chapter concludes with a short summary on the main highlights from this stage of data analysis, along with position of this chapter within the thesis structure.

6.2 Thematic analysis

Qualitative data analysis typically follows an inductive approach to research and leads to the generation of themes which are grounded in the data (Lincoln and Guba 1985). The exploratory interviews are audio-recorded with informed consent from the participants and these are later transcribed for each case study. The textual data are analysed to trace dominate themes within the forecasting processes for each case data. This part of the analysis involved differentiating and combining the retrieved data and the reflections made about this information (Miles and Huberman 1994).

The classic analysis method is followed for distinguishing the coding and themes (Krueger and Casey 2015). The interview transcripts from each case are colour coded to represent the different categories, which is often referred to as the process of coding. These codes are used to retrieve and organise the different categories depending upon their frequencies and extensiveness. This step leads to the determination of the four dominant themes associated with hierarchical forecasting in the after-sales (service) industry.

For example, let’s take one quote from case C where the associate director of operations (C4) says about innovation in the decision-making process: “Who gets the glory, they do. They feel better. They think of more ideas because they got kudos. So, is it about the staff? Yeah it is, they have seen things on the front line and it is vital that you listen to them and understand". In the coding process, four different codes are generated here: team appreciation, non-economic value generated, involvement of different players, and good workplace vibes. These different codes are then clubbed together under the broad theme of social value. This theme is the generation of value achieved by involvement of different hierarchies in the forecast and planning process.

Since the different themes can be defined in various ways, a working definition for each theme has been adopted to reduce ambiguity for both researchers and the participants. These definitions are also mentioned in the questionnaire, to ensure that participants are clear about these themes before attempting their respective sections. Information sharing is defined as the sharing of information (related to the decision-making process of demand forecasting/planning) between different teams within the company/organisation or even team members within the same team. The second theme is *the role that time pressure plays in the decision-making process of demand forecasting/ planning within organisations.*

The next theme of Power is quite broad and can take on different meanings. For this research, it is *restricted to team members' characteristics that can give rise to power struggles within the organisation.* The three characteristics considered are: forecasting work experience, domain expertise (knowledge acquired from formal education in forecasting) and authoritative position (positions within the business hierarchy). Similarly, the theme of Social Value has been defined differently by researchers in the field of Logistics. Here it is defined as *the* *measure of relative importance that people place on their experiences within the company/organisation*. This value is created within team members and also different teams in the company/organisation. This value suggests whether team members feel included and appreciated for their work within the company/organisation. Simple concepts like sharing information across teams, considering everyone's views while making decisions, etc. affect the social value of employees within the company/organisation.

Each of these themes is explored below in light of findings from the case stories in the previous Chapter 5. Like in the first theme of information sharing, example points from the transcripts where managers mentioned about sharing data, soft information, or discussed about the forecasts with team mates are used to highlight how this theme emerged from the interview data. Table 6-1 below shows the distribution of each of these themes within each case story.

Table 6-1: Distribution of themes within the six cases

Cases / ***Themes***	**Case A**	**Case B**	**Case C**	**Case D**	**Case E**	**Case F**
Information sharing	✓	✓	✓	✓	✓	✓
Time pressure	✓	✓	✓	✓	✓	✓
Power	✓	✓	✓	✓	✓	✓
Social value			✓	✓	✓	✓

6.2.1 Information sharing

The first dominant theme in the forecasting process is information sharing (Figure 6-1).

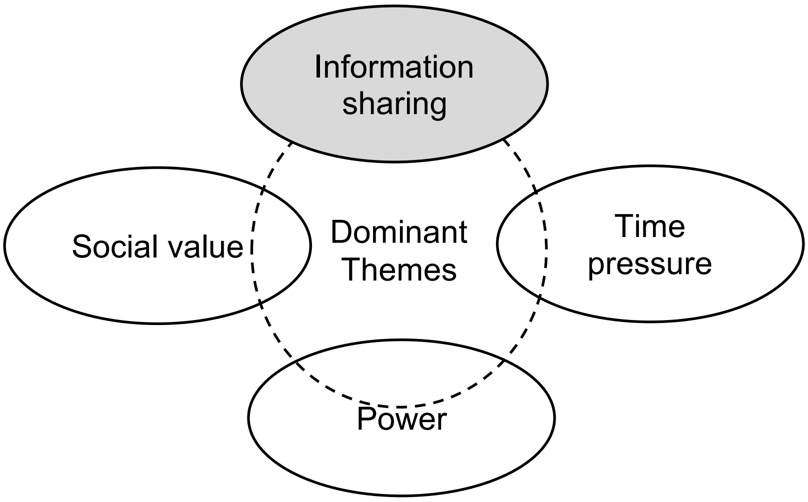

Figure 6-1: Representation of themes: Information sharing

The decision-making process in demand forecasting is not stable (consistent) which makes information sharing a critical means of reducing uncertainty in the forecasts (Ali et al. 2017). As seen from the case stories in Chapter 5, the demand forecasting processes are performed by a group of forecasters, rather than an individual person. When it comes to group decision-making, literature shown in section 3.7 suggests that information sharing has a direct positive effect on the group performances. When more information is shared, the better group decisions will be made thus improving the overall group performance (Moye and Langfred 2007).

Interviewees from all the six cases talked about how information is gathered from different teams when forecasts are produced. For all the cases, the demand forecasting managers(s) speak with teams from the same hierarchical level and from other levels to help in the decision-making process. Generally, there is a software that produces the system (or statistical) forecasts and then managerial judgment is used to incorporate soft elements that are not captured by the software models. Like in case A, forecasting managers gather information from different teams like communication providers (CPs) and operations teams (in case of *Repair* market forecasting) before adjusting the forecasts. CPs share information on their current progress and also on any future strategies.

This idea of information sharing becomes crucial when there is no historical data available for forecasting. For example, forecasting for new product categories like in case B. For the new products, forecasting for the (new) spare parts needs to be carried out. The managers gather information from past compatible products from which statistical models and results can be used for prediction. If in such scenarios, information sharing is not carried by multiple managers from different hierarchical levels, there is danger of introducing cognitive biases within the first set of forecasts.

When it comes to seasonal demand, the software does not perform well as it is unaware of the special days or events. For example, in cases A, B, C, D and E; seasonality plays a major role in the judgmental adjustments made by managers. Here communications from other teams who have more information on such events is always useful. In case D, the demand managers have meetings with the promotional team about different advertisements for pancake day or bake-off challenge that will affect their demand.

There are also other pieces of information that are considered while generating the forecasts. Like from regulators, government agencies and other competitors in the market. In case B, the team has to gather information from their maintenance team but also has to include information from different agencies like FAA and EASA. Similarly, for case F there are a number of regulators like Ofwat and EA, that drive their decision-making process.

It is important that organisations collaborate to communicate such vital information for forecasting both upstream and downstream in the decision-making process. Case C seems to be good at forecasting and delivering their operations department, but not very good at winding that information upstream in their forecasting process. When their operations department carried out one such activity of combining data from their demand points to hospital departments, they were able to address the spikes in the demand flow with proper collaborations.

When it comes to different players within the supply chain like in case E, it is necessary for manufacturers to involve their dealers in the decisions being taken. The depots under the dealers have more local knowledge on what spare parts are being requested as the depot managers have first-hand experience on the shop floor. They can also highlight if a huge order was part of a one-time customer order so that the forecasting software include that as a skewed data point.

On the other hand, information sharing can provide challenges to achieving consensus among different stakeholders. Like in case B, when lower hierarchical level managers provide recommendations it resulted in increased inventory. Then their demand planning team had to assign expiration dates to the information shared in the form of recommendations. In this way, the forecasting team (demand planners) know within what time frame the recommendation is to be considered while adjusting the forecasts judgmentally and when to discard the suggestion for no further use.

6.2.2 Time pressure

The next dominant theme in demand forecasting is time pressure (Figure 6-2).

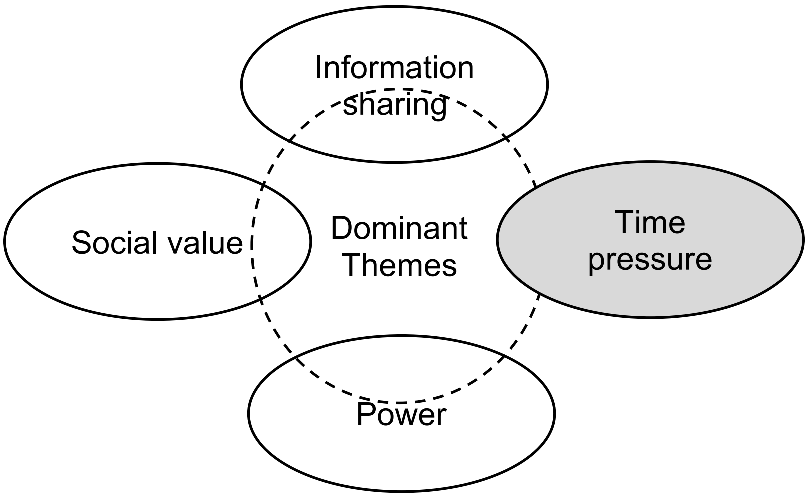

Figure 6-2: Representation of themes: Time pressure

One of the most important dimensions for any kind of decision-making problem is time. Literature suggests that the decision-making quality is highly impacted when there are tight time constraints both at individual and group level (Kocher and Sutter 2006). The imposition of a deadline acts as an extra demand for a decision maker in time-pressured scenarios (Maule, Hockey and Bdzola 2000). This is also evident from the cases described where the teams have scheduled meetings to discuss the managerial judgments regarding the demand forecasts.

It takes time to make a good decision about any forecast and the decisions can change dynamically with time (Ariely and Zakay 2001). The amount of time allowed for preparation of forecasts is an important factor in selection of a forecasting method (Makridakis and Wheelwright 1989). In case B, the recommendations made by the maintenance team is discussed with the demand planning team in a meeting. Because of time pressure, one cannot go through each spare part and discuss the adjustments required. Hence, the products are grouped together in different aggregated levels to make the discussions within the stipulated time period. Time plays a rather important factor as without a component part an aircraft may not be able to fly out of an airport, which can prove to be quite costly for the company.

Similarly, the forecasting teams in case E do not have time to go through the stock (inventory) of each SKU and hence heavily rely on depot managers for their inputs. This is important as before planning an order, one needs to access the stock along with the demand. As lead time for this case is three days, if both items of one SKU are sold, the dealer forecasting team places an order on the spot. This is how the decision-making process can take a different route when there are constraints on time.

The operational forecasting process in case F follows a JIT delivery system, making decisions more critical and vital. The planning team faces most of the pressure as they have deadlines to meet when it comes to delivering the forecast plans. This team is in the forefront exchanging information with other teams and using expert knowledge to adjust the forecasts. On the other hand, this pressure also acts as a catalyst for the business planning process.

Time pressure during the decision-making process in organisations can impair the capacity for information processing and consistency of the process (Kocher and Sutter 2006). From all the cases, it can be seen that depending on the product-types or customer-bases, the forecasting process includes a different percent of information being shared and amount of judgments involved. In case A, the forecasting for new connections (Provisions) have a short lead time of 7-8 days. Hence, once the systematic forecasts are ready, different team members gather to exchange information and make forecast adjustments.

The company policies put extra pressure for the teams to process the forecasts on time. Like the ATP business function of case D. With such a policy, the company is liable to provide answers to customer orders. Their sold products are in customers' carts even before they reach the company warehouses. This means the demand planners have to forecast regularly, checking some items like dairy products on a daily basis, so that suppliers can provide them on the required dates.

When there is information sharing between members in group decision-making, time pressure can have a negative effect on the quality of the decisions being taken (Kocher and Sutter 2006). In case D's upper-hierarchy business planning, the different stakeholders are required to make prompt yet efficient decisions. Due to time constraints, the forecast teams sometimes rely more on information from internal sources (within the same hierarchical level or team) rather than going for external sources (other hierarchical levels or teams within the same organisation).

The above point can be clearly illustrated with the example from case C. First and foremost, out of all cases time is of vital importance to this organisation. Here the failure of a forecast decision can result in patient fatality. Hence, the risk associated with their forecast decisions are much higher than the other private companies. To understand the uncertainty for their demand, the operational team collaborates with different internal and external teams. Such collaborations have led to various initiatives which helped them in saving time, freeing their resources for the next job, and improving their performance levels.

6.2.3 Power

The third dominant theme comes from managerial power in organisations (Figure 6-3). Power has been defined in different ways by different scholars in the literature. Based on the literature review and the data collected from interviews, three sub-themes have emerged within this broader theme of power struggle: experience, expertise and hierarchical position. For the scope of this research, the boundaries are restricted to power struggles due to possession of more experience, expertise (in terms of knowledge) and one's position within the organisational hierarchy.

It is the acknowledged that these three concepts of power are not separate and sometimes they can combine to build a power image for an individual. For example, someone with more experience might be higher up in the hierarchy. But there are also cases when senior managers depend upon product managers for their expert knowledge.

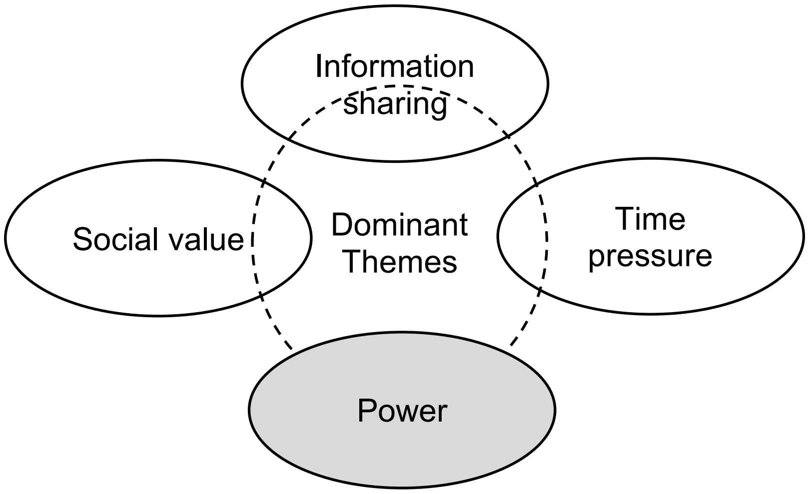

Figure 6-3: Representation of themes: Power

Starting with the first determinant of a manager's power display: their experience. The effects of managerial experience are manifested in terms of selection and use of 'soft' information, amount of information used and the decisions themselves (Perkins and Rao 1990). This can be seen in case F where managers with experience are responsible for the long-term strategic forecasts. They are assumed to be the experts who can understand the uncertainty in the forecasts. Similarly, for case E where managerial judgment is considered based on the manager's experience.

The second aspect of managerial power comes from product expertise. Case C's outsourcing forecasting activity shows their lack of in-house knowledge capability. Due to this constraint, the organisation has to hire knowledgeable consultants to carry out their forecasting and demand planning process. In case B, there is a clear picture of power in terms of product expertise as the demand planners consider those operating at the lowest level of the hierarchy to be novices in forecasting.

In case D, the demand planners have the right to overwrite the forecasts generated from the software in the background. Each of them is regarded as a product expert for their own SKU lines that they are responsible for. And they own those forecasts and are the final decision-maker for those lines. Similarly, case A's upper hierarchy does most of the forecasting for the organisation as they are believed to have better understanding of the long-term trend. This happens even after senior managers agree that lower hierarchies have more information about the market.

Lastly, the most evident power struggle in hierarchical decision-making is that stemming from authority, based on one's position within the hierarchy. Hierarchies pervade social groups, having a profound effect on group decision-making (Anderson and Brown 2010). In cases B, C, D and F, the senior hierarchy has the final say in terms of any conflict of opinions in forecast decisions. In case B, the recommendations put forward by the maintenance team (lower hierarchical level) has to be approved by the head of the demand planning team before incorporating in their forecasting process.

For the public-sector case C, it is a political system where even the government is involved in the decision-making process. One time when the upper hierarchy (senior decision makers and politicians) was not happy about the forecasts, the structure of the project steering team was changed to include a commissioner in it for the next forecast cycle. This way the commissioner is looped into every decision taken during the forecast decision-making process.

In the manufacturer-dealer relationship of case E, the manufacturer holds a powerful authoritative position. There are franchisee agreements that dealers have to adhere to when it comes to forecasting and stocking different spare parts. The entire forecast system is based on the demand from the manufacturer. Whereas, the manufacturer’s forecasting team thinks the entire process is driven by the demand stated by dealer. This is also possible as the forecast is generated at the dealer level and then aggregated upwards in a bottom-up fashion.

This shows how the presence of an influential individual can inhibit the performance of those from lower hierarchical levels (Goodwin and Wright 2014). In case F, there are the regulatory and government agencies that dictate the demand planning teams when it comes to decision-making. This builds tension between the two teams as the demand planners are aware that the information coming from those agencies may not be correct.

On the other hand, power can have a positive impact on the forecasting process. Cases B, C, E and F have different checks in place to make sure individual judgments do not overpower the forecast decisions. In case E, the dealer’s forecasting team checks every input from depots so that they do not over-order. Case C’s upper hierarchy wants every judgmental call to be backed up by some evidence that can corroborate it. These checks are important as different hierarchical levels have different forecast expectations. The upper hierarchy seems to be more revenue-driven, whereas the lower hierarchies have target-driven attitudes.

6.2.4 Social value

The last dominant theme is that of social value generated during the forecasting process (Figure 6-4).

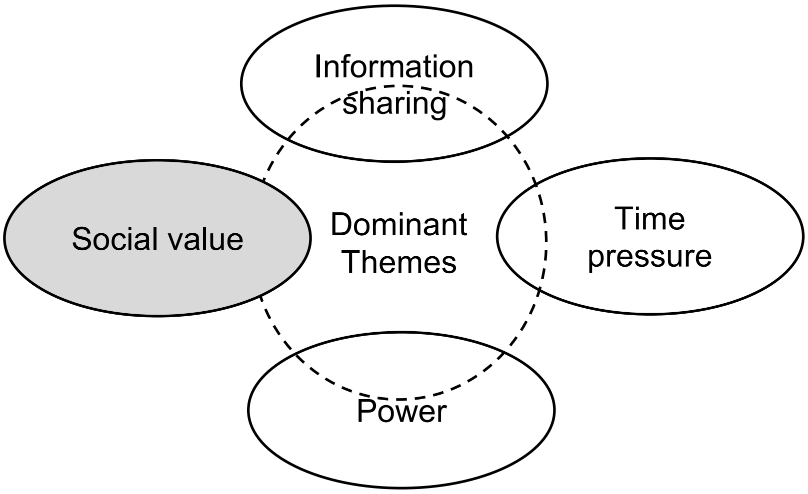

Figure 6-4: Representation of themes: Social value

Social value is defined by the Social value UK (2020) organisation as the "*quantification of relative importance that people place on the changes they experience in their lives".* This last theme is less evident directly from the six case stories. But when the three preceding themes are put together, one can see the importance of bringing in changes into the forecasting process. Forecasters tend to make better forecast decisions by keeping in mind the economic cost associated with those decisions. As in case A where information is collected from the operations teams (lower hierarchy) to assess how much can be saved from the baseline forecasts for the *Repair* market.

However, what organisations tend to forget is that there is a shared value of both economic and social values attached to these decisions. In cases A and C, there are pressures from both upper and lower hierarchies while making the forecast decisions. Now if the respective teams consider inputs from only one hierarchical level, it might help improve the economic value, but the social value associated with employee interaction and engagement will be massively impacted.

In case D, there are different teams that carry out the forecasting process as a whole. There is the business decision-making group (that includes mostly upper hierarchical managers), the demand planning team, and the data science team. However, the process followed is mostly a step-by-step process where one team has no idea what the other team does. The data science team (who develops the forecast software) have no interactions with the demand planning team (who make changes to software forecasts). But when interviewed separately, managers from the three teams agreed that sharing information between them would be beneficial and they would welcome such collaborations.

On the other hand, cases B, C, D and E include information from different hierarchical levels in their decision-making processes. This helps the managers see the business world around them differently and help make better decisions about where to invest more resources. Case B suggests that when communications take place between different hierarchical levels, it has helped the teams to prioritise the work. Participation in the decision-making process has been found to generate a positive effect on work and ultimately resulting in an “effective organisation” (Le Var 1998).

The dealer’s forecasting team of case E includes information from depot managers. The forecasting manager says this helps to build trust amongst the team members generating a high social value within the organisation. Plus, they can rely on the depot managerial inputs before placing the order. These inputs are aligned with the manufacturer's forecasts and changes are made to the ordering decisions. This counts as great help for the forecasting managers as they are responsible for more than one depot and they have to make several forecast decisions within strict time deadlines.

Employees from different teams or hierarchical levels add value to the forecast decisions using their knowledge and skills. Even without knowing, these steps in the decision-making process help to increase the social value within the companies. As interviewee C1 suggested everyone needs to start considering the value generated in the entire organisation and not just one aspect or one department. Within case C, there are opportunities with the operational team where the field operatives can suggest changes to the process. This makes them feel appreciated and receive recognitions, especially in a job where they have to handle adverse patient conditions.

In case F, the planning team faces the pressure of delivering the forecasts accurately on time. The other teams whose inputs are needed do not seem to pay much attention. There is a collaborative process already in place where interactions happen between different teams (like leakage information from operations department). However, it is important that the different stakeholders realise the social value generated from the decision-making process. One way would be for the operations team to discuss and collaborate with the strategy team, as information from both sides can prove to be quite valuable to one another.

From the above discussion, it can be agreed that social value is an important characteristic for the decision-making process. Changes are needed within the current demand forecasting methods by engaging team members from different hierarchical levels. It is important that the lowest hierarchical level, workforce team on the front line, is contacted and collaborated with when decisions are being made. Especially when it comes to the after-sales industry, it is important as they know the market and can sometimes understand the demand better than the upper hierarchical levels, who largely tend to have an umbrella view of it.

6.3 SWOT analysis

Using the SWOT technique (explained in section 3.5); the dominate themes from current forecasting processes within the six cases are assessed. This technique aids in identifying the prospects and challenges that could significantly impact the decision-making processes in these cases. The themes can have different meanings attached to it by individual team members, which make them often conflicting. SWOT can provide a good base for strategic decision-making in business forecasting.

For this research, SWOT is used to identify which element of each theme (factor) is seen as important to forecasting managers. This does not compare strengths to strengths, weaknesses to weaknesses, opportunities to opportunities, and threats to threats. Instead the strength, weakness, opportunity, and threat of each theme is compared within that theme itself. This leads to the design of the questionnaire with sections for each theme where respondents compare SWOT for each one of them. In the last section of the questionnaire, there is a question on comparison between the themes that gives rise to the group priority (explained in the next Chapter 7).

From the thematic analysis in section 6.2, SWOTs of each theme are generated. To maintain homogeneity, only one strength, weakness, opportunity and threat for each theme are included in this research. Strength for a theme is its advantage within the forecasting process as seen from the interviews. Weakness is the disadvantage of having that theme in the same process. Opportunity for a theme is the benefit that it presents to a company when implemented in the decision-making process. And finally, threat is the difficulty encompassing that theme from implementing it in the process.

Below the SWOTs for each theme are listed with a brief outline of how they have been derived from the thematic analysis. Systematic thinking and comprehensive diagnosis, of the dominant themes in the forecast planning process, led to the identification of these statements. These are evidenced from the interviews conducted with the six case companies. This stage of analysis was checked and corroborated by the supervision team before the pilot run of the questionnaire.

6.3.1 Information sharing

When it comes to information sharing in the forecast planning process, different managers have diverse views on it. Seen from cases B and E, a number of group collaborations are formed as a result of information sharing amongst them. The upper hierarchy of case C believes such collaborations leads to informed decisions by the planners. On the other hand, when too much information is shared, achieving consensus amongst the group becomes harder as raised by interviewee D1. Plus, managers from different teams believe time spent on discussing and collaborating with each other can increase their workload.

With those thoughts, the following statements are developed as the SWOTs for this theme of information sharing across teams for effective decision-making*.

S: Information sharing leads to group collaborations. (S1)

W: Sharing information can lead to conflicts within groups. (S2)

O: Information sharing leads to well informed and better decision-making. (S3)

T: Sharing of information increases workload for different teams. (S4)

6.3.2 Time pressure

This theme seems to have a negative connotation to it from the case stories. Many times, the forecasting teams in organisations have to make hurried decisions like in case E. When all shelved items of a part are sold, because of the narrow lead time, the forecasting manager has to place an order for it on the spot. Because of this pressure of time, planning teams cannot afford to discuss each forecast number with other teams. This impacts their decision-making process that can cost a company like B to lose a huge amount of money.

However, some forecast managers view this pressure as benefitting to their work culture. Demand planners for case D recognise time pressure as helping them focus on their forecasting the category of perishable and fast-moving items. Like D2 investigates their dairy forecasts every day first thing in the morning, improving the accuracy for these forecasts.

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*The numbers in parentheses indicate the statement's number in the questionnaire.

In case F, it is mostly the planning team that feels the pressure from different deadlines. And their technical director thinks this works as a catalyst helping streamline their business planning process. Therefore, the SWOTs for this theme on time pressure in forecast decision-making are as follows.

S: Time pressure helps to self-discipline and focus on the one task, improving productivity. (S2)

W: Hasty decisions are made under time pressure. (S3)

O: Time pressure helps to streamline the decision-making process. (S4)

T: Time pressure impacts the information processing capacity. (S1)

6.3.3 Power

Another theme that is usually considered undesirable in the field of business decision-making is that of managerial power. Everyone knows it exists but hardly anyone wants to acknowledge it. In all the six cases, business hierarchies are present, with different levels within that hierarchy having variants of power. With this power, senior managers (in cases B, C, E and F) streamline the forecasting process with various efficiency checks, improving the team productivity.

In case C, the workforce team (operations) are given opportunities for ideas and suggestions by the upper management. If those ideas seem viable, the team member(s) receive training thus, fostering their personal and professional growth. Case D shows evidence of how hierarchical power proves to be a challenge during consensus decision-making. Their stakeholders are each responsible for their own roles and positions within the organisation. This creates conflicts resulting in divides between the different teams, like in case A. The lower hierarchy’s operational forecasts do not match the revenue driven expectations of upper hierarchies. Hence, the SWOT characteristics for this theme of power can be put down in the following four statements.

S: Power in work environment enhances team efficiency and productivity. (S1)

W: Power struggles impact team-level outcomes. (S4)

O: Management power opens up possibilities for personal and professional growth of employees. (S3)

T: Management power creates a divide amongst team members. (S2)

6.3.4 Social Value

This theme is different from the rest, as it has never been explored before in the field of business forecasting. It is seen as a new concept by many whereas it has already been prevalent in organisational culture. For example, case E dealer forecasting managers socialise regularly with the depot managers (lower hierarchy) as it cultivates team building in the workplace. Such steps increase the value employees put into their job experiences. This promotes different innovations in the work environment from team members, as seen in case C.

Although most of the cases show interactive environments between teams, there is no evaluation matrix for the social value generated. Because of the qualitative nature of this theme, it can prove tricky to evaluate. Additionally, like in case F, there are collaborations with different teams during the planning process, but it is important that while doing so the forecast efficiency is not impacted. Although one could argue how does a company define efficiency here, and most of the times it is based on economic returns of the forecasts. The SWOTs for this theme can be represented in the following statements.

S: Increased social value brings in positive vibes into the workplace culture. (S3)

W: The outcome of social value is difficult to evaluate. (S1)

O: Higher employee social values usher workplace innovations. (S2)

T: Social value can divert focus from the economic value of business. (S4)

To conclude, these 16 SWOTs statements show how each of the themes can be developed into feasible strategies for organisations. From these statements, two propositions along with a conceptual framework are suggested in the next section 6.4. As the number of interviewees per case was limited to two or three, the themes using SWOT statements, are further validated using AHP method via a questionnaire.

6.4 Conceptual framework with propositions

Taking into consideration, the forecasting methods within different companies along with their reconciliation processes; a conceptual framework is suggested in Figure 6-5. A conceptual framework "*explains, either graphically or in narrative form, the main things to be studied – the key factors, constructs or variables – and the presumed relationships among them*" (Miles and Huberman 1994). This framework represents a collaborative method for information sharing among multiple hierarchical levels in the after-sales industry. This framework has been adapted from Herrera et al. (1997), where it was put forward for group decision-making purposes in the linguistic literature.

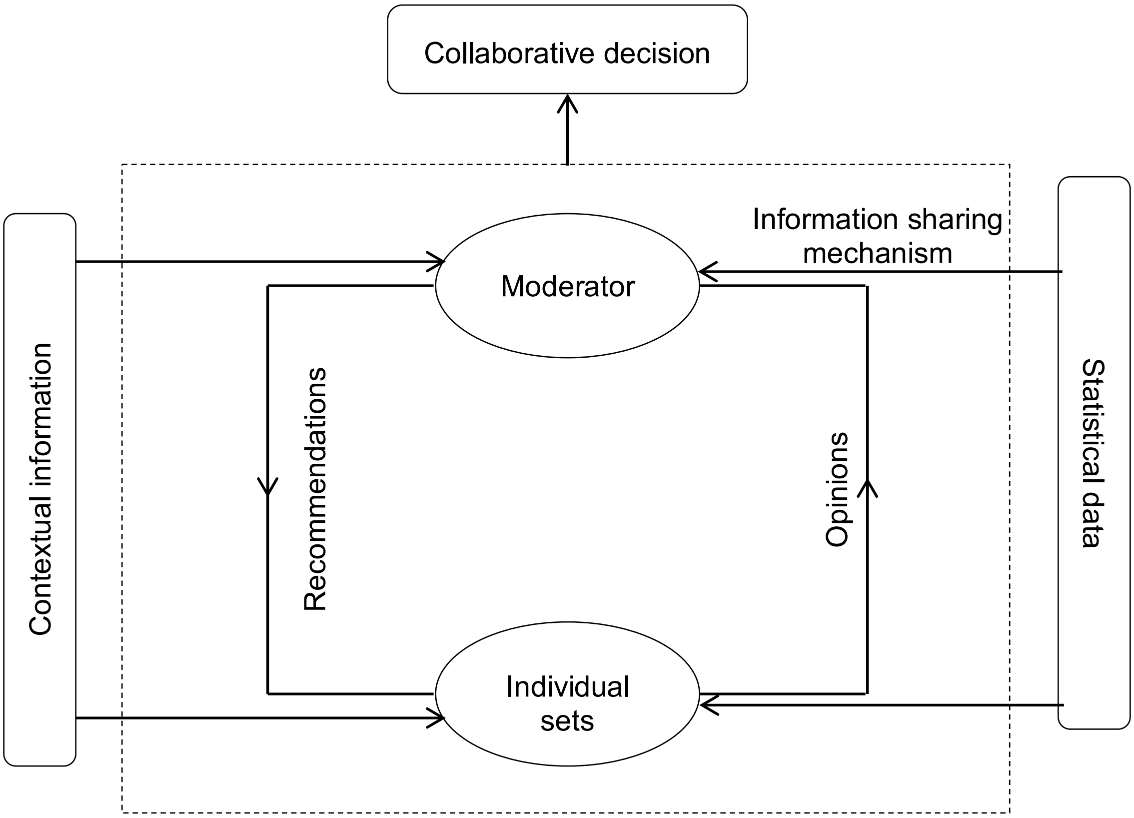


Figure 6-5: Collaborative decision-making process
Source: adapted from Herrera et al. (1997)

This decision-making process is redesigned to include the themes developed from the qualitative interviews (section 6.2). One of the themes arising from the interview data is information sharing between managers from different hierarchical levels. To highlight this theme, the framework allows an information sharing mechanism where managers from all the hierarchical levels have access to different kinds of statistical data and contextual information (soft data).

The forecasts generated from this information are fed as *opinions* to a moderator from each of hierarchical levels, or sometimes even a group of hierarchies. The moderators review all the opinions based on the contextual information and statistical data. They make recommendations to the individual managers, if and when required, to change their individual forecasts (opinions).

Once the moderators are happy with the opinions, a collaborative decision is taken amongst all of them regarding the forecasts. This pathway of having moderators from a middle-level hierarchy who can keep track of all the judgments and information flow, helps to diminish the effect of power on the decision-making process. Every manager or team member gets an equal opportunity to put forward their opinions without any hindrance from other hierarchies.

This process also reflects the other theme of time pressure from the analysis. This theme derived the choice of collaborative decision-making process, rather than consensus or autocratic decision-making processes. Collaborative decision-making process helps make better decisions within time pressures. These different types of decision-making processes have been explained in Chapter 3 (section 3.3). It involves considering representatives from different levels and sub-levels who can provide information independently of the others and discuss on a set of forecasts that all levels agree upon.

This is appealing as different hierarchical levels can have different strengths in different types of data domains (Major and Ragsdale 2001). The time taken to make these kinds of collaborative decisions is lower than the consensus decision-making process but higher than the autocratic related one. However, the quality of results can be quite high both economically and socially as information from all levels is included. This points towards the fourth theme of considering social value in addition to the economic value of forecasts.

From the SWOT statements for each theme (section 6.3) and the conceptual framework, two theoretical propositions are proposed in this research. They reflect the themes within the conceptual framework of collaborative decision-making for after-sales demand forecasting. These propositions are explored in detail, with data from all stages of data collection, in the discussion section of Chapter 8.

Proposition 1 (P1): *Improving information sharing mechanisms increases the social value within work environments*.

Proposition 2 (P2): *Time pressure increases dependency on individual judgments in business decision-making*.

This is the first development stage for the conceptual framework. It will be validated further from the questionnaire responses to the SWOTs for each theme. Similarly, the two propositions are evaluated from the responses in Chapter 8. Analysis of the questionnaire responses have been reported in the next Chapter 7. According to the second stage of findings, the conceptual framework and propositions are confirmed. The framework is revaluated to capture the perceptions of a wider network of forecasting managers from the case companies.

6.5 Summary

Hierarchical forecasting is present in different organisations either in the form of product type or geographical locations or customer-based or just organisational structure. In this chapter, data collected from the first stage of the case study research is analysed. Thematic analysis is conducted on the case stories from the previous chapter Data Analysis Part A to look for common and emerging themes. Four dominant themes viz. information sharing, time pressure, power and social value have been identified. Each of these themes are further explored with examples from each of the case stories (Chapter 5).

In the second section, the four themes are analysed using SWOT technique to find the major strength, weakness, opportunity and threat of each theme. These SWOTs of the four themes aid in designing the second stage of data collection, the questionnaire. The SWOTs are analysed in the next chapter of Data Analysis Part C based on findings from the questionnaire responses.

A conceptual framework is developed for collaborative decision-making process for hierarchical forecasting. The framework takes into account the case stories and their cognitive maps from analysis part A (Chapter 5), reflecting on the four dominant themes from section 6.2. The framework along with the SWOTs are used in proposing two theoretical propositions for this research. These propositions are validated in the last Discussion Chapter 8 with the help of Data Analysis Part C and literature from Chapters 2 and 3.

This chapter Data Analysis Part B answers the second research question of this study. The findings from this chapter (thematic analysis and SWOT analysis) facilitate designing the second stage of data collection: an explanatory stage with questionnaire. The questionnaire data is analysed in next chapter of Data Analysis Part C using MADM methods. This chapter along with the previous Chapter 5 are discussed in Chapter 8, with the help of literature from Chapters 2 and 3, to answer the complete set of research questions for this research. Hence, Figure 6-6 shows the positioning of this chapter within the entire thesis.

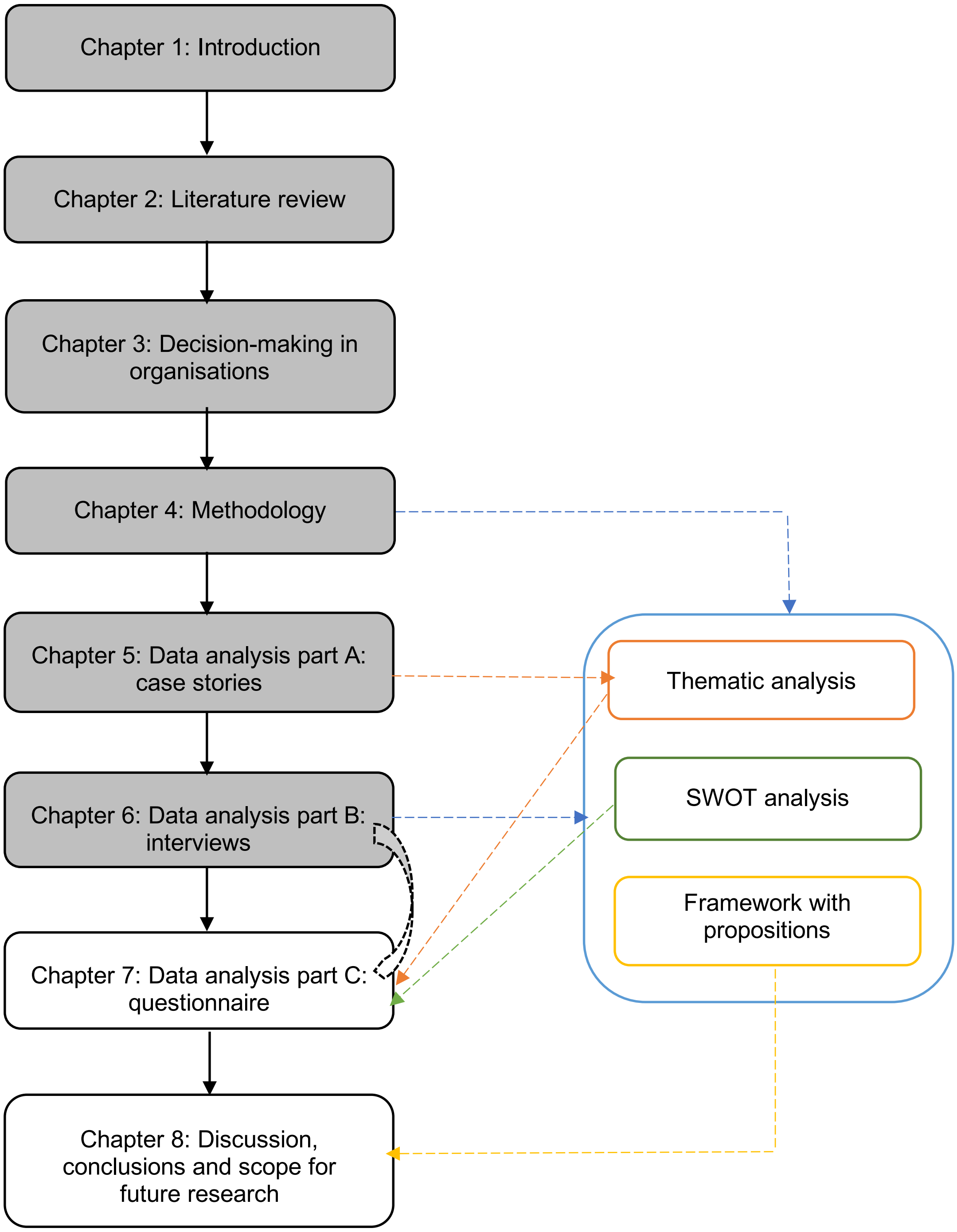


Figure 6-6: Thesis structure (Chapter 6)

Chapter 7

7 Data analysis part C: questionnaire

7.1 Introduction

In this chapter, the analysis for this study is continued and presented in different sections. The thematic analysis of part B along with the case stories from part A designed the second stage of data collection (questionnaire). Here the responses from the online questionnaire have been analysed. The questionnaire, as explained in the methodology Chapter 4, is divided into different segments. Each segment is used to answer different questions that are requirements for the different analysis methods. The questions are based on the SWOT analysis from the previous chapter of data analysis Part B. Multiple attribute decision-making (MADMs) methods are used to analyse the responses via the two methods of AHP and ELECTRE.

A total of 37 (out of 56, 19 of whom did not complete the questionnaire) responses were collected from the five case companies (case B did not participate for this stage). As a limitation of this methodology, there is no way to check whether the right respondents filled up the questionnaire. To make sure the data collected is reliable and the participants are forecasting managers within the case organisations, different background questions are asked in the first section of the questionnaire. These included questions on formal forecasting knowledge and forecasting job experience. Most of the participants had more than 3 months experience in their forecasting job roles, which make them reliable sources. And those with less than 3 months forecasting experience in their current role, either had formal forecasting knowledge or forecasting experience from previous job roles. This shows confidence in the data collected ensuring the validity of this research.

Table 7-1 below shows which parts of the questionnaire have been used in which sections of this chapter.

Table 7-1: Table showing link between questionnaire responses to analysis methods

Question (Appendix B)	Type of questions	Descriptive statistics	AHP	ELECTRE	Cross- case comparisons
A.1 - A.9	Background questions	✓			
B.1.1 B.2.1 B.3.1 B.4.1	Likert scale questions for SWOTS of each factor			✓	
B.1.2 B.2.2 B.3.2 B.4.2	Pairwise comparisons between SWOTS for each factor		✓		
B.1.3 B.2.3 B.3.3 B.4.3	Ranking SWOTS for each factor	✓			
B.1.4 B.2.4 B.3.4 B.4.4	Qualitative question to add on the different factors				✓
C.1	Pairwise comparisons between factors		✓		
C.2	Framework question	✓			
C.3	Anything extra to add				✓

The first nine questions, the background questions, are used for descriptive analysis in section 7.2. This section also includes analysis of responses from the ranking questions, where the respondents were asked to rank the SWOTs within each factor. One of the reflective questions on the collaborative framework from the last segment of the questionnaire is also included for analysis.

Next in this chapter, the MADM methods of AHP and ELECTRE are presented. The AHP methods used pairwise comparisons between SWOTs of each factor as inputs, along with the pairwise comparisons between the factors themselves. This method generates SWOT and factor priorities that are used as part of inputs for the ELECTRE method. Additionally, the ELECTRE method uses the Likert-scale responses for the SWOTs of each factor as decision matrix inputs. Finally, this chapter has two comparisons being drawn between the different cases, and the four factors. These follow from the outputs of the previous analysis sections in combination with the qualitative responses from the questionnaire.

7.2 Descriptive statistics

In this section, some descriptive statistics have been derived from the questionnaire responses. The background questions are used to categorise and visualise these responses using different visual plots. This helps to see variations in the responses from people with different characteristics, in terms of hierarchical position and the decision-making stage within the company. The ranking questions for the SWOTs of each factor are also used to check their consistency with the responses. The R and Microsoft Excel software packages are used to analyse and present the data in this section. R code for this analysis is provided in Appendix C.

7.2.1 Distribution of respondents

This section explains the distribution of (number of) respondents with respect to different characteristics. In the diagrams below, there are six barplots that show the distribution of the sample of respondents with respect to gender, age, formal knowledge in forecasting and/or business decision-making jobs, time worked in the present company, practical knowledge on forecasting and/or business decision-making from previous job roles, and time worked in forecasting and/or business decision-making jobs.

From the first two diagrams (Figure 7-1), it can be clearly seen that this area of forecasting and business decision-making is dominated by middle-age males. From the next barplot (Figure 7-2), 20 out of the 37 respondents had some form of formal education in forecasting and/or business decision-making. Also, the respondents have spent quite a bit of time in the present case company, hence this increases the reliability of their responses.

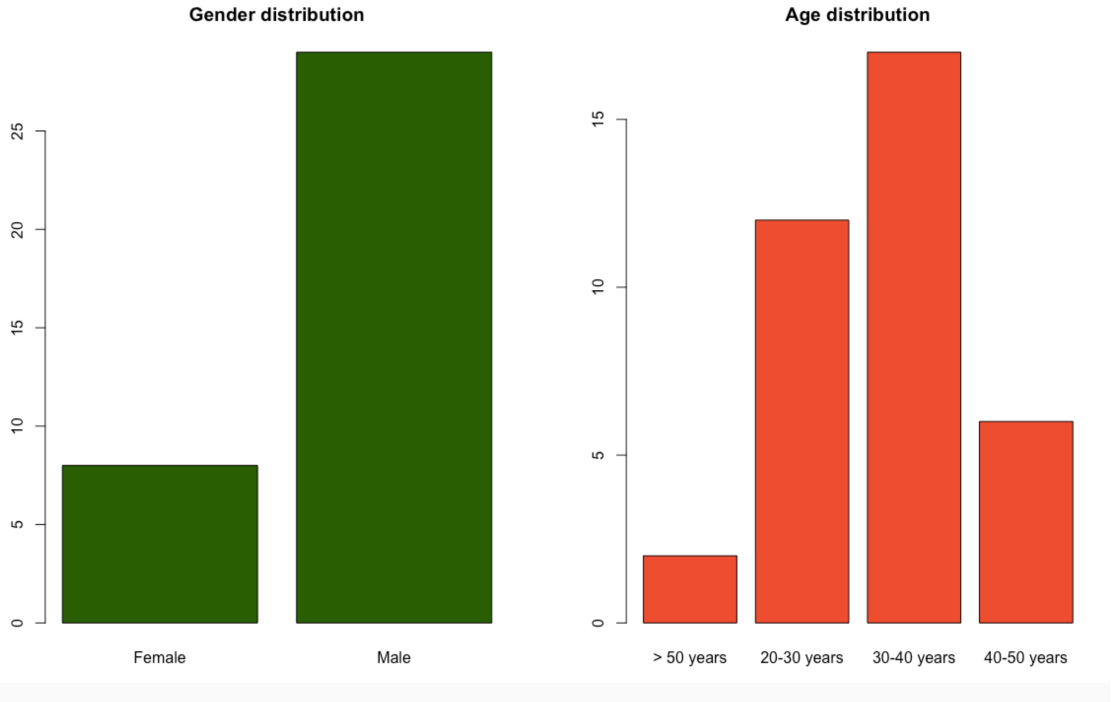


Figure 7-1: Barplot for descriptive statistics 1

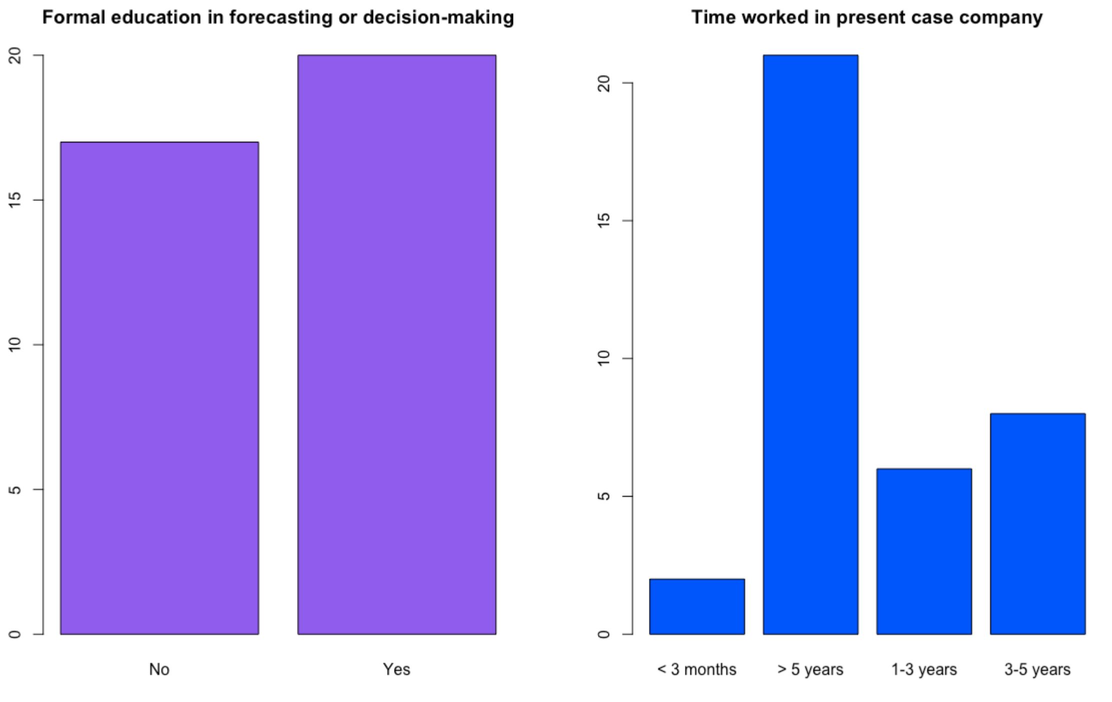


Figure 7-2: Barplot for descriptive statistics 2

In the next barplots (Figure 7-3), it can be seen that most of the respondents did not have any prior practical knowledge on forecasting and/or business decision-making. This is interesting because from the second barplot (Figure 7-3), most of them have worked for more than one year in this domain.

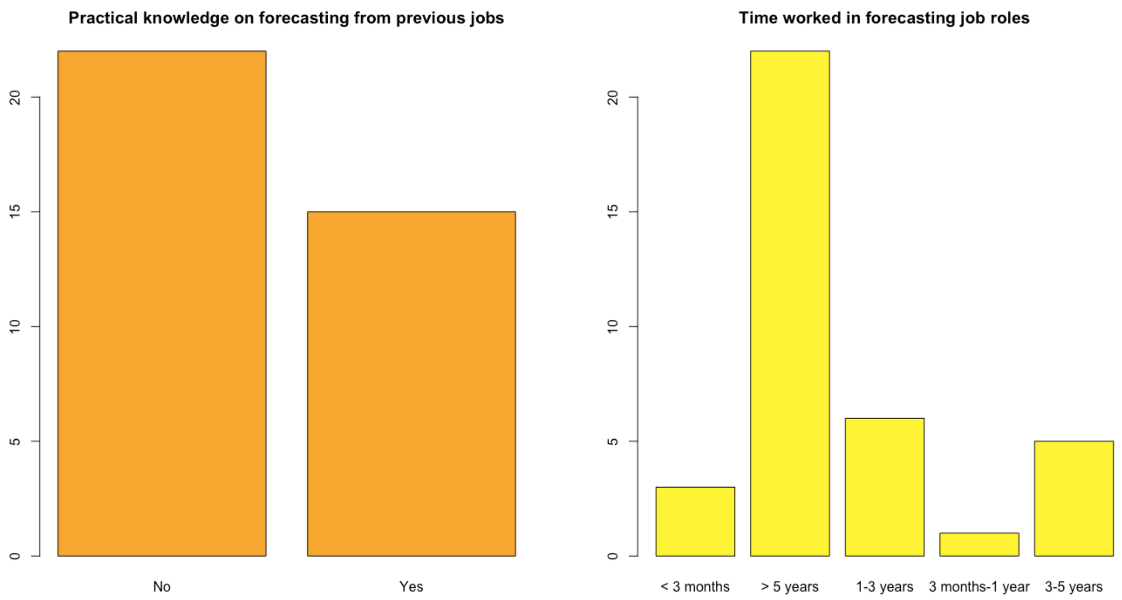


Figure 7-3: Barplot for descriptive statistics 3

Now the two other characteristics of the respondents that are important for this research are: hierarchical level within the case company, and decision-making stage of the present job profile. The first pie-chart show (Figure 7-4) how the respondents are at different levels of the hierarchy: operational level (19%), strategic level (41%), both levels (32%), and remaining are others (research positions or ‘not sure’). This also highlights that one manager can be responsible for more than one level within the business hierarchy. When it comes to their decision-making stages (Figure 7-5), more than half of them (51%) are in the middle stage, 38% in early stage, and 11% are final stage decision-makers.

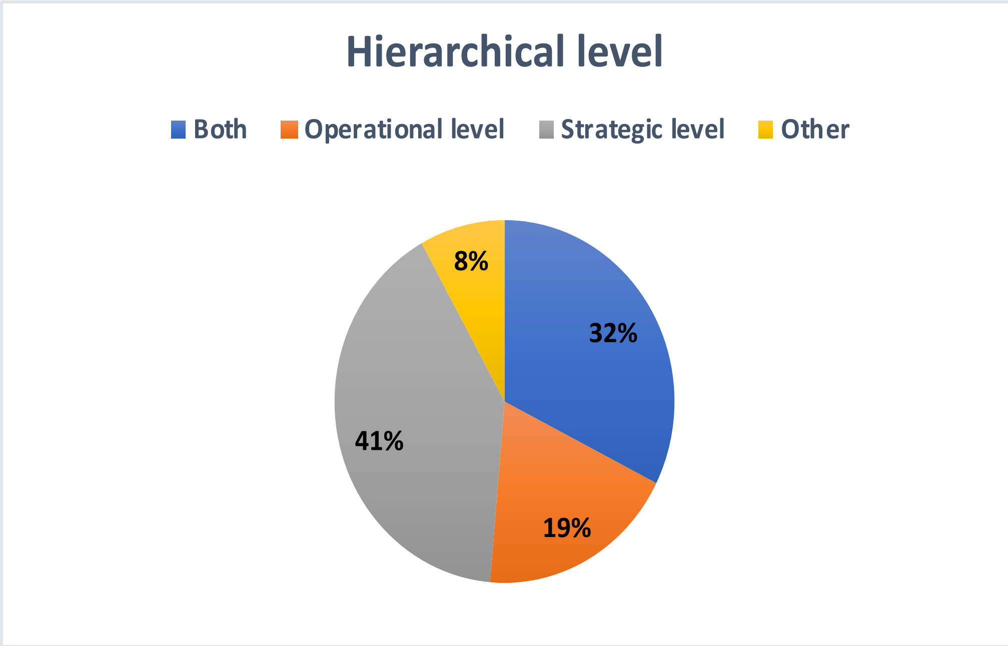


Figure 7-4: Pie-charts for descriptive statistics: Hierarchical level

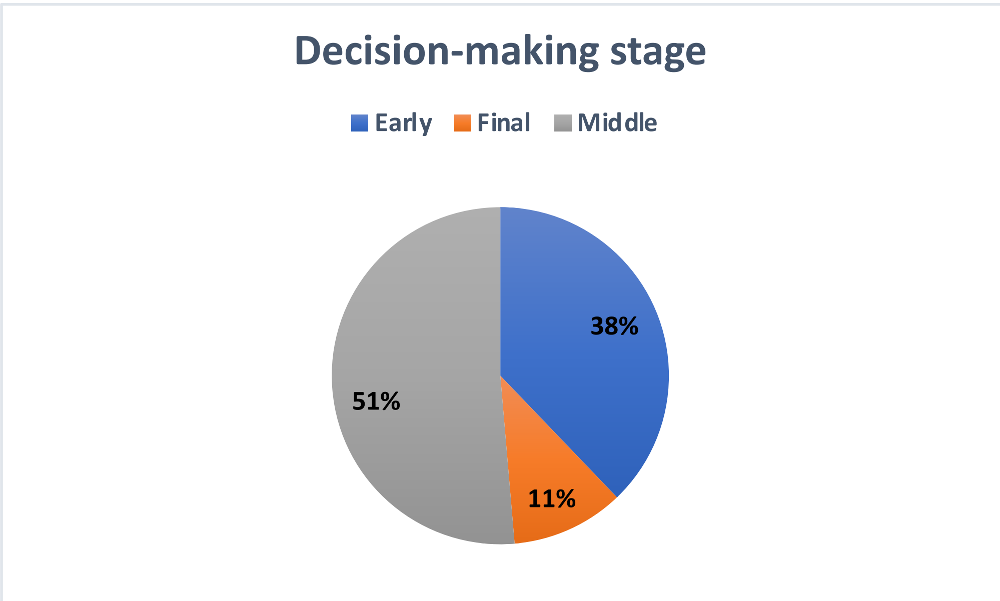


Figure 7-5: Pie-charts for descriptive statistics: Decision-making stage

If this is broken down with respect to both of the above characteristics, the following table (Table 7-2) is found. It is interesting to note that even managers from operational level, generally considered lower in the business hierarchy to strategic level, can be the final decision-maker. And most of the strategic level managers are only middle-level decision-makers. This information will be used in the next Chapter 8 to discuss the concept of uneven power in organisations.

Table 7-2: Distribution based on hierarchical level and decision-making stage

Hierarchical level	**Decision- making stage**		
	Early	Middle	Final
Operational level	4	2	1
Strategic level	5	9	1
Both	2	8	2
Other	3	0	0

7.2.2 Ranking SWOTs for each factor/concept*

Here the ranking questions of the 16 SWOT (4 for each factor) statements are analysed with the help of boxplots and barplots. In the first figure (Figure 7-6), there are four boxplots showing rankings of SWOTs for each factor across all respondents. Within each boxplot, the four plots correspond to the rankings of Strength, Weakness, Opportunity and Threat along the x-axis. These boxplots show us the variation in rankings for the different factors.

*Here the themes are referred to as factors, in line with MADM method linguistics. In the questionnaire, these are called concepts to break down the questions into different segments. Factors or concepts refer to the same four dominant themes of information sharing, time pressure, power, and social value.

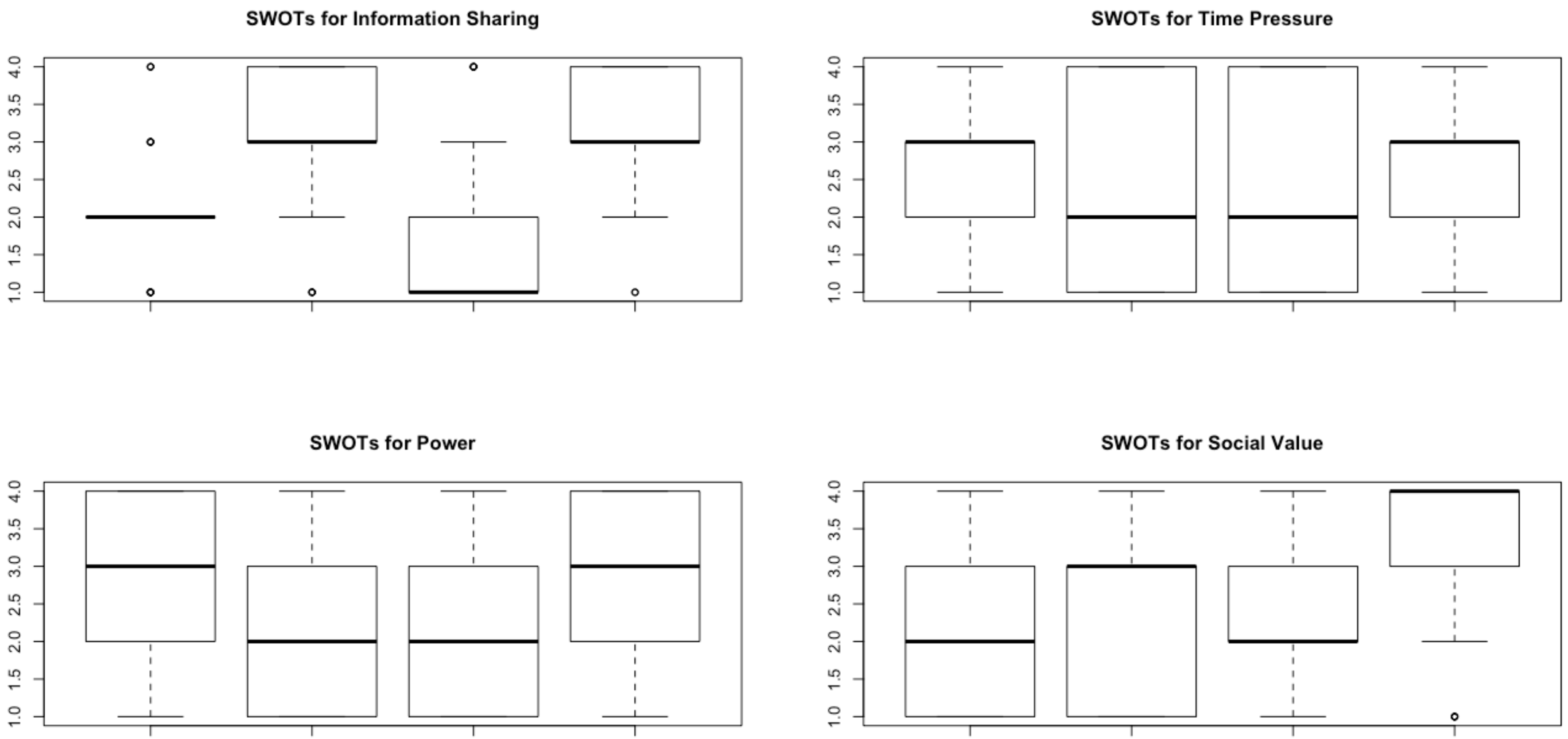


Figure 7-6: Boxplots for all SWOTs

For example, most of the respondents have given rank 2 to the strength of *Information sharing* and hence the median is two. For *time pressure*, it is interesting to note that most of the respondents have ranked its weakness and opportunity as either 1st or 4th. But for others, the rankings are spread across two or three ranks.

To delve into this deeper, rankings of SWOTs for each factor is considered relative to each decision-making stage. The reason behind this is to see how the rankings change between an early stage decision-maker to a final stage one. The thought process for different decisions vary individually and this is reflected in the barplots below for each factor, viz. *information sharing*, *time pressure*, *power*, and *social value*. Here S1, S2, S3 and S4 stands for ranks 1, 2, 3 and 4 respectively for the strength statement. Similarly, are symbols for ranks 1, 2, 3, 4 for weakness (W1, W2, W3, W4), opportunity (O1, O2, O3, O4) and threat (T1, T2, T3, T4).

For *information sharing* (Figure 7-7), its opportunity is ranked the highest across the three decision-making stages. Strength is seen as the second preferred, followed by the weakness, and threat is mostly ranked the last. On the other hand, for the factor *time pressure* (Figure 7-8), its weakness is ranked highest for the different stages. Few respondents have also ranked its opportunity as rank 1. Strength is generally ranked 3rd but there is also a large number of middle decision-makers who ranked threat as 3rd. So, it can be seen that for time pressure, the responses vary for different stages. Similarly, from Figure 7-9 the weakness of *power* can be seen as highly ranked amongst middle stage decision-makers. And its opportunity is the next ranked statement. Figure 7-10 shows *social value*'s opportunity being mostly high ranked, with lower ranks for its threat.

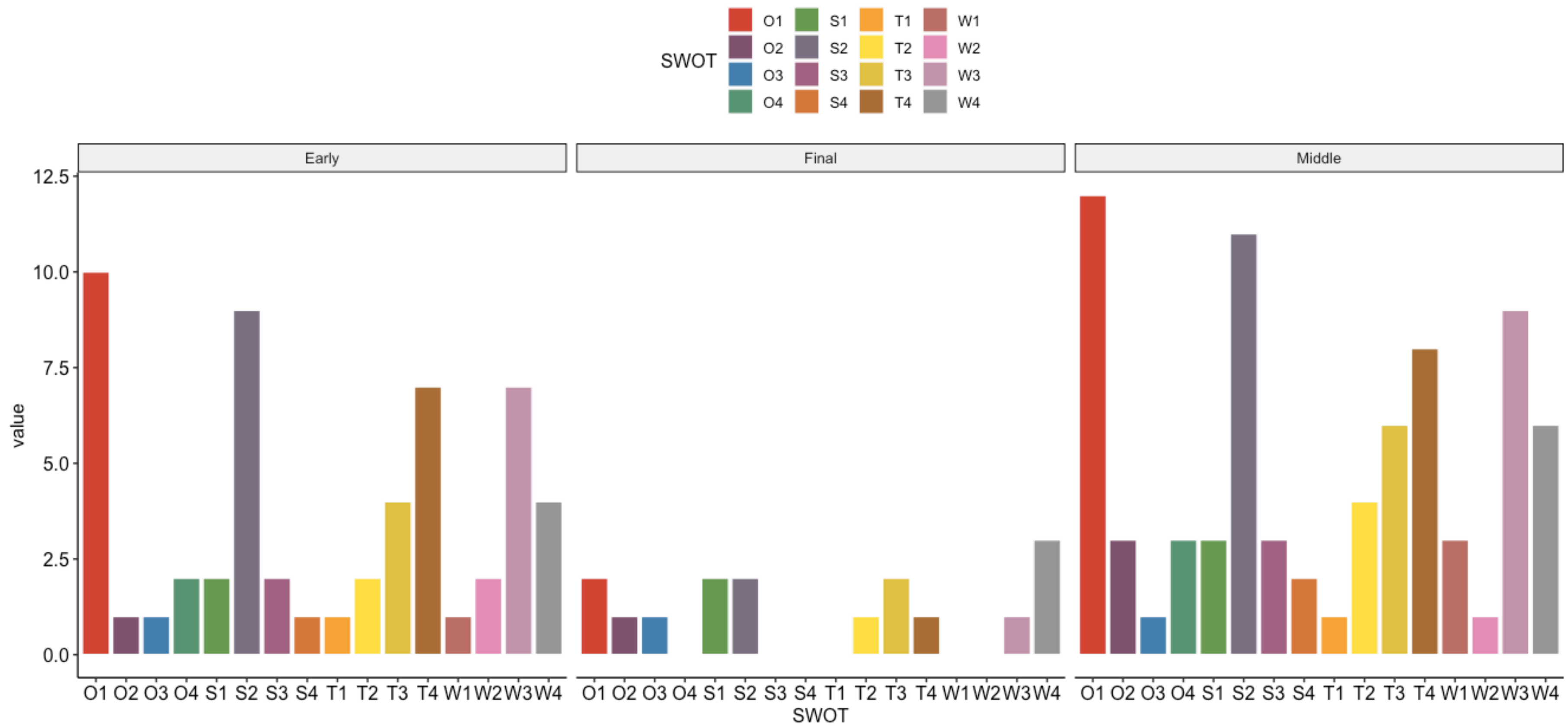


Figure 7-7: Barplot of SWOTs for Information sharing across 3 decision-making stages

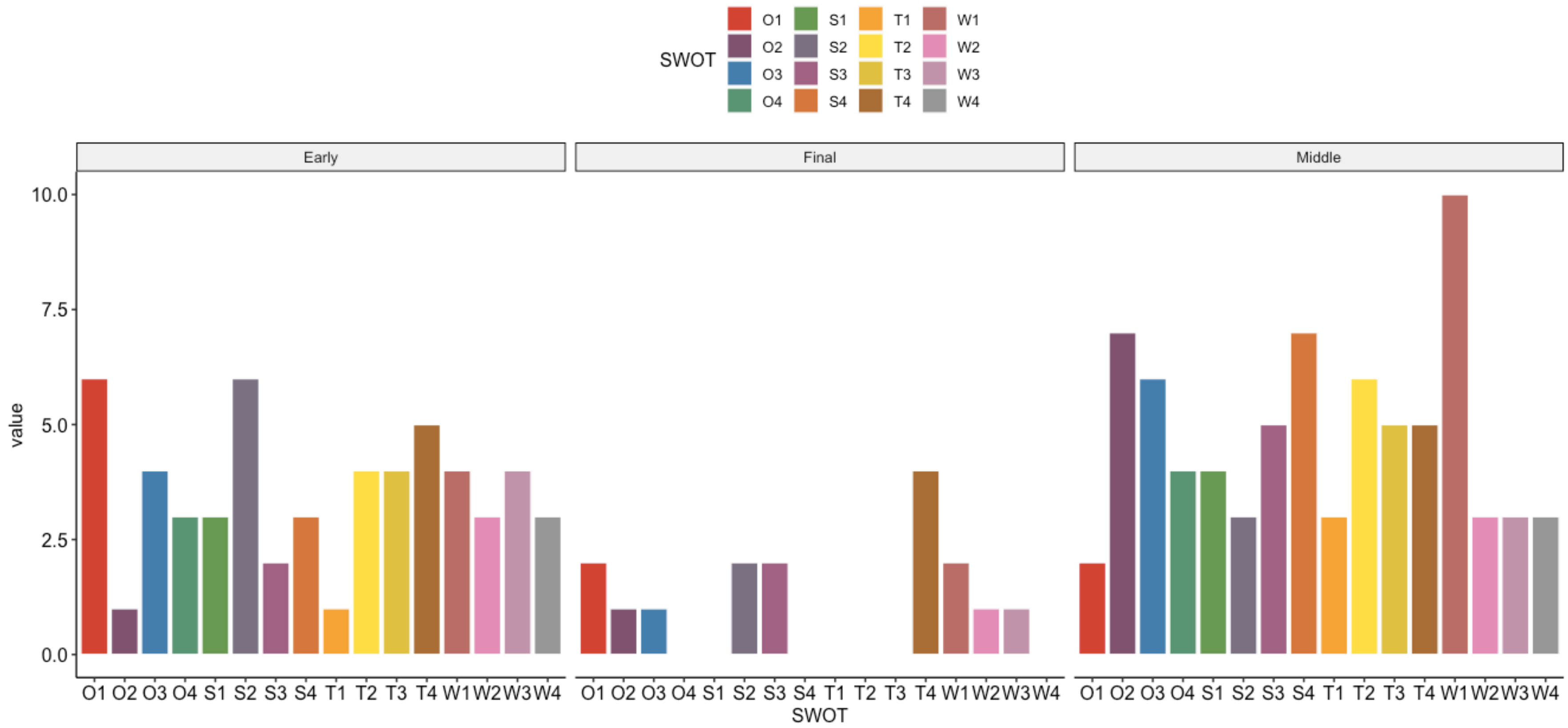


Figure 7-8: Barplot of SWOTs for Time Pressure across 3 decision-making stages

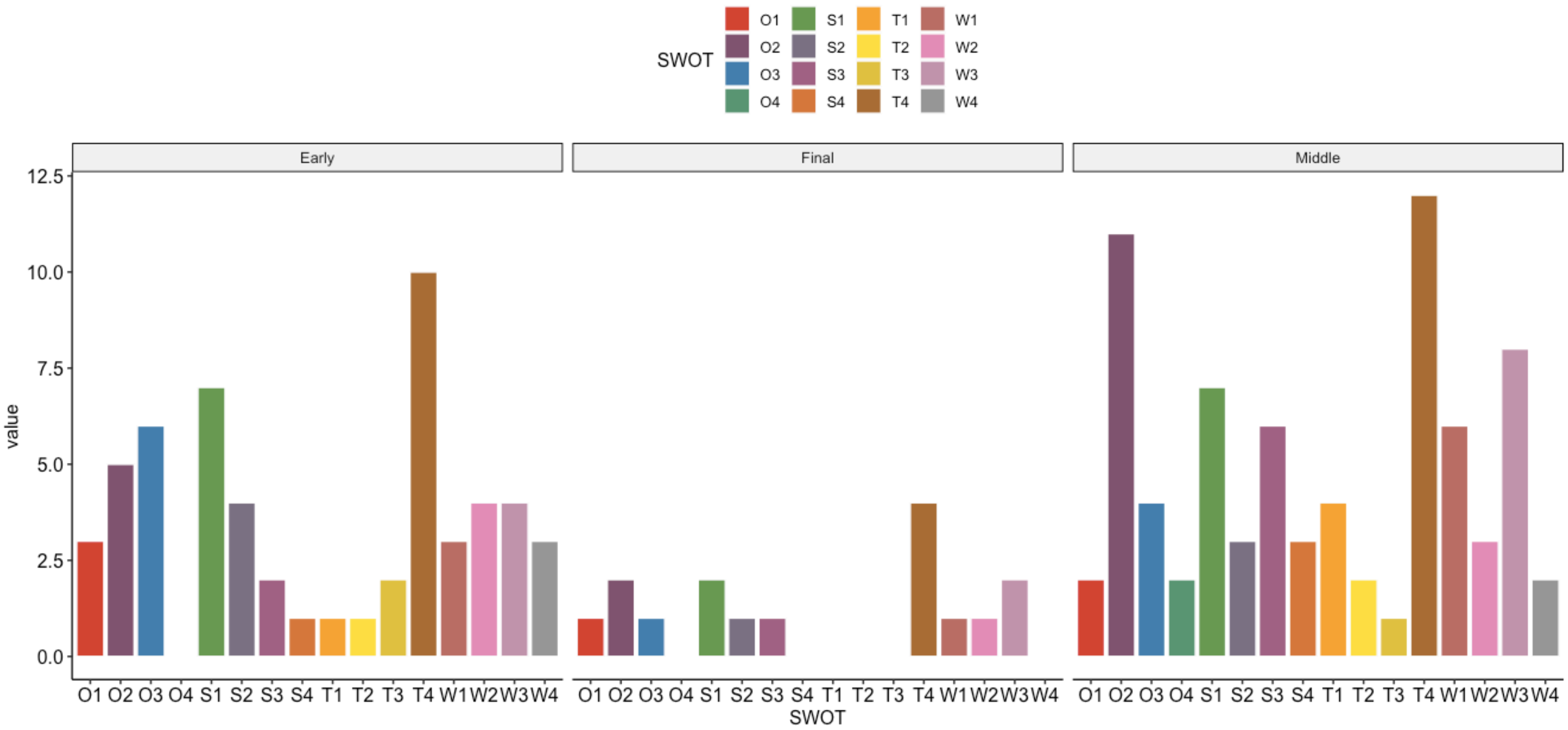


Figure 7-9: Barplot of SWOTs for Power across 3 decision-making stages

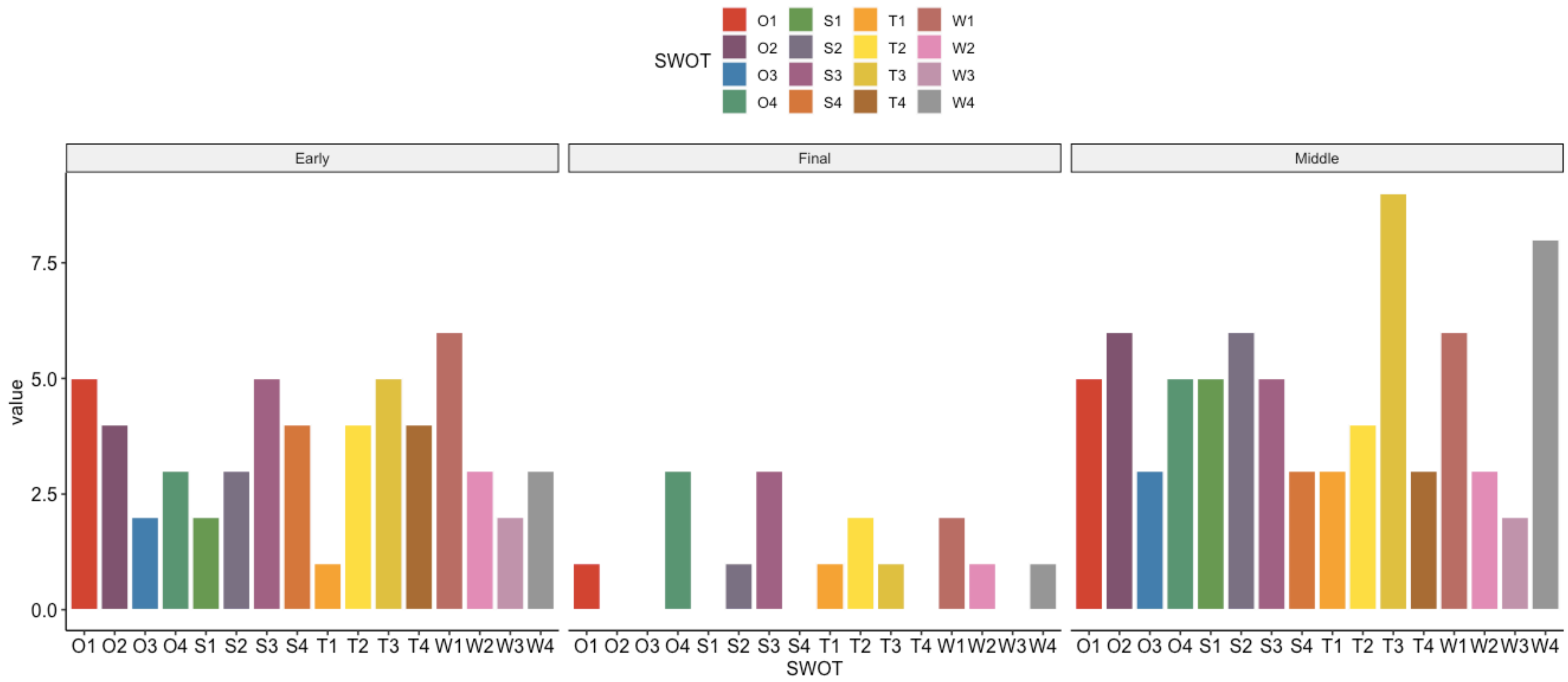


Figure 7-10: Barplot of SWOTs for Social value across 3 decision-making stages

7.2.3 Collaborative framework

Towards the end of the questionnaire, respondents are asked whether they think a decision support framework incorporating the four themes will be useful for their organisation's collaborative demand forecasting/planning. All respondents, except one, have replied 'Yes' or 'Maybe'. This validates the practical impact of this research and how it can help managers from different hierarchies and different work environments make better decisions collaboratively.

7.3 MADM methods

Business decision-making has become even more complex today with uncertainty playing a big role in the planning process. The managerial decisions being made are a direct result of their thought processes. Managers consider multiple criteria before settling on a particular decision, and this is impacted by the work environment, the business hierarchy, time available, amongst other factors. MADM methods allows the aggregation of such individual managerial opinions or judgments to collective ones (Figueira et al. 2005a). These methods help derive rankings or weights between alternatives or choices according to their importance and impact, along with the objective of the decisions to be made (Bhushan and Rai 2004).

Therefore, for combining and analysing the outputs of the different respondents two MADM methods: AHP and ELECTRE have been used. The questionnaire is based on qualitative factors, so these two MADM methods are considered suitable for such qualitative factors (Sabaei, Erkoyuncu and Roy 2015). The questionnaire included pairwise comparisons between the SWOTs of each factor, and between the four factors. The responses to those pairwise comparisons are used for the AHP method. The ELECTRE method uses the Likert scale inputs for all the SWOT statements. Since the SWOT are affected by complex and conflicting views from different hierarchies and work environments, MADM helps to overcome the problem of evaluating performance (Azimi et al. 2011).

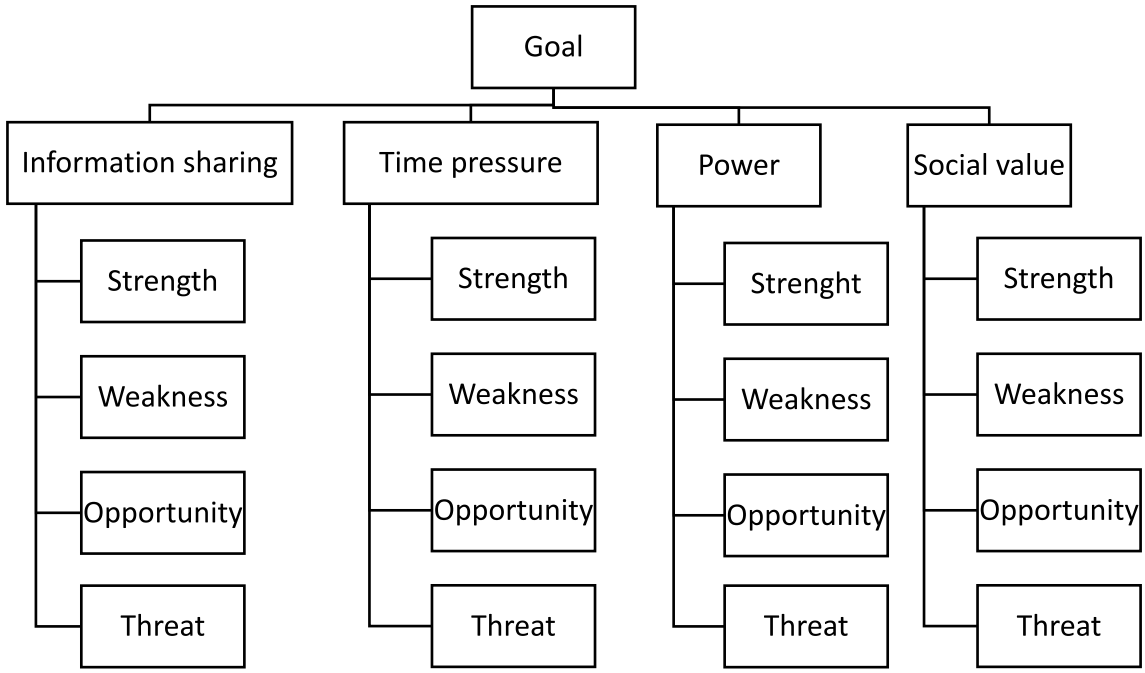


Figure 7-11: Hierarchy for MADM methods

A linear top-down hierarchy (Figure 7-11) is developed to depict the process flow for MADM methods. There is a goal to be achieved by the decision-maker based on four criteria. These four criteria are the four thematic factors generated from the interviews in previous Chapter 6. Each of these criteria has four sub-criteria or alternatives, the four SWOT statements that the decision-maker have to choose from. The responses to these alternatives and criteria are evaluated in two different methods below, first with AHP followed by ELECTRE. AHP helps to evaluate the criteria and ELECTRE is used for ranking the alternatives or sub-criteria.

7.3.1 AHP

Analytical Hierarchical Process (AHP), developed by T. L. Satty in 1971-1975, is a non-linear framework incorporating several factors simultaneously, with numerical trade-offs between them to arrive at a conclusion (Satty 1987). This method helps to manage both quantitative and qualitative elements of decision-making behaviour. The hierarchy, Figure 7-11, represents the network structure of the problem with three levels. Level one is the goal, level two is a range of four criteria, and level three is a set of SWOTs for each criterion.

AHP simplifies rating preferences between decision alternatives by using pairwise comparisons between them. The pairwise comparisons are made between the sub-criteria within each criterion, and amongst the criteria to establish relationships. To assign a number to the pairwise comparisons, a 9-scale point (Table 7-3) developed by Satty (1987) is used. Pairwise comparisons matrices provide the means to calculate importance for each alternative and factor (Görener, Toker and Uluçay 2012).

Table 7-3: Pairwise comparison scale

Importance	Explanation
1	Two criteria contribute equally to the objective
3	Experience and judgment slightly favour one over another
5	Experience and judgment strongly favour one over another
7	Criterion is strongly favoured and its dominance is demonstrated in practice.
9	Importance of one over another affirmed on the highest possible order.
2,4,6,8	Used to represent compromise between the priorities listed above.

Source: Görener, Toker and Uluçay (2012)

The AHP method has been demonstrated with its different steps below, considering the example of participant 26.

Step 1a: Pairwise comparison matrix for SWOTs

The first step (Tables 7-4, 7-5, 7-6, 7-7) involves calculating the pairwise comparison matrix for each factor. These values for the matrices come from the participant's inputs (grey cells) to the SWOTs for each factor. For example, participant 26 gave a number 6 to the pairwise comparison of strength and weakness statements for the factor Information sharing. Its reciprocal value goes under weakness row and strength column.

Table 7-4: Pairwise comparison for Information sharing (Participant 26)

Information sharing	Strength	Weakness	Opportunity	Threat
Strength	1	6	1	4
Weakness	1/6	1	1/7	1/5
Opportunity	1	7	1	6
Threat	1/4	5	1/6	1
SUM	**2.417**	**19.000**	**2.310**	**11.200**

Table 7-5: Pairwise comparison for Time pressure (Participant 26)

Time pressure	Strength	Weakness	Opportunity	Threat
Strength	1	1	1	1
Weakness	1	1	1/3	1/3
Opportunity	1	3	1	1/2
Threat	1	3	2	1
SUM	**4.000**	**8.000**	**4.333**	**2.833**

Table 7-6: Pairwise comparison for Power (Participant 26)

Power	Strength	Weakness	Opportunity	Threat
Strength	1	4	1	4
Weakness	1/4	1	1	3
Opportunity	1	1	1	1
Threat	1/4	1/3	1	1
SUM	**2.500**	**6.333**	**4.000**	**9.000**

Table 7-7: Pairwise comparison for Social Value (Participant 26)

Social Value	Strength	Weakness	Opportunity	Threat
Strength	1	6	3	5
Weakness	1/6	1	1/2	3
Opportunity	1/3	2	1	4
Threat	1/5	1/3	1/4	1
SUM	**1.700**	**9.333**	**4.750**	**13.000**

Step 1b: Normalisation of pairwise comparison matrix

In this step, the above pairwise comparison matrices are normalised by dividing each cell by the total sum of the column. This facilitates the calculation of priorities for each sub-criterion, which are the row averages. Tables 7-8, 7-9, 7-10 and 7-11 show the normalised values for the different themes using participant 26 values.

Table 7-8: Normalised pairwise comparison for Information sharing (Participant 26)

Information sharing	Strength	Weakness	Opportunity	Threat	Priority
Strength	0.414	0.316	0.433	0.357	**0.380**
Weakness	0.069	0.053	0.062	0.018	**0.050**
Opportunity	0.414	0.368	0.433	0.536	**0.438**
Threat	0.103	0.263	0.072	0.089	**0.132**

Table 7-9: Normalised pairwise comparison for Time Pressure (Participant 26)

Time pressure	Strength	Weakness	Opportunity	Threat	Priority
Strength	0.250	0.125	0.231	0.353	**0.240**
Weakness	0.250	0.125	0.077	0.118	**0.142**
Opportunity	0.250	0.375	0.231	0.176	**0.258**
Threat	0.250	0.375	0.462	0.353	**0.360**

Table 7-10: Normalised pairwise comparison for Power (Participant 26)

Power	Strength	Weakness	Opportunity	Threat	Priority
Strength	0.400	0.632	0.250	0.444	**0.432**
Weakness	0.100	0.158	0.250	0.333	**0.210**
Opportunity	0.400	0.158	0.250	0.111	**0.230**
Threat	0.100	0.053	0.250	0.111	**0.128**

Table 7-11: Normalised pairwise comparison for Social Value (Participant 26)

Social Value	Strength	Weakness	Opportunity	Threat	Priority
Strength	0.588	0.643	0.632	0.385	**0.562**
Weakness	0.098	0.107	0.105	0.231	**0.135**
Opportunity	0.196	0.214	0.211	0.308	**0.232**
Threat	0.118	0.036	0.053	0.077	**0.071**

Step 2a: Pairwise comparison matrix for Factors

Similar to the pairwise comparison SWOT matrices, here the pairwise matrix (Table 7-12) for the four factors or criteria is generated from the participant's responses.

Table 7-12: Pairwise comparison for all four factors (Participant 26)

Factor	Information sharing	Time pressure	Power	Social Value
Information sharing	1	2	1	1
Time pressure	1/2	1	1/3	1
Power	1	3	1	1
Social value	1	1	1	1
SUM	3.500	7.000	3.333	4.000

Step 2b: Normalisation of Factor pairwise comparison matrix

Similar to step 1b, the pairwise comparison matrix for factors is normalised and the group priority for each factor is calculated in Table 7-13.

Table 7-13: Normalised pairwise comparison for all four factors (Participant 26)

Factor	Information sharing	Time pressure	Power	Social Value	Priority
Information sharing	0.286	0.286	0.300	0.250	**0.280**
Time pressure	0.143	0.143	0.100	0.250	**0.159**
Power	0.286	0.429	0.300	0.250	**0.316**
Social value	0.286	0.143	0.300	0.250	**0.245**

7.3.1.1 Consistency ratio

AHP incorporates a medium to check consistency of the evaluations made by the decision-maker (participant in this study) when building the pairwise comparison matrices. Consistency ratios are calculated for the five normalised pairwise matrices for all participants' responses. These five matrices include the normalised SWOT pairwise comparison matrices for each of the four factors, and the normalised pairwise comparison matrix among the four factors. In the following steps, the calculation of consistency for SWOTs of information sharing factor in case of participant 26 is shown.

Step 3: Consistency check matrix

Here each column of the matrix in Table 7-4 (from Step 1a) is multiplied by the corresponding priority in Table 7-8 (step 1b). The grey cells in Table 7-14 is the sum of these numbers, which is divided by the same corresponding priority (Table 7-8) to get the bold numbers in the last column.

Table 7-14: Consistency Ratio for SWOT of Information sharing (Participant 26)

Strength	0.380	0.302	0.438	0.528	1.648	**4.337**
Weakness	0.063	0.050	0.063	0.026	0.203	**4.025**
Opportunity	0.380	0.352	0.438	0.792	1.962	**4.482**
Threat	0.095	0.252	0.073	0.132	0.552	**4.178**

Step 4: Calculation of λ_{max}

The average of the numbers from step 3 is calculated as $\lambda_{max.}$

λ_{max} = Average (last column of previous Table 7-14) = 4.256

Step 5: Consistency Index (CI)

Now, Consistency Index (CI) is measured using the following equation:

CI= $(\lambda_{max} – n) / (n – 1)$

Here λ_{max} = 4.256 and n is 4, hence CI = $(\lambda_{max} – 4) / 3$ = 0.0852

Step 6: Consistency Ratio (CR)

Consistency Ratio (CR) = Consistency Index (CI) / Ratio Index (RI)

Here CI is from the previous step 7 and RI=0.90 for n=4 (from Table 7-15).

CR = 0.0852 / 0.90 = 0.095 < 0.1 (significance level)

Table 7-15: Ratio Index Chart for AHP

n	3	**4**	5	6	7
RI	0.58	**0.90**	1.12	1.24	1.32

Source: Satty (1987)

Hence, the pairwise comparisons of participant 26 for SWOTs of Information sharing are consistent. This process is repeated for the other four pairwise comparison matrices for participant 26.

Similarly, this process of checking individual consistencies is continued for all participants. Some participants have perfectly consistent results, with the consistency measure equal to 4, therefore the CIs and CRs are equal to 0.

Step 7: Aggregation of CRs

The individual CRs are averages across all participants to check for consistency in the overall sample. The values are presented in Table 7-16 below, and it can be seen that the CR for Information sharing is the nearest to consistency (0.1). These values can be improved by aggregation of individual judgments (AIJ) via geometric mean rather than aggregation of individual priorities (AIP). The choice behind AIP is explained in the next step.

Table 7-16: Consistency Ratios for AHP

	Information sharing	Time pressure	Power	Social	Group
CR	0.19	0.29	0.40	0.30	0.24

7.3.1.2 Priority matrix overall

Here the priorities of all 37 participants are aggregated to get overall priority for the hierarchy. In the next step (step 8), the priorities are aggregated and step 9 shows the overall priority matrix as a result of step 8.

Step 8: Aggregation of priorities (AIP)

Different people follow different aggregation methods for MADM methods. For this study, arithmetic means (AMs) of individual priorities are calculated to aggregate the opinions. Using Ossadnik et al. (2016)'s paper on group aggregation techniques, aggregation of individual priorities (AIP) is used rather than aggregation of individual judgments (AIJ). This is because AIP supports decisions with both common and diverging goals. It can be applied to any "*multi-personal decision making problems regardless of the group size, the group complication or the decision setting*" (Ossadnik et al. 2016, p. 447).

The reason for using arithmetic mean instead of geometric mean is because AM maintains the normalisation of the priorities even after aggregation. Also, in AIP technique, different weights are multiplied with priorities depending on the individuals. Here, equal weightage has been allocated to every individual by using the average of their individual priorities. Because in this study, all opinions are treated as equally important irrespective of their hierarchical position or influence on the decision-making process.

Step 9: Overall priority matrix

From the AIP technique applied in the previous step, the aggregated priorities for each group factor, and the SWOTs are generated as shown in Table 7-17. When the individual SWOT priority is multiplied with the corresponding group priority, the overall priority for that SWOT is found. Findings from the group priorities show the following ranking for each factor: Information sharing (40.1%), Social value (27.8%), Power (16.2%) and Time pressure (15.9%). Out of the SWOTs, opportunity of information sharing has the highest overall priority of 0.179. For other three individual factors, the weakness of time pressure (5.3%), weakness of power (4.8%) and strength of social value (10.1%) have the highest rankings.

If the priorities are summed up for all the four strengths, weaknesses, opportunities and threats; opportunities for the four factors are seen as the most important with a value of 33.4%. It is followed by strengths (30.4%), weakness (20.3%) and threats (15.9%).

Table 7-17: Overall priority matrix for AHP

FACTOR group	Group Priority	SWOT	SWOT priority within the group	Overall priority
Information sharing	**0.401**	Strength	0.329	0.132
		Weakness	0.101	0.040
		Opportunity	**0.447**	**0.179**
		Threat	0.123	0.049
Time pressure	**0.159**	Strength	0.197	0.031
		Weakness	**0.328**	**0.052**
		Opportunity	0.209	0.033
		Threat	0.267	0.042
Power	**0.162**	Strength	0.243	0.039
		Weakness	**0.296**	**0.048**
		Opportunity	0.269	0.043
		Threat	0.192	0.031
Social value	**0.278**	**Strength**	**0.364**	**0.101**
		Weakness	0.226	0.063
		Opportunity	0.281	0.078
		Threat	0.130	0.036

7.3.2 ELECTRE

ELimination Et Choix Traduisant la REalité (ELimination and Choice Expressing Reality) abbreviated as ELECTRE was developed by Bernard Roy in 1968 (Yücel and Görener 2016). This method coverts quantitative pairwise comparisons for sets of alternatives into verbal results. It belongs to the group of outranking MADM methods. There are different versions (ELECTRE I, II, III, IV and ELECTRE TRI) of this method depending on various features like weight data.

The first version ELECTRE I is used here, where weight data is used to assess the criteria in line with the objective (Uysal and Yavuz 2014) and with concordance-discordance sets. For outranking two alternatives: concordance shows the criteria in favour of this assertion, while discordance shows the distance between the criteria who oppose this assertion (Figueira et al. 2005b).

The steps for ELECTRE method are demonstrated below using the questionnaire data. MS Excel is used for its implementation of this method and the solution is verified with two other software: R and XLSTAT (Excel add-in). They all produce the same result, reassuring the reproducibility of this analysis method.

Step 1: Decision matrix A and criteria weights (w_i's)

The decision matrix (Table 7-18) is the sum of participant responses for the Likert scale questions on SWOTs for each individual factor.

Table 7-18: Decision matrix A of ELECTRE

A =

156	123	126	151
126	138	144	137
170	116	127	141
111	149	115	105

The criteria weights have been borrowed from the aggregated priority AHP weights for the four factors, as shown in Table 7-19.

Table 7-19: Criteria weights for ELECTRE

Criteria	Weights (w_j)
Information sharing	0.4006
Time pressure	0.1591
Power	0.1618
Social value	0.2784

Step 2: Standard decision matrix X

Decision matrix A is normalised using the formula below to get the standard decision matrix X (Table 7-20).

$x_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}}$ where m in the number of alternatives (here m = 4)

Table 7-20: Standard decision matrix X for ELECTRE

X=

0.5467	0.4655	0.4906	0.5609
0.4415	0.5222	0.5607	0.5089
0.5957	0.4390	0.4945	0.5237
0.3890	0.5639	0.4478	0.3900

Step 3: Weighted standard decision matrix Y

The weighted standard decision matrix Y (Table 7-21) is the distribution of factor weights on the standard decision matrix X.

Table 7-21: Weighted decision matrix Y for ELECTRE

Y=

0.2190	0.0741	0.0794	0.1562
0.1769	0.0831	0.0907	0.1417
0.2387	0.0698	0.0800	0.1458
0.1558	0.0897	0.0725	0.1086

Step 4: Concordance (C) and Discordance (D) sets (Table 7-22)

The concordance set is determined by $C_{kl} = \{j,\ y_{kj} \geq y_{lj}\}, k \neq l$. The discordance set consist of j values that do not belong to the corresponding concordance set.

Table 7-22: Concordance and discordance sets for ELECTRE

Concordance Set		Discordance Set	
C(1,2)	{1,4}	**D(1,2)**	{2,3}
C(1,3)	{2,4}	**D(1,3)**	{1,3}
C(1,4)	{1,3,4}	**D(1,4)**	{2}
C(2,1)	{2,3}	**D(2,1)**	{1,4}
C(2,3)	{2,3}	**D(2,3)**	{1,4}
C(2,4)	{1,3,4}	**D(2,4)**	{2}
C(3,1)	{1,3}	**D(3,1)**	{2,4}
C(3,2)	{1,4}	**D(3,2)**	{2,3}
C(3,4)	{1,3,4}	**D(3,4)**	{2}
C(4,1)	{2}	**D(4,1)**	{1,3,4}
C(4,2)	{2}	**D(4,2)**	{1,3,4}
C(4,3)	{2}	**D(4,3)**	{1,3,4}

Step 5: Concordance and Discordance indexes (Table 7-23)

Concordance indexes are given by $c_{kl} = \sum_{j \in C_{kj}} w_j\ , k \neq l$. w_j are the factor weights from Step 1. Discordance indexes are calculated by means of the formula below:

$$d_{kl} = \frac{\max|y_{kj} - y_{lj}\ , j \in D_{kl}|}{\max|y_{kj} - y_{lj}\ , \forall\, j|}\ , k \neq l$$

$C_{threshold}$ and $D_{threshold}$ are the averages of the C and D indexes respectively.

Table 7-23: Concordance and discordance indexes for ELECTRE

Concordance Indexes		Discordance Indexes	
C(1,2)	0.6791	**D(1,2)**	0.2692
C(1,3)	0.4375	**D(1,3)**	1.0000
C(1,4)	0.8409	**D(1,4)**	0.2478
C(2,1)	0.3209	**D(2,1)**	1.0000
C(2,3)	0.3209	**D(2,3)**	1.0000
C(2,4)	0.8409	**D(2,4)**	0.2001
C(3,1)	0.5625	**D(3,1)**	0.2144
C(3,2)	0.6791	**D(3,2)**	0.2144
C(3,4)	0.8409	**D(3,4)**	0.2399
C(4,1)	0.1591	**D(4,1)**	1.0000
C(4,2)	0.1591	**D(4,2)**	1.0000
C(4,3)	0.1591	**D(4,3)**	1.0000
Total C	6	**Total D**	7.3858
$C_{threshold}$	0.50	$D_{threshold}$	0.6155

Step 6: Total dominance matrix

In this step, indexes of concordance and discordance matrices are compared to the $C_{threshold}$ and $D_{threshold}$ respectively. As shown in Table 7-24 below, if C indexes are greater than or equal to $C_{threshold}$ then it is 1 else 0. Similarly, if D indexes are less than or equal to $D_{threshold}$ then it is 1 else 0.

Table 7-24: Comparison of concordance and discordance matrices for ELECTRE

C(p,q)	C(p,q) >= $C_{threshold}$	D(p,q)	D(p,q) <= $D_{threshold}$
C(1,2)	1	**D(1,2)**	1
C(1,3)	0	**D(1,3)**	0
C(1,4)	1	**D(1,4)**	1
C(2,1)	0	**D(2,1)**	0
C(2,3)	0	**D(2,3)**	0
C(2,4)	1	**D(2,4)**	1
C(3,1)	1	**D(3,1)**	1
C(3,2)	1	**D(3,2)**	1
C(3,4)	1	**D(3,4)**	1
C(4,1)	0	**D(4,1)**	0
C(4,2)	0	**D(4,2)**	0
C(4,3)	0	**D(4,3)**	0

From the comparison table, the total dominance matrix (Table 7-25) is generated where each cell is 1 if both the corresponding C and D indexes had 1, else 0. This gives the rankings for the alternatives SWOT and shows the relationships between them.

Table 7-25: Total dominance matrix for ELECTRE

	S	**W**	**O**	**T**	**Ranks**	**Relationships**
S	0	1	0	1	2	S-->W, S-->T
W	0	0	0	1	1	W-->T
O	1	1	0	1	3	O-->S, O-->W, O-->T
T	0	0	0	0	0	

From the total dominance matrix, relationships (Figure 7-12) can be derived amongst the SWOTs. Opportunity (O) has no incoming arrow and is stated to be the most preferred amongst the others. This aligns with the AHP results of ranking the SWOTs all together irrespective of the factor group.

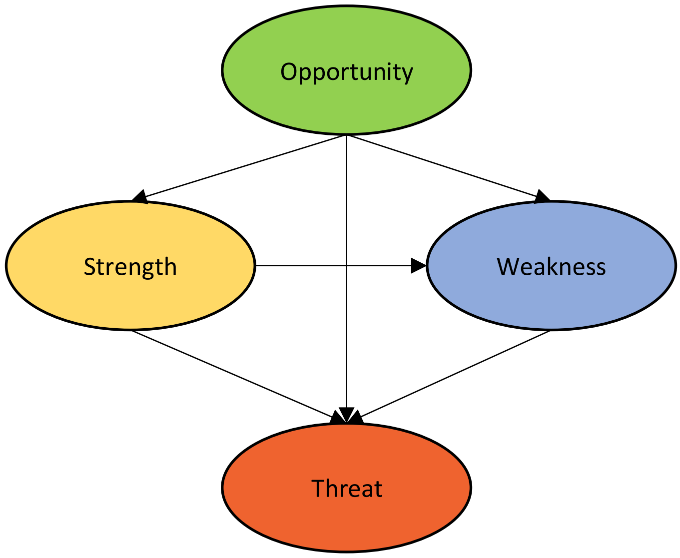


Figure 7-12: Solution for ELECTRE method

7.4 Comparison of factors and their SWOTs between cases

From sections 7.3.1 and 7.3.2, it is clear that the two MADM methods (AHP and ELECTRE) arrive at the same solution. Hence, the results of AHP method are expanded for comparison of factors and their SWOTs between cases. The questionnaire responses are divided into different cases representing the participants. AHP method is used to generate results for each case individually.

Following the same steps (section 7.3.1) for AHP method, SWOTs with highest preference are found for each factor with respect to each case (Table 7-26). For example, responses from participants of case A are aggregated and analysed using AHP method. From the overall priority matrix for case A (like in Table 7-17), the SWOTs with highest value are picked for each factor. When ranking values are similar to the second decimal place they have been considered to be of similar preference. Like for the factor *time pressure,* case A's values for the weakness and threat statements are 0.026 and 0.024 respectively. For overall, the SWOT category with highest sum across the factors is selected.

Table 7-26: Comparison of factors across cases

Cases	**Information sharing**	**Time pressure**	**Power**	**Social value**	**Overall**
A	Opportunity	Weakness, Threat	Weakness	Strength	Strength, Opportunity
C	Opportunity	Threat	Strength	Strength	Strength
D	Opportunity	Weakness	Weakness, Opportunity	Strength	Opportunity
E	Strength	Weakness	Strength	Strength	Strength
F	Opportunity	Weakness	Weakness	Strength	Opportunity
All cases	Opportunity	Weakness	Weakness	Strength	Opportunity

If the results for each individual case is compared to all the cases results from section 7.3.1, it can be seen there are variations between the cases in relation to different factors. There is a negative connotation attached to the factor *time pressure* from all cases and it is seen as weakness by most, except cases A and C where it is seen as a threat. Interestingly, the two factors of *information sharing* and *social value* are considered as an opportunity (expect case E) and strength respectively by managers from all cases.

The factor *power* has the most variations with cases A, D and F considering it to be a weakness, whereas cases C and E prefer its strength over the rest. Managers of case D have given its weakness and opportunity similar preference. This relates well to the theory that some see power as an opportunity for growth, while others consider it as impacting team outcomes.

Private versus public sector

Since the cases are from both private and public sectors, a quick comparison is drawn between their AHP results here. The first contrast is that of factor *time pressure* as it is considered as a weakness by private sector, whereas public sector case C considers it as a threat. This can have a huge impact on their decision-making process as deadlines influence the managers' judgments. Plus, factor *power* is seen as a strength by the managers of this case. This might be related to the fact that all respondents from this case are from the upper hierarchy, making decisions at middle or final stages of the planning process. Hence, there are differences in the managerial culture between the two sectors.

On the other hand, there are similarities as well. Like private sector, case C also value information sharing and social value in workplace environment. Decision-making processes might differ from case to case, but sharing information is crucial to yield productivity. Additionally, managers, irrespective of public or private sector jobs, want to feel appreciated and engaged, with positive workplace vibes.

Participants quotes on different factors

Figure 7-13 shows quotes from participants who have raised their thoughts and opinions on the different factors.

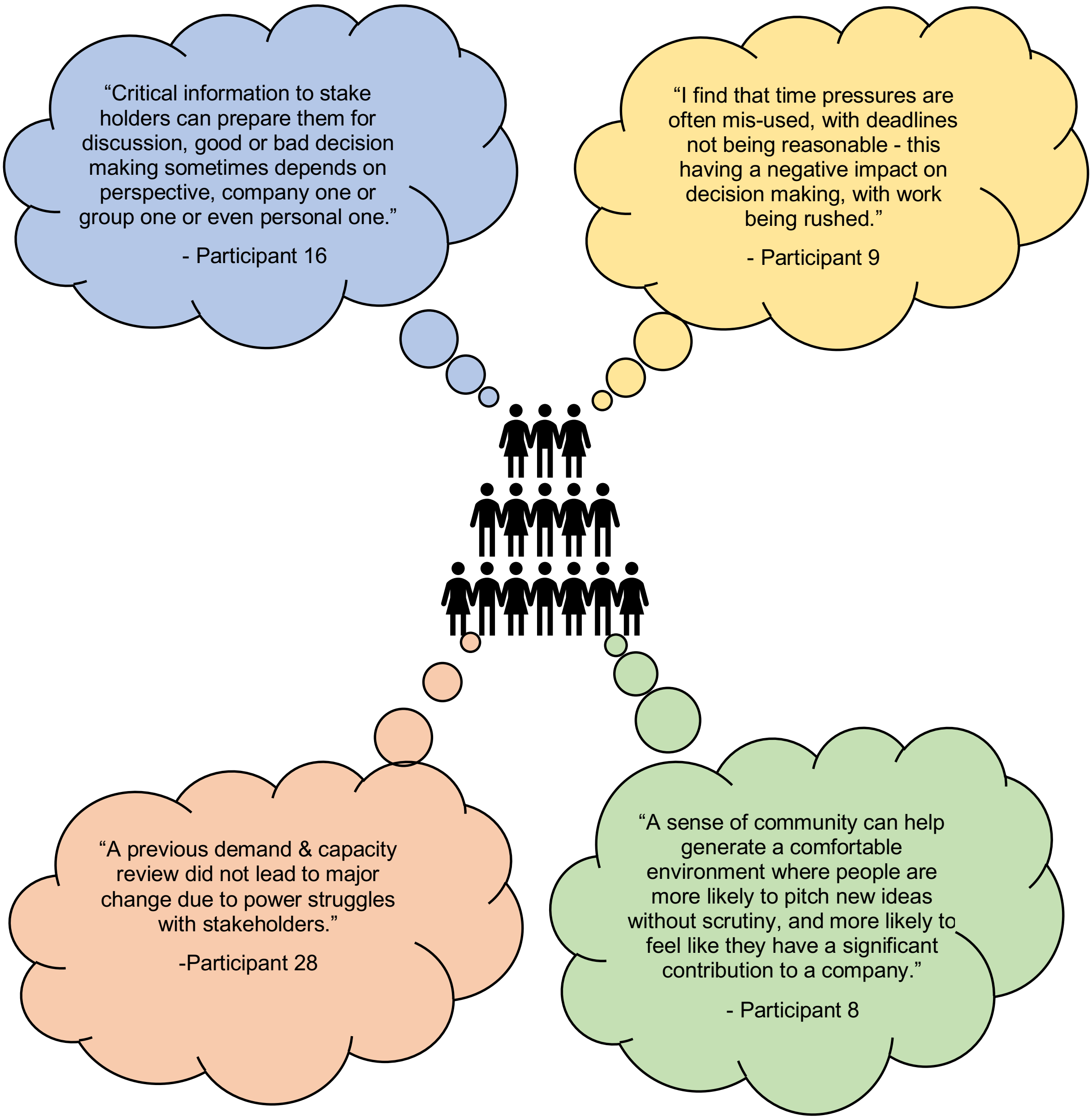


Figure 7-13: Participant quotes on the different factors

In addition to the background questions, pairwise comparisons, Likert scale, and ranking questions; the questionnaire also provided opportunities for participants to include qualitative feedback on any factor. They could give examples or mention any personal experiences regarding the decision-making process in forecasting and planning.

In the Table 7-27 below, some of the quotes for each factor have been presented. The last column includes quotes on the final question of the questionnaire, where participants are asked if they would like to add anything more. These quotes show participants' enthusiasm while filling out the questionnaire, and their willingness to improve the forecasting and planning process for their respective cases.

The quotes have been anonymised using a combination of letters and alphabets. Like the first participant P8(F) is participant number 8 from case F. The numbers have been randomly allocated to the questionnaire respondents (participants).

Table 7-27: Participants' quotes from questionnaire

Information sharing	Time pressure	Power	Social value	Collaborative framework
P8(F): "*Information sharing undertaken in a strategic way will mitigate conflict, and is essential to gain knowledge and progress. Usually it is not the sharing of data that causes conflict, but people who feel uncomfortable with what is potentially confusing or conflicting information.*" **P30(C):** "*Information sharing is crucial - there should be less focus of holding information and more emphasis on sharing knowledge*" **P7(A):** "*An example being where a resource planner at day -1 might say we have X mandays surplus for the following day. A better decision on how best to utilise these will be made through a collaborative process rather than a singular decision.*"	**P37(D):** "*It depends if the time pressure is reasonable/realistic as to how negative the impact is on information processing and hasty decision making.*" **P8(F):** "*Decisions are heavily affected by time as tight deadlines create a stressful environment. Most people's neural pathways reduce under stress affecting their ability to make decisions... Self-discipline and focus is a product of the individual and not time restraints.*" **P30(C):** "*Time pressure as a concept is quite subjective as people work differently with time pressure.*"	**P9(F):** "*Power is often misused. I've seen in multiple companies how empire building & power struggles lead to poor management, duplication of work & highly disengaged staff… A good manager shouldn't use power to get what they want, they should be able to get things done without using their position or authority.* **P37(D):** "*At [case D] Management power has been useful for coaching/development etc whereas I have been in job roles previously where Managers dont know what they are doing and reprimand their team rather than enhancing them and cause conflicts etc all the time.*"	**P7(A):** "*... However a collaborative and innovative workplace where it's safe to try stuff that gets a business outcome is a good place to work.*" **P8(F):** "[Social value] *does not divert from economic values of the business, but allows everyone to succeed in their individual role allowing economic values to thrive.*" **P9(F):** "*Well engaged employees will work harder for you & be more willing to go the extra mile - it's all about give & take.*" **P14(E):** "*I think people are more care about social value nowadays, however it is still not Influential enough to divert focus from the economic value of business.*"	**P28(C):** "*Would agree there is a difference between the technical ability to undertake forecasting and modelling work and the managerial skill to make things happen as a result of this work.*" **P16(E):** "*collaborative decision making is something like democracy. As Churchill said, it is the worst form of governance but I haven't seen something better... In reality, we need common leadership principle and core value to streamline all tiny bits inside a company. Thereby making most of the people run in the same direction and that's why nowadays mission statement like Tesla is very sexy to attract [talents] and push their employee to work together.*"

7.5 Summary

In this Data Analysis Part C, the questionnaire responses from the second stage of data collection have been analysed. The design of the questionnaire is guided by the findings of analysis parts A and B. The case stories of part A and SWOTs of the thematic analysis of part B inform the different sections of the questionnaire. Questions from different parts of the questionnaire are used for different analysis methods. To generate these analytical findings, different software like R, Excel and XLSTAT have been used. Background questions, reflective questions along with SWOT ranking questions are analysed using descriptive statistics. Some trends and traits are seen between different categories of respondents.

MADM methods of AHP and ELECTRE are used to evaluate the pairwise comparisons and Likert scale responses from the questionnaire, respectively. AHP provides the most preferred SWOT amongst each group and the rankings of the four factors amongst themselves. ELECTRE helps to validate these results by exhibiting the most preferred SWOT group amongst others. The AHP method is also used to derive some cross-case comparisons between the 5 cases. It guides to compare the private and public sector cases. Participant quotes from qualitative parts of the questionnaire are presented, which are explored further in the next Chapter 8.

In the next Discussion chapter, the findings from the three data analysis chapters (Parts A, B and C) are brought together along with concepts from Chapter 3 to answer the research questions of this study. The questionnaire findings, supplemented by case stories, are contrasted with present literature to address the research gaps. Reflection from this chapter, along with contribution of this study, are presented in the following sections of the chapter (**Error! Reference source not found.**).

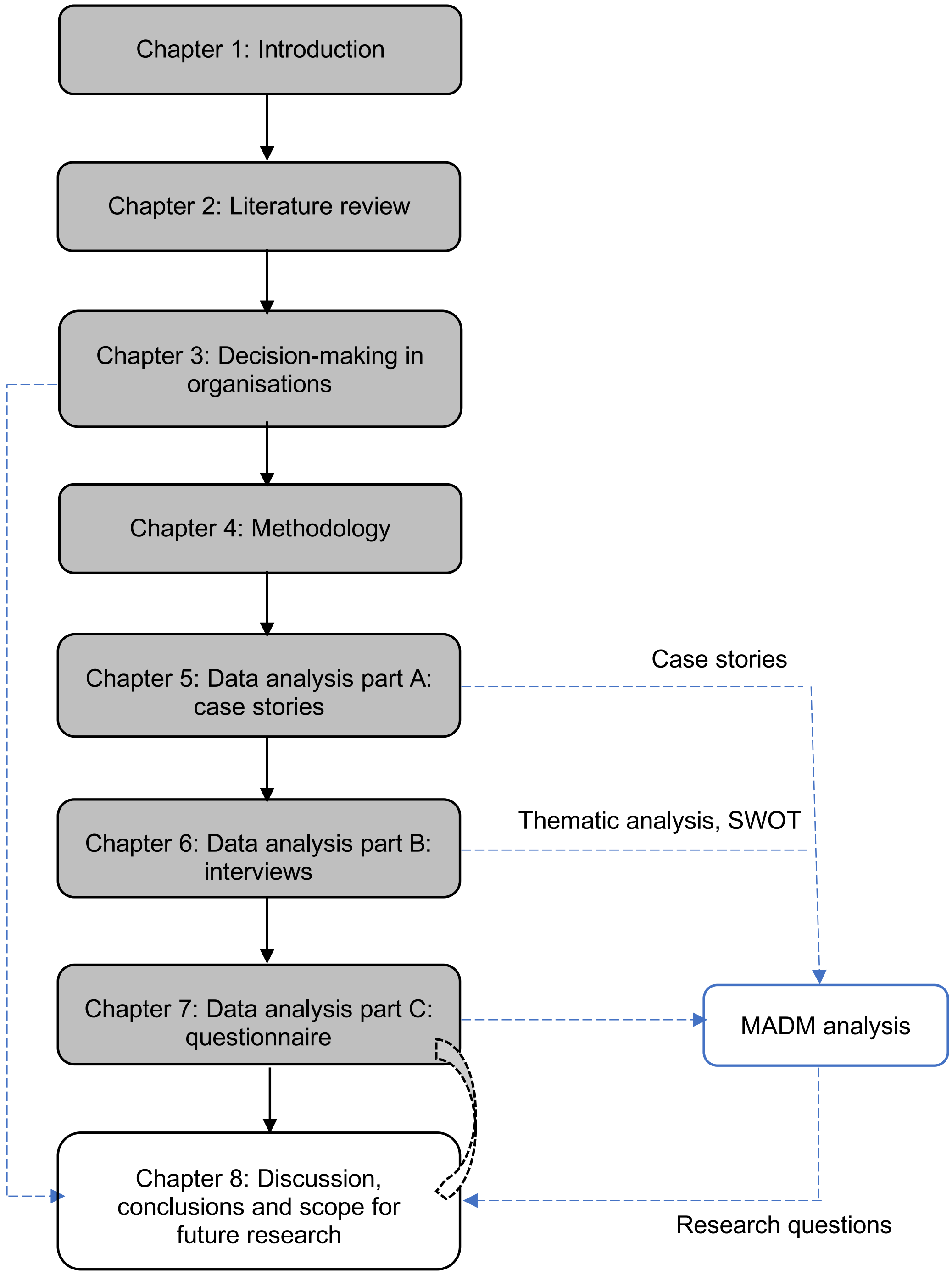


Figure 7-14: Thesis structure (Chapter 7)

Chapter 8

8 Discussion, conclusions and scope for future research

8.1 Introduction

This chapter answers the research questions outlined in section 1.2 of this study. Findings from the three data analysis Chapters 5, 6 and 7 are used to illustrate the answers. Along with the findings, literature from Chapters 2 and 3 are also used to support the answers. As shown in Table 8-1, case stories are used to answer the first research question, thematic analysis of the different attributes answer the second research question, and findings from the MADM analysis of AHP and ELECTRE answer the third one. The fourth research question validates the two propositions and the conceptual framework that can bring improvements to the current process of forecast decision-making.

Table 8-1: Evidence for research questions

Research questions	Evidence	Which chapters?
Research question 1	Case stories (interviews)	2,3,5
Research question 2	Thematic analysis (interviews)	2,3,6
Research question 3	MADM analysis (questionnaire)	3,7
Research question 4	Case stories, MADM analysis (interview, questionnaire)	2,3,6,7

Sections 8.2, 8.3, 8.4 and 8.5 each answer research questions 1, 2, 3 and 4 respectively. In section 8.6, importance of this study within the spare-part industry is highlighted. A short summary concluding the chapter is provided in section 8.7.

The following sections of 8.8, 8.9 and 8.10 provide some personal reflections on this study, research contributions, and research limitations with future research avenues respectively. As a whole, this chapter emerges as a complete view of the overall process.

8.2 Research question 1

What is the current practice in business decision-making within the context of hierarchical forecasting?

To answer this research question, this study adopted a two steps approach: one to skim through the literature for relevant articles, and two to explore this area in real-world organisations through case study interviews. These steps were carried out with an inductive approach aiming to answer the research question with very little previously known information. It is found that literature and empirical data agree with some aspects, whereas in other aspects academic literature is ahead of the real-world forecasting processes (like cross-temporal aggregation).

The findings from Chapter 5 (case stories) indicate that demand is forecasted at different levels of aggregation to support the decision-making processes within organisations. These levels of hierarchy vary across different organisations as it is mirrored with the organisational charts within these organisations. For some cases, the hierarchical levels are based on product-type (cases A, B, C, D, E) or geographical location (cases A, B, C, E, F) or customer market (cases A, C). And instead of these hierarchies being separate ones, they all merge together within the organisations (as shown in Syntetos et al. 2016a).

In addition to the internal teams, there are also a number of other teams within the organisational hierarchy that play a vital role in their forecasting process. Like marketing and promotions teams (cases A, D), maintenance teams or depots (cases B, E), data science or analytics teams (cases C, D, F), and supply chain partners (cases A, B, D, E). There are also a number of external collaborations in these forecasting decision-making processes with regulatory bodies (cases B, F) and other government agencies (case C). These types of partnerships or collaborations in supply chain forecasting have been reported in literature (Eksoz et al. 2019, Fildes and Goodwin 2020).

The hierarchical forecasting process involves a number of factors that contribute towards the decisions being made. It starts with historical data available and how the data is utilised to generate forecasts using different models and software. This step of forecasting in similar to traditional forecasting processes, but what makes it different is the reconciliation of the forecasts across the hierarchy. There are two ways of achieving that: first one is the top-down method where forecasting is carried out at an aggregated level and then divided to get more granular information (cases A, B). The second option is bottom-down where one forecasts for disaggregated historical data, then aggregate the forecasts to support upper hierarchy decisions (cases C, D, E, F). These statistical cross-sectional aggregation methods can be seen in the literature as well (section 2.3).

The novel finding here is there are a number of soft information inputs from other teams and partners during the aggregation process. These are incorporated in the forecasts by means of judgmental adjustments at different hierarchical levels by various stakeholders. And to achieve that, different collaborative approaches like meetings and discussions take place. Such collaborative decision-making helps to reconcile the forecasts across the hierarchy, along with giving forecast satisfaction. This is an example of business decision-making where forecasting software are there to support the experts but cannot substitute them (managerial judgment). This supports the literature from section 3.3 on collaborative decision-making in business and management.

There is another new concept of cross-temporal aggregation found in the literature (Kourentzes and Athanasopoulos 2019, Spiliotis et al. 2020). This combines the two reconciliation forecasting processes of temporal and cross-sectional aggregation. But this is not evidenced from the case stories in this study. The forecasts are separated across time zones, be it operational, tactical or strategic levels. Decision-makers make collaborative decisions across the levels, but the forecasting generation process is separated across the temporal levels.

8.3 Research question 2

What are the different attributes that affect the forecast decision-making process?

The next question after understanding the forecasting process, is to find out the different attributes within this process that guide the decisions being made. To answer this, interview data from the first stage of data collection is used along with support from relevant literature. The interviews, with forecasting managers from cases, provided empirical insights into the decision-making process. A thematic analysis (section 6.2) helped locate the main attributes and categorise them into four main themes of *information sharing*, *time pressure*, *power*, and *social value*.

8.3.1 Information sharing

The first dominant theme that stood out from the interviews was of how information is being shared within the case studies. The information sharing flow can be between the different teams, or team members of the same team, or between managers from different hierarchical levels of the business hierarchy. From the case studies, it can be seen that this information can be quantitative data on historical sales or demand, SFs coming from various software, regulatory figures from external organisations, and others. It can also be soft information shared across departments like promotional campaigns information from marketing (case D), ideas from operational staff (cases A, B, C, E), weather inputs (cases A, F), judgments from different experts (cases C, F), and even opinions of business heads from different hierarchies within the organisation (cases C, D, E, F).

The findings show that sharing information during the forecasting process initiates interactions between different team members, creating a collaborative environment within the organisation as predicted by Ali et al. (2017). It helps non-technical decision-makers understand how the forecasts are generated. It guides the forecasting process by incorporating knowledge from a diverse set of professionals, which has been found to be beneficial towards better forecast accuracy (Nikolopoulos et al. 2015). Exploiting the information from different hierarchical levels within the organisations help make better and proactive decisions (Spiliotis et al. 2020).

8.3.2 Time pressure

The next evident theme that guides all kinds of decision-making is that of time pressure. From the cases, it is evident that business decisions need to be made within different time scales (cases B, D). Such strict deadlines can have a huge impact on the human judgment of the managers and hence, on the decisions being taken (case C). When there is very little time available, the decision-making process changes course from a collaborative approach to a more individualistic one (cases E, F). Sometimes instead of going for a judgmentally reconciled forecast, managers can just pick up the software generated SF. On the other hand, without such timely deadlines one can prolong discussing and sharing forecast information increasing ambiguity in the decisions (Bălău and Utz 2017).

From the cases stories, it can be seen how forecasting processes are dependent on time for effective decision-making. As there are a number of time series involved in hierarchical forecasting, decisions need to be made within an accepted time frame (Spiliotis et al. 2020). The time pressure can lower the quality of the decisions being made. With less time to spare, managers are less motivated to elaborate and discuss their view-points (Bălău and Utz 2017). And a delay in generating a consensus set of forecasts cause losses to organisations, which in case C can be patient fatality. For case B, a delay can result in an airplane not being able to fly out of an airport. And for utilities organisations like in cases A and F, it can impact their service level provided to the public.

8.3.3 Power

Individual forecasters in organisations work in teams, rather than in isolation. Power struggles within such teams are evident and they vastly influence the forecast decisions. Power can have different definitions under different circumstances and for this study, it has been restricted to three characteristics of managers: forecasting work experience, product expertise, and authoritative position (one's position within the business hierarchy). Depending on the sector and type of industry, the cases display a range of magnitudes in terms of power struggles. These power struggles hamper the information sharing mechanism in the forecasting process (Pennings et al. 2019).

There are a number of political factors that determine the human interventions in forecast decision-making processes (Fildes and Goodwin 2020). For case E, the forecasts have to be adjusted because of the complicated manufacturer-retailer relationship. The managers at different hierarchical business levels have access to diverse information and that creates a power difference amongst them, like in cases A and D. Cases B and F have pressure from regulatory boards to comply by while making forecast decisions. Public sector case C have greater disparity in authoritative power than those in private sector. Managers, with more knowledge and experience in generating forecasts, make forecasts on their own for a sense of ownership. But there are also cases of uneven power when managers from higher hierarchical levels reach out to managers at ground level for first-hand updated demand information (cases B, C, E).

8.3.4 Social value

This theme of social value was not distinctly evident while conducting the interviews. However, when the transcript data is analysed, traces of this theme are seen in some of the cases. This shows how managers may not recognise the non-direct values (the direct value is the economic gain) being generated from their decisions. Depending on the team structure and the culture within a team, this social value may vary from person to person. From the case studies, it is evident that some managers give higher importance to aspects of social value than others. For example, when looking at the impact of decisions being made, some chose not to just limit its effect on their individual teams but extend it to all teams that might be influenced by it.

Cases A and B did not mention about social value, or any value created within their forecasting processes for managerial engagement. Case C has great amount of value being placed on its forecasting process as the ground staff, paramedics, deal with unpleasant scenarios in their workplace environment. Managers of cases C, D and E have agreed that coordination amongst managers from different teams increase their job satisfaction. For enhanced decision-making, behavioural aspects of managerial judgment can be utilised by building trust and showing commitment to all teams (Eksoz et al. 2019).

With the four dominant attributes (themes) been identified, the next step is to evaluate their impact on the forecasting and planning process. This is outlined in the next research question 3.

8.4 Research question 3

What impact does these attributes have on the forecast decision-making process?

To answer this research question, the questionnaire data findings are explained. A SWOT analysis of the attributes is carried out to access their impact on the decision-making process. One strength, weakness, opportunity, and threat statements for each attribute are formulated. Using MADM methods these statements are analysed to rank their importance, based on managerial inputs from the questionnaire responses.

Sharing of information is seen as an opportunity by demand managers from the different cases. It contributes to well-informed and better decisions in their forecasting and planning process. This is evident from the case interviews when information from other teams only helped the demand planners to forecast better. Managers from different cases criticise the current demand planning process for not having a proper mechanism of sharing data/information across teams. Through effective use of information sharing in collaborative forecast decision-making process, teams can improve the relationship between the different stakeholders within and outside the process (Eksoz et al. 2019).

On the other hand, time pressure is seen as a weakness for the decision-making process. Hasty decisions are usually made under time pressure as it does not allow time for discussion and collaborations. Tight deadlines make a stressful environment within the organisation, which negatively impact the forecasting and planning process. Time pressure is seen as a distraction from the core responsibilities and lowers the performance of an individual and eventually the group (team). Within such deadlines, managers are unable to process information properly and thus, compromising the consistency of decisions being taken (Kocher and Sutter 2006).

Power is the attribute with a mixed set of responses from the cases. At an overall level, it is seen as a weakness as power struggles impact team-level outcomes. But cases C and E have ranked its strength highest as power can enhance team efficiency and productivity. From the perspective of different decision-making stages, middle stage managers think of power as a weakness, but early stage managers consider it rewarding. Hence management power can go either way: one where managers can misuse the power leading to poor management and disengagement in staff. Another in which managers coach their team members streamlining the decision-making process. Judgmental interventions from different stakeholders are needed to achieve consistent hierarchical forecasts. Therefore, managerial power should be harnessed in a way that the forecasting process meets both the individual and organisational needs.

The last attribute of social value has a unanimous agreement of being a strength for the forecasting process. With an increase of social value within teams, positive vibes are cultured in the workplace environment. Managers see social value empowering the team as a community, generating a comfortable space for people to be innovative and put forward ideas with less scrutiny. With well appreciated team members, an engaged collaborative environment gets cultivated within the workplace. The benefit of having social value is it maximises the value (Social Value UK 2020) created by the forecasting process, by adding social impact along with its economic impact.

8.5 Research question 4

How can a conceptual framework incorporating these themes improve the current forecast decision-making process?

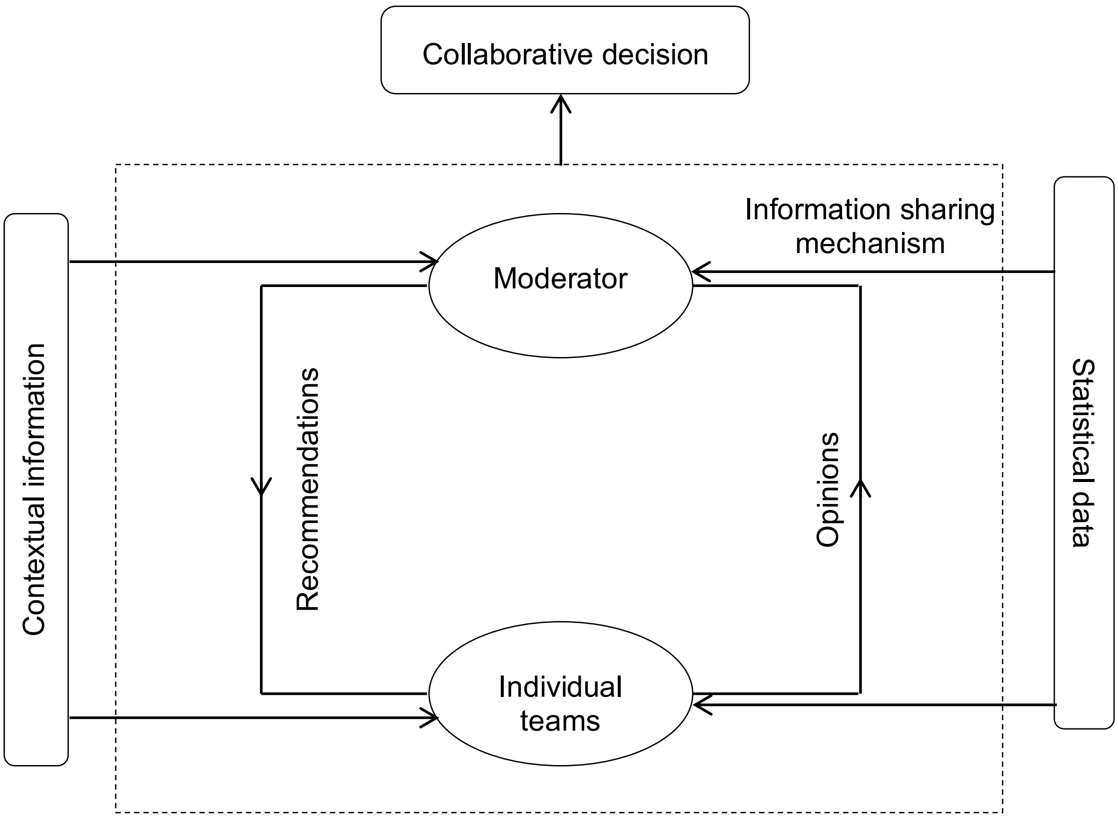
From the above three research questions, the forecast decision-making process, the dominant attributes of this process, and the impact of these attributes on the process have been identified. The overall results from AHP and ELECTRE analyses show the opportunity of these attributes as the most-preferred by the case managers. These attributes show prospects of bringing improvements in the current decision-making process. Therefore, the conceptual framework and the two propositions proposed in section 6.4 are validated here based on the results of this study.

8.5.1 Conceptual framework

Building up from the cognitive maps of the cases, a conceptual framework (Figure 6-5) on collaborative decision-making is proposed in section 6.4. Here it is discussed how this framework highlights the impacts of each attribute from the MADM analysis. This framework reflects the open system approach described in Figure 3-1.

As supply chains are becoming multifaceted and increasingly complex to manage, the importance for collaboration needs to be recognised (Hoberg et al. 2020). Group forecasting techniques have a significant influence towards achieving collaborative forecasting (Eksoz et al. 2015). Hence, this collaborative framework answers the question posed by Fildes and Goodwin (2020) on how organisational and personal barriers can be overcome to achieve more efficient but equally acceptable forecasts.

Error! Reference source not found. shows the collaborative framework for hierarchical decision-making. The advantage of using this conceptual framework for hierarchical decision-making is threefold: first, it involves information sharing amongst all hierarchical levels through a streamlined process. Contextual data from all managers can be shared as opinions that can help make better forecasts. Secondly, it constitutes a collaborative decision-making process whereby moderators are involved to evaluate the opinions from each hierarchical level. This helps reduce the time taken to make decisions compared to each manager talking with each other for every forecast cycle. The collaborative side also helps to keep power struggles at a minimum by including opinions from different levels and teams.



Third as representatives from different levels are involved, the work environment (social value) within organisations is enhanced as managers feel satisfied being a part of the decision-making process. In lines with the findings from Belvedere and Goodwin (2017), such an increased interest with any product category can improve forecast accuracy. Moderators can also access the social value orientations using different sources like survey, face-to-face meetings; which in turn can inform the expectations with respect to information sharing, coordination and time management (Bălău and Utz 2017).

Figure 8-17: Collaborative framework for hierarchical decision-making

Rather than suggesting combination of individual forecast judgments, this framework shows a group collaborative decision-making process. Because it is not just about the quality of forecast being produced. It is for stakeholder management, accountability and value creation within teams that such collaborative meetings are necessary. This way managers go beyond the system recommendations from a black-box to having more trust in the overall organisational system. This is one of the questions raised by Hoberg et al. (2020) on how organisations can be structured so human decision teams can utilise the skills of one another.

With diversity within departments, it acts as an asset when forecasts are produced by a group of decision-makers. This framework allows decision-makers with different backgrounds to state their preferences in a systematic manner. This creates low-risk spaces for team members to think and experiment their ideas with one another. As such, a ripple effect of recognition and appreciation is created that raises the trust and commitment within organisations. This generation of social value in supply chains maximises the impact of those forecast decisions being made. Fildes et al. (2019) suggests that collaborative forecasting systems can have an extensive impact on overall supply chain performance, if they reach out to the different supply chain partners.

Let's see the impact of this framework on my favourite TV series, *Money Heist*. For a successful heist, the team needs coordination between the different players. For effective decision calls, the character of *professor* has to share information from the outside real-world to the rest of the team inside (the bank). At the same time, the team has to provide their regular updates to the *professor*. It is clear from the starting that everything does not go according to plan just like forecasting. There are power struggles within the team and without a moderator between the two sides, things start moving in the wrong directions. Just like this heist, forecasting teams need to be prepared for various scenarios via collaboration and coordination across different departments and hierarchies. Such utilization of behavioural aspects in decision-making result in enhanced operational and strategic decisions with forecast satisfaction.

8.5.2 Propositions

Two propositions have been proposed in section 6.4 along with the conceptual framework. This step follows directly from the analysis of the interview data in first stage of data collection. Here these two propositions are derived based on information from the questionnaire analysis. In the analysis, the priorities for all four themes have been measured and compared with one another. For proposition one (P1), the data for the two themes of information sharing and social value are used. Information sharing across teams is seen an opportunity for well-informed decisions. Social value brings positive vibes to work-place culture. Combining the two it can be seen from the case stories and literature that with social value increased with improved information sharing mechanism. Following same pattern for proposition 2, the theme of time pressure shows its weakness towards the decision-making process. It does not allow time for collaboration and coordination, hence increasing team members reliance on their individual judgments.

P1: *Improving information sharing mechanisms increases the social value within work environments*.

Demand forecasting is a key component of supply chain management and it is impossible for one particular player to manage the process on their own. It requires obtaining data, managing the data, sharing of information, and combining that data and information for forecasting. As a number of teams are involved in these steps, it is necessary for them to generate forecasts that are not just effective but also equally acceptable by all departments. To achieve this, integration of information across different hierarchies is needed. Such information sharing has positive impacts on group forecast decision-making (Eksoz et al. 2019). Hence, the social value generated between teams increases resulting in a more engaged and collaborative environment. This aligns with the findings of Pennings et al. (2019) where interactions between participants stimulated cooperation and reduced forecast biases.

Like in case C, if information is to be shared within the internal departments on what happens to patients after being conveyed to hospitals by ambulances then the forecast decision-making team can think of innovative ways to reduce their call demand. This helps answer questions like why are many red (life-threatening) and amber (serious but not life-threatening) patients self-releasing themselves after being conveyed to the hospitals. If the ambulance service has such patient information, they can be better prepared for the next demand cycle. This shall increase the value captured by the demand forecasts to reflect the perspective of those impacted by the forecasts.

P2: *Time pressure increases dependency on individual judgments in business decision-making*.

As collaborative decision-making involves more than one person, it demands a greater amount of time than individual decision-making. Managers from different teams rely on each other for data, information and judgmental inputs. But when there is a deadline to deliver the decisions, managers tend to skip the steps of gathering information and consulting on data. Rather than prolonging the decision-making process, rushed or quick decisions based on individual judgments become more likely than collaborative ones. Managers' dependency on their own intuition increases with time pressure, resisting the ability to seek wider opinions.

For example, in case E the depot managers have to make quick forecast decisions based on their own judgments when they are sold out of any product. They do not have time to speak to the other teams within the decision-making process because of the lead time required to deliver this product. As this product is highly important for their service level, the managers are required to make those individual judgment calls. This may not be the most effective solution, but it is the best one given the time pressure to make those immediate decisions.

8.6 After-sales or service industry

The answers of the above four research questions have a big impact on the after-sales (service) industry. This industry ranges from spare-part, machinery, utilities to healthcare services. They are mostly characterised with intermittent and slow-moving demand which make it difficult to forecast and plan. There are other operational concerns as well, like perishability, obsolesces, sustainability, and inventory holding costs. Plus, there are a number of other players like regulatory boards, supply chain partners that influence their decision-making process.

As the different organisations in this industry have a contract to follow or a service-level promise to customers, the managers need to be extra careful while making the forecast decisions. Unlike other industries, the demand is erratic as the products and services may or may not be needed every time. This makes storing the products or maintaining the resources very expensive. Hence, managers are required to combine their expert knowledge with forecasting models to support their forecasts decisions.

Traditional forecasting methods using time series data have been found to be inefficient in forecasting intermittent demand for the after-sales industry. The conceptual framework benefits this industry by proactively generating information across teams. The different stakeholders can input their opinions into the decision-making process. Based on the opinions, a moderator can liaise recommendations to the forecasting team. With such a process, the forecast decisions made are not just based on historical data, but also other business expectations like contractual requirements.

8.7 Research summary

Nobel laureate Daniel Kahneman (2011, p. 433) says in his book *Thinking Fast and Slow*:

> *"Making decisions is like speaking prose – people do it all the time, knowingly or unknowingly".*

This study has explored the topic of business decision-making in demand forecasting. Demand forecasting forms an integral part of management, decision-making and planning. To overcome the difficulties in traditional forecasting methods, hierarchical forecasting is used to exploit the hierarchical characteristics within organisations. One type of such hierarchical forecasting is cross-sectional aggregation where the time-series data can be broken down by product-type or geographical locations or customer-types. Many studies have been conducted on forecast consistency of cross-sectional aggregation using statistical methods. In this study, a novel judgmental reconciliation approach is suggested for the cross-sectional aggregation of hierarchical forecasts.

To achieve the overall aim of the research, the following research questions are identified and answered with primary data gathered during the study.

8

RQ1: What is the current practice in business decision-making within the context of hierarchical forecasting?

RQ2: What are the different themes that affect the forecast decision-making process?

RQ3: What impact do these themes have on the forecast decision-making process?

RQ4: How can a conceptual framework incorporating these themes improve the current forecast decision-making process?

A case study research has been adopted to answer the above questions, with 6 case organisations from the after-sales (service) industry. One key attribute of this research is the iterative nature of the research methodology adopted. As explained at various stages throughout the thesis, a non-linear method is used across the different sections of the research path. The research questions are not formulated at the very start of the research but are revised as the research progressed. With the first exploratory research question, interviews are conducted along with two types of literature review (traditional and structured).

The interview data collected from these cases, along with the literature review in Chapter 2, describes the current practice of hierarchical decision-making in demand forecasting. A thematic analysis of the interview data resulted in four dominant themes of business decision-making: *information sharing*, *time pressure*, *power*, and *social value*. This has highlighted the need for wider literature search in the field of organisational decision-making. With interview data (cognitive maps) and knowledge from other disciplines, a conceptual framework for collaborative decision-making is developed along with two propositions.

A questionnaire was designed based on a SWOT analysis of the themes from the first stage of data collection (interviews) and analysis. This questionnaire used MADM methods AHP and ELECTRE as outranking methods to analyse the questionnaire responses. Using this analysis, the last two research questions were answered confirming the propositions and the conceptual framework. This framework showed collaborations between different teams are required to achieve reconciliation of cross-sectional forecasts. The forecasts generated as such are not just effective but also accepted by wider teams within the organisations.

When the propositions and framework were confirmed, an online focus group was organised between academics, practitioners, and policy-makers. This allowed collection of thoughts and perceptions from the participants on the results of this study. At an overall level, the responses were positive with many participants citing examples from real life where these results are applicable. This further enhances the reliability of this study. Because of ethical reasons, this stage is not included within the PhD thesis.

8.8 Reflections

As this is the last chapter of the thesis, I want to reflect on this research process as a whole. Having answered all the four research questions of this study, the research objectives outlined in section 1.2 have been achieved. With the conceptual framework for hierarchical forecasting, the research aim of this study has been fulfilled. Hence, I can't help but wonder about what things went right and what did not.

From a methodological perspective, adopting a case study research provided the perfect platform for organisational analysis. As explained in Chapters 2 and 3, very limited research had been conducted in this field using case study research. The spread of cases across sectors and industries helped to see how the forecasting process differs amongst them. Since a forecasting process can be viewed differently by different individuals, interviews with managers from different teams and hierarchies helped to visualise the process from multiple perspectives.

However, getting access to data, both in the interview and questionnaire stages proved really hard. Had access not been an issue, this study would have been based on pure qualitative data. I had to change my second stage of data collection from in-depth interviews to questionnaire as managers preferred to answer the questions online at their own convenience. Also, the questionnaire provided them an extra layer of anonymity as this study delved deep into power struggles within the organisations. For questionnaire responses, I had to contact the cases several times as managers were not completing the entire questionnaire because of this length (15-25 minutes).

Another reflection is on my personal development during this study. I have learnt multiple ways of analysing data from bringing together individual views via SWOT analysis to development of a conceptual framework. With the support of my supervisors, I have been able to seek unknown territories of MADM methods and apply them in this study. I have learnt how to maintain a balance between academic research and engaged real-world interactions, to be aware of my personal influence on the primary data collection, to make connections and maintain them, to present my research to both academic and non-academic audiences, and to think of the next steps for any research project.

8.9 Research contributions: theoretical and practical

The current findings have several theoretical and practical contributions. The first main finding contributes to the domain of hierarchical forecasting by suggesting a collaborative conceptual framework for decision-making. This study adopts collaborative forecasting approach and encourages its application to real-world practice. The framework addresses the research gap of judgmental reconciliation of hierarchical forecasts via social interactions. It provides empirical evidence of the impact of managerial judgments on the forecasting process, and how to improve them. This advances the research on hierarchical forecasting by bringing in linguistic literature on group decision-making.

Secondly, the study makes a methodological contribution by adopting a case-study research design. This focuses on the research gap of interpretivist case-study based research in forecasting literature, as illustrated in Chapter 3. The case study offers the advantage of exploring the process of forecast decision-making and planning from real-world applications. Because of the spread of these cases across industries and geographies, this research can be generalised for different other organisations.

The analysis of SWOT and MADM methods captures the multiple dimensions of the forecasting process. Although these methods have been used before in the forecasting literature, this is first time they have been used for gathering and evaluating qualitative information from business forecast hierarchies. Even the cognitive maps contribute towards the literature as a soft methodology to analyse forecasting processes from the case stories.

The iterative nature of the research design makes another significant contribution towards academic research. Because the research questions are not predefined, it has provided the space for inter-disciplinary work with borrowed knowledge from other disciplines like psychology, linguistics, and organisational studies. This has helped design the data collection instruments and also informed the findings from the data analysis.

Finally, this study confirms many findings from previous literature on organisational decision-making. The impact of four attributes of information sharing, time pressure, power, and social value is assessed on the collaborative forecasting. Two propositions on these attributes are proposed and validated using empirical data. Plus, this is the first study to introduce the concept of social value in forecast decisions.

From a practical perspective, there are a number of implications for organisations involved in forecasting for after-sales or service industry. These implications are largely drawn from the opinions of the managers raised during the study. A few key recommendations for forecasting practitioners include:

1. Maximising opportunities for collaborative decision-making.
2. Communicating relevant information between teams.
3. Setting achievable timelines for effective decisions.
4. Involving moderator(s) to minimise power struggles.
5. Encouraging teams to look beyond the economic value of forecast decisions.
6. Adopting a ‘bigger picture’ outlook for calculating decision outputs.

With the outbreak of Covid-19, there has been a shift in demand patterns with supply chain disruptions across the globe. This has made forecasting and planning extremely difficult for organisations. To help navigate this situation, collaborative forecasting with proper communication channels are suggested. This is one practical example where the findings of this study can be extended. Hierarchical forecasting act as an asset in this scenario, as the segmentation aid in understanding the changing customer buying behaviours for different products. With a collaborative framework, different stakeholders across organisations can coordinate and integrate the different organisational functions for quick and effective decisions.

8.10 Research limitations and suggestions for future research

It is important to acknowledge the limitations of this study like any other research project. The first limitation is the dominant attributes (factors) of decision-making recognised in this study. There are other factors, like culture, weather and riskiness of decisions, that can impact the forecasting process as well. The current research could be extended by considering those factors. One could also look into the possibility of the factors being interlinked to one another, and their combined influence on the forecasting process.

Another limitation is based on methodological assumptions within this study. Because of the sensitive and qualitative nature of the study, it has been difficult to collect large participant sample. The questionnaire has only 37 respondents and a limitation of this approach is there is no certainty that the right respondents filled up the questionnaire online. Future research can replicate the study by including other case companies with greater accessibility.

Also, this study used SWOT and MADM methods to analyse the questionnaire responses. There are other kinds of MADM/MCDM methods that can be applied for analysis of such questionnaire responses. For example, other versions of ELECTRE like ELECTRE II, III, IV and TRI can be used for further analysis. Future studies could involve other analytical methods like structured equation modelling or field experiments.

Even though empirical findings validated the suggested propositions and conceptual framework, follow-up studies can explicitly test these with real-world applications. When managers participate in such collaborative work, they may find it too time-consuming and start diverting from it. Research could be done on the role of the moderator in such scenarios. Finally, despite the focus of this study on after-sales and service industry, future research can replicate this to other industries. This shall shed further light on the role of industry characteristics towards collaborative forecasting.

Table 7-17 shows the threat element to be quite low for each of the four decision-making dimensions. Future work can evaluate if this changes during special events like a pandemic, financial crash, economic uncertainty, and even terrorism activities. Additionally, a forecast support system (FSS) could be built based on the suggested conceptual framework.

In addition to the above-mentioned future opportunities, a future research agenda would be to conduct research on the grey area between forecasters and decision-makers. Building on the findings of this research, other kinds of organisational decision-making model can be tested for their adaptability to the forecasting process. Another opportunity would be to expand one single case and conduct deeper analysis on their organisational decision-making processes. Like for example, the framework can be expanded for the NHS COVID-19 forecasting process to check how different stakeholders utilise a defined model of decision-making.

To conclude, this study provides a novel collaborative framework for decision-making in hierarchical forecasting. Such collaborative forecasting is strongly impacted by organisational factors like information sharing, time pressure, power, and social value. The findings show how opportunities for information sharing can increase social value within organisations. It shows how time pressure has a negative impact on collaborative decisions, and powerful managers influence the decision-making process more than others. These promising results open up interesting avenues for future research.

Bibliography

Ali, M. M., Babai, M. M, Boylan, J. E. and Syntetos, A. A. 2017. Supply chain forecasting when information is not shared. *European Journal of Operational Research* 260(1), pp. 984-994.

Alutto, J. A. and Belasco, J. A. 1972. A typology for participation in organisational decision making. *Administrative Science Quarterly* 17(1), pp. 117-125.

Alvarado-Valencia J., Barrero L.H., Önkal D. and Dennerlein J.T. 2017. Expertise, credibility of system forecasts and integration methods in judgmental demand forecasting. *International Journal of Forecasting* 33(1), pp. 298-314.

Anderson, C. and Brown, C. E. 2010. The functions and dysfunctions of hierarchy. *Research in Organizational Behavior* 30(1), pp. 55–89.

Anderson, D. R., Sweeney, D. J., Williams, T. A. and Wisniewski, W. 2017. *An introduction to Management Science: Quantitative approaches to Decision Making*. South Western: Cengage Learning.

Ariely, D. and Zakay, D. 2001. A timely account of duration in decision making. *Acta Psychologica* 108(1), pp. 187-207.

Armstrong, J. 1980. The seer-sucker theory: the value of experts in forecasting. *Technology Review* 82(7), pp. 16-24.

Arvan, M., Fahimnia, B., Reisi, M. and Siemsen, E. 2019. Integrating human judgement into quantitative forecasting methods: A review. *Omega* 86(1), pp. 237-252.

Ashton, A. H. and Ashton, R. H. 1985. Aggregating Subjective Forecasts: Some Empirical Results. *Management Science* 31(12), pp. 1499-1508.

Asimakopoulos, S., Dix, A. and Fildes, R. 2011. Using hierarchical task decomposition as a grammar to map actions in context: Application to forecasting systems in supply chain planning. *International Journal of Human-Computer Studies* 69(1), pp. 234-250.

Athanasopoulos, G., Ahmed, R. A. and Hyndman, R. J. 2009. Hierarchical forecasts for Australian domestic tourism. *International Journal of Forecasting* 25(1), pp. 146-166.

Azimi, R., Yazdani Chamzini, A., Fouladgar, M.M., Zavadskas, E. K. and Basiri, M. H. 2011. Ranking the strategies of mining sector through ANP and TOPSIS in a SWOT framework. *Journal of Business Economics and Management* 12(4), pp. 670-689.

Babai, M. Z., Ali, M. M., Boylan, J. E. and Syntetos, A. A. 2013. Forecasting and inventory performance in a two-stage supply chain with ARIMA(0,1,1) demand: Theory and empirical analysis. *International Journal of Production Economics* 143(1), pp. 463-471.

Baecke P., De Baets S. and Vanderheyden K. 2017. Investigating the added value of integrating human judgement into statistical demand forecasting systems. *International Journal of Production Economics* 191(1), pp. 85-96.

Bălău, N. and Utz, S. 2017. Information sharing as strategic behaviour: the role of information display, social motivation and time pressure. *Behaviour &*

Information Technology 36(6), pp. 589-605. DOI: https://doi.org/10.1080/0144929X.2016.1267263.

Beer, S. 1978. Forecasting – a toll of adaptation. In Fildes, R. and Wood, D. eds. *Forecasting and planning*. England: Saxon House in association with Gower Press, pp. 187-199.

Belvedere, V. and Goodwin, P. 2017. The influence of product involvement and emotion on short-term product demand forecasting. *International Journal of Forecasting* 33(1), pp. 652-661.

Ben Zur, H and Breztinz, S. J. 1981. The effect of time pressure on risky behaviour. *Acta Psychologica* 47(1), pp. 89-104.

Bhushan, N. and Rai, K. 2004. *Strategic Decision Making: Applying the Analytic Hierarchy Process*. London: Springer.

Blattberg, R. C. and Hoch, S. J. 1990. Database models and managerial intuition: 50% model + 50% manager. *Management Science* 36(8), pp. 887-899.

Blumber, B. F., Cooper, D. R. and Schindler, P. S. 2014. *Business research methods*. 4th Ed. London: McGraw-Hill Higher Education.

Boylan, J. 2016. Reproducibility. *IMA Journal of Management Mathematics* 27(2), pp. 107-108.

Brunnhofer, M., Gabriella, N., Schöggl, J. P., Stern, T. and Posch, A. 2020. The biorefinery transition in the European pulp and paper industry – A three-phase Delphi study including a SWOT-AHP analysis. *Forest Policy and Economics* 110 (1), 101882. DOI: https://doi.org/10.1016/j.forpol.2019.02.006.

Bryman, A. 2012. *Social research methods*. 4th Ed. Oxford: Oxford University Press.

Bryman, A. and Bell, E. 2011. *Business Research Methods*. 3rd Ed. Oxford: Oxford University Press.

Buchanan, D. A. 2012. Case studies in organizational research. In Symon, G. and Cassell, C. eds. *Qualitative organisational research: Core Methods and Current Challenges*. London: Sage, pp. 351-370.

Budescu, D. V. and Chen. E. 2015. Identifying expertise to extract the wisdom of crowds. *Management Science* 61(2), pp. 267-280.

Büyüközkan, G. and Ilicak, Ö. 2019. Integrated SWOT analysis with multiple preference relations. *Kybernotes* 48(3), pp. 451-470.

Byrne, P. J. and Heavey, C. 2006. The impact of information sharing and forecasting in capacitated industrial supply chains: A case study. *International Journal of Production Economics* 103(1), pp. 420-437.

Chang, P., Wang, C., Yuan, B. J. C. and Chuang, K. 2002. Forecast of development trends in Taiwan's machinery industry. *Technological Forecasting and Social Change* 69(8), pp. 781-802.

Chen, H. and Rakha, H. A. 2016. Multi-step prediction of experienced travel times using agent-based modeling. *Transportation Research Part C* 71(1), pp. 108-121.

Chen, T. 2012. Forecasting the unit cost of a product with some linear fuzzy collaborative forecasting models. *Algorithms* 5(1), pp. 449-468.

Churchill, G. A. and Iacobucci, D. 2002. *Marketing research: methodological foundations*. 8th Ed. South Western: Cengage Learning.

Clarks 2020. *All Styles*. Available at: https://www.clarks.co.uk/All-Styles/c/325 [Accessed: 15th May 2020].

Clemen, R. T. 1989. Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting* 5(4), pp. 559-583.

Cooper, D. R. and Schindler, P. S. 2006. *Business Research Methods*. 9th Ed. Boston: McGraw-Hill.

Creswell, J. W. 2007. *Qualitative inquiry & research design: choosing among five approaches*. 2nd Ed. London: Sage.

Croce, V., Wöber, K and Kester, J. 2016. Expert identification and calibration for collective forecasting tasks. *Tourism Economics* 22(5), pp. 979-994.

Dangerfield, B. J. and Morris, J. S. 1992. Top-down or bottom-up: aggregate versus disaggregate extrapolations. *International Journal of Forecasting* 8(2), pp. 233-241.

Denzin, N. and Lincoln, Y. S. 2005. Introduction: The discipline and practice of qualitative research. In Denzin, N. and Lincoln, Y. S. eds. *The sage handbook of qualitative research.* 3rd Ed. Thousand Oaks: Sage Publications, pp. 1-33.

Easterby-Smith, M., Thorpe, R. and Jackson, P. 2008. *Management Research.* 3rd Ed. *London: Sage.*

Easterby-Smith, M., Thorpe, R. and Jackson, P. 2012. *Management Research*. 4th Ed. London: Sage.

Easterby-Smith, M., Thorpe, R. and Jackson, P. 2015. *Management and Business Research.* 5th Ed. London: Sage.

Eksoz, C., Mansouri, S. F. and Bourlakis, M. 2014. Collaborative forecasting in the food supply chain: A conceptual framework. *International Journal of Production Economics* 158(1), pp. 120-135.

Eksoz, C., Mansouri, S. A., Bourlakisc, M. and Önkal, D. 2019. Judgmental adjustments through supply integration for strategic partnerships in food chains. *Omega* 87(1), pp. 20-33.

Emmel, N. 2013. *Sampling and choosing cases in qualitative research: a realistic approach.* London: Sage.

Ernst, P., Pemantle, R., Satopää, V. and Ungar, L. 2016. Bayesian aggregation of two forecasts in the partial information framework. *Statistics & Probabilistic Letters* 119(1), pp. 170-180.

Fast, N. J., Halevy, N. and Galinsky, A. D. 2012. The destructive nature of power without status. *Journal of Experimental Social Psychology* 48(1), pp. 391-394.

Figlewski, S. and Urich, T. 1983. Optimal Aggregation of Money Supply Forecasts: Accuracy, Profitability and Market Efficiency. *The Journal of Finance* 28(3), pp. 695-710.

Figueira, J., Greco, S. and Ehrgott, M. 2005a. *Multiple Criteria Decision Analysis: State of the Art Surveys.* NY: Springer.

Figueira, J., Mousseau, V. and Roy, B. 2005b. ELECTRE methods. In Figueira, J., Greco, S. and Ehrgott, M. eds. *Multiple Criteria Decision Analysis: State of the Art Surveys.* NY: Springer, pp. 133-162.

Fildes, R. and Goodwin, P. 2013. Forecasting support systems: what we know, what we need to know. *International Journal of Forecasting* 29(1), pp. 290-294.

Fildes, R. and Goodwin, P. 2020. *Stability and innovation in the use of forecasting systems: a case study in a supply-chain company*. Department of Management Science Working Paper 2020:1. Lancaster University.

Fildes, R., Goodwin, P. and Önkal, D. 2019. Use and misuse of information in supply chain forecasting of promotion effects. *International Journal of Forecasting* 35(1), pp. 144-156.

Fildes, R., Goodwin, P., Lawrence, M. and Nikolopoulos, K. 2009. Effective forecasting and judgmental adjustments: an empirical evaluation and strategies for improvement in supply-chain planning. *International Journal of Forecasting* 25(1), pp. 3-23.

Firth, M. 1977. *Forecasting methods in business and management*. London: Edward Arnold.

Fischer, A. M. 2014. *The social value of employment and the redistributive imperative for development.* Human Development Report, UNDP, New York. Available at: http://hdr.undp.org/en/content/social-value-employment-and-redistributive-imperative-development. [Accessed: 12th March 2018].

Fischer, I. and Harvey, N. 1999. Combining forecasts: What information do judges need to outperform the simple average? *International Journal of Forecasting* 15(3), pp. 227-246.

Fliedner, G. 1999. An investigation of aggregate variable time series forecast strategies with specific subaggregate time series statistical correlation. *Computers and Operations Research* 26(10-11), pp. 1133-1149.

Fliedner, G. 2001. Hierarchical forecasting: issues and use guidelines. *Industrial Management & Data Systems* 101(1), pp. 5-12.

Ganesh, M., Raghunathan, S. and Rajendran, C. 2014. The value of information sharing in a multi-product, multi-level supply chain: Impact of product substitution, demand correlation, and partial information sharing. *Decision Support Systems* 58(1), pp. 79-94.

Gavake, R. K. 2014. Multi-Criteria Decision Making: An overview of different selection problems and methods. *International Journal of Computer Science and Information Technologies* 5(4), pp. 5643-5646.

Ghauri, P. and Grønhaug, K. 2002. *Research methods in business studies: a practical guide.* 2nd Ed. England: Pearson Education Limited.

Gilligan, C., Neale, B. and Murray, D. 1983. *Business decision making.* Oxford: Philip Allan.

Goodwin, P. 1996. Statistical correction of judgmental point forecast and decisions. *Omega* 24(5), pp. 551-559.

Goodwin, P. 2002. Integrating management judgment with statistical methods to improve short-term forecasts. *Omega* 30(2), pp. 127-135.

Goodwin, P. 2005. How to integrate management judgment with statistical forecasts. *Foresight: The International Journal of Applied Forecasting* 1, pp. 8-12.

Goodwin, P. 2020. Could These Recent Findings Improve Your Judgmental Forecasts? *Foresight: The International Journal of Applied Forecasting* 56, pp. 7-9.

Goodwin, P. and Fildes, R. 1999. Judgmental forecasts of time series affected by special events: Does providing a statistical forecast improve accuracy? *Journal of Behavioural Decision Making* 12(1), pp. 37-53.

Goodwin, P. and Wright, G. 2014. *Decision analysis for management judgment*. 5th Ed. Cornwall: Wiley.

Görener, A. 2012. Comparing AHP and ANP: An application of Strategic Decisions Making in a Manufacturing Company. *International journal of Business and Social Science* 3(11), pp. 194-208.

Görener, A., Toker, K. and Uluçay, K. 2012. Application of Combined SWOT and AHP: A Case Study for a Manufacturing Firm. *Procedia - Social and Behavioral Sciences* 58(1), pp. 1525-1534.

Graefe, A., Armstrong, J. S., Jones Jr., R. J. and Cuźan, A. G. 2014. Combining forecasts: An application to elections. *International Journal of Forecasting* 30(1), pp. 43-54.

Greer, L. L., Bunderen, L. V. and Yu, S. 2017. The dysfunctions of power in teams: A review and emergent conflict perspective. *Research in Organisational Behavior* 37(1), pp. 103-124.

Grinnell, M., Keeley, S. M. and Doherty, M. E. 1971. Bayesian predictions of faculty judgments of graduate school success. *Organizational Behavior and Human Performance* 6(1), pp. 379-387.

Gross, C. W. and Peterson, R. T. 1983. *Business forecasting*. 2nd Ed. Boston: Houghton Mifflin Company.

Guba, E. G. and Lincoln, Y. S. 2005. Paradigmatic controversies, contradictions and emerging confluences. In Denzin, N. and Lincoln, Y. S. eds. *The sage handbook of qualitative research*. 3rd Ed. Thousand Oaks: Sage Publications, pp. 191-215.

Gummesson, Evert. 1991. *Qualitative Methods in Management Research*. London: Sage publications.

Gupta, U. G. and Clarke, R. E. 1996. Theory and applications of the Delphi technique: a bibliography (1975-1994). *Technological Forecasting and Social Changes* 53(2), pp. 185-211.

Hanke, J. E. and Reitsch, A. G. 1998. *Business forecasting*. 6th Ed. NJ: Prentice-Hall.

Hartmann, C., Ressel, F., Hahmann, M., Habich, D. and Lehner, W. 2019. CSAR: the cross-sectional autoregression model for short and long-range forecasting. *International Journal of Data Science and Analytics* 8(1), pp. 165-181.

Harvey, N. and Harries, C. 2004. Effects of judges' forecasting on their later combination of forecasts for the same outcomes. *International Journal of Forecasting* 20(3), pp. 391-409.

Havlíková, M. 2016. Likert scale versus Q-table measures – a comparison of host community perceptions of a film festival. *Scandinavian Journal of Hospitality and Tourism* 16(2), pp. 196-207.

Herrera, F. and Herrera-Viedma, E. 2000. Linguistic decision analysis steps for solving decision problems under linguistic information. *Fuzzy Sets and Systems* 115(1), pp. 67-82.

Herrare, F., Herrera-Viedma, E. and Verdegay, J. L. 1996. A model of consensus in group decision making under linguistic assessments. *Fuzzy sets and systems* 78(1), pp. 73-87.

Herrera, F., Herrera-Viedma, E. and Verdegay, J. L. 1997. A rational consensus model in group decision making using linguistic assessments. *Fuzzy Sets and Systems* 88(1), pp. 31-49.

Herrrera- Viedma, E., Martínez, L., Mata, F. and Chiclana, F. 2005. A consensus support system model for group decision-making problems with multigranular linguistic preference relations. *IEEE transactions on Fuzzy Systems* 13(5), pp. 644-658.

Hibon, M. and Evgeniou, T. 2005. To combine or not to combine: selecting among forecasts and their combinations. *International Journal of Forecasting* 21(1), pp. 15-24.

Hill, G. W. 1982. Group versus individual performance: are N +1 heads better than one? *Psychological Bulletin* 91(2), pp. 517-539.

Hoberg, K., Thornton, L. and Wieland, A. 2020. How to deal with the human factor in supply chain management? *International Journal of Physical Distribution & Logistics Management*. DOI: https://doi.org/10.1108/IJPDLM-10-2019-0311.

Hochrein, S. and Glock, C. H. 2012. Systematic literature reviews in purchasing and supply management research: a tertiary study. *International Journal of Integrated Supply Management* 7(4), pp. 215-245.

Hodgett, R. E. 2016. Comparison of multi-criteria decision-making methods for equipment selection. *The International Journal of Advanced Manufacturing Technology* 85(5), pp. 1145-1157.

Hogarth, R. M. 1978. A note on aggregating opinions. *Organizational Behavior and Human Performance* 21(1), pp. 40-46.

Hogarth, R. M. 1980. *Judgment and choice*. Chichester, UK: John Wiley & Sons.

Hogarth, R. M. and Makridakis, S. 1981. Forecasting and planning: an evaluation. *Management Science* 27(2), pp. 115-138.

Hughes, G. D. 1987. Sales forecasting requirements. In Makridakis, S. and Wheelwright, S. C. eds. *The handbook of forecasting*. 2nd Ed. United States of America: John Wiley & Sons, pp. 17-33.

Hyndman, R. J. and Athanasopoulos, G. 2014. Optimally reconciling forecasts in a hierarchy. *Foresight: The International Journal of Applied Forecasting* 35, pp. 42-48.

Hyndman, R. J. and Athanasopoulos, G. 2018 Forecasting: principles and practice, 2nd edition, OTexts: Melbourne. Available at: https://otexts.com/fpp2/. [Accessed: 7th May 2020].

Hyndman, R. J. and Koehler, A. B. 2006. Another look at measures of forecast accuracy. *International Journal of Forecasting* 22(1), pp. 679-688.

Hyndman, R. J., Ahmed, R. A. and Athanasopoulos, G. 2007. *Optimal combination forecasts for hierarchical time series.* Working paper 09/07. Department of Econometrics and Business Statistics, Monash University. Available at: http://webdoc.sub.gwdg.de/ebook/serien/e/monash_univ/wp9-07.pdf [Accessed: 18th March 2018].

Hyndman, R. J., Ahmed, R. A., Athanasopoulos, G., and Shang, H. L. 2011. Optimal combination forecasts for hierarchical time series. *Computational Statistics & Data Analysis* 55(9), pp. 2579-2589.

Jouini, M. N. and Clemen, R. T. 1996. Copula Models for Aggregating Expert Opinions. *Operations Research* 44(3), pp. 444-457.

Kaczmarek-Majer, K. and Hryniewicz, O. 2019. Application of linguistic summarization methods in time series forecasting. *Information Sciences* 478(1), pp. 580-594.

Kahneman, D. 2011. *Thinking Fast and Slow*. Penguin Books: Great Britain.

Kahneman, D. and Tversky, A. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47(2), pp. 263-291.

Kahraman, C., Demirel, N. C. and Demirel, T. 2017. Prioritization of e-Government strategies using a SWOT-AHP analysis: the case of Turkey. *European Journal of Information Systems* 16(3), pp.284-298.

Karvetski, C. W., Olson, K. C., David, R. M. and Twardy, C. R. 2013. Probabilistic coherence weighting for optimizing expert forecasts. *Decision Analysis* 10(4), pp. 305-326.

Kerstholt, J. H. 1994. The effect of time pressure on decision-making behaviour in a dynamic task environment. *Acta Psychologica* 86(1), pp. 89-104.

Khan, M., Hussain, M. and Saber, H. M. 2016. Information sharing in a sustainable supply chain. *International Journal of Production Economics* 181(1), pp. 208-214.

King, M. A., Abrahams, A. S. and Ragsdale, C. T. 2014. Ensemble methods for advanced skier days prediction. *Expert Systems with Applications* 41(1), pp. 1176-1188.

Kocher, M. G. and Sutter, M. 2006. Time is money - Time pressure, incentives, and the quality of decision-making. *Journal of Economic Behavior & Organization* 61(1), pp. 375-392.

Kolassa, S. and Siemsen, E. 2016. *Demand forecasting for managers*. Business Expert Press: New York.

Kolios, A., Mytilinou, V. Lozano-Minquez, E. and Salonitis, K. 2016. A comparative study of Multiple-Criteria Decision-Making methods under Stochastic Inputs. *Energies* 9(7), 566. DOI: https://doi.org/10.3390/en9070566.

Kourentzes, N. and Athanasopoulos, G. 2019. Cross-temporal coherent forecasts for Australian tourism. *Annals of Tourism Research* 75(1), pp. 393-409.

Kovács, G. and Spens, K. 2005. Abductive reasoning in logistics research. *International Journal of Physical Distribution & Logistics Management* 35(2), pp. 132-144.

Krueger, R. A. and Casey, M. A. 2015. *Focus groups: a practical guide for applied research*. 5th Ed. London: Sage.

Lawrence, M., Goodwin, P., O'Connor, M. and Önkal, D. 2006. Judgmental forecasting: a review of progress over the last 25 years. *International Journal of Forecasting* 22(1), pp. 493-518.

Le Var, R. M. H. 1998. A questionnaire study of the effect on work of participation in and influence on decision-making. *Research in Post-Compulsory Education* 3(2), pp. 153-173.

Lee, H. L., So, K. C. and Tang, C. S. 2000. The value of information sharing in two-level supply chain. *Management Science* 46(5), pp. 626-643.

Legerstee, R. and Franses, P. H. 2014. Do experts' SKU forecasts improve after feed-back? *Journal of Forecasting* 33(1), pp. 69-79.

Levine, D., Krehbiel, T. C. and Berenson, M. L. 2000. *Business Statistics: A first course*. 2nd Ed. New Jersey: Prentice-Hall.

Lim, J. S. and O'Connor, M. 1995. Judgemental adjustment of initial forecasts: Its effectiveness and biases. *Journal of Behavioral Decision* Making 8(3), pp. 149-168.

Lim, J. S. and O'Connor, M. 1996. Judgmental forecasting with interactive forecasting support systems. *Decision Support Systems* 16(1), pp. 339-357.

Lin V.S. 2019. Judgmental adjustments in tourism forecasting practice: How good are they? *Tourism Economics* 25(3), pp. 402-424.

Lincoln, Y. S. and Guba, E. G. 1985. *Naturalistic Inquiry*. London: Sage.

Little, C. H. 1986. Forecast Bias in Aggregate Business Forecasts: Comparison of Businessmen and Expert Forecasters. *Review of Business* 7(4), pp. 28-30.

Mahmoud, E. 1987. The evaluation of forecasts. In Makridakis, S. and Wheelwright, S. C. eds. *The handbook of forecasting*. 2nd Ed. United States of America: John Wiley & Sons, pp. 504-522.

Maines, L. A. 1996. An experimental examination of subjective forecast combination. *International Journal of Forecasting* 12(2), pp. 223-233.

Major, R.L. and Ragsdale, C.T. 2001. Aggregating expert predictions in a networked environment. *Computers and Operations Research* 28(1), pp. 1231-1244.

Makridakis, S. and Wheelwright, S. C. 1989. *Forecasting methods for management*. 5th Ed. United States of America: John Wiley & Sons.

Mancuso, A. C. B. and Werner, L. 2013. Review of combining forecast approaches. *Independent Journal of Management & Production* 4(1), pp. 248-277.

Markovska, N., Taseska, V. and Pop-Jordanov, J. 2009. SWOT analyses of the national energy sector for sustainable energy development. *Energy* 34 6), pp. 752-756.

Mathews, B. P. and Diamantopoulos, A. 1986. Managerial intervention in forecasting: An empirical investigation of forecast manipulation. *International Journal of Research in Marketing* 3(1), pp. 3-10.

Mathews, B. P. and Diamantopoulos, A. 1989. Judgemental revision of sales forecasts- a longitudinal extension. *Journal of Forecasting* 8(1), pp. 129-140.

Mathews, B. P. and Diamantopoulos, A. 1990. Judgmental revision of sales forecasts- effectiveness of forecast selection. *Journal of Forecasting* 9(1), pp. 407-415.

Mathews, B. P. and Diamantopoulos, A. 1992. Judgemental revision of sales forecasts- the relative performance of judgementally revised versus non-revised forecasts. *Journal of Forecasting* 11(1), pp. 569-576.

Mathews, B. P. and Diamantopoulos, A. 1994. Towards a taxonomy of forecast error measures- a factor-comparative investigation of forecast error dimensions. *Journal of Forecasting* 13(1), pp. 409-416.

Maule, A. J. and Edland, A. C. 1997. The effects of time pressure on judgement and decision making. In Ranyard, R., Crozier, W. R. and Svenson, O. eds. *Decision making: cognitive models and explanation*. London: Routledge & Kegan Paul, pp. 187-204.

Maule, A. J., Hockey, G. R. J. and Bdzola, L. 2000. Effects of time-pressure on decision-making under uncertainty: changes in affective state and information processing strategy. *Acta Psychologica* 104(1), pp. 283-301.

May, T. 2001. *Social Research: Issues, methods and process*. 3rd Ed. Buckingham: Open University Press.

Miles M. B. and Huberman, A. M. 1994. *Qualitative data analysis*. 2nd Ed. London: Sage.

Moreno, B. and López, A. J. 2007. Combining economic forecasts through information measures. *Applied Economics Letters* 14(1), pp. 899-903.

Morris, P. 1977. Combining Expert Judgments: A Bayesian Approach. *Management Science* 23(7), pp. 679-693.

Moye, N. A. and Langfred, C. W. 2007. Information sharing and group conflict: going beyond decision making to understand the effects of information sharing on group performance. *The International Journal of Conflict Management* 15(4), pp. 381-410.

Myung, I. J., Ramamoorti, S. and Bailey Jr., A. D. 1996. Maximum entropy aggregation of expert predictions. *Management Science* 42(10), pp. 1420-1436.

Nelson, R. G. and Bessler, D. A. 1992. Quasi-rational expectations: Experimental evidence. *Journal of Forecasting* 11(1), pp. 141-156.

Nicoleta B. and Sonja U. (2017 Information sharing as strategic behaviour: the role of information display, social motivation and time pressure. *Behaviour & Information Technology* 36(6), pp. 589-605.

Nikolopoulos, K., Syntetos, A. A., Boylan, J., Petropoulos F. and Assimakopoulos, V. 2011. An aggregate-disaggregate intermittent demand approach (ADIDA) to forecasting: an empirical proposition and analysis. *Journal of Operational Research Society* 62(3), pp. 544-554.

Nikolopoulos, K., Lawrence, M., Goodwin, P. and Fildes, R. 2005. *On the accuracy of judgmental interventions on forecasting support systems.* Management Science Working Paper Series, The Department of Management Science, Lancaster University. Available at: https://core.ac.uk/download/pdf/1555406.pdf. [Accessed: 7th May 2020].

Nikolopoulos, K., Litsa, A., Petropoulos, F., Bougioukos, V. and Khammash, M. 2015. Relative performance of methods for forecasting special events. *Journal of Business Research* 68(8), pp. 1785-1791.

Oliveira, J.M. and Ramos, P. 2019. Assessing the Performance of Hierarchical Forecasting Methods on the Retail Sector. *Entropy* 21(4), 436. DOI: https://doi.org/10.3390/e21040436.

Önkal, D., Gönül, M. S. and Lawrence, M. 2008. Judgmental adjustments of previously adjusted forecasts. *Decision Sciences* 39(2), pp. 213-238.

Ord, K. and Fildes, R. 2013. *Principles of business forecasting*. South Western: Cengage Learning.

Ossadnik, W., Schinke, S. and Kaspar, R. H. 2016. Group Aggregation Techniques for Analytic Hierarchy Process and Analytic Network Process: A Comparative Analysis. *Group Decision and Negotiation* 25(2), pp. 421-457.

Owen, D. 2015. Collaborative decision making. *Decision analysis* 12(1), pp. 29-45.

Paola., M. D and Gioia, F. 2016. Who performs better under time pressure? Results from a field experiment. *Journal of Economic Psychology* 53(1), pp. 37-53.

Pathak, D., Rothschild, D. and Dudik, M. 2015. A comparison of forecasting methods: fundamentals, polling, prediction markets, and experts. *The Journal of Prediction Markets* 9(2), pp. 1-31.

Pennings, C. L. P., van Dalen, J. and Rook, L. 2019. Coordinating judgmental forecasting: Coping with intentional biases. *Omega* 87(1), pp. 46-56.

Perera, H. N., Hurley, J., Fahimnia. B. and Reisi, M. 2019. The human factor in supply chain forecasting: A systematic review. *European Journal of Operational Research* 274(2), pp. 574-600.

Perkins, S. W. and Rao, R. C. 1990. The role of experience in information use and decision making by marketing managers. *Journal of Marketing Research* 27(1), pp. 1-10.

Petropoulos, F. 2014. *Judgmental reconciliation of hierarchical forecasts*. Available at: http://www.forsoc.net/2014/06/25/judgmental-reconciliation-of-hierarchical-forecasts/ [Accessed: 19th March 2018].

Petropoulos, F., Goodwin, P. and Fildes, R. 2017. Using a rolling training approach to improve judgmental extrapolations elicited from forecasters with technical knowledge. *International Journal of Forecasting* 33(1), pp. 314-324.

Phadermrod, B., Crowder, M. C. and Wills, G. B. 2019. Importance-Performance Analysis based SWOT analysis. *International Journal of Information Management* 44(1), pp.194-203.

Pickton, D. W. and Wright, S. 1998. What's swot in strategic analysis? *Strategic Change* 7(2), pp. 101-109.

Pidd, M. 2003. *Tools for thinking: Modelling in Management Science*. 2nd Edition. England: John Wiley & Sons.

Pritchard, K. 2012. Combining qualitative methods. In Symon, G. and Cassell, C. eds. *Qualitative organisational research*. London: Sage.

PWC. 2018. *Social capital - valuing the impact business has on society*. Available at: https://www.pwc.co.uk/services/sustainability-climate-change/total-impact/social-capital-valuing-the-impact-business-has-on-society.html. [Accessed: 1st March 2018].

R Core Team 2019. *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. [Computer program]. Available at: https://www.R-project.org/. [Accessed: 17th April 2020].

Raju, P. S., Lonial, S. C. and Mangold, W. G. 1995. Differential effects of subjective knowledge, objective knowledge and usage experience on decision making: an exploratory investigation. *Journal of Consumer Psychology* 4(2), pp. 153-180.

Rehman H-Ur., Wan, G., Ullah, A. and Shaukat, B. 2019. Individual and combination approaches to forecasting hierarchical time series with correlated data: an empirical study. *Journal of Management Analytics* 6(3), pp. 231-249. DOI: https://doi.org/10.1080/23270012.2019.1629342.

Robson, C. 2002. *Real World Research: a research for social scientists and practitioner-researchers*. 2nd Ed. Oxford: Blackwell Publishing.

Rocha, M. S. R. and Clardeira-Pires, A. 2019. Environmental Product Declaration promotion in Brazil: SWOT analysis and strategies. *Journal of Cleaner Production* 235(1), pp. 1061-1072.

Rostami-Tabar, B., Babai, M. Z., Ducq, Y. and Syntetos, A. 2015. Non-stationary demand forecasting by cross-sectional aggregation. *International Journal of Production Economics* 170(A), pp. 297-309.

Rostami-Tabar, B., Babai, M. Z., Syntetos, A. and Ducq, Y. 2013. Demand forecasting by temporal aggregation. *Naval Research Logistics* 60(1), pp. 479-498.

Saaty, R. W. 1987. The analytic hierarchy process - what it is and how it is used. *Mathematical Modelling* 9(3-5), pp.161-176.

Sabaei, D., Erkoyuncu, J. and Roy, R. 2015. A review of multi-criteria decision making methods for enhanced maintenance delivery. *Procedia CIRP* 37(1), pp. 30-35.

Sadiq, N. U. and Chan, E. Y. 2015. Time pressure reverses risk preferences. *Organizational Behavior and Human Decision Processes* 130(1), pp. 58-68.

Salo, A. A. and Bunn, D. W. 1995. Decomposition in the assessment of judgmental probability forecasts. *Technological Forecasting and Social Change* 49(1), pp. 13-25.

Sarma, V. 2015. *Judgmental reconciliation of hierarchical forecasts*. MSc Dissertation. Cardiff University.

Satopää, V., Baron, J., Foster, D. P., Mellers, B. A., Tetlock, P. E. and Ungar, L. H. 2014a. Combining multiple probability predictions using a simple logit model. *International Journal of Forecasting* 30(1), pp. 344-356.

Satopää, V., Jensen, S. T., Mellers, B. A., Tetlock, P. E. and Ungar, L. H. 2014b. Probability aggregation in time-series: Dynamic hierarchical modeling of sparse expert beliefs. *The Annals of Applied Statistics* 8(2), pp. 1256-1280.

Satopää, V., Jensen, S., Pemantle, R., Ungar, L., 2015. *Partial information framework: aggregating estimates from diverse information sources*. Available at: https://pdfs.semanticscholar.org/fdb7/1aa9104995acf5936bff79351a36f58e8b06.pdf. [Assessed: 19th March 2018].

Saunders, M., Lewis, P. and Thornhill. 2012. *Research methods for business students.* 6th Ed. England: Pearson Education Limited.

Scharzkopf, A. B., Tersine, R. J. and Morris, J. S. 1988. Top-down versus bottom-up forecasting strategies. *International Journal of Production Research* 26(11), pp. 1833-1843.

Seifert, M. and Hadida, A. L. 2013. On the relative importance of linear model and human judge(s) in combined forecasting. *Organizational Behavior and Human Decision Processes* 120(1), pp. 24-36.

Selnes, F. and Howell, R. 1999. The Effect of Product Expertise on Decision Making and Search for Written and Sensory Information. In Arnould, E. J. and Scott, L. M. eds. *NA - Advances in Consumer Research*. UT: Association for Consumer Research, pp. 80-89.

Seuring. S. and Müller, M. 2008. From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production* 16(1), pp. 1699-1710.

Silverman, D. 2013. *Doing qualitative research.* 4th Ed. London: Sage.

Silverman, M. 1997. *Business Statistics*. 2nd Ed. England: McGraw-Hill.

Singleton, R. A. and Straits, B. C. 2010*. Approaches to Social Research*. 5th Ed. Oxford: Oxford University Press.

Sniezek, J. A. 1990. A comparison of techniques for judgmental forecasting by groups with common techniques. *Group & Organization Studies* 15(1), pp. 5-20.

Social Value UK. 2020. *What is social value?* Available at: http://www.socialvalueuk.org/what-is-social-value/. [Accessed: 7th May 2020].

Soll, J. B. and Mannes, A. E. 2011. Judgmental aggregation strategies depend on whether the self is involved. *International Journal of Forecasting* 27(1), pp. 81-102.

Song, H., Qiu, R.T.R. and Park, J. 2019. A review of research on tourism demand forecasting. *Annals of Tourism Research* 75(1), pp. 338-362.

Spann, M. and Skiera, B. 2003. Internet-based virtual stock markets for business forecasting. *Management Science* 49(10), pp. 1310-1326.

Spiliotis, E., Petropoulos, F., Kourentzes, N. and Assimakopoulos, V. 2020. Cross-temporal aggregation: Improving the forecast accuracy of hierarchical electricity consumption. *Applied Energy* 261(1), 114339. DOI: https://doi.org/10.1016/j.apenergy.2019.114339.

Spithourakis, G. P., Petropoulos, F., Nikolopoulos, K. and Assimakopoulos, V. 2015. Amplifying the learning effects via a Forecasting and Foresight Support System. *International Journal of Forecasting* 31(1), pp. 20-32.

Staelin, R. and Turner, R. E. 1973. Error in Judgemental Sales Forecasts: Theory and Results. *Journal of Marketing Research* 10(1), pp. 10-16.

Straus, S. G., Parker, A. M. and Bruce, J. B. 2011. The Group Matters: A Review of Processes and Outcomes in Intelligence Analysis. *Group Dynamics: Theory, Research, and Practice* 15(2), pp. 128-146.

Syntetos, A. A. 2014. Forecasting by temporal aggregation. *Foresight: The International Journal of Applied Forecasting* 34, pp. 6-11.

Syntetos, A. A., Babai, Z., Boylan, J., Kolassa, S. and Nikolopoulos, K. 2016a. Supply chain forecasting: theory, practice, their gap and the future. European *Journal of Operations Research* 252(1), pp. 1-26.

Syntetos, A. A., Georgantzas, N. C., Boylan, J. E. and Dangerfield, J. E. 2011. Judgement and supply chain dynamics. *Journal of the Operational Research Society* 62(1), pp. 1138-1158.

Syntetos, A. A., Keyes, M. and Babai, M. Z. 2009a. Demand categorisation in a European spare parts logistics network. *International Journal of Operations and Production Management* 29(3), pp. 292-316. DOI: https://doi.org/10.1108/01443570910939005.

Syntetos, A. A., Kholidasari, I. and Naim, M. M. 2016b. The effects of integrating management judgment into OUT levels: In or out of context? *European Journal of Operational Research* 249(1), pp. 853-863.

Syntetos, A. A., Konstantinos, N. and Boylan, J. E. 2010. Judging the judges through accuracy-implication metrics: the case of inventory forecasting. *International journal of forecasting* 26(1), pp. 134-143.

Syntetos, A. A., Konstantinos, N., Boylan, J. E, Fildes, R. and Goodwin, P. 2009b. The effects of integrating management judgment into intermittent demand forecasts. *International Journal of Production Economics* 118(1), pp. 72-81.

Taylor, C. R. and Yildirim, H. 2010. Public information and electoral bias. *Games and Economic Behavior* 68(1), pp. 353-375.

Teddlie, C. and Tashakkori, A. 2009. *Foundations of mixed method research. London: Sage.*

Thomas, M. C., Evans, M. and Davies, R. L. 1999. Forecasting and scenario planning in the steel packaging industry: Case of tinplate petfood cans. *Ironmaking and Steelmaking* 26(6), pp. 463-469.

Thomson, A. W., Dumyahn, S., Prokopy, L. S., Amberg, S., Baumgart-Getz, A., Jackson-Tyree, J., Perry-Hill, R., Reimer, A., Robinson, K., Mase, A. S. 2013. Comparing random sample Q and R methods for understanding natural resource attitudes. *Field Methods* 25(1), pp. 25-46.

Tranfield, D., Denyer, D and Smart, P. 2003. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management* 14(1), pp. 207-222.

Trapero, J. R., Pedregal, D. J., Fildes, R. and Kourentzes, N. 2013. Analysis of judgmental adjustments in the presence of promotions. *International Journal of Forecasting* 29(2), pp. 234-243.

Turban, E. 1995. *Decision support and expert systems*. 4th Ed. Prentice Hill: New Jersey.

Tziralis, G. and Tatsiopoulos, I. 2007. Prediction markets: An information aggregation perspective to the forecasting problem. *World Review of Entrepreneurship, Management and Sustainable Development* 3(3/4), pp. 251-259.

Ungar, L., Mellers, B., Satopää, V., Tetlock, P. and Baron, J. 2012. *The Good Judgment Project: A Large Scale Test of Different Methods of Combining Expert Predictions*. In The Association for the Advancement of Artificial Intelligence 2012 Fall Symposium Series, Univ. Pennsylvania, Philadelphia, PA.

Uysal, H. T. and Yavuz, K. 2014. Selection of Logistics Centre Location via ELECTRE method: a case study in Turkey. *International Journal of Business and Social Science* 5(9), pp. 276-289.

Velasquez, M. and Hester, P. T. 2013. An Analysis of Multi-Criteria Decision Making Methods. *International Journal of Operations Research* 10(2), pp. 56-66.

Verstraete G., Aghezzaf E.-H. and Desmet B. 2020. A leading macroeconomic indicators' based framework to automatically generate tactical sales forecasts. *Computers and Industrial Engineering* 139, 106169. DOI: https://doi.org/10.1016/j.cie.2019.106169.

Wang, G., Kulkarni, S. R., Poor, H. V. and Osherson, D. N. 2011. Aggregating Large Sets of Probabilistic Forecasts by Weighted Coherent Adjustment. *Decision Analysis* 8(2), pp. 128-144.

Warner, J. 2012. Collaborative decision making. *Ready to Manage*. Available at: http://blog.readytomanage.com/collaborative-decision-making/. [Accessed: 12th March 2018].

Wickramasuriya, S. L., Athanasopoulos, G. and Hyndman, R. J. 2019. Optimal forecast reconciliation for hierarchical and grouped time series through trace minimization. *Journal of the American Statistical Associatio*n 114(526), pp. 804-819.

Winkler, R. L. 1987. Judgmental and bayesian forecasting. In Makridakis, S. and Wheelwright, S. C. eds. *The handbook of forecasting*. 2nd Ed. United States of America: John Wiley & Sons, pp. 248-265.

Wood, D. and Fildes, R. 1978. Forecasting quality - the decision interface. In Fildes, R. and Wood, D. eds. *Forecasting and planning*, England: Saxon House in association with Gower Press, pp. 137-150.

Wright, G. and Rowe, G. 2011. Group-based judgmental forecasting: An integration of extant knowledge and the development of priorities for a new research agenda. *International Journal of Forecasting* 27(1), pp. 1-13.

Yang, D. and Zhang, A. N. 2019. Impact of Information Sharing and Forecast Combination on Fast-Moving-Consumer-Goods Demand Forecast Accuracy. *Information* 10(8), 260. DOI: https://doi.org/10.3390/info10080260.

Yang, M., Hu, Q. and Wang, Y. 2019. Multi-task Learning Method for Hierarchical Time Series Forecasting. In: Tetko, I., Kůrková, V., Karpov, P. and Theis, F. eds. *Artificial Neural Networks and Machine Learning – ICANN 2019: Text and Time Series*. ICANN 2019. Lecture Notes in Computer Science, 11730. Springer, Cham.

Yin, R. K. 2003. *Case study research: Designs and methods* (3rd Ed.) Thousand Oaks, CA: Sage.

Yin, R. K. 2009. *Case study research: Designs and methods* (4th Ed.) Thousand Oaks, CA: Sage.

Yin, R. K. 2014. *Case study research: Designs and methods* (5th Ed.) Thousand Oaks, CA: Sage.

Young, D. L., Goodie, A. S., Hall, B. D. and Wu, E. 2012. Decision making under time pressure, modeled in a prospect theory framework. *Organizational Behavior and Human Decision Processes* 118(1), pp. 179-188.

Yücel, M. G. and Görener, A. 2016. Decision Making for Company Acquisition by ELECTRE method. *International Journal of Supply Chain Management* 5(1), pp. 75-83.

Zellner, A. and Tobias, J. 2000. A note on aggregation, disaggregation and forecasting performance. *Journal of Forecasting* 19(5), pp. 457-469.

Zhang, J. and Chen, J. 2013. Coordination of information sharing in a supply chain. *International Journal of Production Economics* 143(1), pp. 178-187.

Zhao, X., Jinxing, X. and Leung, J. 2002. The impact of forecasting model selection on the value of information sharing in a supply chain. *European Journal of Operations Research* 142(1), pp. 321-344.

Zhou, F., Page, L., Perrons, R. K., Zheng, Z. and Washington, S. 2019. Long-term forecasts for energy commodities price: What the experts think. *Energy Economics* 84(1), 104484. DOI: https://doi.org/10.1016/j.eneco.2019.104484.

Zolghadri, M. and Bourrieres, J. 2006. Data aggregation mechanisms for production planning functions of firms. *Journal of Decision Systems* 15(4), pp. 425-452.

Appendices

Appendix A: Ethics approval form

CARDIFF UNIVERSITY
PRIFYSGOL CAERDYDD

Cardiff Business School
Ysgol Busnes Caerdydd

Sarma, Violina
Cardiff University Business School

03 May 2020

Dear Violina:

Ethics Approval Reference: E12017001
Project Title: Judgmental reconciliation of hierarchical forecasts

I would like to confirm that your project has been granted ethics approval as it has met the review conditions.

Should there be a material change in the methods or circumstances of your project, you would in the first instance need to get in touch with us for re-consideration and further advice on the validity of the approval.

I wish you both the best of luck on the completion of your research project.

Yours sincerely,

Electronic signature via email

Debbie Foster
Chair of the ethics sub-committee
Email: CARBSResearchOffice@cardiff.ac.uk

Appendix B: Questionnaire

Introduction

Introduction.

Welcome !!

This study is being conducted by Violina Sarma, a PhD Student at Cardiff Business School, Cardiff University under the supervision of Professor Anthony Beresford and Dr. Emrah Demir, who can be contacted via following email addresses: *Beresford@cardiff.ac.uk* and *DemirE@cardiff.ac.uk*.

Participation in the study is entirely voluntary and participants can withdraw from the study at any time without giving a reason. The participants will be asked few questions on the demand forecasting and planning process used in their respective companies.

All information provided during the questionnaire will be held anonymously so that it will not be possible to trace information or comments back to individual contributors. Information will be stored in accordance with the current Data Protection Act.

The collected data will be used only for the purposes associated with teaching, academic presentations and publications. The findings of the study will form part of the PhD thesis.

No responses will be shared with any company representative, only analysis reports will be presented.

Participants may also ask questions at any time and discuss any concerns with either the researcher (*SarmaV2@cardiff.ac.uk*) or the supervisors as listed above.

Please tick the following box as consent before proceeding:

- ◯ I give my consent to participate in this study.

Section A: Background questions

QA.1.
BACKGROUND QUESTIONS

In this section, there are 10 background questions to record the demographics (like age, gender, job role) of the participants.

My age:

< 20 years	20-30 years	30-40 years	40-50 years	> 50 years
◯	◯	◯	◯	◯

QA.2. My gender is

Female	Male	Other	Prefer not to say
◯	◯	◯	◯

QA.3. **My job designation is: (Eg. demand planner, forecasting manager, data analyst)**

QA.4.
My job position within the current company/organisation comes under

- Hierarchical level 1 (Operational level)
- Hierarchical level 2 (Strategic level)
- Both
- Other

QA.5. **In the demand forecasting and decision-making process within my organisation, I am the ___________ stage decision-maker**

- Early
- Middle
- Final

QA.6. **I have worked in this company/organisation for ____________.**

< 3 months	3 months-1 year	1-3 years	3-5 years	> 5 years
○	○	○	○	○

QA.7.
I have had some sort of formal education in forecasting or business decision-making (including planning):

Yes	No
○	○

QA.8.
I had gained practical knowledge on forecasting/ planning/ decision-making from previous work experience (before joining the present company/ organisation):

Yes	No
○	○

QA.9.
I have worked in this domain of forecasting or business decision-making (both in this current and previous companies/organisations) for:

< 3 months	3 months-1 year	1-3 years	3-5 years	> 5 years
○	○	○	○	○

QA.10.
How many working days in a week? Please choose option one (1 day) as your answer for this question. This question is to check whether participants are reading the instructions carefully before answering them.

1 day	2 days	3 days	4 days	5 days	6 days
○	○	○	○	○	○

Section B: Concept questions

B.
CONCEPT QUESTIONS

In the preliminary stage of this research, interviews were conducted with managers from different case companies. These companies spread across different industries (like airline, electronics, retail, automobile) and different sectors (public and private). The objective was to explore the demand forecasting/planning process in these companies.

From the interviews, the following four major concepts (also called factors) were found to be common between teams involved in demand forecasting/planning:
Concept 1: Information sharing
Concept 2: Time pressure
Concept 3: Power
Concept 4: Social value

In this section, there are questions for each of these concepts and how these fit within your current work environment. Each of these concepts are *defined below from the perspective of this research. Please refer back to these definitions while answering the questions if needed*.

Each concept has two questions, each on four statements outlining the strength, weakness, threat and opportunity of the concept. Please answer ALL of the questions in this section. There is an open question (optional) at the end of each part for you to highlight any example(s), experience or discussion for each concept.

QB.1.1.
Concept 1: Information Sharing

For the purpose of this research, *this concept is defined as the sharing of information (related to the decision-making process of demand forecasting/ planning) between different teams within the company/organisation or even team members within the same team.*

	Choose one option				
	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
S1: Information sharing leads to group collaborations.	○	○	○	○	○
S2: Sharing information can lead to conflicts within groups.	○	○	○	○	○
S3: Sharing of information increases workload for different teams.	○	○	○	○	○
S4: Information sharing leads to well informed and better decision-making.	○	○	○	○	○

QB.1.2. **For the following set of questions, please choose the number highlighting your agreement with the two statements.**

The options range from 1 (agree to both statements EQUALLY) to 9 (agreeing EXTREMELY STRONGLY to one statement over the other). The nearer the number to each statement (left or right) increases the strength of your preference of it over the other.

Preference leaning towards left column								Equal preference	Preference leaning towards right column							
9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9

For example for the first set S1 and S2:

a) if you choose 3 (right side of 1), it means you agree SLIGHTLY more with S2 than S1.

b) if you choose 7 (left side of 1), it means you agree STRONGLY with S1 than S2.

	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
S1: Information sharing leads to group collaborations.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Sharing information can lead to conflicts within groups.
S1: Information sharing leads to group collaborations.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S3: Sharing of information increases workload for different teams.
S1: Information sharing leads to group collaborations.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S4: Information sharing leads to well informed and better decision-making.
S2: Sharing information can lead to conflicts within groups.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S3: Sharing of information increases workload for different teams.
S2: Sharing information can lead to conflicts within groups.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S4: Information sharing leads to well informed and better decision-making.
S3: Sharing of information increases workload for different teams.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S4: Information sharing leads to well informed and better decision-making.

QB.1.3. **Please rank the following statements according to your agreement, give 1 to the statement you agree most and 4 to the statement you agree least with:**

	1	2	3	4
S1: Information sharing leads to group collaborations.	○	○	○	○
S2: Sharing information can lead to conflicts within groups.	○	○	○	○
S3: Sharing of information increases workload for different teams.	○	○	○	○
S4: Information sharing leads to well informed and better decision-making.	○	○	○	○

QB.1.4. **Would you like to add any specific example, experience or discussion on this concept of information sharing?**

QB.2.1.
Concept 2: Time pressure

For the purpose of this research, this concept is defined as *the role that time pressure plays in the decision-making process of demand forecasting/ planning within organisations.*

Choose one option

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
S1: Time pressure impacts the information processing capacity.	○	○	○	○	○
S2: Time pressure helps to self-discipline and focus on the one task, improving productivity.	○	○	○	○	○
S3: Hasty decisions are made under time pressure.	○	○	○	○	○
S4: Time pressure helps to streamline the decision-making process.	○	○	○	○	○

***QB.2.2.* For the following set of questions, please choose the number highlighting your agreement with the two statements.**

The options range from 1 (agree to both statements EQUALLY) to 9 (agreeing EXTREMELY STRONGLY to one statement over the other). The nearer the number to each statement (left or right) increases the strength of your preference of it over the other.

Preference leaning towards left column								Equal preference	Preference leaning towards right column							
9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9

For example for the first set S1 and S2:

a) if you choose 3 (right side of 1), it means you agree SLIGHTLY more with S2 than S1.

b) if you choose 7 (left side of 1), it means you agree STRONGLY with S1 than S2.

	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
S1: Time pressure impacts the information processing capacity.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Time pressure helps to self-discipline and focus on the one task, improving productivity.
S4: Time pressure helps to streamline the decision-making process.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Time pressure helps to self-discipline and focus on the one task, improving productivity.
S3: Hasty decisions are made under time pressure.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Time pressure helps to self-discipline and focus on the one task, improving productivity.

S1: Time pressure impacts the information processing capacity.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S4: Time pressure helps to streamline the decision-making process.
S1: Time pressure impacts the information processing capacity.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S3: Hasty decisions are made under time pressure.
S4: Time pressure helps to streamline the decision-making process.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S3: Hasty decisions are made under time pressure.

QB.2.3.
Please rank the following statements according to your agreement, give 1 to the statement you agree most and 4 to the statement you agree least with:

	1	2	3	4
S4: Time pressure helps to streamline the decision-making process.	○	○	○	○
S3: Hasty decisions are made under time pressure.	○	○	○	○
S1: Time pressure impacts the information processing capacity.	○	○	○	○
S2: Time pressure helps to self-discipline and focus on the one task, improving productivity.	○	○	○	○

QB.2.4. **Would you like to add any specific example, experience or discussion on this concept of <u>time pressure</u>?**

QB.3.1.
Concept 3: Power

For the purpose of this research, this concept of power *is restricted to team members' characteristics that can give rise to power struggles within the organisation. The three characteristics considered are: forecasting work experience, domain expertise (knowledge acquired from formal education in forecasting) and authoritative position (positions within the business hierarchy).*

Choose one option

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
S1: Power in work environment enhances team efficiency and productivity.	○	○	○	○	○
S3: Management power opens up possibilities for personal and professional growth of employees.	○	○	○	○	○
S2: Management power creates a divide amongst team members.	○	○	○	○	○
S4: Power struggles impacts team-level outcomes.	○	○	○	○	○

QB.3.2. **For the following set of questions, please choose the number highlighting your agreement**

with the two statements.

The options range from 1 (agree to both statements EQUALLY) to 9 (agreeing EXTREMELY STRONGLY to one statement over the other). The nearer the number to each statement (left or right) increases the strength of your preference of it over the other.

Preference leaning towards left column								Equal preference	Preference leaning towards right column							
9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9

For example for the first set S1 and S2:

a) if you choose 3 (right side of 1), it means you agree SLIGHTLY more with S2 than S1.

b) if you choose 7 (left side of 1), it means you agree STRONGLY with S1 than S2.

	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
S1: Power in work environment enhances team efficiency and productivity.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Management power creates a divide amongst team members.
S1: Power in work environment enhances team efficiency and productivity.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S3: Management power opens up possibilities for personal and professional growth of employees.
S4: Power struggles impacts team-level outcomes.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S1: Power in work environment enhances team efficiency and productivity.
S2: Management power creates a divide amongst team members.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S3: Management power opens up possibilities for personal and professional growth of employees.
S3: Management power opens up possibilities for personal and professional growth of employees.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S4: Power struggles impacts team-level outcomes.
S4: Power struggles impacts team-level outcomes.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Management power creates a divide amongst team members.

QB.3.3.
Please rank the following statements according to your agreement, give 1 to the statement you agree most and 4 to the statement you agree least with:

	1	2	3	4
S1: Power in work environment enhances team efficiency and productivity.	○	○	○	○
S2: Management power creates a divide amongst team members.	○	○	○	○
S3: Management power opens up possibilities for personal and professional growth of employees.	○	○	○	○
S4: Power struggles impacts team-level outcomes.	○	○	○	○

QB.3.4.
Would you like to add any specific example, experience or discussion on this concept of power (forecasting work experience, forecasting expertise and authoritative position)?

QB.4.1.
Concept 4: Social value

For the purpose of this research, *social value is defined as the measure of relative importance that people place on their experiences within the company/organisation. This value is created within team members and also different teams in the company/organisation. This value suggests whether team members feel included and appreciated for their work within the company/organisation. Simple concepts like sharing information across teams, considering everyone's views while making decisions, etc. affect the social value of employees within the company/organisation.*

Choose one option

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
S1: The outcome of social value is difficult to evaluate.	○	○	○	○	○
S2: Higher employee social values usher workplace innovations.	○	○	○	○	○
S3: Increased social value brings in positive vibes into the workplace culture.	○	○	○	○	○
S4: Social value can divert focus from the economic value of business.	○	○	○	○	○

***QB.4.2.* For the following set of questions, please choose the number highlighting your agreement with the two statements.**

The options range from 1 (agree to both statements EQUALLY) to 9 (agreeing EXTREMELY STRONGLY to one statement over the other). The nearer the number to each statement (left or right) increases the strength of your preference of it over the other.

Preference leaning towards left column								Equal preference	Preference leaning towards right column							
9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9

For example for the first set S1 and S2:

a) if you choose 3 (right side of 1), it means you agree SLIGHTLY more with S2 than S1.

b) if you choose 7 (left side of 1), it means you agree STRONGLY with S1 than S2.

	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
S1: The outcome of social value is difficult to evaluate.	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	S2: Higher employee social values usher workplace innovations.

S1: The outcome of social value is difficult to evaluate.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S4: Social value can divert focus from the economic value of business.
S3: Increased social value brings in positive vibes into the workplace culture.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S1: The outcome of social value is difficult to evaluate.
S3: Increased social value brings in positive vibes into the workplace culture.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S2: Higher employee social values usher workplace innovations.
S2: Higher employee social values usher workplace innovations.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S4: Social value can divert focus from the economic value of business.
S4: Social value can divert focus from the economic value of business.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	S3: Increased social value brings in positive vibes into the workplace culture.

***QB.4.3.* Please rank the following statements according to your agreement, give 1 to the statement you agree most and 4 to the statement you agree least with:**

	1	2	3	4
S3: Increased social value brings in positive vibes into the workplace culture.	○	○	○	○
S1: The outcome of social value is difficult to evaluate.	○	○	○	○
S2: Higher employee social values usher workplace innovations.	○	○	○	○
S4: Social value can divert focus from the economic value of business.	○	○	○	○

***QB.4.4.* Would you like to add any specific example, experience or discussion on this concept of <u>social value</u>?**

C. REFLECTIVE QUESTIONS

In this last section, there are two questions. Please answer BOTH the questions.

In this first question, you are asked to choose your preference in between the four concepts: *information sharing*, *time pressure*, *power* and *social value*. Please refer back to the definition of these concepts while answering the questions if needed.

Which concept do you think is more important for business decision-making in demand forecasting?
Please choose the number highlighting your preference while comparing each pair of concepts.

The options range from 1 (prefer both concepts EQUALLY) to 9 (prefer one concept EXTREMELY STRONGLY to the other). The nearer the number to each concept (left or right) increases the strength of your preference of it over the other.

Preference leaning towards <u>left</u> column								Equal preference	Preference leaning towards <u>right</u> column							
9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9

For example for the first set C1 and C2:

a) if you choose 3 (right side of 1), it means you agree SLIGHTLY more with C2 than C1.

b) if you choose 7 (left side of 1), it means you agree STRONGLY with C1 than C2.

	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	
C1: Information sharing	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	C2: Time pressure
C2: Time pressure	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	C3: Power
C3: Power	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	C1: Information sharing
C3: Power	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	C4: Social value
C1: Information sharing	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	C4: Social value
C2: Time pressure	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	C4: Social value

QC.2. **Do you think a decision support framework that incorporates these four concepts (*information sharing*, *time pressure*, *power* and *social value*) of collaborative demand forecasting/planning will be useful for your company/organisation?**

Yes	Maybe	No
○	○	○

QC.3. **This is the last question of the survey.**

Is there anything you would like to add on collaborative decision-making in demand forecasting?

Appendix C: R code

1. R script for Descriptive Statistics

```
data1 <- read.csv(file.choose(), header = T)
data1
head(data1)
attach(data1)
View(table(Hierarchical_level)) #used for Excel plot (Excel_plots file)
View(table(Decision.making_stage))
table(Hierarchical_level,Decision.making_stage)

par(mfrow=c(1,2))#this shows diagrams side by side
plot(Gender, col = "dark green", main = "Gender distribution")
plot(Age, col = "red", main = "Age distribution")

barplot(table(Formal_education),col="purple", main = "Formal education in
forecasting or decision-making")
barplot(table(Worked_in_present_company), col ="blue", main = "Time worked in
present case company")

barplot(table(Previous_job_practical_knowledge), col ="orange",main = "Practical
knowledge on forecasting from previous jobs")
barplot(table(Worked_in_forecasting), col ="yellow", main = "Time worked in
forecasting job roles")

par(mfrow=c(2,2))
boxplot(C1_S, C1_W, C1_O, C1_T, main = "SWOTs for Information Sharing")
boxplot(C2_S, C2_W, C2_O, C2_T, main = "SWOTs for Time Pressure")
boxplot(C3_S, C3_W, C3_O, C3_T, main = "SWOTs for Power")
boxplot(C4_S, C4_W, C4_O, C4_T, main = "SWOTs for Social Value")

table(data1$Framework)

library(ggplot2)
install.packages("ggplot2")
install.packages("ggpubr")
library(ggpubr)
theme_set(theme_pubr())
library(vcd)
library(reshape2)
install.packages("readxl")
library(readxl)
install.packages("openxlsx")
library(openxlsx)
library(RColorBrewer)
```

```
------------------------------------------------
#for Information Sharing

View(ftable(Decision.making_stage,C1_S))
View(ftable(Decision.making_stage,C1_W))
View(ftable(Decision.making_stage,C1_O))
View(ftable(Decision.making_stage,C1_T))


data2 <- read_excel("DataForGGPlot.xlsx",sheet = 1)
attach(data2)
balloon_melted<-melt(data2,sort=F)
balloon_melted
colourCount = length(unique(SWOT))
getPalette = colorRampPalette(brewer.pal(9, "Set1"))

ggplot(balloon_melted, aes(x = SWOT, y = value))+
  geom_bar(
    aes(fill = SWOT), stat = "identity", color = "white",
  )+
  facet_wrap(~Decisionmakingstage) +
  scale_fill_manual(values = getPalette(colourCount))

------------------------------------------------
# for Time pressure

View(ftable(Decision.making_stage,C2_S))
View(ftable(Decision.making_stage,C2_W))
View(ftable(Decision.making_stage,C2_O))
View(ftable(Decision.making_stage,C2_T))

data3 <- read_excel("DataForGGPlot.xlsx",sheet = 2)
attach(data3)
balloon_melted<-melt(data3,sort=F)
balloon_melted

colourCount = length(unique(SWOT))
getPalette = colorRampPalette(brewer.pal(9, "Set1"))

ggplot(balloon_melted, aes(x = SWOT, y = value))+
  geom_bar(
    aes(fill = SWOT), stat = "identity", color = "white",
  )+
  facet_wrap(~Decisionmakingstage) +
  scale_fill_manual(values = getPalette(colourCount))
```

```
#-----------------------------------------------
# for Power

View(ftable(Decision.making_stage,C3_S))
View(ftable(Decision.making_stage,C3_W))
View(ftable(Decision.making_stage,C3_O))
View(ftable(Decision.making_stage,C3_T))

data4 <- read_excel("DataForGGPlot.xlsx",sheet = 3)
attach(data4)
balloon_melted<-melt(data4,sort=F)
balloon_melted

colourCount = length(unique(SWOT))
getPalette = colorRampPalette(brewer.pal(9, "Set1"))

ggplot(balloon_melted, aes(x = SWOT, y = value))+
  geom_bar(
    aes(fill = SWOT), stat = "identity", color = "white",
  )+
  facet_wrap(~Decisionmakingstage) +
  scale_fill_manual(values = getPalette(colourCount))

-----------------------------------------------
# for Social Value

View(ftable(Decision.making_stage,C4_S))
View(ftable(Decision.making_stage,C4_W))
View(ftable(Decision.making_stage,C4_O))
View(ftable(Decision.making_stage,C4_T))


data5 <- read_excel("DataForGGPlot.xlsx",sheet = 4)
attach(data5)
balloon_melted<-melt(data5,sort=F)
balloon_melted

colourCount = length(unique(SWOT))
getPalette = colorRampPalette(brewer.pal(9, "Set1"))

ggplot(balloon_melted, aes(x = SWOT, y = value))+
  geom_bar(
    aes(fill = SWOT), stat = "identity", color = "white",
  )+
  facet_wrap(~Decisionmakingstage) +
  scale_fill_manual(values = getPalette(colourCount))
```

2. R script for ELECTRE

```
install.packages("OutrankingTools")
library (OutrankingTools)
performanceMatrix <-
cbind(c(156,126,170,111),c(123,138,116,149),c(126,144,127,115),c(151,137,141,105))
alternatives<-c("S","W","O","T")
criteria<-c("IS","TP","P","SV")

minmaxcriteria<-c("max","max","max","max")

criteriaWeights <- c(0.4006,0.1591,0.1618,0.2784)

Electre_1(performanceMatrix,
	alternatives,
	criteria,
	criteriaWeights,
	minmaxcriteria,
	concordance_threshold=0.5000,discordance_threshold=0.6155)
```

Appendix D: Forecasting methods

1. Time series forecasting methods

The five most common forecasting methods are described using the table from Sarma (2015). These are the Naïve method, Moving (weighted) averages method, and the three types of Exponential Smoothing methods.

Description of statistical forecasting methods from Sarma (2015)

Method	*Mathematical representation*	*Characteristics*
Naïve method	$F_{t+i} = X_t$ F_{t+i} = forecast for period t+i t = present period i = number of periods ahead being forecast X_t = actual value for period t	The most recent available information is used as a forecast. It cannot accommodate randomness.
Moving averages	$F_{t+1} = \frac{1}{N} \sum_{i=t-N+1}^{t} X_i$ F_{t+1} = forecast for period t+1 i = present period N = number of values included in averages X_i = actual value for period i	Average of a number of observed values is taken as forecast for the next period. It allocates same weightage to all the values.
Simple exponential smoothing (SES)	$F_{t+1} = \alpha X_t + (1-\alpha)F_t$, $\alpha = \frac{1}{N}$ F_{t+1} = forecast for period t+1 t = present period N = number of observations X_t = actual value for period t F_t = forecast for period t α = data smoothing factor	It gives most weight to the recent observation and decreasing weights to the older values. It is used for data without any trend or seasonality.
Holt's exponential smoothing	$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$ $S_t = \alpha X_t + (1-\alpha)(S_{t-1} + T_{t-1})$ $F_{t+m} = S_t + T_t m$ F_{t+m} = forecast for period t+m S_t = equivalent of SES smoothed value β = trend smoothing factor T_t = smoothed trend in data series T_{t-1} = last smoothed trend m = number of periods ahead being forecast	It considers the trend factor of the data. It does not consider the seasonality in data.

Holt-Winter exponential smoothing	$S_t = \alpha \frac{X_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + T_{t-1})$ $T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$ $I_t = \gamma \frac{X_t}{S_t} + (1-\gamma)I_{t-L}$ $F_{t+m} = (S_t + T_t m)\, I_{t-L+m}$ S = smoothed value of deseasonalized series γ = seasonality smoothing factor T = smoothed value of trend I = smoothed value of seasonal factor L = length of seasonality (like months or quarters)	It deals with seasonal data series with trend.

2. Forecast hierarchy aggregation methods

The following methods have been described with help from Hyndman and Athanasopoulos (2014, 2018).

a. Bottom-up method

In this method, forecasts are produced at the lower levels of the hierarchy and are aggregated upwards to get the upper level revised forecasts. Therefore, the upper level forecasts are summations of the appropriate lower level forecasts.

b. Top-down method

In this method, the base forecasts for the top level of the hierarchy are generated and then disaggregated to produce the lower level forecasts of the hierarchy. The disaggregation of the top-level forecasts can be done in three ways based on different proportions.

Say, the total sales is denoted by y_j at the top of the hierarchy and the bottom level series is denote by $y_{j,t}$ where j denotes the j^{th} node: j = 1,2,….n_k (n_k is the number of nodes in the k^{th} hierarchical level) and t is the time period 1,2,…T.

i. Average historical proportions:

$$p_j = \frac{1}{T}\sum_{t=1}^{T}\frac{y_{j,t}}{y_t} \tag{1}$$

Here p_j reflects the average historical proportions for the lower level series $y_{j,t}$ with respect to the top level y_t.

ii. Proportions of historical averages:

$$p_j = \sum_{t=1}^{T}\frac{y_{j,t}}{T}\bigg/\sum_{t=1}^{T}\frac{y_t}{T} \tag{2}$$

Here each proportion p_j captures the average historical value of the lower level series $y_{j,t}$ relative to the average total aggregate y_t.

iii. Forecasted proportions:

This third approach improves the historical and static nature of the proportions in the above two methods (a) and (b). Here individual base forecasts are produced for all individual series in the hierarchy. Taking one level at a time, the proportion of each base forecast relative to the aggregate of all the base forecasts of that level is calculated. These are then considered as the forecasted proportions based on which the top-level forecasts are disaggregated to get the revised lower level forecasts. This is repeated from each level from top to bottom of the hierarchy.

$$p_j = \prod_{l=0}^{R-1}\frac{\hat{y}_{j,h}^{(l)}}{\hat{S}_{j,h}^{(l+1)}} \tag{3}$$

p_j denotes the forecasted proportion for the j^{th} node of the R-level hierarchy. $\hat{y}_{j,h}^{(l)}$ is the h-step ahead base forecast of the series that correspond to the node which is *l* levels above *j*. $\hat{S}_{j,h}^{(l+1)}$ is the sum of the h-step ahead base forecasts below the node that is *l* levels above *j*. These forecasted proportions help to break down the h-step ahead base forecasts for the top-level to h-step ahead revised forecasts for the lower levels.

c. Middle-out method

This method is a further extension of both the top-down and bottom-up methods. First step is to choose an intermediate hierarchical level and generate the base forecasts for this level. The revised forecasts for hierarchical levels above the intermediate level are produced by applying bottom-up method on the base forecasts. For the hierarchical levels below the chosen intermediate level, the top-down method is used to generate the forecasts by disaggregating the base forecasts.

d. Optimal reconciliation method

This method reconciles the independent forecasts by using information from all the hierarchical levels. The mathematical derivation of this method is described below.

Let n_i denote the number of series in the i^{th} hierarchical level. The total number of series in the hierarchy will be $1 + \mathrm{n}_1 + \mathrm{n}_2 + \cdots + \mathrm{n}_\mathrm{R} = \mathrm{n}\ (\mathrm{say})$ for an R-level hierarchical structure. Let S denote the n x n_R summation matrix reflecting how the bottom-level series are aggregate consistent within the hierarchical structure. y_t is the vector of all the observations at time t. $y_{R,t}$ is the vector of all the bottom level observations at time t. The above example can be written in matrix notation as:

$$\begin{bmatrix} y_t \\ y_{A,t} \\ y_{B,t} \\ y_{A1,t} \\ y_{A2,t} \\ y_{B1,t} \\ y_{B2,t} \\ y_{B3,t} \end{bmatrix} = \begin{bmatrix} 1\,1\,1\,1\,1 \\ 1\,1\,0\,0\,0 \\ 0\,0\,1\,1\,1 \\ 1\,0\,0\,0\,0 \\ 0\,1\,0\,0\,0 \\ 0\,0\,1\,0\,0 \\ 0\,0\,0\,1\,0 \\ 0\,0\,0\,0\,1 \end{bmatrix} \begin{bmatrix} y_{A1,t} \\ y_{A2,t} \\ y_{B1,t} \\ y_{B2,t} \\ y_{B3,t} \end{bmatrix}$$

This can also be written as $$\mathrm{y_t} = \mathrm{S}\,\mathrm{y_{R,t}} \qquad (4)$$

The method is described as it is in Hyndman and Athanasopoulos (2013). In this method, a linear regression model is used to represent the h-step ahead base forecasts.

$$\hat{y}_h = S\,\beta_h + \epsilon_h \qquad (5)$$

where
$\hat{y}_h$ is the vector of h-step-ahead forecasts for the hierarchy
$\beta_h$is the mean (unknown) for the bottom level forecasts
ϵ_h is the error of the regression model with zero mean
$\sum_h$ as the covariance matrix.

With the assumption that $\epsilon_h \approx S\,\epsilon_{R,h}$ (the errors of the regression model approximately satisfy the same aggregation structure as the original data with $\epsilon_{R,h}$ denoting the bottom level forecast errors); the best linear unbiased estimator for β_h is found to be

$$\hat{\beta}_h = (S'\,S)^{-1}\,S'\,\hat{y}_n(h) \qquad (6)$$

This gives the set of revised forecasts as:

$$\bar{y}_h = S\,(S'\,S)^{-1}\,S'\,\hat{y}_h \qquad (7)$$