SUPPORTING THE FORECASTING OF UNCERTAIN PRODUCT DEMAND IN SUPPLY CHAIN WITH DIGITAL TOOLS

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STATEMENT OF ORIGINAL AUTHORSHIP

I, Elias ABOU MAROUN declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Computer Science School / Faculty of Information Technology and Engineering at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

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Elias ABOU MAROUN

Dedication

This dissertation is dedicated in memory of my dear father Dib Tanios ABOU MAROUN and beloved maternal grandmother Nelly MAROUN, whom both entered eternal life during this research project.

To my dear father Dib, you played a significant role in my life, and I cannot thank you enough for the numerous sacrifices you made for the family. With your inspiration, love, and support, I have been able to meet challenges head-on. In your final moments, you were filled with words of encouragement and support, which I drew on to persevere with my studies and fulfil my ultimate goal. I promised to make you proud by continuing my studies to achieve this significant academic goal. I wish you were with me to share in the celebrations and success of my achievement.

To my beloved grandmother Nelly, your faith, cheekiness and words of wisdom are forever cherished. Thank you for supporting me spiritually throughout this research project.

"One of the hardest lessons in life is letting go.

Whether it's guilt, anger, love, loss.

Change is never easy, you fight to hold on, and you fight to let go".

Khalil Gibran

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This thesis is only a beginning of my journey.

Elias Abou Maroun

"Progress lies not in enhancing what is, but in advancing toward what will be."

Khalil Gibran

List of papers/publications included

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Abstract

This thesis examines the barriers faced in forecasting uncertain product demand within an electrical luminaire manufacturer in Australia. As luminaire technology has rapidly advanced in the last decade, the organisations' processes and systems for forecasting demand are no longer adequate. The accurate forecasting of uncertain product demand in the supply chain is understood to have financial consequences for organisations at all levels. Forecasting uncertain product demand is a fundamental part of the supply chain's sales and operations planning process. It lies at the strategic and tactical level within an organisation. The size and complexity of forecasting uncertain product demand are regarded as one of the more challenging activities in the supply chain. This is especially the case in the luminaire industry, where demand uncertainty, lack of historical data, and competitive environments coexist. Hence, judgemental adjustments are required to the forecast. The goal of adjusting the forecast is to optimise accuracy by allowing forecasters to contribute to the organisations' sales forecast. Our industry research's general premise is that the process of forecasting uncertain product demand in the supply chain could be improved in terms of transparency, efficiency, effectiveness, and useability by embedding a form of a digital toolkit. Many of the existing methods, tools, and approaches in forecasting uncertain product demand are either too complex for practice or cannot solve the barriers. In this research, we take a design science approach to investigate both state-of-the-art and state-of-the-practice to identify the barriers in forecasting uncertain product demand. We then develop and evaluate a software toolkit to support practitioners in forecasting uncertain product demand.

The first stage of the research is a systematic literature review involving a thorough review and critical analysis of existing theories on forecasting uncertain product demand. A pilot

study is then conducted to gain in-depth information about the overall supply chain domain and understanding who should formally be interviewed. The activities were informal and ad-hoc, it involved a walk around the office and asking informal questions to supply chain stakeholders, observing how people perform tasks and reading existing documentation. This is followed by a field study at the Australian Luminaire Manufacturer (ALM[1]), which consists of semi-structured interviews with end-to-end supply chain stakeholders and the elicitation of stakeholder requirements which we prioritise by using the card-sorting method. Based on the requirements prioritised, a toolkit is designed and developed to support the organisation in forecasting uncertain product demand. The designed and developed toolkit provides a set of tools, yet a cohesive set of software components that can be utilised to support the forecasting of uncertain product demand. The toolkit includes market segmentation and market intelligence reporting, a full forecasting model, and a framework to make forecast adjustments. The final stage of the research involved the evaluation of the toolkit. This involved a focus group and questionnaire with end-users. The research findings were also presented to the organisations executive management.

The empirical evaluations conducted showed that the toolkit improves the overall effectiveness of forecasting uncertain product demand. It was also revealed that the consideration of judgemental adjustments in the forecasting toolkit was both beneficial and practical for stakeholders.

This thesis offers interesting insights and valuable directions for managers contemplating investing in improving accuracy in forecasting uncertain product demand in the supply chain.

[1] Fictitious name used to maintain confidentiality

The research methods used and the successful application of the toolkit in the ALM were both novel and unique from previous work on forecasting uncertain product demand.

1 Introduction

1.1 Chapter Overview

This chapter establishes the context for the research being undertaken. It introduces the dissertation topic, provides background information on the dissertation's theoretical and academic context, and identifies the industry environment and industry problems for the research study. Justification for conducting the research and a brief description of the methodology is also included. The chapter also outlines the research scope and establishes the goals of the research. Finally, this chapter concludes with the research contributions and a brief outline of this dissertation's subsequent chapters.

1.2 Background

Inventory investment is one of the most significant financial investments made for most manufacturing or distribution organisations. For many organisations, their inventory has a limited lifespan due to being perishable. Therefore, organisations need to try to hold as low inventory levels as possible while still meeting the required customers' product demand. Organisations are intensely under pressure due to competition and the expectation to provide customers with the product shortly after the customer orders that product. This next day or same day service expectation from customers creates a strain on the organisations' supply chain. Supply chains are known to be large, complex and often unpredictable (Arshinder et al.'s, 2008). Operational management of supply chains requires methods and tools to enable organisations to better understand how unexpected disruptions occur and what impacts they will have on the flow of goods to meet customer demands (Qi et al.'s, 2017).

Traditionally supply chains had a 'make-to-stock' paradigm which in many cases have been replaced by 'make-to-order', where the final part of manufacturing a product is performed after a customer order is received. This make-to-order model is particularly suited in organisations that produce customised products. Organisations need to decide on the number of components they source or stock-keeping units (SKU) they manufacture before the customer demands it in the next sales. This problem is known as *uncertain demand forecast* and is established to be one of the more critical and challenging activities within the sales and operation planning (S&OP) conducted by organisations when managing supply chains. Sales and operations planning involves a combination of people, process and technology (Noroozi and Wikner, 2017). S&OP is defined as 'a process to develop tactical plans that provide management with the ability to strategically direct its businesses to achieve competitive advantage continuously by integrating customer-focused marketing plans for new and existing products with management of supply chain' (Richard E. Crandall, 2018, p.153). In this context, three major types of uncertainty arise, the uncertainty of the demand forecast, uncertainty in the external process and uncertainty in the internal supply process (Keskinocak and Uzsoy, 2011). The forecasting of uncertain product demand and inaccuracy in forecasts remain areas of most importance to researchers and practitioners. Over the last decades or so, forecasting demand in Australian Luminaire Manufacturer (ALM) has been established as a more critical and challenging activity.

Therefore, the industry research described in this thesis studies, constructs and evaluates a toolkit to support the organisation in its sales and operations planning (S&OP) activities. This thesis aims to support and enable greater transparency in forecasting and collaboration between supply chain stakeholders. The aim is achieved through a set of four goals. This research investigates the barriers faced in forecasting uncertain product demand, and if a software toolkit could be designed and constructed, that would lead to improvements in terms of transparency[2], efficiency[3], effectiveness [4]and useability[5]. In particular, we are interested in supporting the organisations forecasting capabilities. Our aim also relates to the gaps identified in our systematic literature review (section 2.5)

1.3 Industry Environment

Australia's largest luminaire manufacture and distributor (ALM) has a wide range of product portfolios focusing on serving the roadway & infrastructure, commercial & industrial, consumer and retail market segments of the electrical industry. ALM incorporates engineering and design, research, manufacturing, international sourcing, importation and distribution. It allows ALM to develop new products for consumer acceptance. It also offers flexibility in designing variations and bespoke designs from one unit to thousands of units. There are currently over 15000 stock keeping units (SKU's) ranging in complexity from small and inexpensive products to large heavy-duty products for industrial use. Most of these SKUs are variations of the main product types, either directly sourced from suppliers and are known to be box-in-box-out products or assembled in house from basic components and/or intermediate products' suppliers provide.

ALM's commercial business procures approximately 11000 components sourced from over 20 manufacturing suppliers located mainly in China and some European countries. 5 suppliers are used frequently while over fifteen are used very infrequently. One of the suppliers is ALM's manufacturing plant, the sole manufacturing facility of luminaire goods in

[2] Transparency refers to the information that flows amongst stakeholders to inform informed decision-making and take the right action (Hosseini et al.'s, 2018).

[3] Efficiency refers to the resources (such as time or effort) expended with the speed with which users can achieve goals (Standardization, 2013).

[4] Effectiveness refers to the accuracy and completeness with which users can achieve specified goals (Standardization, 2013).

[5] Useability refers to the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use (Standardization, 2013).

Australia. The distribution of SKU's of every single supplier follows the typical ABC [6] analysis pattern, where many SKUs show no demand or consumption in one or more years. The ordering policy of the procurement department is supplier dependent. At the time of the study, there are two types of purchasing instruments used by ALM, system forecasting and customer demand-driven purchasing. System forecasting is based on material requirements planning (MRP), a planning and inventory control system in the enterprise resource planning (ERP) system. It aims to safeguard adequate inventory levels are kept and assure that the required materials needed to manufacture goods are available when needed. Consideration needs to be taken if stock is ordered and does not meet the minimum requirement of the supplier; does the organisation proceed with the sale and purchase excess stock and risk having an overstock which results in additional overheads. Customer demand-driven orders (Indent Stock) is the second instrument, this instrument does not consider historical sales. The sales forecasting side of indent stock is complex, as customers can make a frequent or infrequent purchase of small to large item quantities and expect immediate service. Large "institutional" customers (hospitals, retail, sports stadiums, commercial buildings, industrial and large manufacturers) typically place large orders through contractors or wholesalers but usually allow a reasonably long delivery time.

1.4 Industry Problem – the context

The Australian electrical luminaire industry has intensely changed in the last decade due to the rapid advancements in technology. Traditionally, for decades the luminaire industry was labour intensive and low value-adding. However, since replacing traditional and fluorescent

[6] A method for classifying inventory items based on consumption value

luminaires with the introduction of light-emitting diodes (LED), the lighting industry has turned into a semi-conductor based industry. This technology change has introduced many challenges, the most relevant challenges include:

- Traditionally, the conception and manufacturing phase for a luminaire product was relatively extensive, for example, organisations may spend 1-2 years developing a new product. The demand for the new product design and production of this product can last for a long period, such as 4-5 years or even longer. However, since the introduction of the LED luminaire, products now have a very short lifetime. The product development phase is only 3-6 months. New product designs and tooling for manufacturing, such as components, fixtures, moulds and cutting equipment etc., can only be used for 6-9 months until the next product generation is introduced.
- Traditionally, lighting source/control gear and luminaires are generally different products. Luminaire organisations would design light fittings only and not be involved in selecting light source and control gear. However, since the introduction of LED, organisations need to design the light source and electronics to ensure they are compatible with the design.
- The luminaire industry's manufacturing has changed from sheet metal forming, die castings, assembly to surface mount technology (SMT), a method that produces circuit boards by placing components directly to the surface of the printed circuit board (PCB). This manufacturing method is different from legacy lighting sources such as incandescent and halogen as it requires a controlled environment.
- Technological advances have changed the landscape of the luminaire industry and created a homogenous environment. Formerly the industry was dominated by a handful of large organisations with a strong footprint in signature designs. However,

today organisations are using the same product designs. Where there is innovation in a product, it is often replicated and spread out to the whole industry quickly.

- The luminaire industry is now even more innovative compared to the old luminaire industry. Since the competition is very intensive and margins are eroding, organisations are trying their best to make themselves a step ahead of their competitors. Due to the intense competition, organisations have tried to reduce costs by using thermal plastics to replace sheet metal, using non-isolated driver technology to replace traditional transformer driver technology, or even using graphene to replace die castings to reduce weight.
- Moore's law (1965) applies in the semiconductor industry, where the unit cost is falling as the number of transistors in dense integrated circuit boards rises. In the luminaire industry, product prices drop every 6 months as next-generation products' performance improves over the same period. However, since 2-3 years ago, LED chips contribute a smaller percentage to the overall cost of the product as it seems, Moore's law is slowing down. However, the market is not stable, varied products and prices cause additional confusion to the consumer.
- Due to the rapid improvements in technology, the product lifespan has changed to as low as 6 months, hence the speed to market is crucial. The supply of products is an intricate part of the industry as it consists of multiple segments of the electrical industry, currently, the flow of information in the supply chain is siloed and information cannot be easily shared and accessed.
- Since LED first appeared in the market, it was recognized as high-end technology for the future, so many organisations rushed into the luminaire industry, however, they did not realise that besides the LED chips and packaging, everything else is still just

simple assembly. Hence, the entry-level into the industry was low and the large amounts of capital money invested created tremendous competition in the lighting industry compared to the previous decades.

The above-listed industry problems are mostly found in the lighting industry which has created challenges in forecasting product demand by the Australian Luminaire Manufacturer. Other known industries that face similar problems include agriculture (Shukla and Jharkharia, 2013), fashion (Nenni et al.'s, 2013) and spare parts (Van der Auweraer et al.'s, 2017). Chapter 4 will discuss the specific organisational challenges in forecasting uncertain product demand being faced.

1.5 Pilot Study

A preliminary exploration was conducted at ALM to evaluate the current process of forecasting uncertain product demand in the supply chain. The pilot study involved a series of pre-interview exploration activities at ALM to gain in-depth information about the overall supply chain domain and understanding who should formally be interviewed. The activities were informal and ad-hoc, it involved a walk around the ALM office and asking informal questions to supply chain stakeholders (informal chats), observing how people perform tasks and reading existing documentation that was made available. This exploration confirmed and improved our existing knowledge of the supply chain before conducting the full-scale research project. Through exploration, a lack of a holistic picture was found on where and how technology supports the processes carried out. The process include ordering a product from a supplier through to the customer delivery. This resulted in designing a supply chain process map (section 4.3). The supply chain process map was developed to demonstrate the main touchpoints from a customer ordering a product to the sourcing and manufacturing to consumers afterward. The map intends to increase our understanding of the overall supply chain domain at ALM and help us determine the activities and behaviours that impact achieving accurate forecasting of uncertain product demand. The process map provides a quick visual overview of the processes taken in the organisation and is used as a reference tool during the identification of the barriers in forecasting uncertain product demand. The process map was in continuous development until the solution phase (chapter 5) because of the changing business environment/model, processes and technologies. We do not suggest that every supply chain process or technology is identified in the process map, however, we suggest that the map illustrates the core processes from ordering a product through to delivery.

1.6 Research Scope

Although forecasting uncertain product demand has received a reasonable degree of attention in the research literature to date, there remains a justified need for new tools that the practitioners can easily utilise in a luminaire manufacturing organisation. The Australian Luminaire Manufacturer is the sponsor of this research study. In this industry research project, we are interested in investigating the state-of-the-art and the state-of-the-practice in an Australian luminaire manufacturer to develop and evaluate a toolkit that assists practitioners in forecasting uncertain product demand. This research's principal focus is on improving the organisations' transparency, efficiency, effectiveness, and useability in forecasting uncertain product demand. These terms have been defined in section 6.2. The following constraints limit the scope of the research:

1. Many barriers can be considered in forecasting uncertain product demand, however, this research primarily focuses on improving only the agreed prioritised business requirements introduced by the organisations executive leadership team.
2. Many methods have been proposed in the literature to improve the accuracy of forecasts, e.g. (Croston's method, Bootstrap, Auto-Regressive Moving Average, Holt-Winters etc.). However, in this thesis, we focus primarily on utilising an existing time series method and improving judgemental adjustments by developing a collaborative forecasting model. It is important to note that the extent to which this work's contribution can improve the accuracy of the forecast is considered outside of the scope due to inherent limitations such as the time required to test and evaluate the forecast and complexities involved.
3. We develop and test the Australian luminaire manufacturer's toolkit, while other applications in industries such as fashion and agriculture are not fully explored. This limitation is per the industry doctorate program agreement.
4. We develop a toolkit as a proof of concept for the research project. Since the software is in prototype form, the Australian manufacturer's software testing is informal and hence user-level security access is not essential.

This industry research can attract wide interest among practitioners, therefore we believe that the toolkit developed for this organisation would benefit most industries that face the same barriers in forecasting uncertain product demand. In particular, the toolkit enables a collaborative approach where multiple stakeholders can work towards a common goal.

1.7 Goals

Our industry research's general hypothesis is that the organisations' process of forecasting uncertain product demand in the supply chain could be improved in terms of transparency, efficiency, effectiveness, and useability by using a digital toolkit. Furthermore, it is hypothesised that the digital toolkit developed would be particularly beneficial for the organisations' stakeholders (category managers, sales managers and demand planners) when performing forecasting.

As described and evaluated in this thesis, we design and develop a toolkit that provides transparency, efficiency, effectiveness, and useability in the forecasting process and enables collaboration within the stakeholders involved in the organisation. Subsequently, the following research goals and related questions have been established to examine and validate these hypotheses.

Research Goal 1: Review and critically analyse the existing state-of-the-art in forecasting uncertain product demand in the supply chain from empirical literature, including the existing methods, barriers, and solutions.

Research question 1: What methods are used in forecasting uncertain product demand in the supply chain?

Research question 2: What are the barriers faced in forecasting uncertain product demand in the supply chain?

Research question 3: What solutions have been adopted to address the barriers in forecasting uncertain product demand in the supply chain?

Research Goal 2: Investigate and survey the current state-of-the-practice in forecasting uncertain product demand in Australian Luminaire Manufacturer.

Research question 4: What do supply chain stakeholders from the Australian Luminaire Manufacturer perceive as state-of-the-practice in forecasting uncertain product demand?

Research question 5: What are the high-level requirements from the Australian Luminaire Manufacturer to address the barriers of forecasting uncertain product demand?

Research Goal 3: Design a toolkit to support the organisation in forecasting uncertain product demand.

Research question 6: Can the identified high-level requirements be used to design and implement a toolkit to support the organisation in forecasting uncertain product demand?

Research Goal 4: Evaluate the toolkit's performance for supporting forecasting uncertain product demand in terms of improvements in transparency, efficiency, effectiveness and useability.

Research question 7: How transparent is the toolkit in the forecasting process and results of forecasting uncertain product demand?

Research question 8: How efficient is the toolkit in improving the process of forecasting uncertain product demand?

Research question 9: How effective is the toolkit in improving the process of forecasting uncertain product demand?

Research question 10: How useable is the toolkit in improving the process of forecasting uncertain product demand?

1.8 Research Design

Design science research is the research methodology used in this thesis (Chapter 3), according to Hevner et al.'s (2004), design science creates and evaluates IT artefacts intended to solve identified organisational problems. In this study, the toolkit developed is referred to as the artefact. Following the design science research process, we develop our research design organised into three phases (Figure 1).

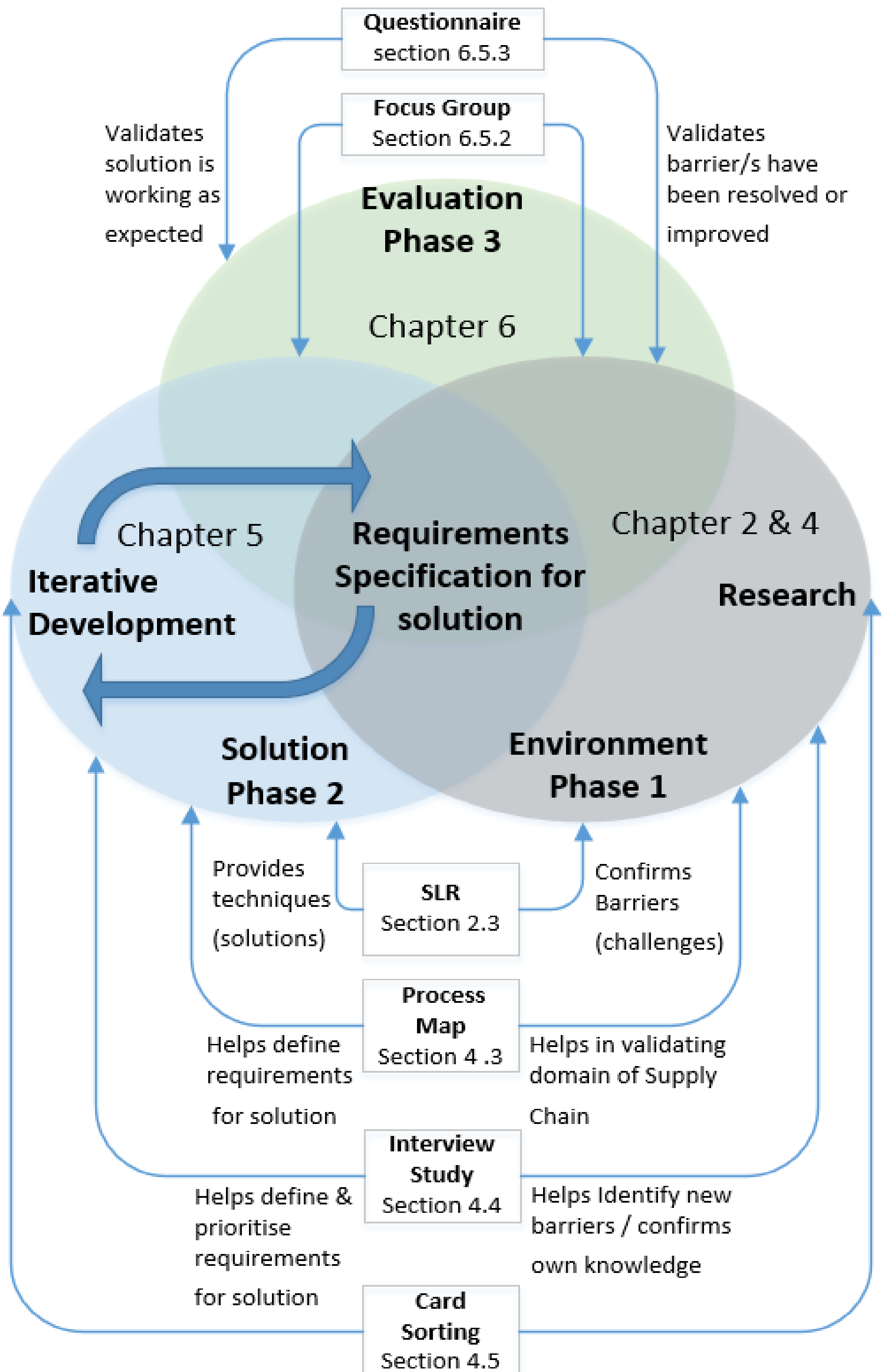

Figure 1 Research model and methodology

Phase 1 is focused on defining the state-of-the-art and state-of-the-practice and identify industry problems (chapters 2 & 4). In phase 2 we build artefacts (chapter 5) based on the identified problems in phase 1. The artefact as an outcome of this phase becomes the research study's object and is the final deliverable to the organisation. Phase 3 (chapter 6) evaluates the artifact developed in phase 2 to establish if the artifact works as intended and the defined goals have been achieved. The artefacts are developed as a prototype for evaluation purpose. It is important to understand the why and how of the artefact to ensure that it worked or failed in practice. According to the principles of design science research, the evaluations also contribute to the continuous improvement and iterative development of the artefacts as prior phases are revisited to refine the solution as deemed essential. This evaluation process is a crucial and essential activity. It guarantees that the goals of the newly designed and developed artefacts in the design science research are achieved and that the artefact work as intended (Gonzalez and Sol, 2012, Peffers et al.'s, 2012).

1.8.1 Phase 1: Environment

The design science research methodology starts with reviewing the most important works on the industry research problem. This is a crucial phase of the research process, as it provides a broad view of current studies that experts in the field have presented. Phase 1 of the thesis comprises the following activities: (1) A scoping exercise to document the current end-to-end supply chain at a high level (pilot study). This is presented in section 4.3. The scoping allowed us to map the overall supply chain and identify the pain points in the organisation and confirm our knowledge of the supply chain. (2) A systematic literature review is undertaken to identify the barriers, methods and adopted solutions in forecasting uncertain product demand. This is presented in chapter 2. The primary objective of the review is to provide a foundation for the research, this involved a thorough review and analysis of empirical studies on and around forecasting uncertain product demand. This systematic literature review identified that judgmental forecast adjustment is the most cited supply chain literature barrier. (3) A field study to understand the current state-of-the-practice in forecasting uncertain product demand. This is presented in section 4.4. This involved in-depth interviews with practitioners who are involved in the forecasting of product demand in ALM.

The field study's purpose was two-fold: (i) to understand the barriers faced in the state-of-the-practice in forecasting uncertain product demand; (ii) to elicit the high-level requirements of the toolkit development in phase 2. Furthermore, this provided us with the ability to triangulate the results. Triangulation is used to cross-validate the literature review study (the state-of-the-art) and field study (the state-of-the-practice). As part of the problem identification in the environment, it was revealed that the decision-making process in judgemental adjustments is not robust and systematic enough. The systematic literature review and field study findings have led to the development of a conceptual framework (Chapter 2). This framework was refined further once the field study was completed.

1.8.2 Phase 2: Solution Build

The solution phase involves designing and developing the toolkit to support the organisation in forecasting uncertain product demand (Chapter 5). The toolkit will provide transparency in forecasting, efficiency in the numbers, effectiveness in the process, and being useable. The solution was built based on the conceptual framework defined in phase 1 to guide stakeholders' decision-making process. Phase 2 is composed of the following activity: (4) Card Sorting exercise used to prioritise business requirements elicited from the field study. The card sorting exercise provided us with the rationale behind practitioners' requirements and prioritisation reasons. The solution development involved an iterative process where prototypes are revised based on stakeholders' feedback and design rationale over multiple development sprints. Iterative development aims to ensure that different viewpoints are explored in the organisation and unnecessary assumptions are not made. This phase of the project remained in progress until the final refinements made and after receiving feedback and performing rigorous evaluation in Phase 3.

1.8.3 Phase 3: Evaluation of the Toolkit

According to design science procedure, it is critical to evaluate whether the designed artefact can effectively solve the problem that motivated its creation (Hevner et al.'s, 2004). We evaluate and validate the artefacts developed in the build phase to determine if we have achieved our research goals. Phase 3 of the thesis comprises the following activities: (1) Focus group for obtaining qualitative insights and evaluation feedback from practitioners of the toolkit. This is presented in chapter 6. The goal of using the focus group method was to encourage dialogue between participants and provide a means of gathering information for iterative development. (2) The questionnaire will gather quantitative and qualitative data for analysis as they are efficient and less intrusive data collection methods. The evaluation also provides empirical evidence from the organisation about the toolkit's performance for forecasting uncertain product demand to improve transparency, efficiency, effectiveness, and useability. We directly address our Research goal 4 in chapter 6 **Error! Reference source not found.**by empirically evaluating the toolkit.

1.9 Research Contributions

This industry research uses the design science method (Hevner et al.'s (2004)) to identify critical barriers in forecasting uncertain demand. Thus digital artifacts are produced as solutions to support the organisation's ability to forecast uncertain demand. The research presented in this thesis provides several valuable contributions to the body of knowledge and to supply chain management.

The following are the key contributions of this research:

1. A detailed systematic literature review and analysis of the current state-of-the-art in forecasting uncertain product demand, including the barriers, techniques and solutions adopted to address the barriers.

2. A novel decision-making framework to help practitioners make judgmental adjustments to a forecast through a repeatable and clear decision-making framework.

3. A qualitative field study that covers the end-to-end barriers in forecasting uncertain product demand in the supply chain of the ALM organisation.

4. Novel digital toolkit to support the supply chain management process and overcome some of the barriers in forecasting uncertain product demand in the ALM organisation.

5. Empirical evidence on the toolkit's performance for forecasting uncertain product demand regarding transparency, efficiency, effectiveness, and usability.

1.10 Practice Contributions

In addition, the research presented in this thesis provides several helpful solutions to the problems in practice, including:

1. Directly addressing the area of judgmental adjustment by implementing and encouraging an appropriate degree of structure and rigour.

2. Using the presented approach and the digital toolkit for forecasting, this thesis demonstrates that practitioners will manage detailed level forecasts better and have greater transparency in the forecasting process.

3. The digital toolkit presented in the thesis addresses the lack of market intelligence and segmentation; the toolkit enables practitioners to visualize and reference large amounts of information effortlessly.

1.11 Novelty and Originality

The novelty and originality presented in the research were not restricted to the specific industry of the investigated organisation. Triangulation of methods used to investigate the barriers in forecasting uncertain product demand (i.e. industry process map, systematic literature review, field study) ensured the research's novelty and originality was not restricted to the specific context. Furthermore, the use of open source technology and forecasting method as a mechanism to build the digital toolkit and provide the capability for practitioners to make judgmental adjustments was new and innovative and allowed us to implement forecasting intelligence into the toolkit for stakeholder dashboard visualisation. The literature review yielded no results about applications of a specific algorithm to the specific research problem. To support this claim, the literature review lack of sources on showing the algorithm being used .

1.12 Outline of this Thesis

The rest of this thesis is structured as follows:

Chapter 2: Systematic Literature Review

This chapter presents a review of the available literature on forecasting uncertain product demand in the supply chain, including barriers faced, methods used, and solutions adopted to address the barriers. This chapter aims to provide a theoretical underpinning for the research by critically analysing and synthesising empirical studies.

Chapter 3: Methodology and Research Design

This chapter introduces the research methodology and design adopted for this industry research project. We select design science as the appropriate research methodology to answer the research questions and deliver a digital artefact to solve the problems in the ALM organisation. The research activities are presented and then described.

Chapter 4: Field Study

In this chapter, we survey the current state-of-the-practice barriers of forecasting uncertain product demand. We present the initial scoping of the overall supply chain and challenges practitioners face within the ALM organisation. The results of the in-depth interviews we conducted with practitioners is presented and discussed. The elicitation of high-level requirements and their prioritisation using card sorting is also presented.

Chapter 5: Solution Design

This chapter presents the forecasting toolkit designed and developed to address the organisations' barriers in forecasting uncertain product demand. The purpose of this chapter is to provide practitioners with a toolkit that enhances and solves a number of the barriers faced in forecasting product demand in the ALM organisation.

Chapter 6: Evaluation

This chapter empirically evaluates the toolkit developed by way of a focus group and questionnaire. This chapter aims to determine the transparency, efficiency, effectiveness, and usability of the toolkit developed.

Chapter 7: Conclusion

In this chapter, we conclude the research by detailing the contributions to the body of knowledge, the solutions to the problems in practice, and the research's novelty. This chapter summarises the originality, value, and importance of the research project and future works.

2 Systematic Literature Review

2.1 Chapter Overview

In the previous chapter, we introduced the background of the Australian Luminaire Manufacturer organisation and the main aspects of the industry research, including the industry problem, scope, goals, methodology and contributions. As a result, we were able to identify a real need for the development and enhancement of a new and improved forecasting approach for uncertain product demand. The goal of the new approach is to improve transparency and efficiency in the organisation. This chapter will review the relevant theoretical concepts and background that underpin the research presented in this thesis. This chapter aims to provide a theoretical foundation for our research by conducting an extensive literature search and investigating the state-of-the-art in forecasting uncertain product demand (Research Goal 1). There have been several systematic reviews in the supply chain that have used guidelines such as (Hart, 1998, Bryman, 2012): (1) source identification, (2) source selection, (3) source evaluation, and (4) data analysis. We examine evidence-based research related to forecasting uncertain product demand in the supply chain related to our industry problem. The literature review was initiated by following guidelines of (Kitchenham and Charters, 2007). According to the guidelines, researchers must develop a plan and execution process of the systematic literature review to show the rigour of the review and make the results reliable and transparent. The protocol developed is presented in full details in Appendix F. The literature review provides a context for the research from both empirical and theoretical perspectives. A good review should provide comprehensive coverage and focus on the concepts related to the research problem by following a structured approach of locating all the relevant sources for review (Webster and Watson, 2002). The findings from this systematic review provide important insights and directions for our research in a particular direction for the field study (chapter 0) and solution design (chapter 5). The systematic literature review execution and qualitative results are presented in full details in Appendix G.

This chapter is organised as follows: A background is first provided on supply chain and forecasting uncertain product demand (chapter 2.2), followed by a systematic analysis of the state-of-the-art in forecasting uncertain demand focusing on the available methods (chapter 2.3.1), barriers (chapter 2.3.2), and solutions adopted (chapter 2.3.3). This will be followed by our analysis and discussion on the relationships between the barriers, methods and solutions (chapter 2.4.1), the benefits and limitations of uncertain product demand (chapter 2.4.2) and proposing a decision making framework for judgemental adjustments (chapter 2.4.3. A summary (chapter 2.5) of the entire chapter is then provided.

2.2 Background

There are three significant types of uncertainty that plague supply chains: uncertainty of the demand forecast, uncertainty in the external process, and uncertainty in the internal supply process (Keskinocak and Uzsoy, 2011). These can be attributed to three forces: (1) supplier uncertainty, arising from on-time performance, lateness, and degree of inconsistency; (2) manufacturing uncertainty, arising from process performance, machine breakdown, supply chain performance; and (3) customer/demand uncertainty, arising from forecasting errors, irregular orders (Chen and Paulraj, 2004). To manage and reduce uncertainty in the supply chain, frameworks such as (Angkiriwang et al.'s, 2014, Wadhwa et al.'s, 2008) have been developed to deal with changing business environments by achieving better supply chain flexibility. However, achieving flexibility in organisations has been noted to be costly (Gunasekaran and Ngai, 2004).

This study researches the customer/demand uncertainty as the need for accurate forecasts of uncertain product demand (UPD) is well recognised in literature Syntetos and Boylan (2005), (Danese and Kalchschmidt, 2011b, Syntetos and Boylan, 2001), for both operations management (Amoako-Gyampah and Meredith 1989), and supply chains (Cox and Loomis, 2006; Ekzos, C., Mansuri, S. A., Bourlakis, M., 2006; Parvin Jr. and Beruvides, 2017). The following section describes what uncertain product demand is.

2.2.1 What is uncertain product demand?

Uncertain product demand relates to customer orders that are not known in advance, where certain product demand is when standard orders are placed based on a known demand (Doukidis and Vrechopoulos, 2006).

Traditionally supply chains had a 'make-to-stock' paradigm which in many cases have been replaced by 'make-to-order' where the final part of manufacturing or configuration of a product is postponed as much as possible, usually, until a customer order is received (Lee and Tang, 1997). This make-to-order model is particularly suited for organisations that produce customised products to satisfy demand in a market environment where there are diverse customer taste and preferences, rapid developments in technology and globalization of management (Hsu and Wang, 2004). Organisations need to decide on the number of components they source or stock-keeping units (SKU) they manufacture before the customer demands it in the next sales. This problem is known as *uncertain demand forecast* and has widely been studied in economics and supply chain management (SCM) (Kempf et al.'s, 2018).

2.2.2 Overview of Supply Chain

Supply chains are known to be large, complex and often unpredictable as they are spread over multiple organisational departments and include four essential functions: sales, distribution, production, and procurement (Arshinder et al.'s, 2008). However, to obtain effective output, supply chains' operational management requires robust methods and strategies that serve dual purposes. First, these strategies should help a firm reduce the cost and/or improve customer satisfaction under normal circumstances (Tang, 2006). Second, the same strategies should enable organisations to better understand how unexpected disruptions occur, the impacts they will have on the flow of goods to meet customer demands (Qi et al.'s, 2017) and how to sustain the organisations' operations during and after a major disruption (Tang, 2006). The ability to have visibility in the supply chain provides opportunities for managers to plan efficiently and react appropriately to accurate information (Ali et al.'s, 2017). The visibility in the supply chain created a flow of information that directly impacts the production scheduling, inventory control, and delivery plans of members in the supply chain (L. Lee et al.'s, 2004).

2.2.2.1 Sales and Operations Planning

Supply chain management involves the sales and operations planning process which lies at the strategic and tactical level. Sales and operations planning (S&OP) involves a combination of people, process and technology (Noroozi and Wikner, 2017). The demand forecast is a process that is carried out within the S&OP process of an organisation. S&OP is defined as 'a process to develop tactical plans that provide management with the ability to strategically direct its businesses to achieve competitive advantage continuously by integrating customer-focused marketing plans for new and existing products with management of supply chain' (Richard E. Crandall, 2018, p.153). Several authors (e.g. (Grimson and Pyke, 2007, Wallace, 2008, Oliva and Watson, 2011, Noroozi and Wikner, 2017)) have suggested that five formal steps are performed in S&OP. Research has also focused on the design and methodology approach of S&OP (e.g. (Kjellsdotter et al.'s, 2015, Wagner et al.'s, 2014, Belalia and Ghaiti, 2016, Jesper and Patrik, 2017)). Based on these studies, it is suggested that S&OP is not a 'one-size-fits-all' process and that there is a need to consider the internal company context, external company context and the specific industry to address the unique S&OP problem (Jesper and Patrik, 2017). In the supply chain context, there are integration issues that impact the S&OP process. Integration can be considered both vertical and horizontal, where vertical integration refers to linking the strategic plan, business plan, financial plan and long-term objectives to short-term operational planning. Horizontal integration is concerned with the "cross-functional" integration considering both inter-and intracompany activities (Thomé et al.'s, 2012, Thomé et al.'s, 2014). Grimsson and Pyke (2007), state that traditional S&OP is 'internally focused and technologically challenged'. The S&OP process is considered more about employees participating in the process setup than just using a set of models or software (Bower, 2012, Grimson and Pyke, 2007, Petropoulos and Kourentzes, 2014). It is more important to have a well-documented and understood S&OP business process than to have sophisticated software (Grimson and Pyke, 2007).

2.2.2.2 Forecasting methods

There has been significant research on forecasting methods in the supply chain, largely work of Croston's influential article (Croston, 1972) which for many years has been neglected but in the last 15 years has gained prominence i.e. 286 citations (Scopus accessed July 27, 2019), to the adaptions of Croston's method such as Syntetos-Boylan Approximation (SBA) (Syntetos and Boylan, 2001). Alternative approaches have been proposed such as

Bootstrapping the use of statistical models such as Auto-Regressive Moving Average (ARMA), Discrete ARMA (DARMA) model, and integer-valued ARMA (INARMA). Most forecasting methods are completely or partially based on the observations of historical data and deal with a limited range of variations of the demand these are well suited for known demand (WemmerlÖV and Whybark, 1984). There are multiple reviews (e.g.(Jesper and Patrik, 2017, Noroozi and Wikner, 2017, Thomé et al.'s, 2012, Tuomikangas and Kaipia, 2014) in SCM and related concepts, however, they do not adequately cover forecasting uncertain product demand. On the other hand, there are paucity methods used for uncertain demand as uncertainty has usually been associated with known demand (Bartezzaghi et al.'s, 1999).

Over the last 3 decades, it has been found (Cox and Loomis, 2006) that there has been a trend in textbooks to include more statistical and judgmental methods. Also, it was found that textbooks spend more time on integrating judgement with quantitative methods. A vast debate is ongoing regarding the usefulness of quantitative methods and qualitative methods such as judgmental adjustments, for example, Sanders and Manrodt (2003), provide a review on the contributions to this debate. Eksoz et al.'s (2014) find that judgmental adjustments cannot be ignored due to contextual information in uncertain demand. Therefore, it is a requisite to modify statistical forecasts due to the descendent information available such as a forecaster's experience, competitor related and /or environmental related rumours.

2.2.2.3 Forecasting Challenges

Forecasting is the fundamental step of demand management that optimizes customer satisfaction through the supply chain's capabilities (Albarune and Habib, 2015). The inaccuracy in product forecasting has been understood to have dire consequences for the supply chain's intra- and inter-organisational levels (Fildes et al.'s, 2009). Poor accuracy in the forecast leads to stockouts (Fildes et al.'s, 2009), excess inventory (Worthen, 2003), and not achieving target service levels (Baecke et al.'s, 2017, Fildes et al.'s, 2009). Accurate forecasting is complex and hence difficult due to the inter-related nature of the data series, the presence of unusual non-repetitive events, trend shifts in demand (Fildes and Beard, 1992), and the antecedent factors of global sourcing (Stanczyk et al.'s, 2017), including bullwhip effect arising from dynamics of inventory management in supply chains (Lee et al, 1997; Chen and Paulraj, 2004).

The size and complexity of forecasting uncertain demand at the individual Stock Keeping Unit (SKU) create additional difficulties in forecasting each period and necessitates the use of statistical methods (Syntetos et al.'s, 2010b), such as, simple exponential smoothing (SES), Croston's method (Croston, 1972), and Syntetos-Boylan Approximation (SBA) (Syntetos and Boylan, 2005). While statistical methods have been studied and compared (Petropoulos et al.'s, 2019) they alone cannot solve all the barriers faced in forecasting uncertain product demand. The use of judgmental adjustments to existing statistical method forecasts is typically relied on by organisations to improve forecast accuracy because domain experts' knowledge represents a previously unmodelled component (Lawrence et al.'s, 2006). Several studies (e.g. (Fildes et al.'s, 2009, Trapero et al.'s, 2013, Goodwin and Fildes, 1999, Goodwin, 2002)), have demonstrated that experts can still add value because they are better at recognizing when adjustments to a forecast are made based on their experience, additional information, and when unexpected events occur. However, other studies (e.g. (Syntetos et al.'s, 2009, Franses and Legerstee, 2013, Lawrence et al.'s, 2006)), found that experts place too much weight on their forecast adjustments and the overall improvement does not significantly outperform statistical forecasts as the accuracy of judgmental adjustments reduces over time.

The current literature lacks a sound theoretical basis to link the barriers in forecasting uncertain product demand with forecasting methods and adopted solutions. Our research results (chapter 2.3) provide a theoretical foundation and systematically identify diverse literature to investigate uncertain product demand forecasting in the supply chain, barriers being faced, forecasting methods used, and forecasting solutions adopted in supply chain.

2.3 Results from Systematic Literature Review

This section presents the SLR results related various concepts used for problem definition and scoping of the research and to answer the research questions for Goal 1. The results for the following research questions are reported:

Research question 1: What methods are used in forecasting uncertain product demand in the supply chain?

Research question 2: What are the barriers faced in forecasting uncertain product demand in the supply chain?

Research question 3: What solutions have been adopted to address the barriers in forecasting uncertain product demand in the supply chain?

2.3.1 Forecasting methods used for uncertain demand

There is a total of 38 methods identified, to give a more comprehensive picture of the results obtained, **Error! Reference source not found.**Table 1 maps the studies against each method adopted.

Table 1 Forecasting Methods

Forecasting Methods	Description	Extracted from the following studies
Single/Simple Exponential Smoothing. (SES)	This method is based on averaging (smoothing) past values of a time series exponentially by using a smoothing factor between 0 and 1.	(Fildes et al.'s, 2009), (Huang et al.'s, 2014), (Petropoulos et al.'s, 2014), (Petropoulos et al.'s, 2016b), (Syntetos et al.'s, 2010a), (Ma et al.'s, 2016), (Syntetos et al.'s, 2015), (Trapero et al.'s, 2012), (Zied Babai et al.'s, 2014), (Goodwin et al.'s, 2007), (Heinecke et al.'s, 2013)
Other Derived Methods	Other custom methods or modifications are not common in the literature. i.e. integer programming, Sample Average Approximation (SAA) method	(Chao, 2013), (Chen-Ritzo et al.'s, 2010), (Franses and Legerstee, 2013), (Hansen and Grunow, 2015), (Hemmelmayr et al.'s, 2010), (Krishnan et al.'s, 2011), (Laurent Lim et al.'s, 2014), (Disney et al.'s, 2016)
Croston's Method	A method specialized for dealing with intermittent demand and evolved from the SES method.	(Petropoulos et al.'s, 2014), (Petropoulos et al.'s, 2016b), (Snyder et al.'s, 2012), (Syntetos et al.'s, 2015), (Zied Babai et al.'s, 2014), Heinecke et al., 2013)
Syntetos-Boylan Approximation (SBA)	Developed based on Croston's method to decrease the error of bias.	(Petropoulos et al.'s, 2014), (Petropoulos et al.'s, 2016b), (Syntetos et al.'s, 2010a), (Syntetos et al.'s, 2015), (Zied Babai et al.'s, 2014), Heinecke et al., 2013)
Naïve	Simple method where last periods actuals are used as this period's forecast without any adjustments.	(Fildes et al.'s, 2009), (Petropoulos et al.'s, 2014), (Petropoulos et al.'s, 2016b), (Trapero et al.'s, 2012), (Zied Babai et al.'s, 2014), (Goodwin et al.'s, 2007)
Autoregressive AR (1)	Autoregressive is a stochastic calculation in which the forecast is estimated based on a weighted sum of past values.	(Ali et al.'s, 2012), (Krishnan et al.'s, 2011), (Trapero et al.'s, 2012), (Ali et al.'s, 2017)
Simple Moving Average (SMA)	Assumes the average of the actual period is good behaviour for forecasting the future. It is also used to forecast long term trends	(Ali et al.'s, 2012), (Petropoulos et al.'s, 2014), (Trapero et al.'s, 2012), Ali et al., 2017)
Holt's Exponential Smoothing (Holt)	Sometimes called double exponential smoothing, it is an extension of SES with a trend factor.	(Petropoulos et al.'s, 2014), (Moser et al.'s, 2017), (Goodwin et al.'s, 2007)
Bootstrap	A modern approach to a statistical method where alternative estimates can be derived.	(Fildes et al.'s, 2009), (Porras and Dekker, 2008), (Syntetos et al.'s, 2015)

Damped Exponential Smoothing (Damped)	This variation offers a dampening factor multiplied on the trend component of Holt's method to enhance control over the trend which may dominate the forecast.	(Petropoulos et al.'s, 2014), (Goodwin et al.'s, 2007)
Teunter, Syntetos and Babai (TSB) Method	Forecasts of the non-zero demands are multiplied by the forecast of the probability that a non-zero demand will occur	(Petropoulos et al.'s, 2014), (Zied Babai et al.'s, 2014)
Base-times-lift	A simple exponential smoothing model generates baseline forecasts, and then makes adjustments for any incoming promotional event.	(Huang et al.'s, 2014), (Ma et al.'s, 2016)
Auto-regressive moving average (ARMA)	This model is primarily used to forecast stationary products.	(Ali et al.'s, 2012), Ali et al., 2017)
Autoregressive Distributed Lag (ADL)	It is a simple regression style model that can consider the effect of the price and promotional variables.	(Huang et al.'s, 2014), (Ma et al.'s, 2016)
Poisson distribution (P)	A model used to forecast the probability of events occurring.	(Porras and Dekker, 2008), (Snyder et al.'s, 2012)
Average of statistical and judgmental	The average of a chosen statistical method and the average of judgmental adjustment are added together to form a forecast.	(Petropoulos et al.'s, 2016a), (Fildes and Goodwin, 2007)
Decision Support System	An information system containing data and rules used to help decision makers come up with a forecast value.	(Nenes et al.'s, 2010), (Trapero et al.'s, 2013)
Lease absolute shrinkage and selection operator (LASSO)	A statistical regression method that performs both variable selection and additional information to enhance accuracy.	(Huang et al.'s, 2014), (Ma et al.'s, 2016)
Holt-Winters	Involves the use of three smoothing factors, a simple smoothing factor, a trend smoothing factor and a seasonality factor.	(Petropoulos et al.'s, 2014)
Linear Regression	A method that measures one variable's relationship to another such as the demand to time; each of which is dependent.	(Petropoulos et al.'s, 2014)
Linear Trend also known as Trend-Line	Provides a line of best fit to a time series of historical data.	(Petropoulos et al.'s, 2014)
Zero Forecast	Forecasting Series that uses previous Actuals as a baseline.	(Snyder et al.'s, 2012), (Zied Babai et al.'s, 2014)
Negative binomial	This is an extension of the Poison model where better predictions may be obtained from distributions.	(Snyder et al.'s, 2012),
Hurdle shifted Poisson	Where a probability of a non-zero demand in a period is allowed to change over time and where demand occurrence is smoothed over time.	(Snyder et al.'s, 2012),
Autoregressive Integrated Moving Average (ARIMA)	Ability to model stationary and non-stationary data	(Trapero et al.'s, 2012)

Theta	The method aims at breaking down the data into simpler series, a decomposition approach is used to create the so-called Theta-lines.	(Petropoulos et al.'s, 2014)
Normal distribution (N) model also known as Gaussian distribution	A continuous probability model that occurs naturally in many situations. This can also be referred to as the bell curve.	(Porras and Dekker, 2008)
Generalized Bass	Used to model the likelihood of a new product being adopted.	(Krishnan et al.'s, 2011)
Aggregate-disaggregate intermittent demand approach (ADIDA)	A method used to reduce lower frequency demand by reducing zero demand or disaggregating the demand.	(Petropoulos et al.'s, 2016b)
Inverse Aggregate-disaggregate intermittent demand approach (iADIDA)	A method used to reduce the variances in demand sizes and focuses on the estimation of inter-demand variables	(Petropoulos et al.'s, 2016b)
Judgmental adjustment alone	An intuitive judgment used when there is a lack of data i.e. (when a new product is being launched, or when a new competitor enters the market)	(Fildes and Goodwin, 2007)
A statistical forecast judgmentally adjusted	A statistical method is used and adjusted manually by the forecaster.	(Fildes and Goodwin, 2007)
Average of two statistical methods	The average of two different statistical method results is added together to produce a forecast.	(Goodwin et al.'s, 2007)
Bayesian forecasting	Used to calculate the probability of future uncertain events that are based upon relevant evidence relating to historical data.	(Yelland, 2010)
Echelon	An echelon model consists of three decision areas: the forecasting and orders sector tracks the incoming customer orders, maintains the echelon sales forecast, and generates material orders.	(Udenio et al.'s, 2015)
Harvey and Fernandes	Uses a discounted moving average instead of an exponentially weighted average and a negative binomial distribution instead of a Poisson distribution.	(Snyder et al.'s, 2012)
Variable Neighborhood Search (VNS)	Set of predefined neighbours are explored in iterations to provide a better result.	(Hemmelmayr et al.'s, 2010)
Blattberg-Hoch	'50% method, 50% manager' involves taking the mean of a judgmental and a statistical forecast.	(Fildes et al.'s, 2009)

Out of 66 papers, 30 studies investigated several different forecasting methods with a total frequency of 90. Two papers (Petropoulos et al.'s, 2014) and (Zied Babai et al.'s, 2014) evaluated five or more forecasting methods. According to Table 1**Error! Reference source not found.**, out of 66 papers, 11 studies have examined simple exponential smoothing (SES) and a further 6 studies have looked at Croston's Method, Syntetos-Boylan Approximation (SBA) and Naïve. These methods have attempted to address some of the barriers in forecasting uncertain demand. Our analysis of these methods did not reveal if there is one best method to overcome the barriers in forecasting uncertain demand. These methods will be further analysed in chapter 2.4.2.

The included studies were used to evaluate the wide range of industries where the forecasting methods have been applied (see Table 2). There are 23 industries that the studies cover, SES was the most used method in our studies used 21 times across 10 different industries. Simple exponential smoothing was the first forecasting method proposed in 1956 to be used for uncertain demand (Brown, 1957). Several papers indicate that using SES works and performs well (Snyder et al.'s, 2012, Syntetos et al.'s, 2015, Petropoulos et al.'s, 2014), whether or not a more complex method is worth the considerable added complexity is questionable. Our data analysis also supports this, showing many complex statistical methods are used less across industry. In contrast, judgmental adjustment and SES are applied across many industries that produce goods, particularly electronics manufacturing.

Table 2 Domain application of forecasting methods.

Forecasting Methods / **Domain Application**	Automobile manufacturer	Retailer	Pharmaceutical	Military sector	Food Manufacturer	Household product manufacturer	Electronics Manufacturer	Mining and metal firms	Real estate, Banking & Insurance	Logistics, cosmetics & publishing	Construction & chemical	IT & Telecommunications	Blood Bank	Wholesaler	unknown	**Total**
Single/Simple Exponential Smoothing	3	4	2	3	2	2	2				1			1	1	**21**
Syntetos-Boylan Approximation (SBA)	3	1		3			2				1				1	**11**
Average of statistical and judgmental			1		1		1	3		3		1				**10**
Judgmental adjustment alone					1		1	3		3		1				**9**
Statistical forecast judgmentally adjusted					1		1	3		3		1				**9**
Croston's	3	1		2			1								1	**8**
Naïve	1	1	1	1	1	2									1	**8**
Bootstrap		2	1		1	1	1		1							**7**
Holt's Exponential Smoothing (Holt)			1						2		1				1	**5**
Autoregressive AR (1)		3				1			1							**5**
Simple Moving Average (SMA)		3				1									1	**5**
Base-Times-Lift		2	1		1											**4**
Lease Absolute Shrinkage and Selection Operator		2	1		1											**4**
Blattberg-Hoch		1	1		1	1										**4**
Teunter, Syntetos and Babai (TSB)	1			1											1	**3**
Zero Forecast	2			1												**3**
Auto-Regressive Moving Average (ARMA)		2														**2**

Autoregressive Integrated Moving Average		1				1										**2**
Autoregressive Distributed Lag (ADL)			1		1											**2**
Poisson distribution (P)	1								1							**2**
Aggregate-Disaggregate Intermittent Demand Approach	1			1												**2**
Inverse Aggregate-Disaggregate Intermittent Demand Approach	1			1												**2**
Decision Support System	1					1										**2**
Holt-Winters															1	**1**
Damped Exponential Smoothing															1	**1**
Linear Regression															1	**1**
Linear Trend															1	**1**
Negative Binomial	1															**1**
Hurdle Shifted Poisson	1															**1**
Theta															1	**1**
Normal Distribution (N)									1							**1**
Generalized Bass									1							**1**
Average of two statistical methods															1	**1**
Bayesian																**1**
Echelon											1					**1**
Harvey and Fernandes	1															**1**
Variable Neighborhood Search (VNS)													1			**1**
Other Derived Methods	1	1	3						1	2			1		1	**11**
	21	**24**	**13**	**13**	**11**	**10**	**9**	**9**	**8**	**5**	**4**	**3**	**2**	**1**	**14**	**155**

Over time improvements have been made to forecasting methods, the development of Croston's method is based on exponential smoothing is said to be much more beneficial for uncertain demand over SES. Many improvements have been made to Croston's original method, including the Syntetos and Boylan method (known as the SBA method for Syntetos-Boylan Approximation). In the empirical study, Gutierrez et al.'s (2008) have tested all three: SES, Croston's original method, and the SBA method. These methods also had the highest frequency in the selected studies and are used in multiple industries including the electronics industry

2.3.2 Barriers faced in forecasting uncertain demand

The barriers identified are divided into two categories namely, internal barriers and external barriers. In Table 3 we present all the barriers given in the studies that are considered to be causing internal and external barriers in forecasting uncertain product demand. Internal barriers are found to be within an organisations' internal environment made up of employees, management, communication and culture (Parmar et al.'s, 2016). The external barriers relate to outside factors that can impact an organisation in its ability to forecast demand.

Table 3 Forecasting barriers grouped against category & dimension

Category	Dimension	Forecasting Barrier
Internal	Technology	Fragmented information technology
		Difficulties analysing information being shared
		Changes in technology
	Product	Product price change
		New product introduction
		Substitute product introduction
		Product customization
		Large product range
		Short product lifecycle
	Marketing	Promotions and advertising activity
	Management	Senior management influence
		Political influence
		Lack of agility
	Communication	Judgmental adjustment
		Poor communication
	Operations	Safety stock
		Rough estimates on inventory level
		Too many forecast methods
External	Culture	Lack of trust
		Exaggeration of demand forecast
	Environment	Weather

		Holidays
		Strikes
		International crisis
		Change in Government policy/regulation
		Unique events i.e. sporting event
		Seasonality
	Suppliers	Lead times
		Loss of key players i.e. supplier, manufacturer
	Technology	Social media
	Competitors	Competitor activities i.e. promotions, advertising

Out of the 66 studies, 33 studies express internal barriers faced in forecasting uncertain product demand and make 50% of the results, while 17 papers are reporting external barriers only. It is interesting to note that in our SLR we found that many forecasting demand barriers still exist today, the most prominent problem identified by the internal category is product related and for external, it is the environment. Figure 2 shows the percentages of the studies selected that have barriers in these dimensions.

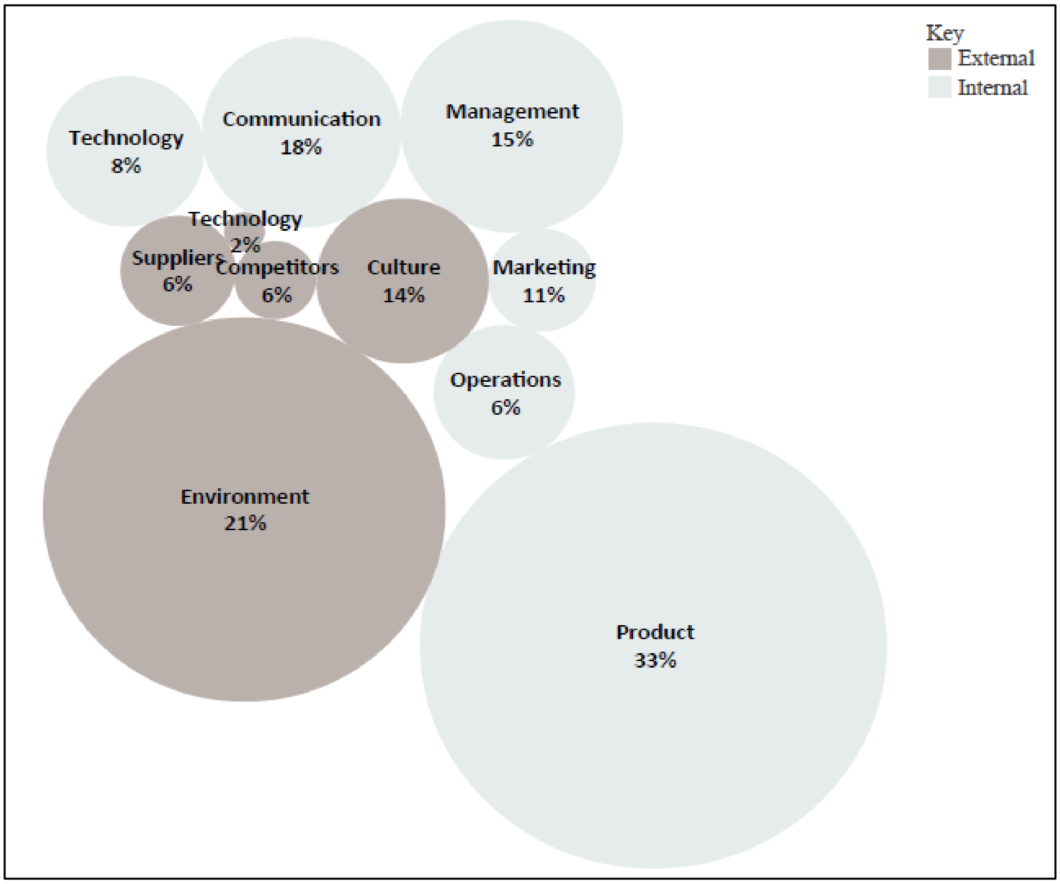

Figure 2 Percentage of barriers in the internal and external dimension

The most frequent barrier occurring in the product dimension is the product price change which impacts the ability to forecast demand accurately. The highest frequent barrier occurring within the environment dimension is the seasonality, which affects customer purchasing habits and the demand for products. Overall the highest barrier mentioned in the studies is the judgmental adjustments from the internal category and communication dimension, which causes bias and reduces the forecast accuracy. Several studies (Fildes and Goodwin, 2007, Fildes et al.'s, 2009, Syntetos et al.'s, 2016) have attempted to address this barrier by asking managers to justify their adjustments which have shown to discourage adjustments made without a factual basis. The comparison of previous judgmental adjustment performance has also been used in several studies (Fildes and Goodwin, 2007, Franses and

Legerstee, 2013, Goodwin et al.'s, 2007) to try and reduce this barrier by allowing forecasters to compare previous results of their adjustment to help them understand the sales forecast. A brief description of these dimensions follows:

1. Technology. This dimension encompasses technological barriers faced in forecasting demand. A representative article is “Organizational factors in sales forecasting management “ by (Davis and Mentzer, 2007) found that sales forecasting information resides on multiple systems maintained by different functional areas, or, in the worst case, by an employee in a personal program on a desktop computer. It also states that fragmented Information Technology resources require manual intervention that introduces errors that degrade data integrity. The technology dynamics are also discussed by (Vanpoucke et al.'s, 2014). The paper found that introducing new technology requires a dynamic environment where organisations can adapt to change. For instance, (Fildes and Goodwin, 2007) found that one of the reasons for using judgmental adjustments is due to changes in technology.

2. Product. This dimension discusses the product-related barriers such as product customization, product price change, new or substitute product introduction, large product ranges and short product lifecycles. A representative article is “Sales and operations planning in systems with order configuration uncertainty” by (Chen-Ritzo et al.'s, 2010). This study discusses order configuration uncertainty created by configure-to-order supply chains. A stochastic model was used, and it was shown to have significant benefits in profit and revenue. Several organisations today require product customization abilities to remain competitive. For instance, (Poulin et al.'s, 2006) developed a framework that

comprised eight personalization options for golf clubs that can be combined to perform a complete personalized offer. The business orientation is said to be important for the strategy an organisation takes on its product range. For instance, (Lynch et al.'s, 2012) found that having a balanced business orientation approach reduces vulnerability to change within the supply chain and enables a more flexible and agile response. For example, having a production orientation forces the decision to rationalize product range to meet customization needs.

3. Marketing. This topic relates to promotions, campaigns and advertising that aim to modify customer behaviour. A representative article is “Against your better judgment? How organizations can improve their use of management judgment in forecasting” by (Fildes and Goodwin, 2007) This research demonstrated that promotional and advertising activities were the main reasons for adjusting statistical forecasts. Applying a statistical method to these events would be difficult due to the lack of history. Incorporating marketing information, including prices and promotions on the focal product's sales, has been studied: e.g, (Huang et al.'s, 2014) refined the marketing information then identified the most relevant explanatory variables and applied the Autoregressive Distributed Lag (ADL), model. It was found that the method generated substantially more accurate forecasts across a range of product categories than the benchmark models that were simple exponential smoothing and base-times-lift. However, the study also found that an automatic ADL model proved to be costly and seen to be difficult to implement for most organisations due to the lack of expertise.

4. Management. Articles on this topic typically focus on political influence on a forecast by management in an organisation. A representative article is “The effects of integrating management judgement into intermittent demand forecasts” by (Syntetos et al.'s, 2009). This study looks at the value being added, or not, when statistically derived forecasts are judgmentally adjusted by management. The study finds that an excessive upward adjustment to inventory levels can be motivated by political factors such as pressure from senior management to obtain high service levels. It has also been found that negative adjustments or inventory replenishment related decisions by management perform better than positive ones. Other studies have concluded that management generally deviate from the outcomes of a statistical method. For example (Boulaksil and Franses, 2009) survey results suggest that one out of every two experts completely ignore statistical-based forecasts and create their own.

5. Communication. This topic tends to contain articles identifying communication barriers within firms such as the lack of cross-functional communication in marketing, sales, operations and finance. A representative article is “Effective forecasting and judgmental adjustment: an empirical evaluation and strategies for improvement in supply-chain planning” by (Fildes et al.'s, 2009) examined 16 case studies. They found that the coordination and communication between the different organizational units involved in the supply chain operations are flawed. (MacGregor, 2001) also found that poor communication leads to double counting or omissions in the forecast.

6. Operations. Articles look at the SCM as a cross-functional company concept to improve coordination of entire value chains and the bottlenecks that arise. A representative article

is “Electronic supply network coordination in agri-food networks. Barriers, potentials, and path dependencies” (Fritz and Hausen, 2009). The study establishes barriers to adopting SCM improvements such as the need for high safety stock due to varying demand that often leads to large remaining stocks and the inefficiencies in order processing. The study finds that due to different structures, behaviours, a large variety of process and interface variants leads to inefficiency of the entire value network and too low reactivity in the production of products.

7. Culture. Research in this topic includes forecasting exaggeration, trust between supply chain partners and the contracts that can mutually reinforce each party. A representative article is “A rewarding-punishing coordination mechanism based on Trust in a divergent supply chain” by (Pezeshki et al.'s, 2013). This study develops a new rewarding-punishing coordination mechanism based on trust between supply chain tiers. Honest and deceptive partners are a differentiation factor that is considered. The results show that including a trust decimal factor performs better than having no trust mechanism in all situations.

8. Environment. This topic has articles exploring areas such as international crisis, holidays, seasonality, and unique events that impact product demand forecasting. A representative article is “'Horses for Courses' in demand forecasting” (Petropoulos et al.'s, 2014). Through empirical investigations of popular forecasting methods, the study found that seasonality is one influence that needs to be considered in forecasting intermittent demand. Another article (Fildes and Goodwin, 2007) found that there are many environmental reasons i.e. weather, holidays strikes, for why statistical forecasts are adjusted to cater for this uncertainty. Further results by (Gil-Alana et al.'s, 2008) results

show that a simple method with seasonal variables outperforms more complex methods over short horizons.

9. Suppliers. This topic relates to the barriers faced with lead times and the loss of key players in the supply chain such as suppliers. A representative article is “ An examination of the role of Business orientation in an uncertain business environment” (Lynch et al.'s, 2012). This paper investigates whether an over-dependence on a dominant business orientation increases the risks in sustaining successful business performance in an uncertain business environment. Some characteristics with a production orientation organisation found lead times had to be reduced from their supplier from 11-12 weeks to 7-8 weeks. This is due to the heightened uncertainty of demand levels and the desire to hold fewer inventory levels. In a relationship orientation organisation, a loss of key players at both the manufacturing and supplier level was shown to result in heightened tension amongst the horizontal layers within the supply chain.

10. Competitors. This dimension relates to competitor activities such as competitor promotions product launches or product price changes that may impact the demand forecast. A representative article is “The value of competitive information in forecasting FMCG retail product sales and the variable selection problem" (Huang et al.'s, 2014). This study finds that in a competitive market, tension increases among suppliers as all players fight hard to chase sales in a difficult market. A competitive market's effect leads to an abundance of information such as promotions that are also noted to be overlooked by organisations.

It is important to note that these dimensions are not mutually exclusive, where some overlap, such as in the internal environment, marketing overlaps with operations. The creation of promotions by marketing can cause a lack of inventory in operations which creates a strain on uncertain product demand forecasting. The overlaps between these barriers can be due to a lack of vertical or horizontal integration in a firm. There are also external barriers that overlap such as government policy and lead times. The change in government policy may increase lead times of importing products and lead to barriers in forecasting uncertain product demand. The identified internal and external barriers inform future researchers of the barriers that need to be considered in the field. Several of the dimensions should be given priority for future research such as the product, management, and communication for internal barriers and environment and culture for external barriers as they make up most of the selected studies' barriers.

2.3.3 Solutions addressing barriers in forecasting uncertain demand

To effectively provide solutions to address the barriers in forecasting uncertain product demand, it was very important first to identify the barriers. Not all the studies explicitly mentioned how to address the barriers identified in forecasting uncertain demand. Out of the 66 studies only 35 studies 53%, present a solution on how these barriers can be addressed and improve the forecast accuracy. The solutions have been categorised by internal solutions and external solutions (Table 4). Internal solutions can be applied within an organisation whereas external solutions can be applied externally in the supply chain such as with suppliers or retailers. It is also noteworthy that not all the dimensions from the barriers were used, the dimensions are not exclusive to the internal or external category as they may overlap when looking at an end to end supply chain.

Table 4 Forecasting barriers and adopted solutions grouped against category & dimension

Category	Dimension	Forecasting Barrier	Forecasting solution adopted
Internal	**Technology**	Fragmented information technology Difficulties analysing information being shared Changes in technology	Deployment of IT
	Product	Product price change New product introduction Substitute product introduction Product customization Large product range Short product lifecycle	Product rationalisation and standardisation Timing New Product release
	Marketing	Promotions and advertising activity	Not mentioned
	Management	Senior management influence Political influence Lack of agility	Use multiple measures of forecast accuracy Compare past performance of various forecasting methods. Gatekeeping decisions Strong leadership support Improve functional alignment Combine forecasts from approaches that differ
	Communication	Judgmental adjustment Poor communication	Judgmental Adjustment Ask managers to justify their judgments
	Operations	Safety stock Rough estimates on inventory level Too many forecast methods	Redistribution of stock Vendor managed inventory

			Integrated with divergent supply chains
External	**Culture**	Lack of trust	Not mentioned
		Exaggeration of demand forecast	
	Environment	Weather	Not mentioned
		Holidays	
		Strikes	
		International crisis	
		Change in Government policy/regulation	
		Unique events i.e. sporting event	
		Seasonality	
	Suppliers	Lead times	Not mentioned
		Loss of key players i.e. supplier, manufacturer	
	Technology	Social media	Information sharing
	Competitors	Competitor activities i.e. promotions, advertising	Incorporate competitive information

The top occurring internal solution that we identified in 12 out of the 35 studies was judgmental adjustment which belongs to the communication dimension. In hindsight, this also was the most occurring barrier faced in our studies. The most frequently occurring solution for the external category was information sharing which belonged to the technology dimension, sharing information between supply chain stakeholders provides a better outcome in forecasting demand. The highest cited papers (>100 citations, checked on 15/12/2018) in our selected studies that provide solutions to address forecasting uncertain product demand barriers is (Fildes et al.'s, 2009);(Mollenkopf et al.'s, 2011) (Rahman and Subramanian, 2012); (Fildes and Goodwin, 2007). These papers do not cover any of the external solutions in our findings and primarily focus on 9 out of the 12 internal solutions. A summary of the dimensions used follows:

1. Technology. Articles on this topic identify technological solutions to overcome the barriers in forecasting uncertain product demand. A representative article is "Operating internationally - The impact on operational performance improvement" (Demeter, 2014). This study investigates how the level of international presence impacts the operational performance of companies. The study finds that the best operational performance strategy is by having a strategy that supports investment in supply chain management, technology, quality, and human resource. It was found that well-developed information technology provides a higher rate of information sharing between partners on forecasts and inventories, leading to shorter reaction times to changes. (Vanpoucke et al.'s, 2014) found that sharing information through supplier integrative capability (SIC) enabled buyers to sense changes in the supply environment, enhancing process flexibility and cost-efficiency.

2. Product. This topic has articles exploring areas such as product rationalisation and standardisation of products to improve forecasting demand accuracy. A representative article is "The antecedents and consequences of product variety in new ventures: An empirical study"(Patel and Jayaram, 2014). (L. Fisher and D. Ittner, 1999) defines an organisations product variety as the "breadth of products that a firm offers at a given time". The study finds that product and process modularity enhance the benefits of product variety and mitigates the costs that arise from increasing product variety further. Product

modularity is said to share common modules, where features of products are designed around a standard base unit.

3. Management. Articles on this topic typically discuss cultural improvements such as strong leadership support, gatekeeping decisions that can be made to address the barriers in forecasting uncertain product demand. A representative article is “Creating value through returns management: Exploring the marketing-operations interface“ by (Mollenkopf et al.'s, 2011). This study explores the returns management phenomenon across a multi-disciplinary, managerial spectrum. The study finds that the functional integration at the marketing and operations interface in an organisation leads to better alignment of corporate resources and creates higher levels of customer value. (Slagmulder et al.'s, 2003) study finds that Sainsbury sales managers develop a culture change so that people with different talents continuously offer ideas to improve the existing supply chain.

4. Communication. Articles on this topic typically discuss ways to communicate better judgmental adjustments made to statistical forecasts. A representative article is “Against Your Better Judgment? How Organizations Can Improve Their Use of Management Judgment in Forecasting” (Fildes and Goodwin, 2007). The study explores how to communicate management judgement in the forecasting process effectively. The study finds if organisations follow basic principles such as requiring managers to communicate their adjustment by justifying in writing and assessing the adjustment results it would improve forecast accuracy.

5. Operations. This topic tends to contain articles that relate to managing supply chain operations in an organisation. A representative article is “Does supply chain visibility enhance agility” by (Brusset, 2016). This study addresses how best to achieve agility in supply chain management. To achieve this operational capability the study shows that having external and internal managerial processes enhance agility. (Davis and Mentzer, 2007) Developing cross-functional processes secure a “buy-in” from key stakeholders in the organisation, which assured that a consensus sales forecast was used in decision-making across the organization's functional areas.

6. Competitors. Articles look at the use of competitors’ information to achieve superior forecasting performance. A representative article is “The value of competitive information in forecasting FMCG retail product sales and the variable selection problem” (Huang et al.'s, 2014). This study investigates competitive price and competitive promotion in forecasting products at the Universal Product Code (UPC) level for retailers. The study finds that the value of using competitive information in forecasting retailer product sales at the UPC level is substantial as forecasting accuracy improves as the forecast horizon increases.

2.4 Discussion

This section elaborates on the findings by identifying the relationships between forecast barriers, solutions that address these barriers, and the related forecasting methods used in the studies. We also provide the benefits and limitations of the most common methods.

2.4.1 Relationships between barriers, solutions and methods

On examining the barriers in forecasting uncertain demand from the SLR, links and commonalities were observed amongst the barriers we identified. Our systematic review provides insights into some of the barriers faced in forecasting in the last decade's empirical findings. According to the analysis of our results identified in Table 3, forecasting barriers may be encountered internally within the organisation or externally (Govindan, 2015). The barriers extracted from our studies have also been grouped against an internal or external category and several dimensions (see Figure 3).

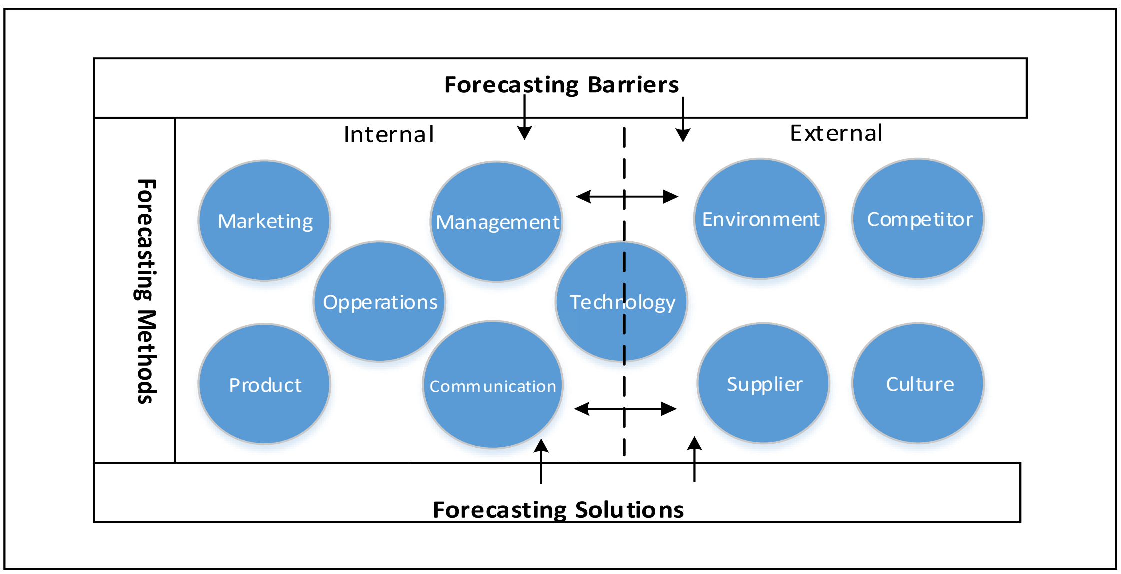

Figure 3 Internal and External dimensions of Barriers, and solutions

These dimensions are not exclusive to one category as they may overlap between the internal and external category. The arrows demonstrate the overlapping that can occur between these categories. It is noteworthy that the barriers and the solutions share the same dimensions, (see Table 4**Error! Reference source not found.**), however, the marketing, culture, environment and supplier dimensions are the ones that solutions have not been mapped against. The most frequent barrier found in the studies internally was judgmental adjustment which is also one of the frequently used methods in our empirical studies for forecasting, used across 11 industries with total use of 31 applications as depicted in Table 2.

We have further mapped the relationships between the barriers and solutions to address the barriers (see Figure 4) and the methods that support the solution (see Figure 5) used in the 66 empirical papers. To navigate the information provided in Figure 4 and Figure 5, we give an example. The last row of the Barriers' list on the left-hand side table is the "competitor activities" barrier. The solution offered in the literature in the middle table is two: "Information sharing" and "incorporate competitive information". The methods used with the information sharing solution is "simple moving average" which is on the right-hand side table. We concede that the list we have provided in Figure 2 does not imply that all the possible methods for all possible solutions are covered. However, to report our SLR findings, we need to remain faithful to the selected studies' information.

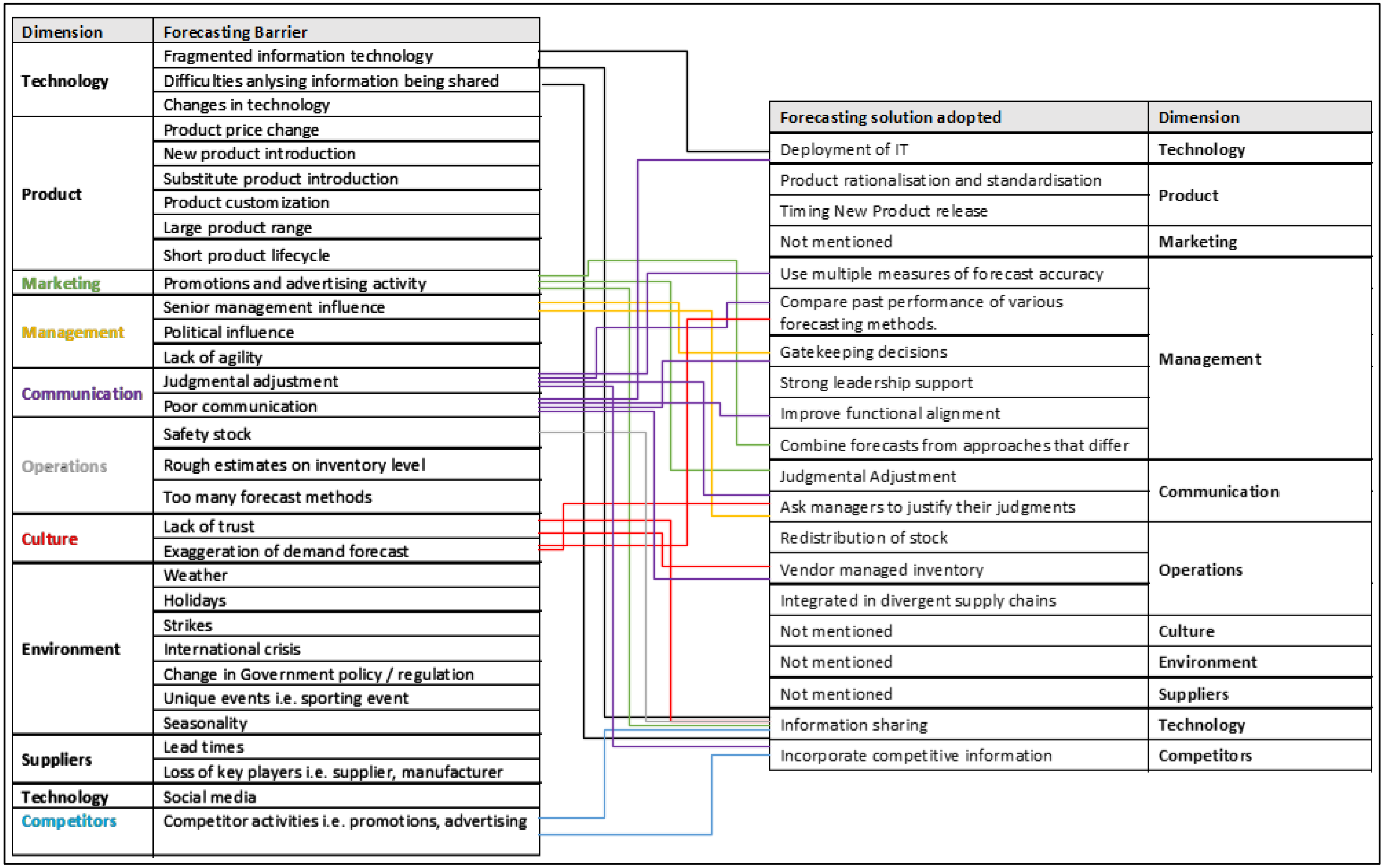

Figure 4 Relationship between forecasting barriers and adopted solutions for uncertain product demand in supply chain

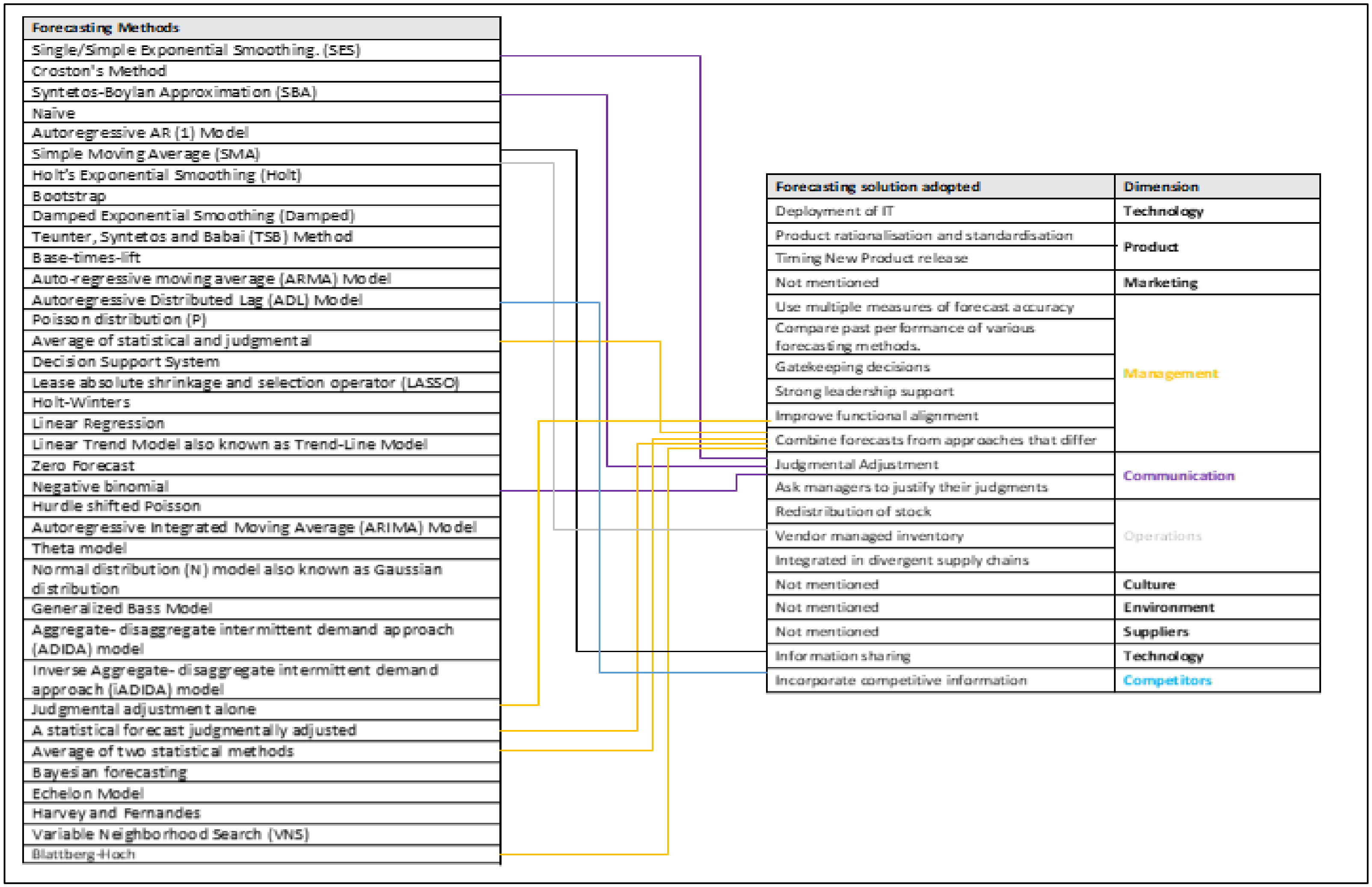

Figure 5 Relationship between forecasting methods and adopted solutions for uncertain product demand in supply chain

Our analysis reveals how organisations address the barriers we identified in RQ2, with the relevant methods RQ1.

Figure 6 encapsulates our overall structure of the research results into a research framework made up of three main parts; the barriers in forecasting uncertain product, which have been categorized against dimensions, the forecasting methods and the adopted solutions used to address the barriers. This generic framework will be valuable to supply chain practitioners as it integrates the three parts and provides a high-level view of uncertain product demand in any supply chain context.

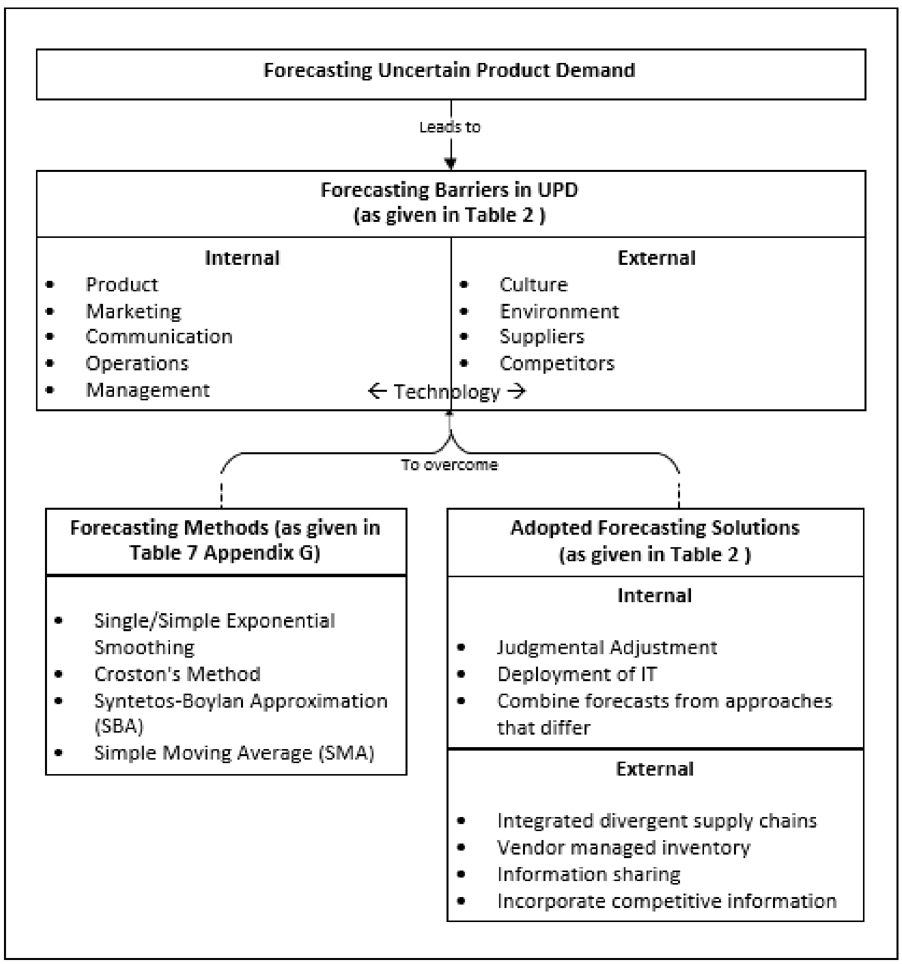

Figure 6 Encapsulation of barriers, solutions & methods of uncertain product demand in the supply chain into a research framework

It is noteworthy that the relationship of the mapped forecasting methods derived against the solutions in Figure 5 shows the solutions that they address from the empirical papers and are not exclusive to these solutions only. Any of these forecasting methods may be used in combination with judgmental adjustment to improve the accuracy of the forecast, however, the appropriateness between the forecast method and particular domain should be considered, as the success of the forecast can vary depending on the company context (Fildes et al.'s, 2009, Danese and Kalchschmidt, 2011a). The solution that covered the most barriers (6 in total) is information sharing that was applied to the following barriers:

1 Competitor Activities
2 Trust
3 Inaccurate estimates on inventory level
4 Safety Stock
5 Promotions and advertising activities
6 Difficulties analysing information being shared

Davis and Mentzer Davis and Mentzer (2007), consider three types of information as being appropriate to forecasting: data concerning the financial development of the market (e.g., inflation, foreign currency rates, etc.), data gathered from individual customers (e.g., sales plan, customer forecast, etc.), data concerning the particular market sector (e.g., overall technology trends). Considering all the information relevant to forecasting and assessing how each data can be blended into a forecast is vital to enhance forecast accuracy (Danese and Kalchschmidt, 2011a).

Several papers describe the large amounts of available data within organisations that can be used to improve forecast accuracy. However, due to the scale and difficulty of the forecasting task, it is overall complex and often impractical for all SKUs to be given specific consideration by demand planners (Fildes et al.'s, 2009, Huang et al.'s, 2014). Also, to include any alternative explanatory variables such as a reason for a judgmental adjustment at this level becomes cumbersome (Franses and Legerstee, 2013). Research literature suggests that decision-makers often struggle to make sense of the available data and use it wisely (Shang et al.'s, 2008, Huang et al.'s, 2014).

Information sharing can be considered as a solution to forecasting uncertain demand. Mollenkopf et al.'s (2011), found evidence by conducting interviews with global supply chain directors, operation managers and marketing director in Italy and the USA. The study suggested the more marketing and operations groups share information (regarding customer orders, pricing, delivery options and the underlying operational costs of various sale terms), the better aligned the two groups will be. Dubey et al.'s (2018), also concluded that sharing relevant, complete, accurate and confidential information would contribute to better visibility in terms of inventory and demand in supply chains. However, it is noteworthy that the abundance of information available and the complex task at hand in forecasting means that this is not a simple solution. Wang et al.'s (2005), finds that information sharing cannot eliminate the bullwhip effect; however, it can eliminate the effect of uncertain information distortion and improve the performance of supply chains effectively. Further research could investigate how best to capture and share this information to improve uncertain demand forecast. This is considered as a gap in the body of work reported in the SLR.

2.4.2 Benefits and Limitations of UPD forecasting methods

The most common methods used widely in different forecasting demand domains are simple exponential smoothing (SES), Croston's, Syntetos-Boylan Approximation (SBA) and Naïve method. These methods have the highest frequency in our studies (Table 6 Appendix B). All of them except for Naïve are known to be parametric methods (Ma et al.'s, 2016) which have mainly been demonstrated to provide a practical use for forecasting. These methods need less computing power, which is important when demands for very large SKUs have to be forecast (Ma et al.'s, 2016). These methods also require less specialist knowledge and are thus more transparent and resistant to potentially damaging judgmental interventions (Syntetos et al.'s, 2015). Table 5 provides the benefits and limitations of the most common methods in our studies. It is important to note that the benefits and limitations derived are based on various data sets and accuracy measures used in the studies.

Table 5 Benefits and limitations of UPD forecasting methods

Forecasting Method	**Benefits**	**Limitations**
Single/Simple Exponential Smoothing. (SES)	This method is a simple parametric method that requires little specialist knowledge and is thus more transparent and more resistant to potential harmful judgmental adjustments(Ma et al.'s, 2016). It is the most popular and cost-effective statistical extrapolation methods(Yelland, 2010). SES is said to be stable and best used when the focal product is relatively stable and is not on promotion(Huang et al.'s, 2014). This method also requires a smaller amount of computing power, which is important when many SKUs have to be forecast (Ma et al.'s, 2016).	Single Exponential Smoothing (Single) adopts no trend or seasonal patterns, hence it does not perform well for long forecasting horizons as it cannot predict the trend in data (Petropoulos et al.'s, 2016b). It neglects promotions or the fact that, even during the periods when the focal product is not being promoted, its sales could also be driven by promotions of other competitive products (Huang et al.'s, 2014).

Croston's Method	Croston's method is based on exponential smoothing and is also a parametric method(Ma et al.'s, 2016), it has been found to perform well for intermittent demand (Petropoulos et al.'s, 2014, Syntetos et al.'s, 2015). Although this method's considerable bias exists both theoretically and empirically, the Croston method achieves good inventory performance (Zied Babai et al.'s, 2014, Petropoulos et al.'s, 2016b).	Croston method is biased high due to an error in the mathematical derivation of expected demand. This leads to overcompensation and increased customer service and inventory investment (Syntetos et al.'s, 2015, Zied Babai et al.'s, 2014).
Syntetos-Boylan Approximation (SBA)	Syntetos-Boylan Approximation (SBA) is also a parametric method. It has been found to produce overall better performance than Croston's method as it produces fewer biases in forecasts (Petropoulos et al.'s, 2016b).	Despite SBA designed to advance Croston's method, the Croston method consistently gave better stock level performance than the SBA method (Syntetos et al.'s, 2015).
Naïve	Naïve is the best option if there is a presence of randomness (Petropoulos et al.'s, 2014). Naïve also was found to achieve superior accuracy in datasets that are highly intermittent (Petropoulos et al.'s, 2016b) and where a large forecasting horizon is required (Petropoulos et al.'s, 2014).	Does not perform well with zero forecast values (Petropoulos et al.'s, 2016b).

Our research identifies more complex methods, (e.g. IADIDA, ADIDA, ADL); however, these do not seem to be used widely. This may be because the methods are difficult to interpret, and they rely on the expertise that may well not be available in an organisation (Huang et al.'s, 2014). While both qualitative and quantitative forecasting methods are essential, our findings reveal that using the judgmental adjustments method is still the highest occurring barrier. It has been stated that it is impossible to claim that companies applying quantitative and complex methods (such as LASOO or ADIDA models) achieve better results (Lawrence et al.'s, 2000) than using only the Judgmental method (Makridakis et al.'s, 1998). The combination of various forecasting methods may drive an increase in efficiency of accuracy (Makridakis et al.'s, 1998). The '50% model, 50% manager' heuristic suggested by (Blattberg and Hoch, 1990) includes taking the mean of management judgments and statistical forecasts such as SES or SBA. Blattberg and Hoch found that this simple strategy was successful because of statistical methods and human judgment's complementary strengths and weaknesses. In fact, Vereecke et al.'s (2018), conclude that mature companies use methods that include the effective combination of statistical methods and human judgment, taking into account contingencies and product segmentation. This may explain why 31 applications in our studies have used a combination of qualitative and quantitative method.

2.4.3 Judgmental adjustment decision making framework

Judgmental adjustments was the barrier with the highest frequency in our SLR due to various reasons, such as the subjective responses to demand signals that result in increases in internal costs, uncertainty, and volatility (Duan et al.'s, 2015). The empirical studies also indicated that sales managers might face political pressures to favour a particular outcome. For example, Syntetos et al.'s (2016) found that when performance is measured and rewarded according to service levels achieved, managers will generally overstate the forecasts to prevent them from running out of stock. This can lead to manufacturers carrying more inventories, especially when the order frequency is uncertain or because managers adjust their forecasts based on overreactions (Duan et al.'s, 2015, Chao, 2013). The managers may also tend to 'see' patterns where there are not necessarily any patterns at all. Typically, more minor forecast adjustments are made to the forecast that by no means account for any benefits or, even worse, they may also damage the forecast accuracy (Syntetos et al.'s, 2016). There have been contradictory views in the literature. Some have shown that minor adjustments were often ineffective in improving the forecast and that significant adjustments are especially useful in correcting statistical forecasts (Fildes et al.'s, 2009). However, these adjustments can be needless or even damaging when used without understanding how the method chosen derived the forecast (Syntetos et al.'s, 2015). It can be said that judgmental adjustment is essential with any chosen statistical method; however, this does not guarantee an improvement in the forecast.

We have developed a decision-making framework (Figure 7) from our findings to help forecasters make judgmental adjustments through a repeatable and clear decision-making process. The literature has noted that frequently forecasts are adjusted because forecasters are confused with decisions (Fildes et al.'s, 2009). The proposed framework could be used as a process to avoid optimism bias and confusion of forecasts and decisions on judgmental adjustments. Table 6 explains each reason in the framework when an adjustment is not essential or needs to be revised. The footnotes against the judgmental adjustment decision are reflected in Figure 7.

Table 6 Reasons for judgmental adjustment decision

Judgmental Forecast Adjustment decision	**Reason**	**Studies**
1. Adjustment not essential	Small adjustments were often ineffective in reducing forecast error.	(Fildes et al.'s, 2009)
2. Revise Adjustment	Forecasters did not attempt to review the reasons for previous wrongly interpreted judgmental adjustment, which, is a cause of major forecast error.	(Fildes et al.'s, 2009) , (Fildes and Goodwin, 2007)
3. Revise Adjustment	Without understanding the previous accuracy measures or how the forecast was produced, these adjustments can be unnecessary or even harmful.	(Davis and Mentzer, 2007), (Syntetos et al.'s, 2016), (Trapero et al.'s, 2013), (Ali et al.'s, 2017)

4. Revise Adjustment	Positive adjustments tended to lead to larger errors than negative ones.	(Syntetos et al.'s, 2016), (Fildes and Goodwin, 2007), (Goodwin et al.'s, 2007)
5. Revise Adjustment	There is a lack of communication and coordination among different business departments engaged in supply chain operations, sales or marketing.	(Davis and Mentzer, 2007), (Fildes and Goodwin, 2007)

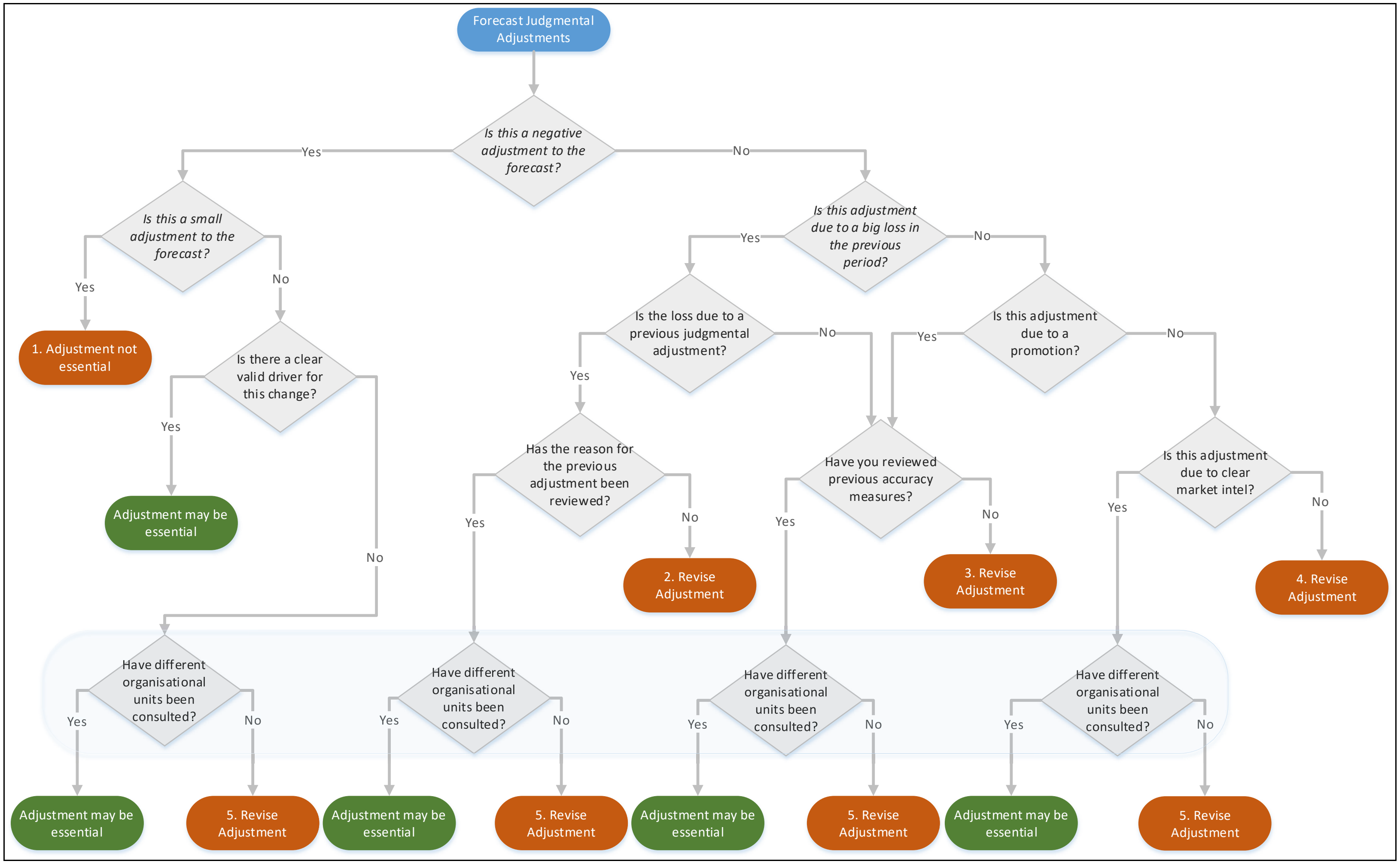

Figure 7 Decision making framework for UPD using judgmental adjustments

It is important to note that any essential adjustment made through the decision making framework should also justify the adjustment. This is in line with (Syntetos et al.'s, 2016) where it was found that there is the potential of forecast performance improvement from adjustments that are made with a justification. Not only does this help with the performance but it will also be useful in the learning process of practitioners and towards an understanding of why decisions may still be erroneous (Franses and Legerstee, 2009). It is also important to point out that all essential adjustments need to be communicated with the different organisation business units to ensure information is being shared. The only adjustment that may be essential and does not require organisational units to be consulted is when a clear valid driver for a negative forecast adjustment is present. Studies found forecasters achieve better forecasts when making negative adjustments because their information is more realistic (Fildes et al.'s, 2009, Trapero et al.'s, 2013).

2.5 Chapter Summary

This chapter presented a systematic literature review of 66 scholarly articles that deal with forecasting uncertain product demand in supply chain, one that is recent and relevant to supply chain practitioners and academics. The SLR has painted a rich picture of the complex practices by including many internal and external barriers that play their role in forecasting uncertain product demand, the methods being used, and solutions offered to address the barriers, as encapsulated in an integrated framework. The SLR enabled us to organise and structure these barriers into related themes and identify the most frequent barriers discovered in the literature of the last decade. The most frequently used methods by industry have also been identified. These results help us understand all the issues related to the design of more effective strategies for forecasting in the supply chain domain. Furthermore, our SLR results inform us about various aspects of the internal/external organisation barriers faced and how they can be mitigated. Our research has also enabled us to develop a novel framework for judgmental adjustments.

Our study has revealed an extremely large body of research literature both empirical and non-empirical available on this topic. However, while analysing the included studies to answer our research questions, we found some literature gaps. Figure 24 highlights the current research and industrial practice gaps. The following is a list of concepts that are not adequately explored within the current empirical literature that provides convincing evidence for our research:

1. Judgmental adjustments are a double-edged sword, it has been claimed to improve forecasting uncertain demand and decrease forecast accuracy. The success of this crucial part of forecasting needs to be further explored
2. The combination of solutions such as statistical methods, judgmental adjustments and information sharing that mitigate the barriers of forecasting uncertain demand in the literature is not empirically investigated and measured.

3 Methodology and Research Design

3.1 Chapter Overview

The previous chapter reviews the available literature on forecasting uncertain product demand in the supply chain, including barriers faced, methods used, and solutions adopted to address the barriers. This chapter aims to introduce the research methodology and design adopted for this industry research project. Design science research methodology is chosen for this industry research project to discover and identify opportunities and problems in forecasting uncertain product demand relevant to the Australian Luminaire Manufacturer (ALM) and inventing or creating new or improved digital artefact to address the problems. There are other relevant methodologies, such as action research (Adelman, 1993) and applied research. However, action research is suited for social science, where understanding human-interaction touchpoints are critical during the problem identification phase (Iivari and Venable, 2009). Applied research is used to increase what is known about a problem and aims at arriving at research findings that can solve the problems (Hedrick et al.'s, 1993). Design science research is suitable for this research as it is centred on practical problem-solving. The results from scientific justification such as understanding, predicting or explaining a phenomenon can be used to design solutions to solve complex and relevant problems faced in the real world and, by that means, to contribute to the theory of the discipline in which it is applied (Lukka, 2003).

Given the nature of the industry research project, proposing and developing a solution for a real-life problem, the researcher decided to proceed with the design science research method. This method will be used to ascertain and recognise problems applicable to the ALM organisation and provide an unambiguous approach to formulating the design and building a novel artefact that deals with the barriers in forecasting uncertain product demand. Figure 8 depicts the overall relationships between design science research, the research goals and the research chapters.

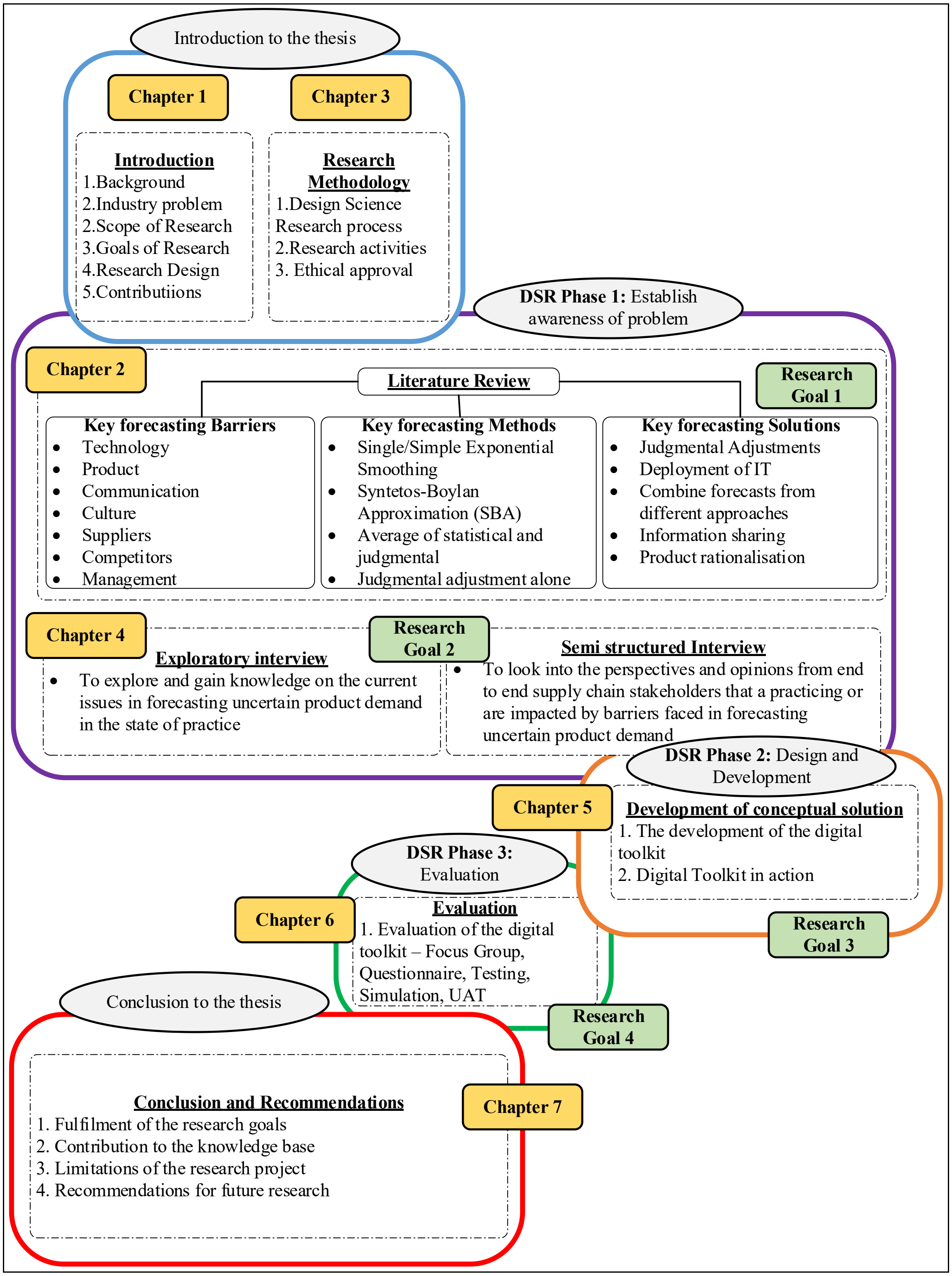

Figure 8 Relationship between DSR process, research goals and research chapters

First, a pilot study exploration was carried out at ALM about the overall supply chain and concepts relevant to the study was provided. Our existing knowledge of the organisation was confirmed (Chapter 4.2). Subsequently, a systematic review of the literature associated with forecasting product demand was performed to understand the theoretical background and obtain deeper insights into the research problem (Chapter 2). Further to this, a survey of the current state-of-the-practice is performed through a qualitative field study to explore what the experts thought and the daily barriers they faced in forecasting uncertain product demand (Chapter 4.4). The qualitative field study results provided the preliminary requirements elicitation tasks that were essential to extract initial requirements and features of the toolkit.

Furthermore, the two chapters' results (Chapter 2 & Chapter 4) allowed for the iterative update of our supply chain mapping. In the development phase, the actual deliverable (i.e., the toolkit) was designed and developed (Chapter 5). This artefact was then evaluated (Chapter 6) and the industry research was concluded (Chapter 7).

In this chapter, we will describe in detail the methodology and research design we have applied. This chapter begins by elaborating on the chosen research design and provides an overview of the basis of design science research. We provide the research outputs and discuss the activities we have completed as part of the research method. We also provide the overall research strategy and the relationship between the design science research process, our research goals and the research chapters in this thesis. Finally, the limitations of the research design and our ethical considerations are provided.

3.2 Research Methodology

Hevner et al.'s (2004) identifies two main research paradigms in the information systems (IS) discipline: natural science and design science. Natural science (also known as behavioural science paradigm), is concerned with developing and verifying theories explaining or predicting human and organizational behaviour. The design science research (DSR) paradigm seeks to create innovation through analysis, design of artefacts and implementation that extends the capabilities of human and organisation behaviour.

March and Smith (1995) describe the two research paradigms as follows:

1) Natural science tries to understand reality by explaining how and why things are. Natural science comprises traditional research in physical, biological, social, and behavioural domains.

2) Design science attempts to create things that serve human purposes. It is technology-oriented. Its products are assessed against value or utility criteria (i.e. does it work? Is it an improvement?). Rather than producing general theoretical knowledge, design scientists produce and apply knowledge of tasks or situations to create effective artefacts.

The first characteristic of design science research is that it is driven by problem-solving and the second distinguishing characteristic is the rigid nature of the research outcome. The design science research, which is the driver of this research project aims to create new and innovative solution artefacts such as governance strategies, decision support systems and methods for information system evaluations (Shrestha et al.'s, 2014). In addition, March and Smith (1995) looked at design science research to seek and explore new solution alternatives to solve problems, explain this exploratory process, and improve the problem-solving process and serve human purposes. Furthermore, the artifact's interaction with its environment may lead to theorizing about the artefact's internal workings or the environment.

Design science research includes four output types: constructs, models, methods, and instantiations. These research outputs are described by (March and Smith, 1995) as follows:

Constructs: Provides the vocabulary and symbols used to define and understand problems and solutions. Instances include concepts, syntax or language (vocabulary and symbols) used in a specified context of a problem to find a solution. They have a significant impact on how problems are conceived, and they enable the construction of models for the problem and solution domains.

Models: A set of statements or propositions that describe a set of constructs to solve a problem such as, mathematical models, diagrammatical models, logic models, abstractions and representations. These can simply be viewed as a representation of how things are.

Methods. A set of steps that are used to achieve a task such as, algorithms and guidelines. They are based on the underlying constructs (language) and a representation (model) of the solution.

Instantiations. A realization of an artefact in its environment for example an information system that stores, retrieves and analyses customer data. Instantiations ultimately provide real proof that the constructs, models and methods can be operationalised and work in a real-world context.

3.3 Research Activities – Method used in this research study

Design science consists of three cycles of development activities (see Figure 9), the environment which is where researchers establish awareness of the problem (chapter 3.3.1), the designing, building of the artefact (chapter 3.3.2) and evaluation (chapter 3.3.3). The environment cycle results in observations and interactions among people, organisation and technical systems to achieve a particular goal (Iivari, 2015). In the context of this research project, the interactions are conducted in the ALM environment and supply chain domain, particularly for knowledge analysis, scoping and gap analysis. This design science environment research cycle becomes the foundation for the next cycle: designing, building (chapter 3.3.2), and evaluation (chapter 3.3.3) of the artifacts. The design cycle is regarded as the heart of any design science research project (Hevner and Chatterjee, 2010). We refer to Wieringa (2009) in chapter 3.4 to describe the type of problems we are investigating. Once the problems have been observed and identified the development of the initial artefact is followed. Subsequently, once the artefact is built, the developed artifact's evaluation process is initially required to justify solving the identified problems. This requires multiple iterations of the design cycle in design science research before commencing the third (rigour) cycle. Hevner (2007) points out that evaluating a design science research artefact must be well conducted to ensure its validity. In particular, Hevner et al.'s (2004) propose that the evaluation could be *analytical, case study, experimental, field* study or *simulation*. In the context of our research project, the evaluation processes involve: feedback from ALM experts, questionnaire, focus group, testing and role-play simulation. The evaluation process will be elaborated in detail in this chapter.

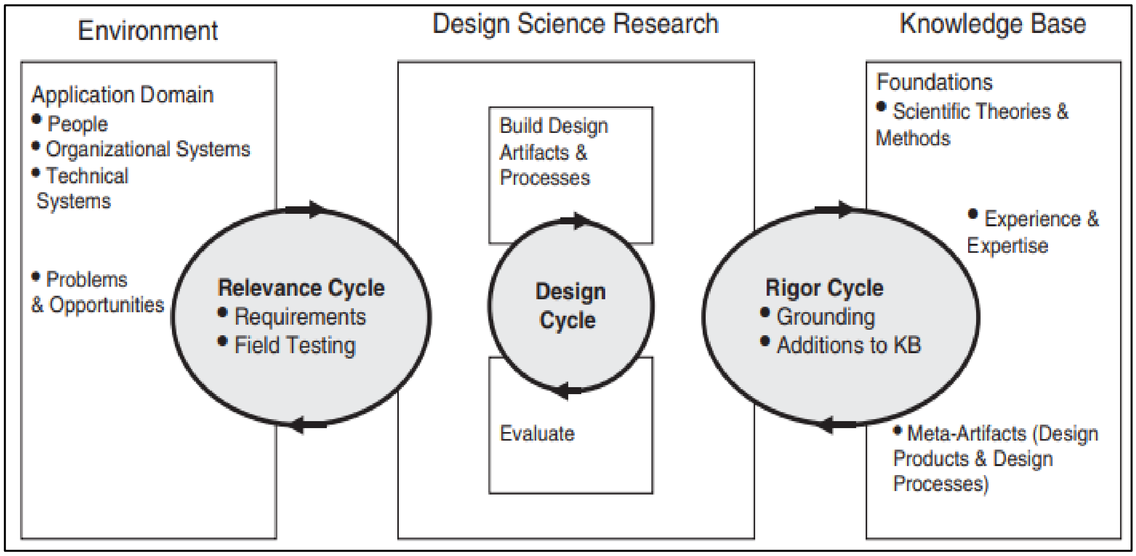

Figure 9 Hevner (2007) Design Science Research Cycles

The third stage of Hevner's three-cycle design science research activities is the rigour cycle (Figure 9). This is the justification of whether the research contributes to a new knowledge base (Gregor, 2006). It is contingent on thorough research and referencing the knowledge base to guarantee that the designs produced are research contributions and not routine design (Hevner et al.'s, 2004). The research outcome, that is the artefact per se, should be communicated for the theoretical contribution of the research (Shrestha et al.'s, 2014) or the research artefact should help address the current problem for practitioners (Sein et al.'s, 2011). In addition contributions to the knowledge base as results of design science research may include extensions to original theories and methods discovered during the research, new meta artefacts such as design processes and products, and all the experiences gained from performing the research and field testing of the artefact in the application environment (Hevner, 2007).

This research is constructed in three phases as depicted in Figure 1. **Phase 1** focuses on defining the research problem (Chapter 2) and understanding its application (Chapter 0).

Phase 2 is the design and development of the toolkit solution (Chapter 5). This toolkit is designed and developed based on the identified challenges in forecasting uncertain product demand identified from the previous phase. The output of this phase is the initial design and development of the digital toolkit. In **Phase 3**, the toolkit developed in Phase 2 is evaluated. The evaluations performed (Chapter 6) to the toolkit contribute to the continuous improvement of the developed artefact. The evaluation ensures that the developed toolkit works as intended. The evaluation aims to show that the artefact can be implemented in the environment and used by practitioners. The evaluation also demonstrates that the forecasting toolkit results will drive an improvement in transparency, efficiency, and effectiveness in the product demand forecasting process in the organisation.

3.3.1 Phase 1: Environment

The environment is a critical phase of the research cycle. It establishes an awareness of the research problem and provides the foundations that set the research project's direction. This phase of the research is also known as the problem investigation. Information about the application domain such as the people, organisational systems and technical systems is asked and understood. The information includes the industry research project's contextual background, any existing theories that form part of a precursor to the research process. Wieringa (2009) describes four categories of how a problem is investigated and each of these leads to different emphases in the problem investigation process:

- Problem-driven investigation – stakeholders experience problems that need to be diagnosed before solving them. Important tasks in the problem-driven investigation describe problematic phenomena, formulating and testing a hypothesis about their causes and identifying priorities for problems to be solved.

- Goal-driven investigation – considers a situation in which there are maybe no problem experienced but where there are nevertheless reasons to change the world in agreement with some goals. In all cases of solution-driven problem investigation, important tasks are describing stakeholder goals, defining and operationalising them, and identifying priorities of goals.

- Solution-driven investigation – technology is in search of problems that can be solved with it. Problem investigation, in this case, would start with an investigation of the properties of the new technology; and solution design would be an exploration of ways in which it could be used to achieve new goals.

- Impact-driven investigation – also called evaluation research, focuses on the outcome of past actions rather than preparing to design future solutions. Important tasks in evaluation research describe solutions implemented earlier, identifying their impacts and explaining these impacts in terms of properties of the implemented solutions, identifying relevant stakeholder goals, translating these into criteria and applying these to the impacts.

This industry research project falls under the category of problem-driven investigation, which begins by identifying and defining opportunities and practical problems in an actual application environment (ALM). It starts by looking into the realm of inquiry, a study of the existing knowledge (chapter 2). At this stage, the theory is used to understand the problems i.e. the barriers in forecasting uncertain product demand in supply chain. The design science research Phase 1 of this thesis is composed of three corresponding activities (see Figure

10), three types of research methods were used to gain knowledge of the problem, namely literature review (chapter 2), pilot study and field study (chapter 0). The following sections described how those methods were carried out.

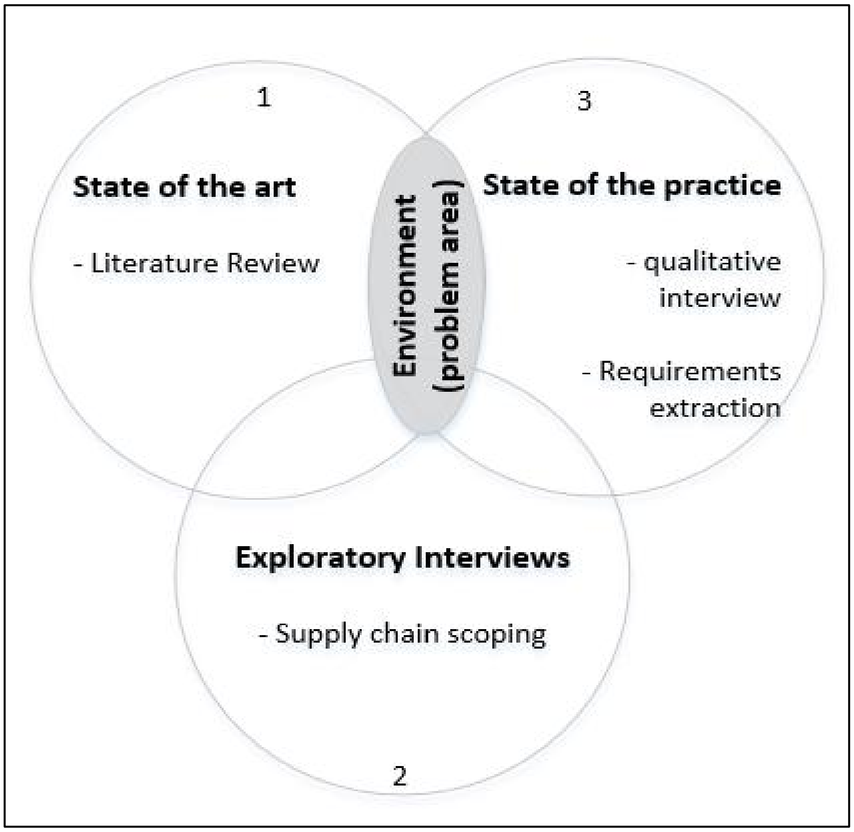

Figure 10 DSR research environment cycle

3.3.1.1 Systematic Literature Review

A systematic Literature review is an approach to methodically recognise, evaluate and integrate all the applicable studies on a specified matter (Petticrew and Roberts, 2008). A systematic literature review was conducted to critically appraise research studies in the supply chain domain and synthesize our qualitatively and quantitative findings. Our systematic literature review results helped guide and inform the formalisation of the industry research problem. Before commencing our literature review, a systematic literature review (SLR) protocol was developed (see Appendix F) for conducting the SLR. The protocol contained our search strategy's details guided by the research questions, inclusion/exclusion criteria, quality assessment criteria, data extraction strategy, and data synthesis and analysis guidelines. The protocol was tested for evaluating the completeness of our search string, and the correctness of our inclusion/ exclusion criteria and data extraction strategy. The protocol was sent to one external reviewer who is an expert in SLR. Minor recommended changes from the reviewer related to the research questions were incorporated. During the execution, the steps of the protocol were further refined. The literature review was then initiated by following guidelines of (Kitchenham and Charters, 2007), These guidelines propose three main phases of SLR, (1) planning, (2) execution, and (3) reporting results (see Figure 11). The execution and results of the SLR phases are explained in chapter 2.

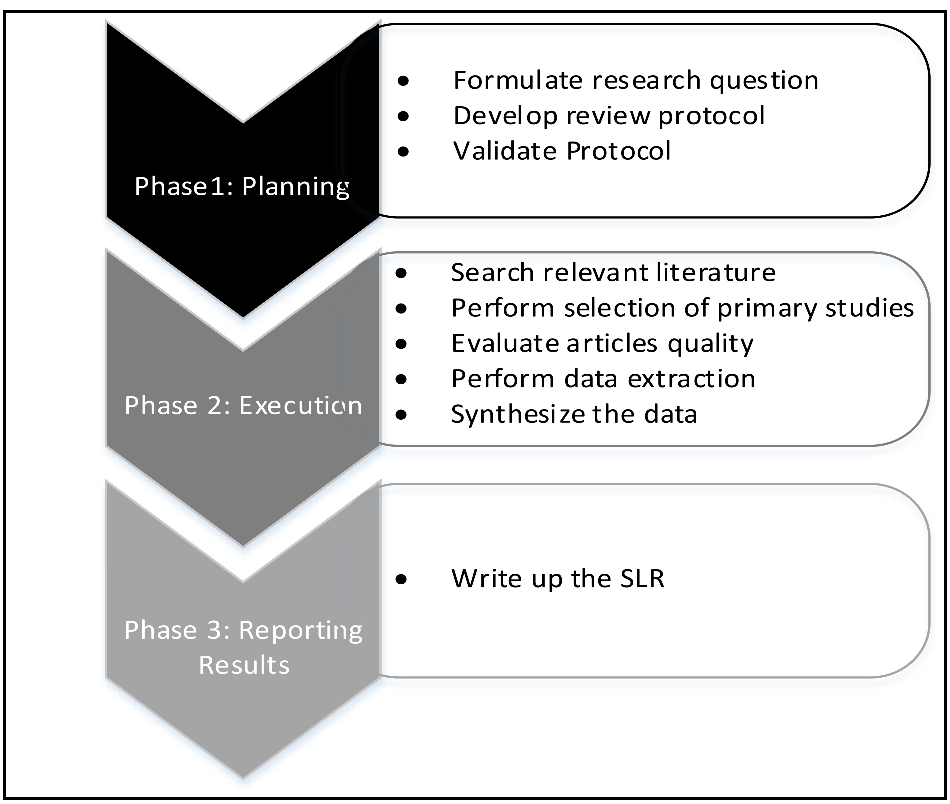

Figure 11 SLR research Methodology

The systematic literature review's goal was to undertake a comprehensive search for empirical publications on digital electronic databases with the follwong aims. (1) identify the barriers faced in forecasting uncertain product demand in supply chain, (2) identify the forecasting methods used for forecasting product demand; and (3) identify how the barriers of forecasting uncertain product demand be addressed. The review resulted in 66 studies from the literature for the period 2008-2019. Our findings revealed many barriers in forecasting product demands that still exist today apart from choosing the most appropriate forecasting technique. Chapter 2.3.2 lists the top ten barriers of forecasting uncertain product demand mentioned in the literature

The execution of the literature review process is detailed and discussed in Appendix G1. All the barriers and gaps are presented and examined based on the existing works of literature. The literature review confirmed an important research gap in addressing the barriers in forecasting uncertain product demand in particular judgemental adjustments made to a statistical or mathematical forecast. The systematic literature review is presented and discussed in chapter 2.

3.3.1.2 Pilot Study

We conducted a pilot study containing a series of pre-interview exploration activities at ALM to gain in-depth information about the overall supply chain domain and understand who should formally be interviewed. The activities were informal and ad-hoc, it involved a walk around the ALM office and asking informal questions to supply chain stakeholders (informal chats), observing how people perform tasks and reading existing documentation that was made available. These exploratory activities allowed us to confirm our domain knowledge and understanding of the organisation, job roles within the forecasting process and the overall supply chain processes. It also ensured our understanding of the problem made sense and allowed us to identify who in the supply chain should be interviewed formally (chapter 4). The additional insights gained allowed us to develop a process map of the supply chain and map the main pain points experienced by supply chain stakeholders. The process map was part of making sense of the environment and documented in chapter 4.2**Error! Reference source not found.** of this thesis.

3.3.1.3 Field Study

The field study's primary goal (chapter 0) was to investigate the barriers faced in forecasting uncertain product demand in ALM and leading to eliciting high-level requirements for a possible solution to the problem of forecasting uncertain product demand. The qualitative field study specifically intended to explore what the experts thought and the daily barriers they faced in forecasting uncertain product demand and what they believed would overcome these barriers. Furthermore, the field study was anticipated to triangulate the result of the literature review (chapter 2), the purpose of triangulation is to cross-validate the literature review study (the-state-of-the-art) and field study (state-of-the-practice).

Following the process map and SLR, we planned for conducting an interview study in the field. Alternative to interview study is focus group or observation. We did not do a focus group because we did not want participants to be influenced by one another. As we were talking to different groups, we wanted to discover the individuals own knowledge and experience. Face-to-Face interviews were our choice for gaining a deeper understanding of the barriers in the manufacturing organisation. A Survey was also not appropriate as it only captures surface knowledge and not deep knowledge. Our SLR provided us with state-of-the-art knowledge and understanding of the forecast methods used (chapter 2.3.1), barriers in forecasting uncertain product demand (chapter 2.3.2) and the solutions that can be adopted to overcome them (chapter 2.3.3). Interviews offer rich qualitative data when a topic needs deeper insight (Schultze and Avital, 2011). Interviews acquire participants' views and thoughts by speaking face-to-face with them and allowing participants freedom to express their thoughts and experience on the topic. Using our supply chain knowledge and the knowledge gained from the first two steps of our research, we designed a set of interview questions, among other topics, to identify the barriers faced by participants. The interview questions that were used during the study can be found in Appendix I.

3.3.1.3.1 Interview questions

The interviews were semi-structured and open-ended questions. Open-ended questions do not have any prescribed answer to be selected by participants. The questions were aimed at three specific business units in the organisation. A set of generic questions was derived for all participants and a set of specific questions for the operations participants and the sales/category. The interviewees were asked to provide their views and experiences related to the questions asked. The interview questions were focused on exploring how forecasting is currently carried out in ALM, what barriers are being faced and how participants believe these barriers can be overcome. The relatively detailed questions from the specific set of questions allowed the interviewer to pay close attention to the participants’ experience. In contrast, the open-ended answers allowed the interviewer to follow up with probing questions with any specific questions during the interview.

3.3.1.3.2 Participants

The criterion for selecting the interviewees was that participants were involved in the forecasting of product demand or were impacted by it. Based on the criterion the participants were from across the supply chain. The participants belonged to the following three business units: sales/category, operations and finance/IT. An external supplier and customer of ALM were also selected as they impacted the supply chain forecasting. Human ethics approval (chapter 3.5) was obtained from the UTS Human Research Ethics Committee (HREC) before contacting any participants. The participants were approached by sending them an invitation letter (Appendix A) from the university supervisor via email. A participant information sheet that outlined their rights was also included. Follow up email was used to secure an appropriate time and location for the interview appointment.

A total of 21 participants were invited to participate in the interview study. 20 participants accepted, all 20 interviews took place during April–May 2018 in Sydney and each lasted an average of 39 minutes. At the time of the interview, participants were given a consent form (Appendix A). They were asked to read it carefully and understand their rights. The participants were also briefed on their data, data safekeeping, and the complaints procedure to UTS HREC. Once participants expressed their understanding and acceptance they were asked to sign the consent form. The interviews were audio-recorded, however, participants were also informed that at any time during the interview they were free to ask not to be recorded. At the end of the interview, participants were informed that they could contact us if they would like to know the research's progress and would also be notified about any publications made from the study. Each interview record was named with a code as a means for de-identification and later transcribed. A separate list of participants details and the code assigned to them is kept separately and confidential. Out of the 20 participants, 8 belong to the sales and category teams, 5 working in operations. 5 had experience either in finance, or information technology. One external customer and an international supplier were also part of the 20 interviews. The interviewees' names, the companies or their job titles will not be revealed in this research within compliance with HREC's confidentiality obligation at UTS to accept this research. The transcripts of the interviews were analysed using NVivo^{TM} software.

3.3.1.3.3 Data Analysis

The method adopted for data collection was directed qualitative content analysis (QCA)(Hsieh and Shannon, 2005). The conventional approach of content analysis is limited as it fails to develop a complete understanding of the context, thus failing to identify key categories (Hsieh and Shannon, 2005). Multiple studies (Hsieh and Shannon, 2005, Elo and Kyngäs, 2008, Zhang and Wildemuth, 2009, Mayring, 2014) suggest different strategies for conducting directed QCA. The directed content analysis approach aims to validate or conceptually extend a theoretical framework or theory (Hsieh and Shannon, 2005). Directed content analysis was selected because it enabled us further to describe the existing prior research (SLR). We adopt (Hsieh and Shannon, 2005) second analysis strategy, the first strategy is similar however it deals with reading the textual data and highlighting the text first before coding. The method was selected because it allowed the initial coding to start with a theory or relevant research findings. We feel confident that our initial coding will not bias the identification of relevant text as they were not used to form interview questions.

The steps of the analysis strategy used once all the interview recordings were transcribed are as follows:

1. Setting the initial categories and codes based on the results of the systematic literature review.
2. Reading the whole text and mapping of the respondent's answers to interview questions against relevant predetermined codes from SLR.
3. Identification of new categories and codes from interview data

4. Performing gap analysis from the interview data and SLR

Figure 12 illustrates the strategy used for the qualitative field study.

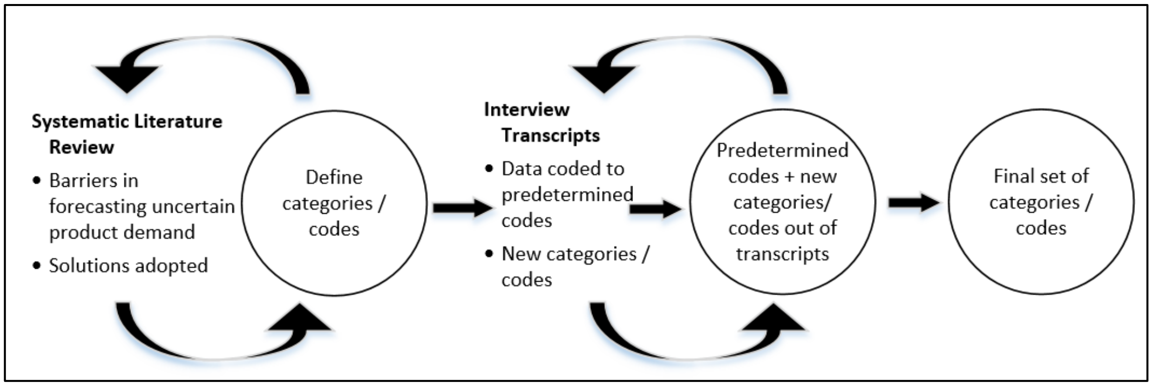

Figure 12 Directed quality content analysis strategy used

These steps will be discussed further below.

First, the list of barriers in forecasting uncertain demand was initially developed based on the systematic literature review (SLR). These factors were then used to develop the initial nodes in NVivo.

The interview transcripts were read carefully and analysed individually highlighting all the text representing the barriers of forecasting uncertain product demand. The next step of the analysis was to code all highlighted passages using the predetermined codes from the SLR. In this research, coding is the process of generating nodes that contain references to the actual data (Richards and Morse, 2012, Richards, 2014). In the initial coding of themes (guided by the literature review), 31 nodes were used in the initial coding and 11 categories. Any data that could not be coded with the initial coding scheme would be given a new code and/or category if required. Newly identified categories or codes either offer a contradictory view of the phenomenon or might further refine, extend, and enrich the theory (Hsieh and Shannon, 2005). Annotations were also written to store the researches reflection and ideas that emerged about the particular text.

The gap analysis attempts to find the differences between the SLR barriers and the findings from the interview study. By mapping the answers to the interview questions, the differences and irrelevant nodes from both the literature review and interview findings can be identified. This analysis can be used to help gain further insights from the initial findings. An item by item comparison was conducted to identify which dimensions and factors found in interview transcripts are not supported by the SLR findings. The emerging pattern of themes from the data not in the initial findings is looked at. The identification and analysis of the new themes will be discussed in chapter 0

3.3.2 Phase 2: Design and Build

Following the design science research paradigm, this phase discusses an artifact's design and development to solve the problem identified in Phase 1. This is essentially the design cycle of Hevner's DSR three-cycle (Hevner, 2007). Figure 13 depicts a high-level view of the solution produced at the end of the research project. The design framework's input is the results of phase 1 of the DSR cycle (problem area).

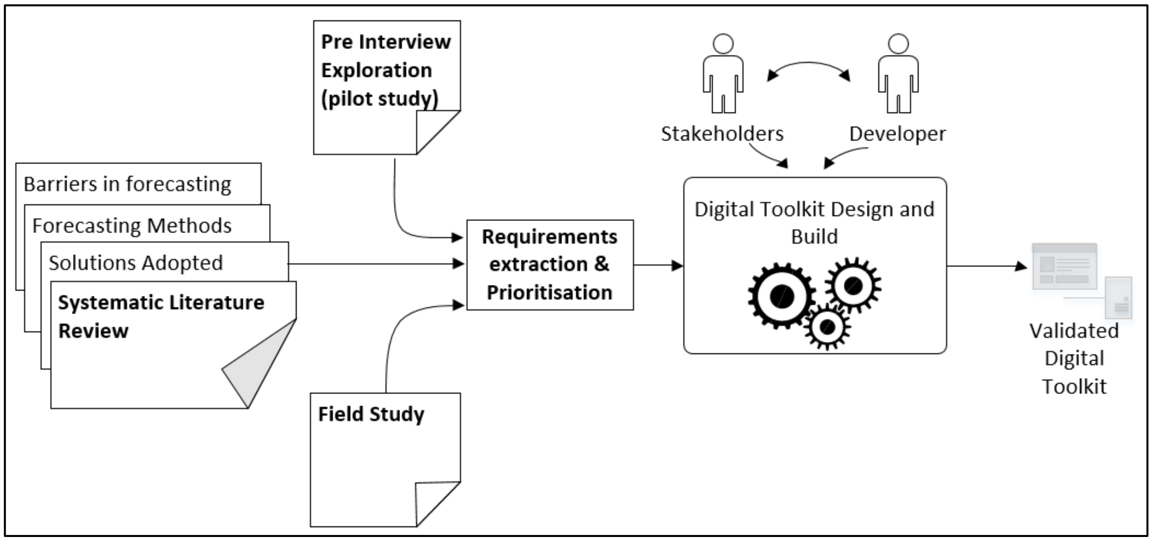

Figure 13 Digital toolkit development cycle

The literature review provided the grounding to the research project and showed the barriers faced, forecasting methods used and adopted solutions. The literature review also found that judgemental adjustments are among the most used techniques used in forecasting uncertain product demand and the highest barrier in forecasting demand. This research allowed us to develop a novel decision-making making framework embedded in the toolkit design (Chapter 5). The pilot study confirmed our knowledge of the environment and informally identified the forecasting demand barriers at ALM and developed a map of the overall supply chain. The results from the field study lead to eliciting high-level requirements for a possible solution to the problem. The requirements were prioritised (Chapter 3.3.2.1) by the executive stakeholders to determine the required features of the solution. The purpose of the iterative development cycle between the developer and stakeholders is to validate and verify the digital toolkit as soon as the features are made available. This is to ensure most errors identified are fixed before moving onto the final stages of testing and deployment.

In design science research, there have been various evaluation techniques proposed (Prat et al.'s, 2014a, Peffers et al.'s, 2012, Pries-Heje et al.'s, 2008b, Venable et al.'s, 2012b, Gonzalez and Sol, 2012). Peffers et al. Peffers et al.'s (2012) describe the evaluation process by defining that it can be conducted “ex ante” (before) or “ex post” (after) the artefact construction. This evaluation is a crucial and an essential activity. It guarantees that the new proposed and developed artefacts in the DSR are achieved and works as intended (Gonzalez and Sol, 2012, Peffers et al.'s, 2012). Phase 2 of the design science research will be revisited to refine the toolkit as results of the evaluation conducted in Phase 3.

3.3.2.1 Requirements prioritisation

Requirements prioritization is recognised as an important activity in the requirements engineering lifecycle (Moisiadis, 2002) and product development (Lehtola et al.'s, 2004). In most projects not all the requirements can be implemented because of limited time and resources. Therefore, decisions need to be made about which requirements need to be delivered first and the remaining removed for future release. According to Wiegers (Wiegers, 2003) information about priorities is needed, not just to ignore the least important requirements but also to help project managers solve conflicts, plan for staged deliveries, and make the necessary trade-offs. Prioritization is an essential element in considering changes in requirements, particularly rapid changes over time often referred to as requirements volatility. Zowghi and Nurmuliani (2002) refer to requirements volatility as the potential for change in the business environment, fluctuation in users’ requirements (instability), and disagreement among users/stakeholders on requirements (diversity).

Requirements prioritization is the setting of ranks or ratings of importance to a set of requirements based on certain criteria like goals, risks, quality, value to the stakeholders according to the views of various stakeholders who have a vested interest in the success of the development project (Moisiadis, 2002). Various approaches can be used to prioritize requirements, e.g. analytical hierarchy process (AHP) (Saaty, 1988), planning game (Bergin, 2001), cost-value approach (Karlsson and Ryan, 1997), Wiegers' method (Wiegers, 2003) and may others. Each approach used to prioritize requirements have different methods, for example, some have adopted a quantitative ranking system for requirements prioritization. Wiegers technique uses quantitative ranking for factors like cost, risk and importance (Wiegers, 2003). However, requirements prioritization is also recognized as a very challenging activity (Lehtola et al.'s, 2004, Heavin and Power, 2018). For example, Firesmith, D. (Firesmith, 2004) reports that numerous challenges must be addressed when prioritizing requirements, for example, having a large number of requirements to prioritize, limited resources, changing business priorities, incompatible priorities and incompatible requirements. The below chapters describe the card sorting technique and how the ALM practitioners prioritize the requirements. We further gain insights into the feedback practitioners provided for their prioritization of the requirements, which helped us understand the problem's multifaceted nature.

3.3.2.1.1 Card sorting Technique

The Card Sorting technique is well-established for eliciting knowledge from people (Maiden, 2009). It is broadly used in several fields such as web site design to organise information for the website (Zimmerman and Akerelrea, 2002), website usability tests (Whang, 2008), psychology to investigate subjects categorizations (Gerrard and Dickinson, 2005), knowledge engineering and software engineering (Upchurch et al.'s, 2001).

The utmost problem for Card Sorting effectiveness is that the participants and the researcher involved should understand the domain adequately (Maiden and Rugg, 1996). In this study, the participants were familiar with and understood the domain (Chapter 2) being elicited (i.e. forecasting uncertain product demand in the supply chain). Furthermore, the researchers' understanding of barriers in forecasting uncertain product demand and requirements prioritization has improved significantly through the long-term field study (Chapter 4) at the ALM.

There are two primary methods for performing card sorts, Open card sorting and Closed card sorting (Spencer, 2004). Open card sorting typically requires the stakeholders to sort a series of cards containing a description of domain entities into groups according to their understanding. Furthermore, the stakeholder must explain the rationale for how the cards are sorted (Zowghi and Coulin, 2005). To make this technique more effective, it is important that all the essential entities are included in the process and requires that both the analyst and participants have sufficient knowledge of the domain; otherwise, this technique produces wrong results (Rehman et al.'s, 2013). Closed card sorting is identical to Open card sorting except participants are asked to place cards into pre-established groups (Spencer, 2004).

Studies have shown that card sorting has many benefits that make it a useful technique for eliciting knowledge. First, the card sorting process is simple to understand and simple to do (Maiden, 2009, Fincher and Tenenberg, 2005). Second, card sorts require minimal technology to be performed almost anywhere (Maiden, 2009). Third, the card sorting results can serve as inputs for another technique (Upchurch et al.'s, 2001). Finally, the card sorting results can also be used to develop further classifications such as information architecture hierarchies for web sites (Zimmerman and Akerelrea, 2002). Figure 14. Depicts the card sorting steps that were carried out at the organisation. The overall card sorting was completed over four days.

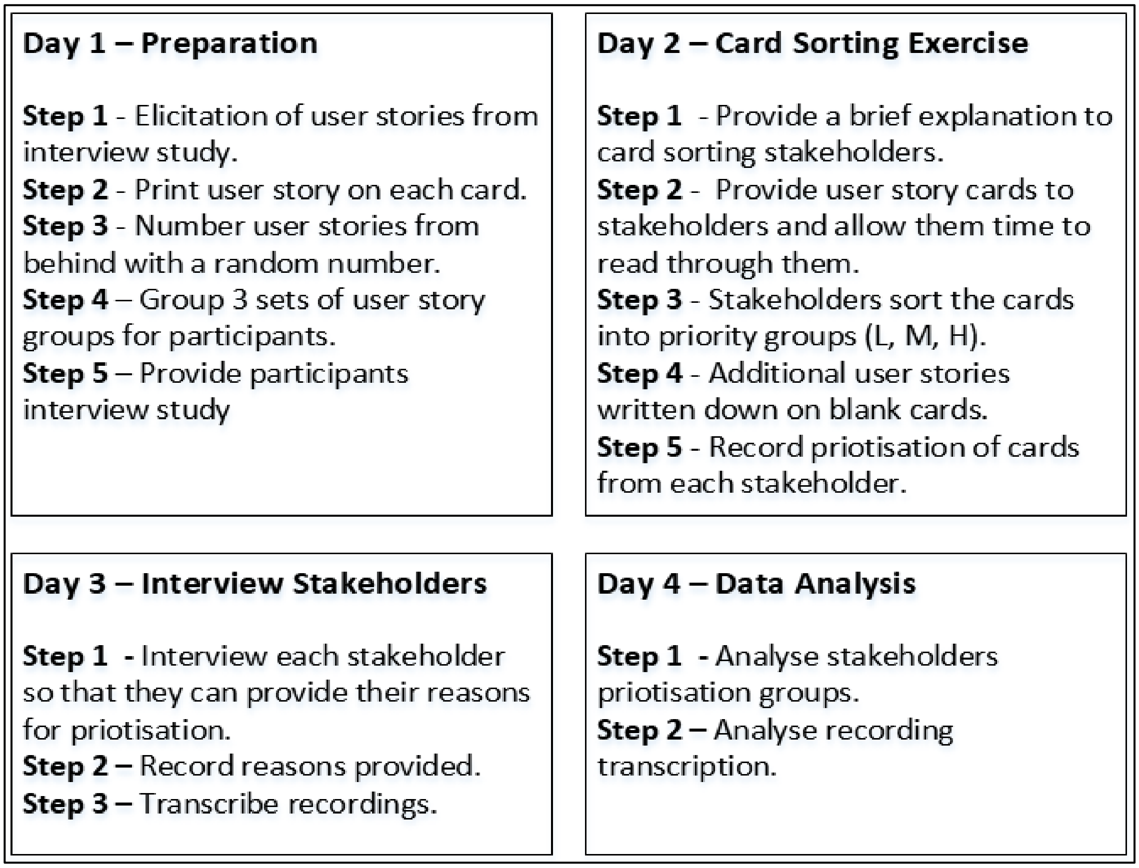

Figure 14 Card sorting steps

3.3.2.1.2 Participants

The closed card sorting exercise involved executive management stakeholders in our card sorting exercise. The management members selected were the chief financial officer, chief transformation officer and operations manager, we sent a meeting invitation to participants requesting their contribution to the study. Before the card sorting exercise, the participants were also sent a copy of the field study to provide them with more context around the high-level user stories that we derived from the field study. The 3 participants involved in this study were selected because they represented key decision-makers in forecasting product demand in the supply chain and have a high-level view of the organisation. These participants accepted to take part in the Card Sorting exercise, which was planned over a combined one-hour meeting time slot organised according to all the participant's availability.

3.3.2.1.3 Card sorting materials

Prior to the Card Sorting exercise commencing, a list of high-level user stories was prepared. The user stories can be viewed in Appendix B. User stories describe functionality that will be valuable to a system user (Cohn, 2004). The user story typically follows a simple template: As a <user>, I want < goal> so that <reason>. These user stories were extracted from the results of ALM elicitation interviews with stakeholders. We elicited the barriers (pain points) in forecasting uncertain product demand from 20 participants belonging to the following three business units: sales/category, operations and finance/IT.

A set of 25 cards were produced, each with a short user story. The user story includes the stakeholder requesting the change, the requested change in functionality and, the rationale or reason for the requested change. Each user story was typed on a 3" x 5" card. The cards used were numbered and were all identical in colour, dimension, so that the results can be recorded after each session. In addition to the 25 cards, 3 blank cards were also produced to allow the stakeholders to write a user story that they believe was important and not present. In total there were 28 cards available for each stakeholder.

3.3.2.1.4 Card sorting procedures

The primary and secondary researcher coordinated a card sort activity conducted over a one-hour session with the participants. Since the requirements at this early stage are usually expressed as high-level product features or functions, the interaction between various stakeholders can be done quite easily (Moisiadis, 2002). Subsequently, with the executive stakeholders' daily tight schedule and very limited time available, this exercise involved only ‘single-criterion sorts’, (i.e. sorting the identical set of cards, by relative importance criterion).

Prior to the card sorting activity proceeding, we provided a short presentation and discussed the overall research project progress. Following this discussion, the card sorting activity commenced in the following seven steps:

1. Instructions and a brief explanation of how to perform the card sorting exercise was given to the participants. The sorting's main purpose was to prioritize user stories related to the barriers in forecasting uncertain product demand.
2. The participants were each given a set of 28 cards. Before sorting the cards, the participants were given time to read over all the cards and familiarise themselves with the cards' contents.
3. According to their criteria, the participants were advised to arrange the cards into categories of low, medium and high priority. Each participant placed a set of cards on the table and organised them into three categories. The participants were permitted to discuss or seek clarification of the user stories between themselves or with the facilitator as they felt necessary. Figure 15 illustrates the participant’s sorting the cards.
4. The participants were also instructed that if they thought of an additional user story based on their expertise which is not covered in the cards provided, they can write it down on the blank cards provided.
5. Upon completion of the card sorting, each card's unique numbers are used to record the participants’ chosen prioritization group of each user story and recorded on a spreadsheet.

6. Following the analysis of the results, the results were deidentified and shared amongst the three participants.
7. A meeting was organised with each participant to obtain further information about the participants' reason why they chose to prioritize the cards in the manner they did. These meetings were recorded and later transcribed for analysis.

Figure 15 Card sorting exercise taking place at ALM

3.3.2.1.5 Analysis

The purpose of the study was to validate and establish prioritization of the user stories for our solution, the data collected (priorities and reasons) are in textual form and the analysis of the results is qualitative. Considering that we used a small group of participants (3) from one organisation, statistical analysis is not suitable. This study's data were analysed in terms of: number of cards prioritized by category, lists of user stories stakeholder, lists of the participants' reason for prioritization, and the commonality (agreement) between the participants on the prioritizations.

The agreement between participants reason for the prioritization of the requirement is important. There are two types of agreement, verbatim and gist. Verbatim agreement occurs when two or more participants use precisely the same words as each other. Gist agreement occurs when two or more participants use different words for the same meaning (Kent, 2002). An example of a gist agreement between two card sorting exercise participants is the following; "The reason I have put that as a low is simply because I do not believe the sales representative should be driving the supply chain I see it as the other way around". Another participant stated, "The reason why I put that as low because I do not think the sales representative needs to do that. He needs to have trust in people to come up with that thing". Content analysis was used to assess the commonality between the respondent's reasons for the card prioritization. The respondents' reasons are grouped into dimensions for each priority. Where there is an agreement, the situation is straight forward, where there is a disagreement, this needs to be investigated if possible (Rugg and McGeorge, 2005).

3.3.3 Phase 3: Evaluate

According to the framework for design science, it is critical to evaluate whether the designed artefact can effectively solve the problem that motivated its creation (Hevner et al.'s, 2004). There is limited guidance in the design science literature on the strategies and methods for empirical evaluation of information system (Kitchenham et al.'s, 2006, Prat et al.'s, 2014b). Hevner et al.'s (2004) identify evaluation as crucial and summarise five classes of evaluation methods appropriate in the design science methodology, with 12 specific methods (mentioned in brackets).

1. Observational (Case Study, Field Study)
2. Analytical (Static and Dynamic Analysis, Optimization and Architecture analysis)
3. Experimental (Controlled Experiment, Simulation)
4. Testing (Black Box, White Box)
5. Descriptive (Informed Argument, Scenarios)

However, there is a lack of guidance for selecting between designing the evaluation part of design science research (Venable et al.'s, 2012a). Pries-Heje et al.'s (2008a) proposes a 2-by 2 design science research method selection framework (see Figure 16 below) and provides guidance for considering how to choose among them.

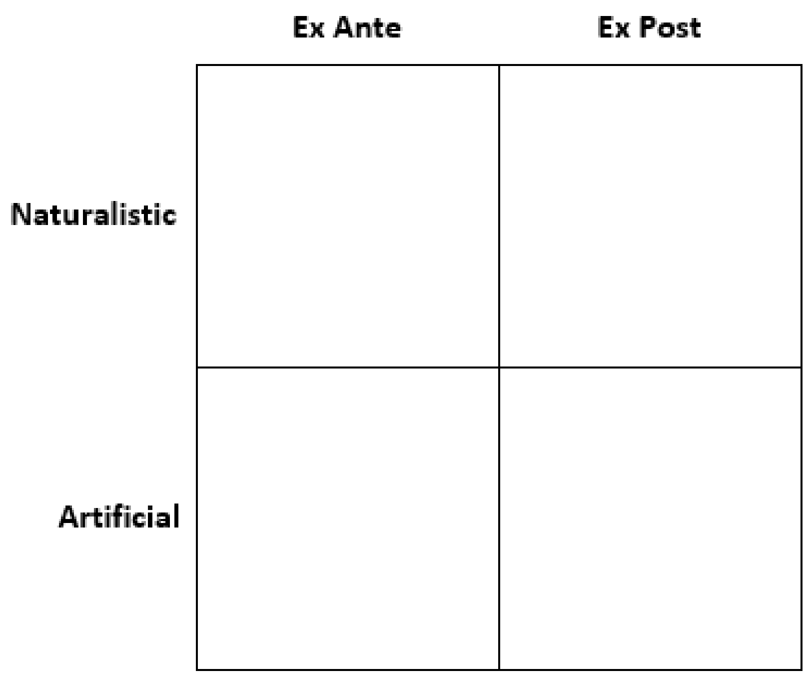

Figure 16 Design science research framework (adapted from (Pries-Heje et al.'s, 2008a))

The framework encompasses both Ex Ante (before artefact construction) and Ex Post evaluation (after artefact construction) orientations as well as naturalistic settings (e.g., case studies) versus artificial settings (e.g., lab experiments).

Ex Ante evaluation provides models for theoretically evaluating an artefact design based on an uninstantiated artefact such as a system design specification alone or a partial prototype. The evaluation is primarily dominated by the economic concerns of whether the system is worth the cost. Ex post evaluation is an evaluation after an artefact has been constructed. (i.e. an instantiation)

The naturalistic evaluation setting explores an artifact's performance within its real environment (in our case this is the ALM organisation). The evaluation involves a real setting with real people and real systems (Sun et al.'s, 2006), therefore it is always empirical. Naturalistic methods include case studies, focus groups, surveys, phenomenology and action research. The naturalistic paradigm's dominance is that it brings design science research a stronger internal validity (Venable et al.'s, 2012a).

An artificial evaluation setting evaluates an artefact in a contrived and non-realistic way. According to (Sun et al.'s, 2006), it is unreal in some ways, such as unreal users, unreal systems and especially unreal problems. The evaluation involves laboratory experiments, simulations, mathematical proofs, theoretical arguments, field experiments and criteria bases analysis. Artificial and naturalistic evaluations each have their strengths and weaknesses. Venable et al.'s (2012a) noted that more than one method could be used, mixing artificial and naturalistic evaluation and qualitative and quantitative methods, leading to a robust design science research evaluation.

In this research project, Phase 3 uses various evaluation methods to validate the digital toolkit output of Phase 2. We establish an evaluation framework (chapter 6.3) to define and relate the evaluation's key concepts. Early on in the development phase, the research project deploys iterative testing by the researcher and feedback from executive stakeholders to ensure any inadequacies identified in the digital toolkit are resolved during the development iteration. The refinement of the digital toolkit during the development iteration paves the way for greater validity in the artifact's design and development. The validation in this phase evaluated the artefact to determine if the research goals have been achieved.

3.4 Limitations of research design

As with all qualitative based research methods, there are natural limitations to the research design. The qualitative research method is more concerned with the details of the samples studied rather than the representation of a population (Creswell, 2009, Leedy and Ormrod, 2005) Hence, the results obtained from the qualitative method may not apply to other contexts. However, it is not the intention of this research project to generalise the results obtained. The research design and execution of this research project has been explained insufficient details in the research introduction (chapter 1.8) and later on in the research method (chapter 3) and field study (chapter 0), to make the study repeatable, so that other researchers may be able to perform similar studies in different contexts.

The number of respondents and the detail of the questions could also be considered as limitations on the research project, however, this has been minimized by the strict criteria for participation, the iterative analysis and refinement of the questions and the opportunity for follow-up questions and response clarification during the study.

Cultural and educational biases may also be a factor. Some respondents originate from a more technical and process-oriented environment, whereas others from a more managerial, financial or sales background. The respondents' memory and opinions may be overly affected by their more recent experiences or by their most significant successes and failures. To reduce this bias, invitations to participate in the interview study were not sent by the researcher who worked in the organisation. The principal supervisor was brought in to ensure the outcome and overall results of the qualitative field study remained unbiased.

Limitations in the data collection tools also exist, specifically semi-structured interviews. The interview participants' responses were based on their opinion, memory, and experiences. It is possible that the responses did not factually describe what actually happened. The semi-structured interview was designed to repeat some similar questions at different stages of the process. This allowed the participants' responses to be verified, and further clarification could be sought from the participants if required.

We acknowledge that the focus group results may have been biased as it was conducted by the researcher, who is also an employee of the organisation. However, this was counteracted by providing participants with an anonymous questionnaire and ensuring the moderator did not attract additional attention during evaluation by attempting to make the researchers' involvement as unobtrusive as possible. However, we concede that the digital toolkit developed should also be tested in other industries to see if it is appropriate to be applied in different contexts and if the evaluation results are alike.

3.5 Ethical Considerations

For this industry research project, the University of Technology Sydney (UTS), Human Research Ethics Committee (HREC) approval was obtained before conducting the field study and contacting any participants involved in the research project according to the UTS guidelines. An application was prepared and submitted for UTS HREC. The approval was granted in March 2018; the approval number is UTS HREC REF NO. ETH17-2021. The purpose of obtaining ethics approval is to ensure that the research was conducted with integrity, and the confidentiality and privacy of the participants were maintained. All the participants should be protected from harm, loss of privacy and deception. All the participants must also be invited to join this study; hence, the interview could not take place without written consent from the participants. The participants were approached by sending them an invitation letter (see Appendix A) from the university supervisor via email. A participant information sheet (see Appendix A) which outlined their rights was also included. Participants were also given a consent form (see Appendix A), they were asked to read it carefully and understand their rights. The participants were also briefed on their personal data, data safekeeping, and the complaints procedure to UTS HREC. Once participants expressed their understanding and acceptance they were asked to sign the consent form. Participants were also informed that they could contact us if they would like to know the research's progress.

3.6 Summary

This chapter reviewed the research based on the design science research methodology used in this thesis. A design science approach is followed to design and develop a toolkit to support ALM stakeholder in forecasting uncertain product demand. This research is organized in three iterative phases. Phase 1 is the identification and establishment of the research problem. There are three activities undertaken in this phase. Phase 2 fundamentally is the artefact design and development based on the environment in Phase 1. Phase 3 is the evaluation phase of the artefact. All these phases are elaborated on in corresponding chapters in this thesis and shown in Figure 8.

4 Field Study

4.1 Chapter Overview

In the previous chapter, we described and justified the research methodology we have chosen, and activities performed to address the research and industry problem. This chapter will provide our pilot study and the specific activities we performed to survey and map the supply chain process of the Australian Luminaire Manufacturer (ALM). This chapter aims to provide a foundation for our research by investigating and surveying the current state-of-the-practice in forecasting uncertain product demand in the Australian Luminaire Manufacturer. The pilot study's outcome was to help us further understand the sales and operations planning process (chapter 4.2) at ALM and document a process map of the supply chain (chapter 4.3). The process map graphically shows the path of the current processes in the end-to-end supply chain. The process map provides a quick high-level visual overview of the end-to-end process flow involved in receiving customer orders to manufacture and deliver the products. The extensive field study (chapter 4.4) investigates the current state-of-the-practice in forecasting uncertain product demand (Research Goal 2) in ALM. The results from our qualitative interview study form our high-level requirements. The technique used to prioritise the requirements is discussed (chapter 4.5) followed by a discussion (chapter 4.6). Following a summary is presented (chapter 4.7) of the entire chapter.

4.2 Sales and Operations Planning at ALM

The below section details the sales and operations planning process at ALM. This has been documented through our informal discussions during the pilot study.

The sales and operations planning (S&OP) is a process in the supply chain that is performed once a month where ALM executive management meets to review projections for demand-supply, inventory, and the resulting financial impact. The S&OP is a decision-making process that ensures the company tactical plans align with the overall business strategy (Cox and Blackstone, 2002). Several steps are carried out monthly in the S&OP process, these have been grouped into 4 stages. Figure 17 illustrates the steps that are taken and the sequence they are performed.

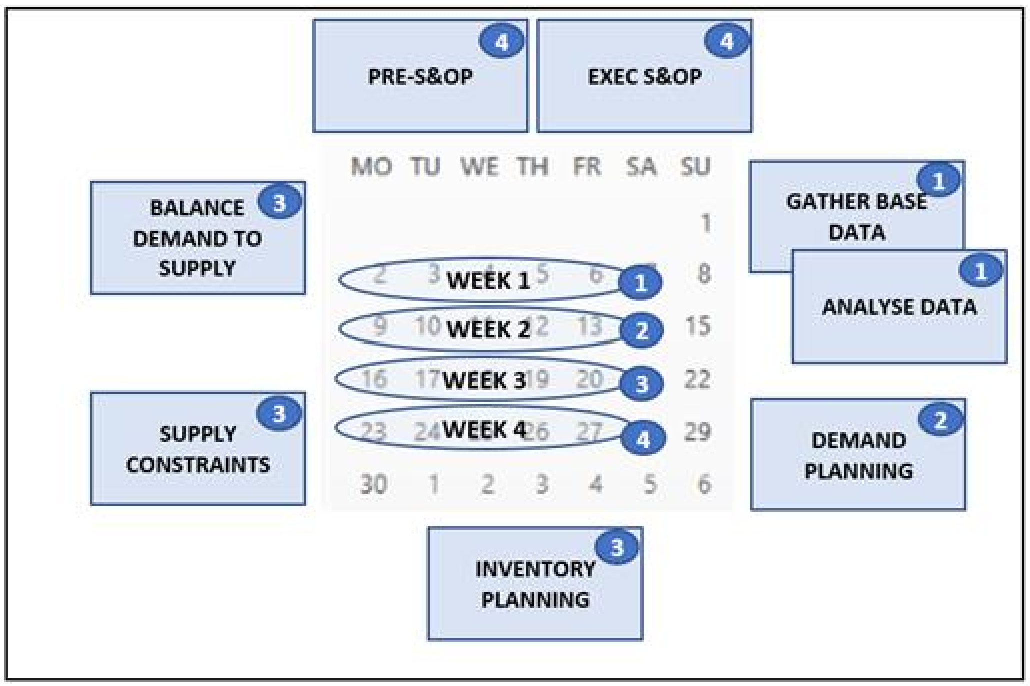

Figure 17 Sales and operations planning schedule and steps

The below sections will discuss the steps that are performed as part of the S&OP process.

4.2.1 Step1. Gather base data and analyse

The first step of the sales and operations planning is the data gathering, this step prepares the relevant data to be sufficient to answer the question regarding the expected product demand.

However, the data required to represent product demand accurately is not readily available for reasons that include the changing competitive landscape, non-stationary demand, the inability to record lost sales and the challenge of quantifying expert opinion (Chen-Ritzo et al.'s, 2010). The data gathering process at ALM is time-consuming due to the double handling of the data each month. There are 5 data sources that are used to extract the required demand data. These include the enterprise resource planning (ERP) Movex system, demand solutions (DSX) system, TM1 online analytical processing database, customer relationship management (CRM) system and any market intelligence.

The ERP system data provides a snapshot of the position of the business. Data such as the inventory position, ABC frequency at SKU level, what business areas they sit in, item type of product and all the other characteristics of the item. This ensures that the data can meet all stakeholder requirements. The DSX system provides a statistical SKU level forecast by the district based on historical sales adjustments. Judgemental adjustments are made to this forecast by supply chain stakeholders before loading this through to the ERP system. A new product development forecast is also derived through the TM1 system. This originates from the Gross Margin Return on Investment model (GMROI), which contains all the relevant details and expected forecast for 12month. The category team manages this due to the lack of historical data available for the DSX system to perform a forecast. The S&OP analysis is multilayered as it involves a range of data sets from the actual historical sales, stock on hand, order book, proposal and manufacturing orders. A substantial amount of work is carried out to align the data by the product SKU. Once these are aligned, the analyst manually pivots the data into excel and saves a file for each month. It has been noted that the data gathering and analysis process lacks automatic processing and business rules. This process's ultimate goal is for the analyst to determine the base forecast and the lumpy demand. The lumpy demand is defined as sales that are either a specific project, container buys, promotions, or new product launches. Following the gathering and analysis of the data, the demand plan is created.

4.2.2 Step 2. Demand Planning

The demand plan produces the initial cut of the first forecast (Chen-Ritzo et al.'s, 2010), it mainly focuses on forecasting demand for present and new products based on past events (Noroozi and Wikner, 2017), with all the assumptions that have been collated from the various systems above. Additionally, the demand plan also acknowledges the uncertainty associated with the initial demand plan's forecast set (Chen-Ritzo et al.'s, 2010). For example, what opportunities does the business foresee winning based on what they think will happen? Meetings are scheduled at ALM with regional managers, executive sales managers, and the category team to gather any market intelligence. The business is planning to move out of a particular technology and towards a new form. These meetings are scheduled to determine the demand and inventory perspective from the supply chain stakeholders. During these discussions, the S&OP analysts have validated the positions of the projects, by knowing what the stakeholders believe they are going to win and what they are communicating with the customers. Based on these discussions the demand plan is then created to align with the outcome of the discussions. Following the demand plan, the inventory and supply of products are considered in the next step of the S&OP process.

4.2.3 Step 3. Inventory and Supply Planning and Balancing

The demand plan is then used for the supply planning and balancing step where capacity planning is performed based on, available capacity and inventory levels (Noroozi and Wikner, 2017). An analysis is performed on the core range of product inventory to determine if there is a critical stock situation for the top-selling 50 SKUs. If a critical stock level is found and the business will go below safety stock levels the business determines what action it needs to take. The analysts try and determine why there is not enough stock to attempt to address this problem, this could either be that ALM either oversold stock or did not manage the stock levels correctly. Meetings are carried out with the purchasing team and manufacturing for the capacity planning of manufacturing. People must gather from different related areas to provide a platform for cross-functional discussion and decision-making (Wallace, 2004).

These meetings' objective is to determine if there are any constraints in manufacturing the stock such as resources constraints, supplier or vendor problems, or if the safety levels are set too low. Any concerns at this point are escalated to ALM management and a balance demand and supply meeting is scheduled. The balance demand and supply meeting is performed with key stakeholders, including the chief operations officer (COO), to evaluate what demands the business can meet, what demands the business cannot fulfill, the impacts, and any ongoing issues. The chief operations officer determines any actions that need to be performed before the final pre-S&OP and S&OP meeting.

4.2.4 Step 4. Pre- S&OP and S&OP

In the Pre-S&OP a meeting is held to discuss what has taken place in steps 2 and 3. The chief operations officer (COO) can sign off on certain things so the operations team can progress with the plan. Following the pre-S&OP meeting, an executive S&OP meeting is scheduled and it is when the business puts forward its operations plan to the executive team. At this meeting adjustments to the S&OP forecasts can still be made by the executive team.

4.3 Findings from the pilot study

We now present the pilot study findings that resulted in a process map of the supply chain at ALM.

Figure 18 demonstrates the front end processes of the supply chain at ALM. There are two possible ways for an opportunity to be identified for ALM. Firstly a sales representative obtains a lead and enters the details into the customer relationship management (CRM) (1. Enter in any new opportunities not captured from BCI). The other way is to retrieve opportunities from the online building and construction information (BCI) platform and load them into the CRM system. The BCI data contains all development approvals (DA) submitted to the local government authority for approval. A filter is applied to the BCI data to ensure only opportunities with a DA value greater than $50,000 are retrieved and loaded into the CRM.

Once the opportunity data is in the CRM system it is reviewed and allocated to a sales representative to pursue (2. Review & allocate opportunities). The sales representative will engage with the customer (3. Customer engagement) to determine customer requirements. A customer master quote (4. Create master quote) is produced for the opportunity. The purpose of the master quote is so that the sale representative can reproduce the quote for multiple wholesalers or contractors who are tendering for the same opportunity. Individual quotes can then be produced (5. Create individual customer quote) by duplicating the master quote to be sent out to multiple contacts such as wholesalers or contractors. These individual quotes can be modified to meet the specific needs of the wholesaler or contractor. Multiple versions can exist of a quote and the one that the customer accepts (6. Quote accepted) proceeds to an order. A customer order is created (7.customer order created) in the CRM sent through to the enterprise resource planning (ERP) system. This order can still be modified however not in the CRM, it can only be updated in the ERP system. Once the order is finalized, the products are sent out with the invoice to the customer. Table 7 highlights the front end supply chain barriers that have been identified as the process map was produced.

Table 7 Front end supply chain barriers

Process Number	Barriers identified
1.Enter in new opportunities	N/A
2.Review & allocate opportunities	N/A
3.Customer engagement	• Misunderstanding of product specification requirement • Customer not clear on lead times required for product
4.Create a master quote	• Master quote does not reflect the individual quote
5.Create individual customer quote	• Customer accepts product specifications without all key project stakeholders approval i.e. Architect
6.Quote accepted	• Customer changes product required • Customer overstates order requirements
7.Customer order created	• Customer order in CRM does not match the original order created • The customer order is not the same as the quote

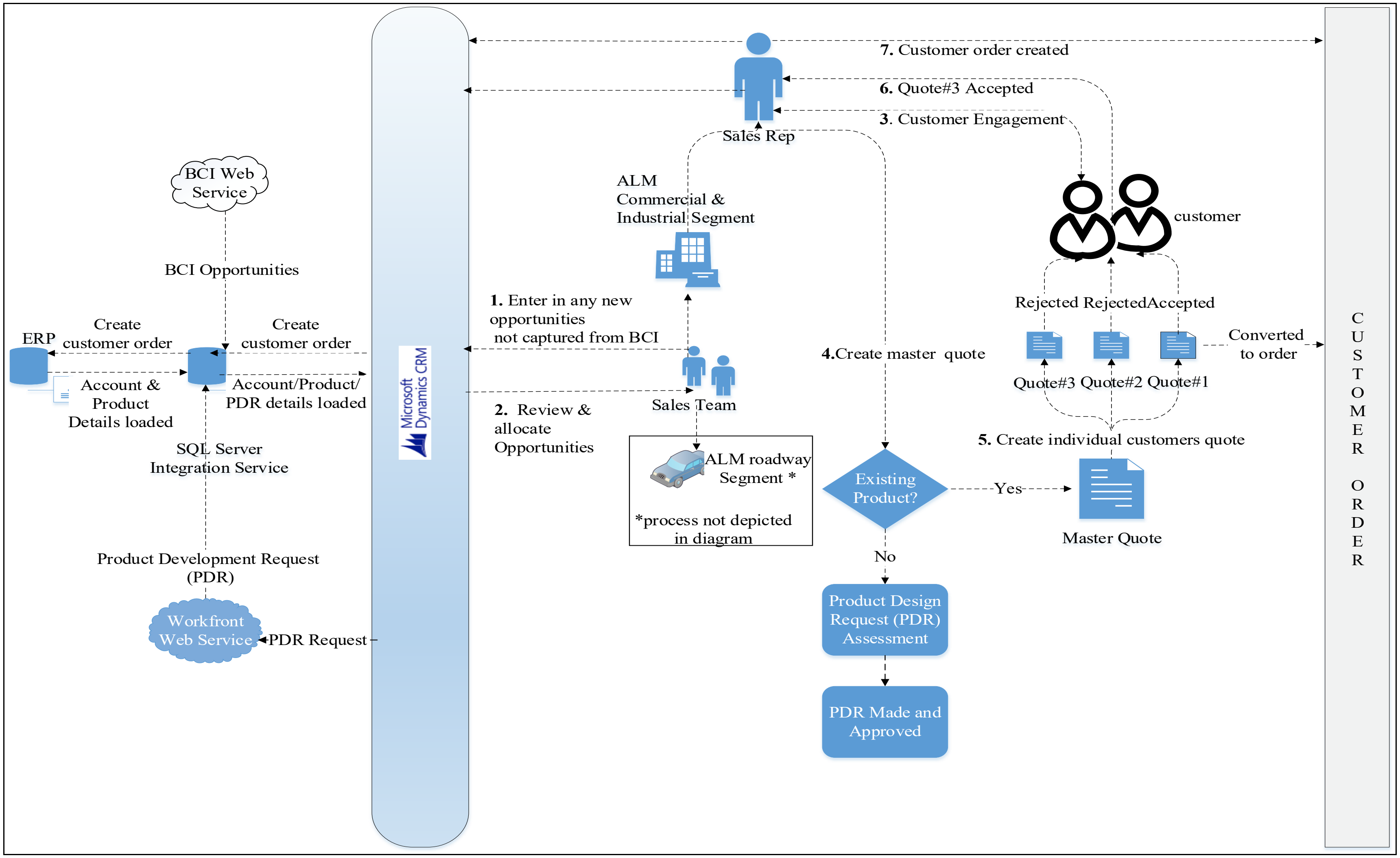

Figure 18 Figure 18Front end of supply chain at ALM (sales order process)

The back end of the ALM supply chain Figure 19 demonstrates the steps that take place once an order has been placed. There are three sources of products that ALM offers customers. The three sources are; 1. Overseas finished goods, 2. Locally manufactured or 3. Locally modified. Overseas finished goods are products that are bought from overseas and on-sold to ALM customers. Locally manufactured products are where components are bought from suppliers and the product is manufactured/assembled in the ALM factory once all the components are available. Locally modified products are when existing products are modified locally to meet a specific customer requirement. Table 8 highlights the back end supply chain barriers that have been identified as the process map was produced.

Table 8 Back end barriers of supply chain

Product Source	**Barriers identified**
1 Overseas finished good	• Supplier may no longer make the component required • Supplier may no longer exist • Supplier makes a slight modification to the component after the first batch is sent
2.Locally manufactured	• Products are miss placed in the warehouse and not found when required.
3.Locally modified	N/A

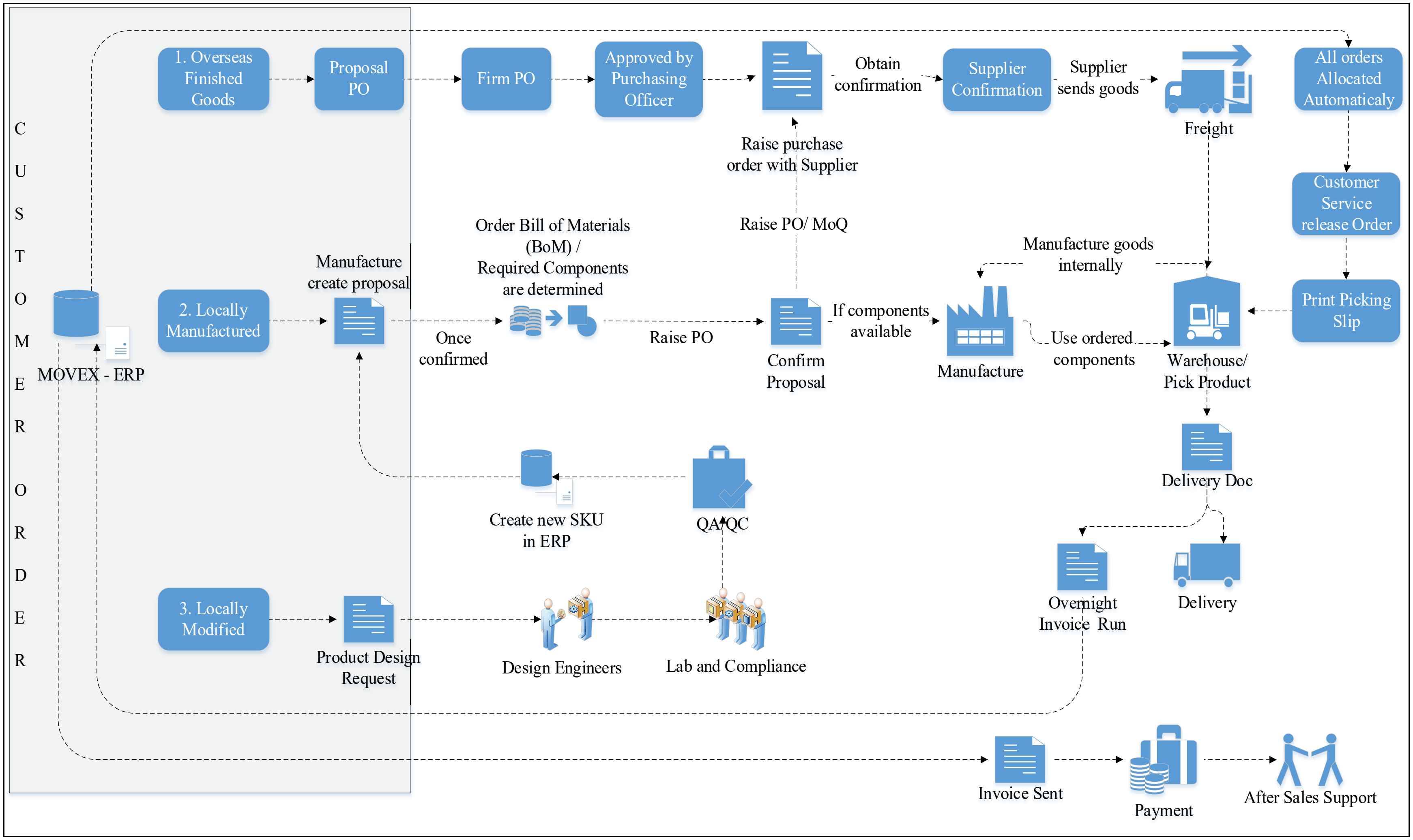

Figure 19 Backend of supply chain (sourcing, manufacturing and distribution)

4.4 Findings from the interview study

We now present the quantitative findings that resulted after evaluating the barriers in forecasting uncertain product demand.

Figure 20 shows all the categories that were identified after the data analysis was completed. The customer and culture categories are two new categories that were established and were not part of our SLR. The total number of participants who mentioned a barrier in forecasting uncertain product demand is primarily dominated by the culture, product, technology and communication. These four categories contained the highest contributions from all participant groups. The results of all the categories will be presented further below.

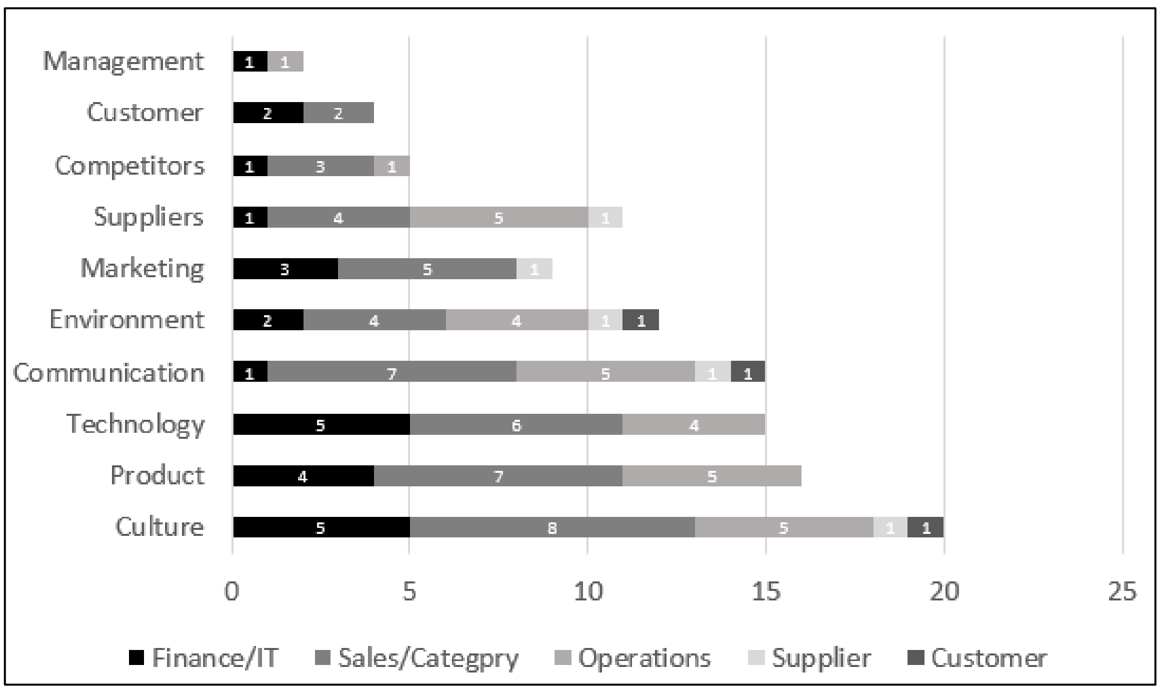

Figure 20 Number of participants contributed against the derived category

The top 10 barriers mentioned by the participants are shown in Figure 21. Some theme names come from the SRL e.g. seasonality and poor communication others purely from the thematic analysis, e.g. lack of understanding and lack of data governance. Overall the barrier with the highest number of mention is a lack of commitment.

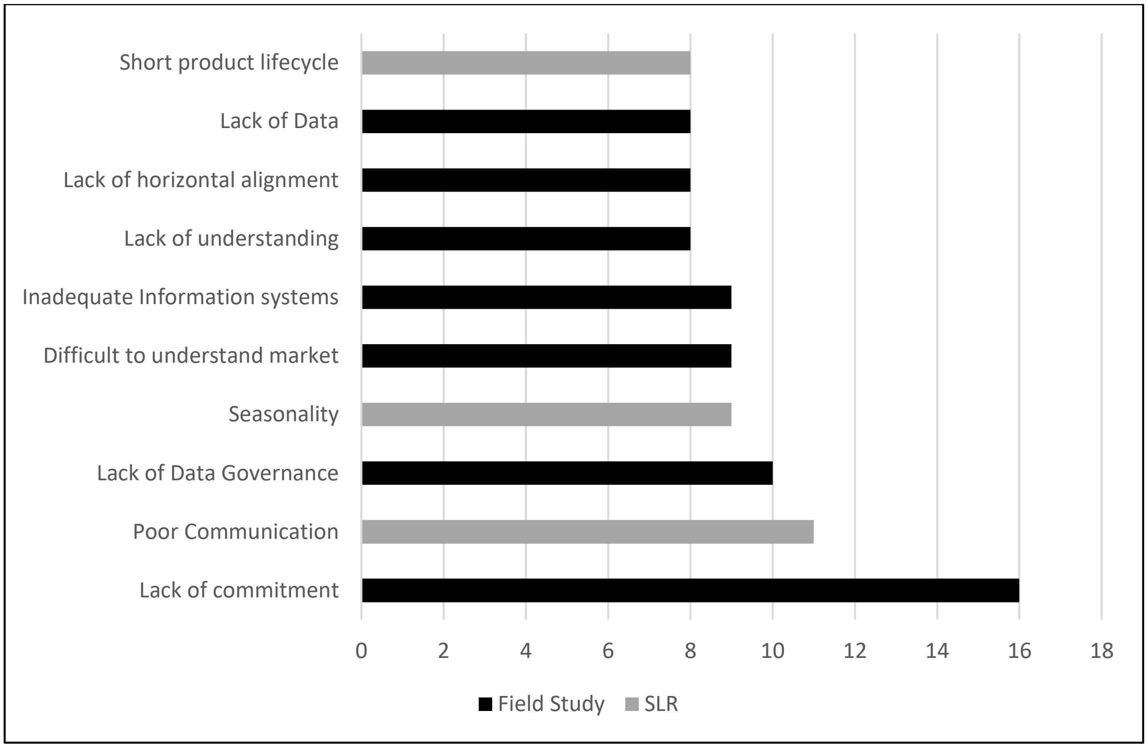

Figure 21 Top 10 barriers in forecasting demand

The results in Figure 22 illustrate that each business group interviewed have a different set of their top 10 barriers. The sales and category teams are the only ones included in all the top 10 barriers.

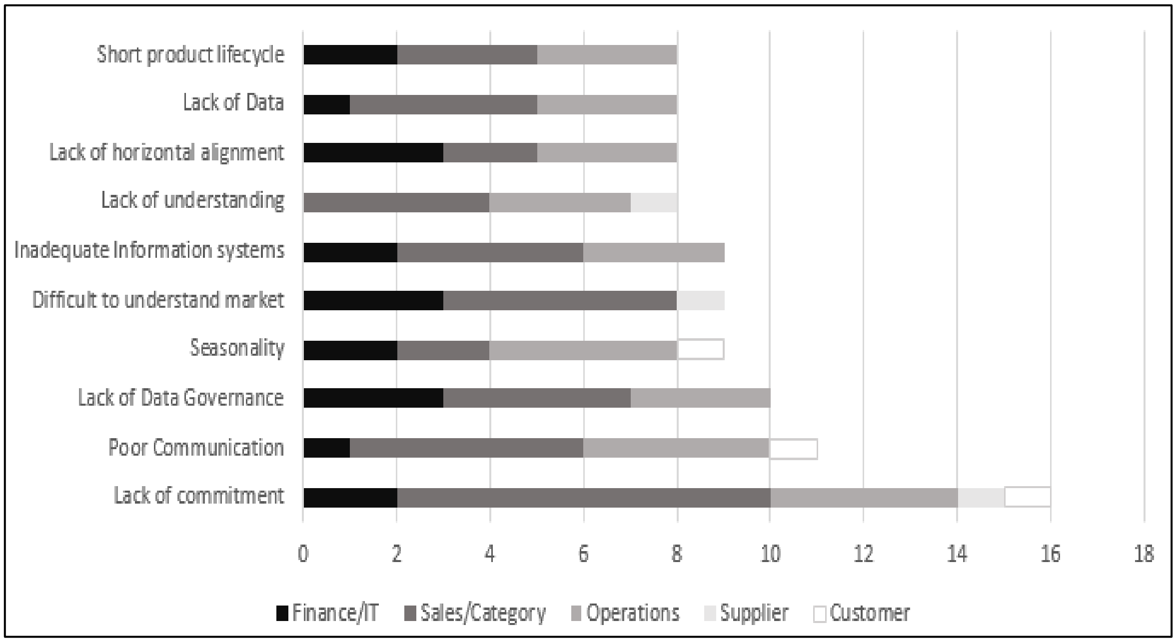

Figure 22 Top 10 barriers by participant groups

Our findings have been grouped into internal and external barriers. Internal barriers are found to be within an organisations' internal environment made up of employees, management, communication and culture (Parmar et al.'s, 2016). The external barriers relate to outside factors that can impact an organisation in its ability to forecast demand. A brief description of our findings including quotations from the interviews within each of the categories follows.

4.4.1 Internal Barriers

Organisations are known to suffer significantly from the insufficiencies of their supply chain and as a result, they need to recognize their supply chain positioning and the variables outside their control (Adebanjo, 2009). Internal barriers are found to be within an organisations' internal environment which is made up of employees, management, communication and organisational culture (Parmar et al.'s, 2016). The internal barrier is a high-level category that contains all the barriers related to the organisation factors.

4.4.1.1 Organisational Culture

This category relates to the behaviours and needs of supply chain stakeholders, including customer behaviour and their service/product needs. Studies (Min et al.'s, 2005, Thernøe et al.'s, 2003) have referred to culture as a driving force behind effective supply chain management and organisational collaboration. All participants interviewed have expressed at least one barrier related to culture that impacts forecasting uncertain product demand. These will be discussed in more detail below:

- **Lack of commitment:** Commitment refers to the willingness and dedication one gives to a cause or activity. 18 interviewees stated that lack of commitment was a contributing barrier in forecasting uncertain product demand. Although organisations may have forecasting plans in place, they typically require the cooperation of many people, Armstrong and Brodie (2005) found that sometimes an organisation fails to do what it intends to do because of a lack of commitment to the plan by key people such as senior managers. This is evident in ALM, a sales and category group participant who indicated that ALM faces its own internal barriers in lacking commitment in the forecast, "*We all need to own this process not just the person that's having that conversation with the customer*". This lack of commitment is also stated to impact the supplier and the cost of products: "*The business requests a better price except they do not commit for a long-term forecast...*"

- **Lack of horizontal alignment:** This barrier refers to the alignment between an organisations functional units, it can be defined as the coordination or fit of strategic goals, structures, and tactics of different units of the organisation with each other

(Rosemann and vom Brocke, 2015, Palmer III, 2007). Almost half of the interviewees expressed that a lack of horizontal alignment is a contributing barrier in forecasting uncertain product demand. The results demonstrate that there appears to be a disconnection between different departments in the organisation. A participant from the Finance/IT group stated, *"They come up with these great ideas what they want to do, but the impact on the other departments they have got no idea*". Key performance indicators (KPI) are also said to be contributing to this barrier, a participant from the operations team stated "*one team's KPIs is to reduce the number of SKUs we have they just keep killing and switching things off. The other team's KPIs is to introduce new products and they conflict with each other.*

- **Lack of confidence:** Christopher (2004) defines supply chain confidence as how much faith the various stakeholders in the supply chain have in themselves to do what they say they are going to do. 6 respondents stated that there is a lack of confidence in the sales forecasting numbers and process. It has been stated by a participant from the Finance/IT group that "*historically we have issues with salespeople trying to over-promise the quantity, then the demand planner will cut off, okay if you say 10,000 I am only going to order 8,000, that is one of the things that they do and then all of a sudden we need 12,000 and we do not have enough."* A supplier also found ALM to be lacking confidence in the forecast numbers stating, "*Since I have worked with ALM I have always struggled with getting a right forecast… "*

- **Lack of trust:** 6 interviewees have stated that lack of trust was a barrier in achieving accuracy in forecasting demand. Trust is a term with many meanings (Williamson and economics, 1993), it is a term for clustering of perceptions (C, 1992) and is central and critical during periods of uncertainty (McKnight et al.'s, 2000). Most respondents state that the lack of trust is due to salespeople over-promising the forecast demand. In addition to this, a sales and category team members stated that "*Salespeople have a history of telling customers what they want to hear which just gets us into trouble further down the track.* . Only one participant from the operations group stated that lack of trust is a barrier; "*Whatever their budget number was, was what they'd tell you they're going to sell and there was no honesty in that. From an operational point of view, I understand what you're giving the board but that was 6 months ago, I want to know what we are doing in the next 3 months. if that is lower or higher I do not care, we are here to make sure that the right stock is here for you".*

- **Lack of agility:** Agility in the supply chain refers to the ability to quickly react to changes such as new product innovations and market demand changes (Christopher, 2000). To gain market share and achieve a forecast, timing to market and agile supply chain management is known to be important in modern logistics (Miao and Xi, 2008). Overall the results demonstrated that ALM is lacking in the ability to adapt its sales forecast, It has been stated a participant from the Finance/IT group: "we need to be quicker" another participant from the sales and category group stated: "*When we develop a product we are developing it with a view to bringing it in within the next 6 months. The fact of the matter is it's generally 9 months before we get it in and what's happened in the market in that period can have an impact on demand."*

- **Fixed mindset:** This barrier assumes a person's ability, talent or intelligence are simply fixed. Two participants from the Finance/IT group stated this as a barrier, one responded said: "*A lot of things are just done because that's how they've always done it, which I find bizarre*". It was also stated that "*a lot of staff don't like change, long term, staff that have been here a long time can be poisonous to other staff if they're not happy. That's a real problem because they can wear you down with their negativity.*"

- **High staff turnover:** 2 respondents believe that there have been a lot of people departing the business and new people joining the business which has impacted ALMs forecasting capability, one participant from the sales and category group stated: *"I think we've lost that art, and we'll get it back but it will just take time, of having that deep and meaningful conversation with the customer".*

4.4.1.2 Product

This category relates to forecasting barriers related to the organisations' products. This category shows that 15 respondents state that there are forecasting demand barriers related to the product category.

- **Short Product Lifecycle:** Lapide (2001) defines a short lifecycle product as one that is only sold for a limited or finite period, at least in its most recent formulation. 8 respondents stated that the products short lifecycle plays a role in forecasting product demand. Several respondents stated that the product lifecycle is 6 months before it is superseded with a new product. A participant from the operations group has stated that this short product lifecycle is due to "*the speed that technology is changing*". A participant from the sales and category group also states that "*things that I forecast today for the next 3 months, in month 2 can suddenly change the demand just because new technology is coming in that month*".

- **New Product Introduction:** 6 participants stated that a new product introduction into the market causes forecasting barriers. A participant from the operations group expressed that "*when we release a new product we don't provide the sales team with all the details and specs, such as what is good about this product and the sales team don't know when new products are coming".* A participant from the sales and category group also stated that "*sometimes new product launch will just completely replace something that you have already, you can cannibalise on some of your sales"* it's been said by an operations participant that "*if it's our own product eating us or the competitor product, we need to know so we can drop the forecast*".

- **Product Price Change:** All respondents that believe the product price change is a barrier in forecasting product demand are from the sales and category group. One participant stated that "*our pricing system is too complicated".* The other participants all related this barrier to the price erosion of products, "the *forecast links into your price point, say we are forecasting today the launch of the product is 5, 6 months so price might already have moved in the market, you might be out of the market with your price".*

- **Substitute product introduction:** This barrier relates to products that are replaced with another to provide alternatives to customers. 2 respondents stated this to be a barrier in forecasting demand. A participant from the sales and category group states that the transitioning from one product to another cause's issues within the organisation and the customer: "*We might change the style of the product a bit because it will be the next generation and that can create a problem for us, reintroducing the next generation and it will have an impact on demand because the market had this code item listed on their system and although fundamentally it's the same, it's our new improved version, it's now a different code, either A they can't find it or B they haven't loaded it"*.

- **Product customisation:** The customization of products is an important offering for ALM as it provides a competitive edge against the competitors. Both respondents for this barrier are from the operations group and they state that "the *trouble I find all the time is we tend to want to do variations too much*. I*f they keep chopping and changing and making their own special key or version for this customer just for 5, 10, 15 pieces is it worth going through the headache and hard work behind there to supply. If it's a bulk order a couple of thousand units it would make it worth it.* ".

- **Large product range:** ALM benefits from offering a large array of products to appeal to a wide range of potential customers, these products may be a variation of the same product in different sizes and colour. The difficulties in forecasting a large product range has been stated by participants in the sales and category group and operations "*ALM has more than 30,000 SKU right, we have to forecast a lot of different products."* The drawback of offering a wide range of products creates additional data and complexity in managing the product range. It is noteworthy that the organisation is in the process of rationalizing the product range to alleviate this barrier.

- **Safety stock:** This relates to ALM's additional quantity of products or components that are held to reduce the risk of being out of stock and also ensure there is a buffer if there is a spike in customer orders. 2 participants stated this as a barrier, a participant from the operation group stated that safety stock should be revised given that the forecast is being missed due to a lack of components, *"Who knows what we should be holding. Who knows how much buffer stock we should be holding for the contract. We should just bring in low-value components that are required…"*.

4.4.1.3 Technology

This category refers to the information technology tools/applications that are used in the organisation. The technology category results show that 16 respondents believe that inadequate information technology is a barrier for forecasting uncertain product demand. 4 respondents are from the Finance/IT group, 7 sales and category group and the remaining 5 from operations. No supplier or customer of ALM considered information technology as a barrier.

- **Inadequate Data Governance:** Newman and Logan (2006) define data governance as "the collection of decision rights, processes, standards, policies and technologies required to manage, maintain and exploit information as an enterprise resource". Data governance is important because it defines policies and procedures to ensure proactive and effective data management. The adoption of data governance enables collaboration from various levels of the organisation to manage enterprise-wide data and it provides the ability to align various data related programs with corporate objectives (Wende, 2007)**.** Most respondents from this factor stated that ALM is reliant on excel and many things are done manually, "*we do a lot of manual work here and it's very easy to make mistakes or misread some things*." Further to this, a participant stated that, "*the forecast we do here is too brief and there are too many forecasts, there should only be one forecast, it should be a bottom-up forecast*". Another participant raised the same point stating, "*The thing is we still have the actual forecast, the potential forecast, we even have the contracts*".

- **Lack of Data:** Most participants also believe that there is a lack of available data, "*in our industry, there are no reports on competitors' products,* customer feedback, customer pricing, market analysis*; it's mostly what you sort of create from what you find out, there is no database or anything". Another participant raised the same point "we don't see what the competitors are selling, it's only a bit of experience and there's no place we can go and buy the data because there isn't any. You talk to the wholesalers and if you're lucky you might get their volumes". Further to this one interviewee said "people are reluctant to give you data and it's a unique industry like that because you can't get the data".* A different perspective was given by a participant when *there is data, it can vary across the country, "even though we have one industry, it varies dramatically from state to state because there are dominant players in certain states."* The methodology used for the data analysis also stated to be inadequate due to the lack of available data, "*we use historical data for our reference when we do forecast but our industry has changed; we are part of electronic products right now.*

Electronic for the like of PCB boards and chips, they change every three to six months and when we are still using the traditional method using historical data from Excel spreadsheets…"

- **Inadequate Enterprise Information Systems:** ALM embraces enterprise information systems such as Movex for its enterprise resource planning system (ERP), demand solutions (DSX) for statistical forecasting, customer relationship management system (CRM) for managing, project opportunities, quotes and orders. Almost half of the interviewees stated barriers in enterprise information systems, from the reliability of the systems such as, "*we can't rely only on the CRM data only, we need to build relationships with the sales team and managers*", through to concerns with the data in the systems such as "*we could do much better with the accuracy of the information*. An interesting point made by a participant is that human intelligence is still required with the CRM system, "*with CRM it's all about scanning that data and separating real versus fiction because a lot of quotes are repeated, multiple customer has been quoted the same item, what's real, what timelines are really true, a quote was done 3 months ago, the customer wanted it in June the project is now delayed to July so unless you have that human interface who is talking to the customer all the time, or that human interface updating CRM all the time, that discipline I don't think is there in the business as of now which needs to improve..".* It is noteworthy to note that the CRM system is also fairly new in the business as stated by an interviewee "*It is new to the business, so the business is learning in terms of how effective it can be…"* Other systems that the participants found contributing to the barriers include the DSX where one participant stated, "*DSX worked well with our traditional product* *when they were around longer, but now it's not as good*". Another participant put this down to "I don't think that there's enough… qualitative input". Further to this an interviewee stated that "*the DSX doesn't know what's coming in the future, it needs at least 12 months' worth of data*". In addition to these system barriers, participants also stated interconnectivity between systems as a problem, "*I think if CRM and Movex were a little bit more connected, it might help in terms of having all the history of sales of the item, like if you have that, it might help*".

4.4.1.4 Communication

This category refers to the communication and collaboration between stakeholders of the supply chain. Results show that 7 participants from the sales/category team and 5 operations participants experience communication barriers in achieving forecasting accuracy for uncertain product demand. We now give more details about all the barriers under this category.

- **Ineffective communication**: Participant from the sales and category group states that during the holiday period the organisation fails in communicating, "*There's an email that goes out to everyone saying Chinese New Year so get your orders in before February, okay well does that mean everything or what does that mean, what products, you know what does it actually impact on - is it all the metal products...*" This was also raised with the business's communication during the European vacation in August or September. Another participant from the sales and category group states that the business fails in communicating new generation products well, "*we haven't communicated a new generation of product through to our customers well and expect* *the product continually to have growth, instead it goes through a ramp process*". Communication in the organisation is also said to be poor by an operations participant when a products bill of material (BOM) is being changed due to a product development request (PDR), "*we don't know what they've changed to the BOM so if they change it to different drivers and boards they've still got to be tested and stuff to make sure it works and it's quality tested. That's where we shouldn't be promising any dates or lead times…*" Another participant from the operations group also touched on this point and the poor communication on PDRs, "*They want a fitting, but it's slightly modified, this is what I want. You look at it and then see all the holes, the questions that need to be asked. You haven't told me what type of ceiling it's going to go into, you haven't told me what colour you want it painted, you haven't told me...*"

- **Lack of understanding**: Due to poor communication, respondents' lack of understanding is also a highly noted barrier. Interviewees stated that there is a lack of understanding when forecasting demand, "*The margin cycle is not understood, and the category person had a lack of understanding of the industry and a lack of understanding of the product itself*". The sales team also face this barrier in the organisation "*I think the biggest thing with forecasting for this organisation is just people understanding it. I still get frustrated with some of my sales representatives, they see that we have something in stock and they don't forecast it...*" Another participant also highlighted a similar point, "*I think one of the big things is our sales team don't fully understand the backend of operations. Technology has got us to the point where you and I can hop on the internet tomorrow and get something from e-Bay, Ali Baba and it's delivered within 4 to 5 days. So, I think a lot of the guys in the* *sales team think that they actually don't understand the complexity of the supply chain and they don't understand why it's not sitting on the shelf*." Overall the results for communication demonstrate that poor communication and a lack of understanding are two factors that are playing a part in the barriers of forecasting uncertain product demand in the organisation, one interviewee stated that "Y*ou would talk forecast and demand to some of the other business units and it will go over the top of their head because it's not anything of interest and that really affects me*".

- **Judgmental adjustment:** This node refers to forecasters incorporating factors that may not be accounted for in a statistical forecast, such as promotions, large sporting events, holidays, or recent events that are not yet reflected in the data. However, the advantages of judgmental adjustments come to fruition only when the right conditions are present and come with biases and limitations (Hyndman and Athanasopoulos, 2018). It is noteworthy that this factor had the lowest mention in the communication category. Only one interviewee from the sales and category group stated this factor "A *60% project win certainty to someone could mean something different to someone else*". The participants' view is that a judgmental certainty percentage placed on a project being won could be interpreted differently by the business.

4.4.1.5 Marketing

This category relates to the overall electrical industry market and ALM's marketing strategy. The role of marketing in the supply chain is to balance the procurement by providing demand information and improving the growth of the business by providing industry knowledge (Min and Mentzer, 2000). Overall almost half of the participants stated it is difficult to understand ALM's market. 5 out of the 8 interviewees are from the sales and category group.

- **Difficult to understand the market:** Participants have raised multiple points, a participant from the Finance/IT group stated that ALM is said to be "sales *led here not marketing led*". Several participants have mentioned that there is a lack of data from the overall industry market*, a participant from the* Finance/IT *group put this down to "our market research is not that great*". One participant from the Finance/IT group went further to state that "*there is lots of competition in the market, so we try and please the customer with any way we can and put the pressure back on the business and supply chain.*" A participant from the sales and category group stated that the trouble in achieving a better forecast is that "*the industry is very misunderstood, it's not well defined because you got multiple players who are not in the industry but are still selling products from the industry*". Another participant from the sales and category group stated that not only does ALM require local market knowledge from the sales team and people such as specifiers and contractors but ALM "*needs to engage the manufacturer that means China suppliers right now. We need to know what happens in the market globally, like US or European, what are they doing…"* A supplier participant also confirmed the ALM market is a challenge by stating that ALM is "*a small-scale market and very fragmented in Australia compared to the rest of our customers. It's not like the UK and USA where there is a dominant player such as home depot or cooper, their position on their forecast is more accurate, but I think it's because of the nature of the market*". Overall one interviewee from the sales and category group summed the market barriers as "*our business market share* *is less than 20 per cent, we have 5,000 competitors, and everyday everything changes very, very quickly. We are the largest yet we only own 20 per cent, so you can understand the complexity…*"

4.4.2 External Barriers

The external barriers relate to outside factors that can impact an organisation in its ability to forecast demand. Below are the external barriers that impact ALM in forecasting product demand.

4.4.2.1 Environment

The environment category refers to either ALM'S surroundings, including natural, seasonal and political forces that have an impact on the environmental surroundings. 12 participants provided insights into the barriers faced in this category.

- **Seasonality:** participants from the finance/IT and sales/category group stated that ALM "*needs to consider the Chinese shut down period*". The reason for this was stated by a participant "*every year we have issues during Chinese New Year time that either - everything gets sent too early or because the factories are closing down, we can't do anything until Chinese New Year is over and then we have to get a delivery then, that costs a lot of air freights…*" The results for operations group show that forecasting demand is impacted during Christmas period. "*On the big projects the guys want to finish their projects by December, there are those targets, everyone tries to work towards getting the job done before Christmas shutdown. So, end of the year gets crazy*". However, another participant stated the opposite of this "*in ALM it's totally different, our demand goes down during November, December because that's when a* *lot of contractors go on leave.*" The customer participant stated that "*the holiday period impacts our projects and at most times we don't consider our suppliers holiday shut down and their own suppliers' shutdown as well"*.

- **Change in government policy/regulation:** A participant from the sales and category group stated that "*from the manufacturing side and China government, they have imposed a heavy law or regulation against the environmental protection in China and also most of the carton-making manufacturers, also some of the die-casting manufacturing plant and powder-coating plant; so they have to move away from the city area and then they tighten the control about the regulation and environmental ethical issues. So most of the factory in this section closes. It impacts the whole supply chain. So, the minimum order quantity of the printing, the ordering of the ink or the powder we use; that will have a serious impact on the whole manufacturing supply chain*". ALMs supplier also stated that "*due to what's going on between China and the United States some of the components such as semiconductors are taking longer to retrieve"*.

4.4.2.2 Supplier

This category relates to the barriers faced with suppliers of components or finished goods to ALM. 7 participants stated that there is a form of barrier in forecasting product demand due to ALM suppliers. These barriers are the following:

- **Minimum order quantity (MoQ):** The minimum order quantity is the lowest amount of stock that ALM is willing to sell to a customer. 5 participants stated that the MoQ of suppliers creates a barrier in meeting ALMs forecast. A sales and category group member stated that “we might have an MOQ of 5,000 pieces but if our annual sales are 3000, what do we do? do we do it or don't we do it, probably not”. If ALM decides to purchase the excess stock, it has been stated by a sales and category group member that ALM “*need to find another channel to sell*”. An interviewee also from the sales and category group stated that ALM’s own MoQ can impact the forecast, “*customer can say that your MOQ is too high and then, you go back to the supplier, you give them the order, they increase the price and that changes your numbers”*.

- **Lead times:** Only ALMs supplier stated that the lead time has an impact on the forecast, “we cannot go to our sourcing supplier and negotiate components for a certain price and secure timing as the category team have no obligation to commit to the forecast”.

- **No Golden Sample:** This is the final approved product sample created by the factory manufacturing the product. One participant from the finance/IT group stated that at times there are “*issues with QA, somehow the golden sample does not arrive here to be tested and all of a sudden the product arrives which has happened to us…”* This relates to receiving the products ordered before receiving the golden sample for testing and quality assurance.

4.4.2.3 Competitor

This category relates to the barriers faced in forecasting due to ALMs competitor activities.

- **Competitor activities:** 5 participants stated barriers in forecasting demand due to competitor activities, most participants stated that there has been an increase in competitors coming into the market. A participant from the sales and category group stated that "*the market is a very highly competitive market*". Further to this, a participant from the sales and category team stated the reason for the increase in competition is because "*there's no risk - the barrier to market is very, very low. So, I can set up a business and go to China today and be a distributor for a company and the product is half the price and my overheads are very low*". A participant from the sales and category group also highlighted that at times ALM's competitors are also their customer: "*some of our customers are our competitors, that makes it even more interesting because you get, let's say our wholesaler selling to you, they're buying from us, grab our product, find out where we're buying it from in China and go to them direct and brand it as their own brand. They know it's proven, we've done all the testing on it, why buy from us*".

4.4.2.4 Customer

This category relates to ALM's customers who purchase products directly or indirectly through wholesalers.

- **Sell-in and Sell-through:** This category refers to wholesalers or retailers buying goods from ALM as sell-in and customers that buy the products from the wholesalers or retailers as sell-through. Two participants stated that ALM needs to better understand this, one participant from the finance/IT group stated that: "*we might be number one in selling in and number five in selling out which means that we're leaving* *a lot of stock in a channel which means that we can't then sell new products because they're not going to take new products until they've sold the old products. We need to understand all those different permeations*". A participant from the sales and category group stated that: "*one of the problems affecting our forecasting demand, was the sell-through. We were getting sales into a branch but then we weren't getting repeat orders, repeat business which obviously impacts on our demand. The reason why was because they weren't selling it back out into the market*".

- **Return of products:** This category refers to customers returning products back to ALM resulting in an impact on forecasting demand. Only one participant from the finance/IT group mentioned this barrier and stated that "*we'll take it back but tell them there's a restocking fee, they've always got a story. They hang up and they ring the rep, the rep goes to the manager, the manager goes I'll waive the restocking fee so then we bring it back*". It has also been mentioned that in some instance *"they're happy to bring the stock back and if you do a value to order, so if they say we want to bring these ones back because they're not moving, and there's $2,000 worth, we have to put another order through for $2,000 then we waive the restocking fee because they're just swapping the stock over*". This relates to old stock that is returned and no fee is applied, the old stock is then put back into the warehouse and has an impact on inventory as most likely a different product has superseded it.

4.5 Findings from the requirements prioritisation

We now present the findings from the cards prioritisation technique used on our requirements.

At the end of the card sorting session, the participants were asked to provide their reasons for the prioritization of the requirements. A one-on-one time slot session with each participant was arranged according to the participants' availability. During the session, participants were also asked to provide their opinion on the card sorting technique performed. Overall the participants viewed card sorting as a good technique to use for prioritization. The following are comments that reflect the participants' positive view:

"I found it quite simple, it is an easy way of doing it"

"… It is interesting to see how the cards are categorised in the end, in particular how our selections compare with each other"

"… good, easy and a fast way of getting it done"

For the reasons on the prioritization, one participant provided their reasons for placing the cards for each category (H, M, L). The other two participants provided reasons for the prioritization of each card. The reasons expressed by these two participants were recorded, and a transcript was generated using an online software translation tool[7]. The reasons provided by the participants were used to gain further insights into the prioritization of requirements.

Lehtola et al.'s (2004) study indicate three main points of view are more or less explicitly taken into account when setting priorities. We use these points of view to create dimensions that can enable us to develop a multi-dimensional matrix for all requirements. The particularly

[7] https://www.rev.com

useful dimensions constructed for the reasons of prioritizing requirements are customer, business and implementation. The customer dimension involves the customer relationships and the importance of these to the organisations' profit. The business dimension involves business issues that may influence a requirement, such as competitor behaviour or government regulation. The implementation dimension deals with the importance of the requirements' logical implementation order, associated cost, and resources. The multi-dimensional matrix may be populated with all the requirements after categorisation has been carried out. For example, when stakeholders need to prioritize the requirement, they can refer to the matrix to determine the implementation effort, customer significance and the business justification for each requirement for their prioritization. These dimensions will be discussed further below. Figure 23 encapsulates the primary reasons participants chose against each dimension for the high priority category. In the customer dimension, any requirement viewed to be important to ALM external customer is said to be a reason to prioritize as high. The business dimension considered the impact the requirement had on the organisations' suppliers and the importance of having data integrity and visibility. The implementation dimension considered requirements that were achievable and had a positive effect on the requirements dependencies.

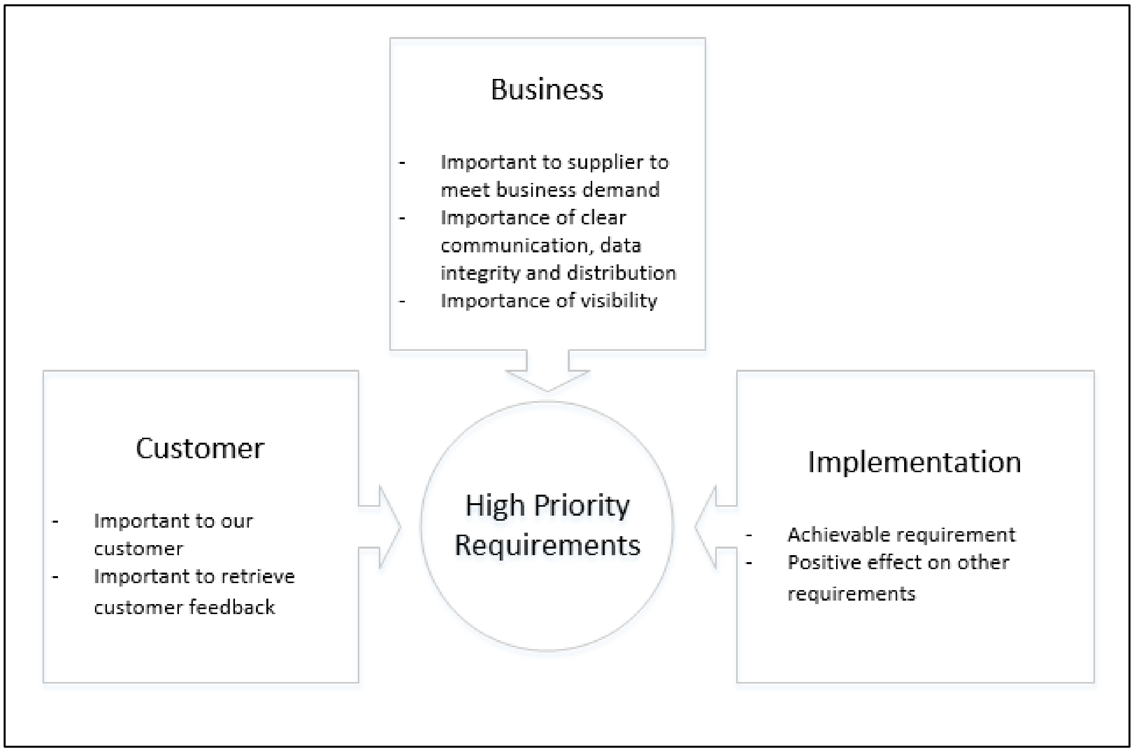

Figure 23 Dimensions to consider for high prioritization (Lehtola et al.'s, 2004)

Table 9 depicts the participants' reason against each dimension for medium and low prioritization category. It's noteworthy that our interview study's low requirements were seen to be more of a cultural and training problem in the business dimension. For example, "As a sales representative, I want details of new products available so that I am knowledgeable." This requirement is viewed as a training issue and deemed a low priority for a digitization solution.

Table 9 Dimensions for medium and low prioritization

	Customer	**Business**	**Implementation**
Medium Priority	Needs will never be perfect	Doesn't have to be perfect. It just has to be accurately correct	Achievable behind the scenes once the high priority requirements are accomplished

	Flexibility is essential and required	Can't match competitors, need to have a balance	Limited value for the effort required
		Not critical for day to day activities	
		Not relevant to stakeholders' job	
Low Priority	Not critical for customer	Communication issue	NA
		Training required	
		Not part of stakeholder's job	
		Teamwork required	

User stories may be deemed to be important for the user story stakeholder, however they are not viewed by the card sorting participants as important to ALM external customers, for example, "As a product engineer, I want a commitment on the product specifications so that we can plan more accurately". Two participants view this requirement to have a negative impact on ALM customers therefore it has been categorised as a low requirement.

The ALM participants who were engaged in the card prioritisation session displayed a wide variety of expertise about the difficulty related to the barriers in forecasting uncertain product demand. Throughout the card prioritisation session, we have note that each participant viewed the reasons for prioritizing the requirements differently. For instance, 5 cards had different prioritization from each participant. Each participant raised different reasons, such as the Chief Financial Officers' reason for prioritization, that the requirement can be accomplished by achieving the higher categorised requirements first. Other participants such as Chief Transformation Officer was mostly concerned about the requirement and the reason for his priority was that it was a main pain point for the business. Understandably, the ALM practitioners used their expertise and knowledge according to their role and experience to prioritize the requirements. Understanding the various opinions and the relationship between business units and area of concern is particularly valuable for prioritizing requirements.

The prioritization of requirements arising from our Card Sorting exercises contributes considerably to refining our solutions. Given that the study was carried out in the ALM setting, the requirements prioritization and reasons for them will be particularly applicable to this organization's work. Appendix H provides the quantitative results from the card prioritisation technique used. The technique we described here could easily be replicated by any organisation that requires the understanding of prioritization of requirements.

Although prioritizing the requirements described in this study emerged from practitioners of one organisation, many reasons for prioritization are generic and indicative within other organisations. Finally, this card sort exercise's outcomes are an important source of information for the design and development of our digital toolkit (chapter 5).

4.6 Discussion

The findings' analysis provides insights into the barriers faced in forecasting uncertain product demand from the industry's perspective. The interview study allowed us to extract user stories which then become our high-level requirements. The Card Sorting exercise at ALM has emerged as a highly useful technique for examining the practitioner's view on requirements prioritization. To our knowledge, the Card Sorting technique has never been used in ALM previously, it has received positive feedback from all the stakeholders who were engaged in the card sorting exercise. The participants revealed the card sorting technique to be simple to use and felt that it supported them to collaborate when considering and deciding on requirements prioritization.

Figure 24 provides the result of our comparison of the literature review findings and the interviews, highlighting the current research and industrial practice gap. The systematic literature review covers different industries where the interview study is from the Australian electrical industry.

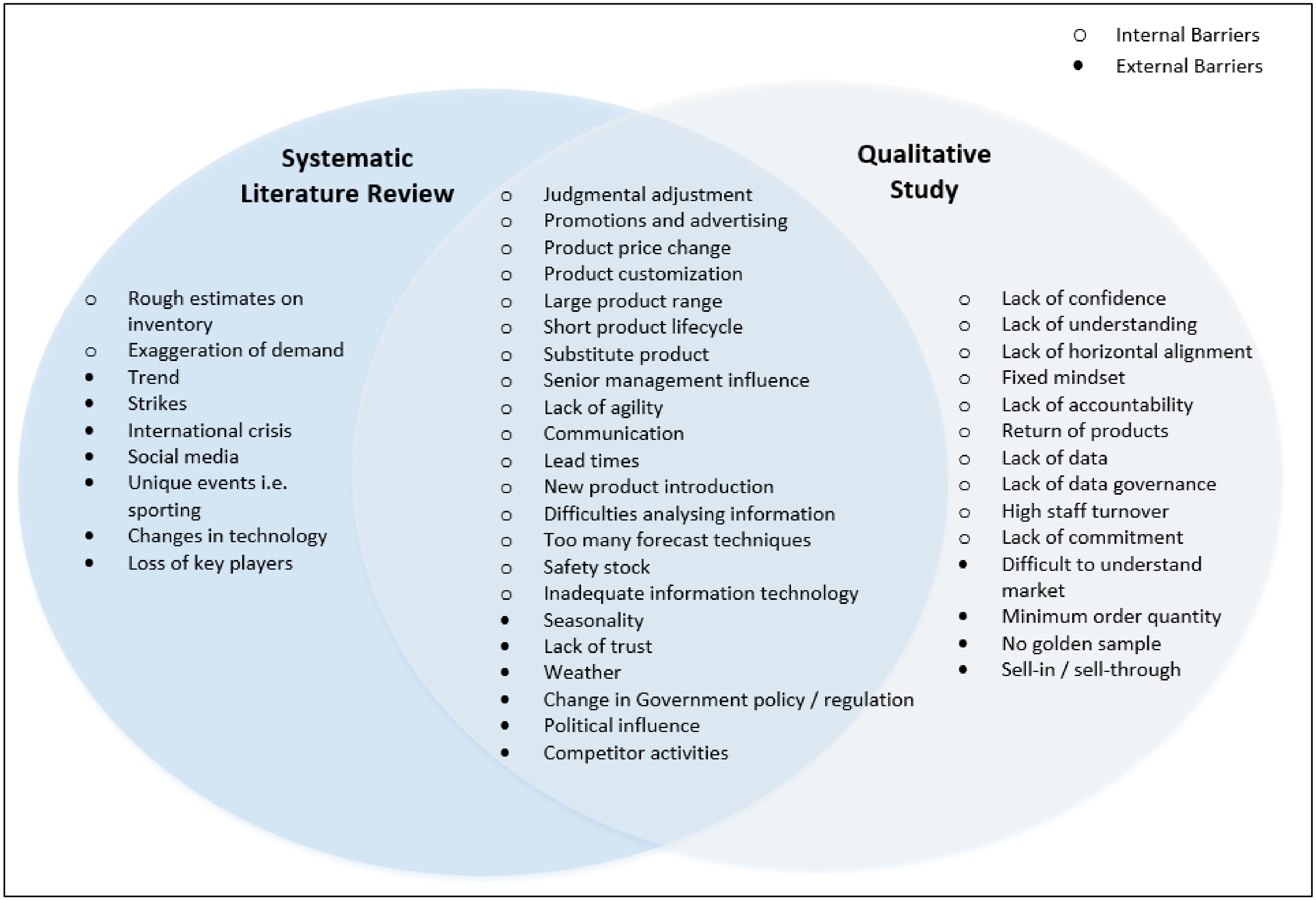

Figure 24 Ven diagram of forecasting barriers from SLR and ALM field study

ALM field study includes most of the barriers identified from the research literature. Out of 31 barriers provided by the research community we have mapped 22 of those in our interview study and created an additional 14 barriers which were not present in our SLR. Many of the barriers from the interview study originate as organisational barriers. These barriers have been used to create a fishbone analysis diagram (Figure 25). The fishbone diagram and analysis typically evaluate the causes and sub-causes of one particular problem and, therefore, help uncover all the symptoms of any business problem (Bose, 2012).

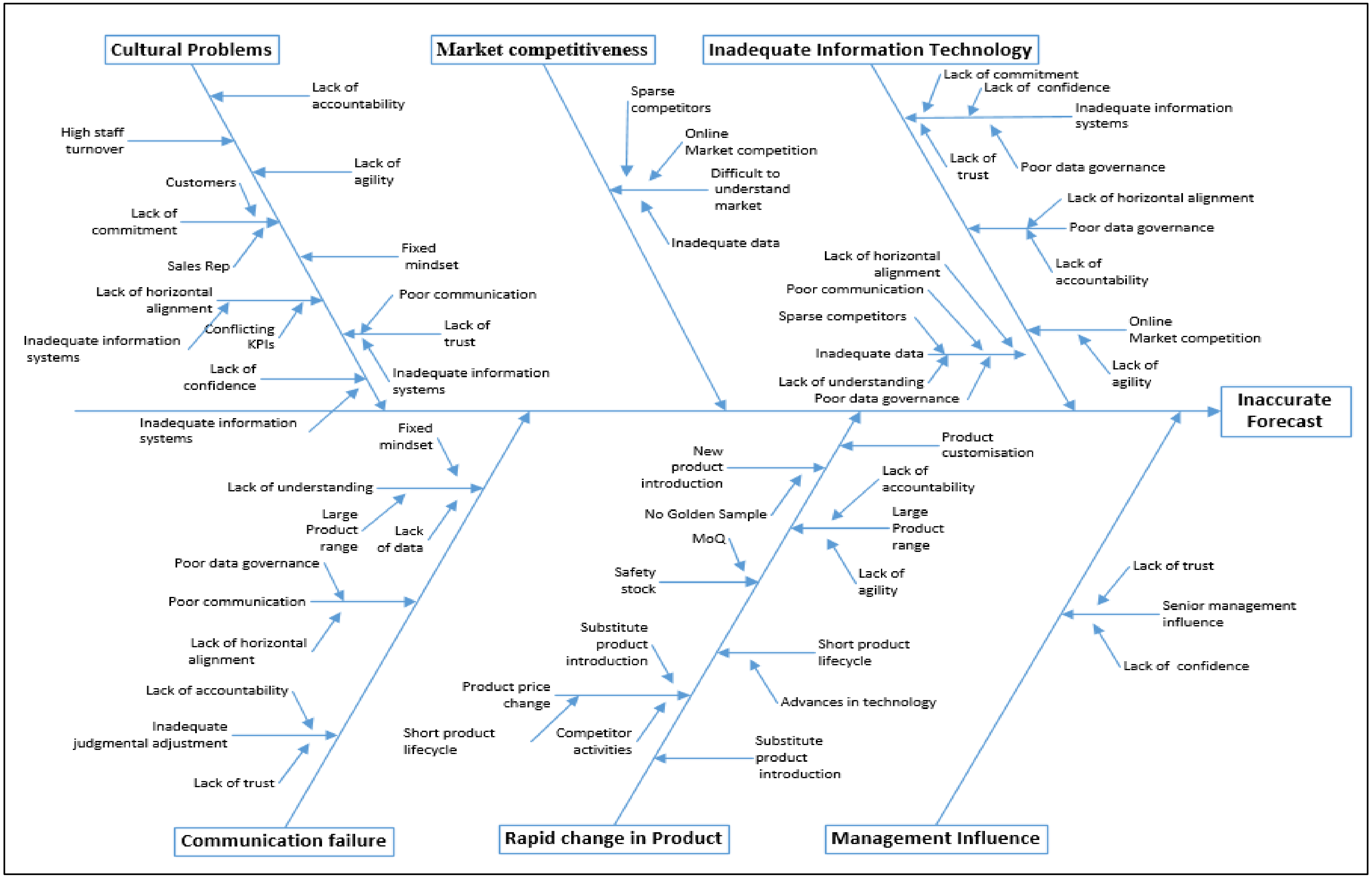

Figure 25 Fishbone diagram of the internal organisational barriers

The fishbone analysis depicted reveals that the major issue here is an inaccurate forecast. Forecasting provides the input for planning production; process design, capacity planning, aggregate planning, scheduling and inventory management (Kumru and Kumru, 2014). Inaccurate forecast leads to stockouts (Fildes et al.'s, 2009), excess inventory (Worthen, 2003), and not achieving target service levels (Baecke et al.'s, 2017, Fildes et al.'s, 2009). The fishbone analysis helps to go inside the root cause, ALM fishbone analysis reveals the main problems for inaccurate forecasts and the driving barriers and reasons.

When carrying out exploratory research such as this research, Strauss and Corbin (1998) explain the value of returning to the literature after data collection is completed to confirm the findings. As such, the literature is used to provide an additional source of data providing triangulation.

Cultural Problems: Organisational culture is known to be a resisting force to effective supply chain management (Fawcett et al.'s, 2008). In ALM It's noteworthy that except for high staff turnover all of the cultural barriers are also sub-causes in the other 5 categories depicted in Figure 25, strikingly most appear under inadequate information technology. This establishes that culture and information technology barriers are closely connected. This is also consistent with Cabrera et al.'s (2001) findings that successful technology assimilation requires either the technology to fit the organizational culture or the culture to be shaped to fit the behavioural requirements of the technology. As identified in the findings, the cultural barrier was mentioned by the highest number of participants in our study, however, there is a lack of research that focuses on cultural barriers of forecasting product demand. According to a survey conducted by Beardsley et al.'s (2006), to shape culture in an organisation, executives indicated that they need to focus on the more complex aspects of culture, such as how people make decisions, how they interpret instructions and deadlines, and how they resolve conflict. Martin and Grbac (2003) study found that an organisations orientation also shapes culture. An organisation focused on having a market orientation is found to have a culture driven towards generating market information, cross-functionally sharing that market information, and rapidly responding to that market information to positively impact the organization's performance.

Rapid product change: The growing speed of change in technology, increased competition and global operations sets new requirements for managing products. Manufacturers production capacity is often capable of producing a broad range of low-cost, high-quality products with short lead times in varying lot sizes according to customer specifications (Mason et al.'s, 2002). ALM is capable of producing customer-specific products, however, due to the rapid advancement in technology, its product lifecycle has changed in the last 10 years, participants state that this has brought additional barriers in forecasting product demand, from having a large range of products to difficulties in managing pricing of products and long product launch processes. Kaipia et al.'s (2006) empirical study also find that the large growth in the number of active product families and product introductions in an electronics company increases the complexity in planning for demand and supply. The large growth of product also creates more data for the organisation; Varma and Khan (2015) found that due to the increased complexity of data, uncertainty risk in supply chains is growing. Kaipia et al.'s (2006) study concluded that due to the large product offering, the managing of products in different life cycles becomes more important and the management of the product portfolio must become a routine day-to-day business for companies

Inadequate Information Technology: Information Technology provides a mechanism for organisations to effectively gather, store, access, share, and analyze data (Swafford et al.'s, 2008). Having more information about the end consumer of products and services provides a critical means of reducing future demand uncertainty (Ali et al.'s, 2017). In ALM, its enterprise information systems are deemed inadequate due to poor data governance and a lack of commitment. We argue that the increase in products and complexity of data such as different rebate structures, pricing points and changing product group mix creates additional complexity in analysing the data. The use of multiple excel files to perform tasks results in a high risk of errors and repetition in tasks. The creation of multiple forecast versions and excel files creates complexity. Simultaneously, ALM experiences a lack of data and the inability to share data with stakeholders in the supply chain. Fawcett et al.'s (2007), found that there are two distinct dimensions for information sharing, connectivity and willingness which both impact operational performance and are critical to developing a real information sharing capability. The willingness to share information proves to be the backbone for various formal coordination initiatives such as Collaborative Planning, Forecasting and Replenishment (CPFR), Efficient Consumer Response (ECR) and Forecast Information Sharing (FIS) (Ali et al.'s, 2017). Sharing information has forced organisations into significant supplier reduction programs and a partnering mentality with fewer strategically chosen suppliers (Flint, 2004). Information sharing processes are seen as supply chain improvement strategies (Cavusoglu et al.'s, 2012).In the supply chain literature, the dominant view suggests that the process should be formalized and strictly scheduled (Oliva and Watson, 2011). However, barriers arise in organisations because the managers dealing with the supply chain do not realize the real benefits of information sharing and do not have confidence in information-sharing systems (Marsh and Flanagan, 2000). Hence, designing enterprise information systems not only has technological or informational dimensions, but also involves the coordination and facilitation of cross-organisational interactions of multiple departments, which is necessary to make information sharing system function. Thus, it is only through integration of information and resources can a supply chain adapt as demand changes.

Communication Failure: There is evidence from ALM participants that the channels of communication are inefficient. Certain teams do not liaise effectively with each other, resulting in poor information flow. The lack of trust in using new systems such as CRM has also resulted in poor communication this may be attributed to people being change-averse and unwilling to share information for fear of exposing their weakness to others (Fawcett et al.'s, 2008). It is important in a manufacturing environment where product variety is high to react to changing conditions fast and as important as timely information is that the information is correct. Sigala (2007) study found that enabling easier real-time information sharing among supply chain partners fosters and supports new collaboration forms. However, we argue that a lack of data governance information may not be reliable and might result in even poorer communication and performance.

Market competitiveness: Marketing covers a wide domain (e.g., branding, competitive behaviour, segmentation, advertising and positioning), however, from a supply chain perspective, organisations need to consider and understand what their downstream clients and their customers' customers need and want. Despite the speed of market change brought by numerous factors, not least of which is technological and economic, the lack of marketing intelligence creates barriers for ALM to accurately forecast product demand. It's been stated by participants that ALM is a sales-oriented organisation and not marketing, Flint (2004) research shows that organisations that have a market orientation are focused on gathering, disseminating, and responding to market data better than those that are not which enhances the effectiveness of their marketing strategies. ALM's lack of data in market intelligence may explain why the organisation is sales-oriented, where the primary focus is on making a sale with products available. However, this may be limiting ALM'S capacity, where (Martin and Grbac, 2003) research shows that by having a market orientation organisation, rapid reactions to shifts in the demand of consumers and to competition activities, which in turn leads to superior business performance, are not achievable in other respects.

Management Influence: Our findings concur with Fildes and Goodwin (2007), where management influences their own forecasts or adjust forecasts without consulting the forecasters - possibly for political reasons. Nevertheless, we also argue that these adjustments frequently disguise the underlying cause of forecast performance. For example, a narrow focus on forecast accuracy ignores the significant effects of timeliness on sales forecasting performance. (Davis and Mentzer, 2007).

4.7 Chapter Summary

In this study, we determined the major barriers in forecasting uncertain product demand in an Australian electrical manufacturer supply chain. We examine the barriers faced in forecasting. While these barriers may appear trivial when stated in an article, they often become the major roadblock to successful forecasting applications. Ultimately after the analysis our two-step exploratory research has concluded the following points:

- From the 32 barriers covered in the research literature, 22 have been identified in our study. Furthermore, an additional 14 barriers have been identified in this field study. All these are considered forecasting uncertain product demand barriers present in ALM.
- The number of interview participants that reflected a barrier in forecasting product demand was highest among the cultural barriers followed by product, technological and communication.
- The fishbone analysis of qualitative empirical data suggests that the barriers are closely intertwined.

Finally, this research forms part of our ongoing project for developing a digital toolkit solution that addresses the organisations highest prioritised barriers in forecasting uncertain product demand.

This will help the supply chain research community recognize, appreciate and provide solutions to the 'real' industry problems, rather than working on research artifacts such as forecasting techniques without real industrial consideration, evaluation and feedback.

5 Solution Design

5.1 Chapter Overview

In the previous chapter, we analysed and presented the field study on the barriers of forecasting uncertain product demand from the Australian Luminaire Manufacturer (ALM). We extracted high-level requirements from the field study and described the method performed for prioritisation of the requirements. Insights into the organization's barriers were presented, including a fishbone diagram that depicts the major issues in inaccurate forecasts.

In this chapter, we will present our solution and give details of the toolkit developed based on the design science methodology (chapter 3). We will describe the toolkit's development and its features (chapter 5.3) we will also present the tool in the organisation setting (chapter 5.7). This will be followed for a discussion (chapter 5.8) and summary (chapter 5.9) of the entire chapter.

Therefore, this chapter aims to present the design and implementation of a toolkit that supports the organisation in forecasting uncertain product demand. **(Research Goal 3)**. The tool's overriding intention is to improve transparency in the forecasting process (*Research Question 7*) -and making forecasting product demand more effective and efficient to practitioners and helping the organisation achieve its goals. We also aim to offer researchers an example of how the toolkit developed can be applied in the industry where barriers in forecasting product demand are experienced.

5.2 Background

Sales Forecasting accuracy is a challenging yet worthy task that many organisations aim to improve. Organisations tend to use historical sales data to predict the future; however, this data may not be a good indicator. Due to the historical data's uncertainty, organisations can use different attractive tools to help them improve overall forecasting performance. Most of these tools are quantitative in nature, where the organisations' historical sales data is used to identify patterns in the demand and forecast future demand. However, because historical data is unlikely to be a good indicator of what will happen in the future, judgemental adjustments are required to the forecasts. The goal of adjusting the forecast is to optimise accuracy by allowing forecasters to contribute to the organisations' sales forecast.

Judgemental adjustments enable collaborative forecasting, collecting and reconciling the information from diverse sources inside and outside the organisation (Singh, 2002). For judgemental adjustments to be helpful in the forecasting, they need to be input at the stock keeping unit SKU required level and frequent. The forecast level is crucial as it can provide different views such as aggregate levels by region, customer chain and product groups. It is well known that data aggregation leads to better statistical results (Singh, 2002).

As a result, the aim of the developed forecasting toolkit described in this chapter was to design, develop and implement tools that offer solutions to the barriers identified in the field study conducted at the organisation. Our toolkit is intended to be used by stakeholders involved in forecasting product demand in the organisation. The forecasting toolkit results will also drive an improvement in transparency, efficiency, and effectiveness in the product sales forecasting process in the organisation.

5.3 Development of the tool

The industry tool's development was subject to several important constraints, which had to be considered since they influenced design and development. Firstly, the system had to be developed for the industry organisation (section 4.5), thereby running on the organisations' infrastructure platforms and standard operating environment (section 5.3.2). Secondly, the system had to be developed in the organisation with the researcher and available resources within an appropriate timeframe to the stakeholder's concerned and the industry doctorate program's overall schedule. Finally, because the system was developed using design science methodology, the development had to support an interactive and incremental approach with stakeholders within the organisation (Hevner et al.'s, 2004).

The previous chapters described the research problem in the state-of-the-work and the state-of-the-practice. This discovery phase provided the preliminary requirements elicitation tasks essential to extract the tool's initial requirements and features.

5.3.1 High-Level Requirements

The detailed list of all the high-level requirements (user stories) synthesised from the interview study (See Appendix B). Based on the card sorting exercise (Chapter 3.3.2) the user stories with the highest priorities and most consensus were used to form the requirements for the tool. At a high level, and following the research goals, the tool should 1) improve the efficiency of forecasting product demand with a minimum amount of wasted effort and expense. 2) Directly address selected barriers often encountered during forecasting product demand in practice, and 3) deliver a suitable and effective tool for forecasting product demand by providing the ability for practitioners and the organisation to achieve its goals

The two main functional areas required within the tool were established through the elicitation process as 1) visualization of information 2) Product Forecasting model. Although the tool use was in workshops for evaluation, it was determined that the tool should be used in this setting and within the day-to-day business environment.

5.3.2 Architecture and Technologies

The architecture and technology used to develop the forecasting tool needed to conform to the organisations' available systems and resources. Subsequently, through evaluation of available technologies, it was decided that the visualisation part of the tool would be an online dashboard application. Utilising the organisations existing architecture and technology platform (Microsoft PowerBI business analytics service, Infor enterprise resource system, WhereScape RED data warehouse) with R programing language incorporated where necessary. The architecture and technologies used for the forecasting model were based on a business performance management software suite that the organisation used (IBM Planning Analytics formerly known as Cognos TM1) with Python and Excel incorporated to facilitate the requirements. The advantages of the specific technologies chosen include the fact that they are existing platforms embedded in the organisation and that the current stakeholders are involved in using these technologies hence there is a minimal learning curve for the stakeholders. Furthermore, the amount of time required to produce a working solution for the functionality required to address the organization's barriers is considered less time consuming when compared to introducing other new technology options into the business such as Microsoft Analysis Services with XMLA scripts. Given the underlying environment, the tool was intentionally developed in a modular design to allow it to be scalable and flexible to changing business needs and potential integration of other new technologies and tools that may be introduced into the organisation over time.

5.3.3 Data Repository

The foundation of the tool is a central data warehouse (DW) that consists of multiple repositories such as the enterprise resource planning system (ERP), customer relationship management (CRM), customs export data and financial sales targets. The DW enables the retrieval of large amounts of data from disparate systems for different periods. The DW enables integrating data from disparate system across the business for analysis and visualisation using the toolkit developed.

5.3.4 User Interface

The main user interface (UI) consists of a dashboard that provides users the capability to navigate through the different components of the toolkit while interacting with the available tools. Figure 26 displays the main dashboard window after a successful login. There are three major functions, being 1) Market Segmentation 2) Market Intelligence 3) Collaborative Forecasting Model.

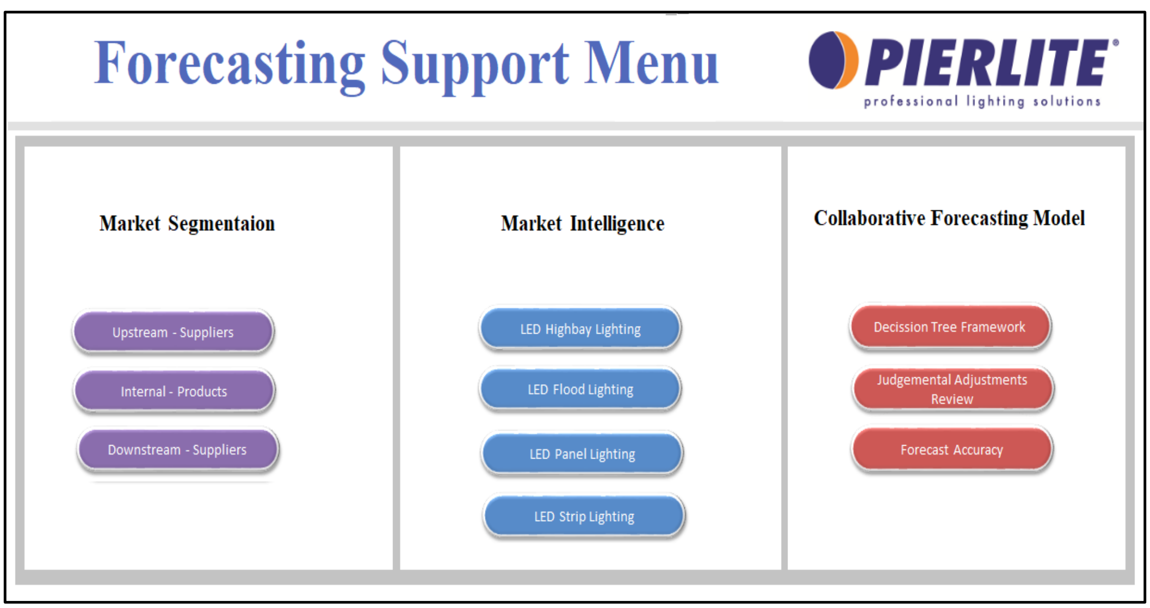

Figure 26 Main user interface

5.4 Market Segmentation Tool

Market Segmentation is a tool for discovering a group of categories/classes of customers which can naturally be grouped according to the information available (Ren et al.'s, 2010, Hong, 2012). The improved identification and classification of various market segments, help match the customer wants and needs and the organisations' ability to satisfy them (McDonald et al.'s, 2003). The overall aim of the market segmentation tool is to identify high-profit segments, which is the segments that are likely to be the most profitable or have the potential to become profitable. Segmentation also enables the organisation to focus on the selected segment and tailor specific strategies or refine existing marketing strategies to match each segment. Furthermore, in addition to identifying and defining market segments, the market segmentation tool addresses some of the barriers often experienced in forecasting uncertain product demand. Specifically, this tool addresses the following user story "as a regional manager, I want consistency and integrity in the data so that I can manage outcomes better".

There are various clustering techniques used to derive market segmentation in practice (Chang et al.'s, 2007, Wang, 2010, Yiakopoulos et al.'s, 2011), each technique has its drawbacks and benefits. In consultation with stakeholders within the organisation, the tool's segmentation is based on revenue dollars and standard variable margin percentage. Other factors that could be taken into consideration in further development of the segmentation include demographic (customer statistics), geographic (location), volume (amount purchased) and benefits (product features). The results of the four-quadrant analysis depicted in Figure 27 identify the area where the company should focus.

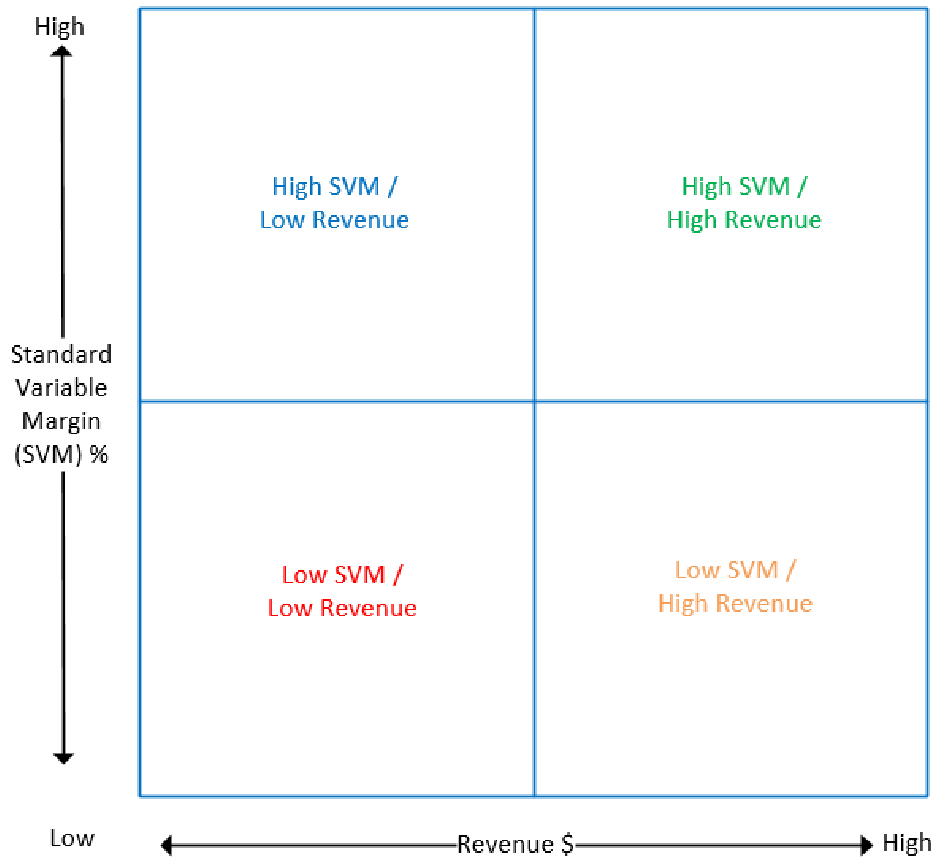

Figure 27 Four-quadrant segments

Each quadrant contains a segment where the data is plotted based on the revenue and standard variable margin. This allows the organisation to adapt individual strategies i.e. pricing, cost control, sales stimulation and marketing for each segment. Further to this, to obtain an overall view of the end-to-end supply chain, the market segmentation tool was developed with the following three options:

Upstream - involves anything received by the organisation such as raw materials or finished goods from its external suppliers.

Internal - the product groupings (Light Source) that the organisation offers

Downstream - the organisations' external distributors also known as the customers of the organisation.

The market segmentation model enabled users to view a screen for each of the above options. Figure 28 below demonstrates the visualisation tool for customer segmentation.

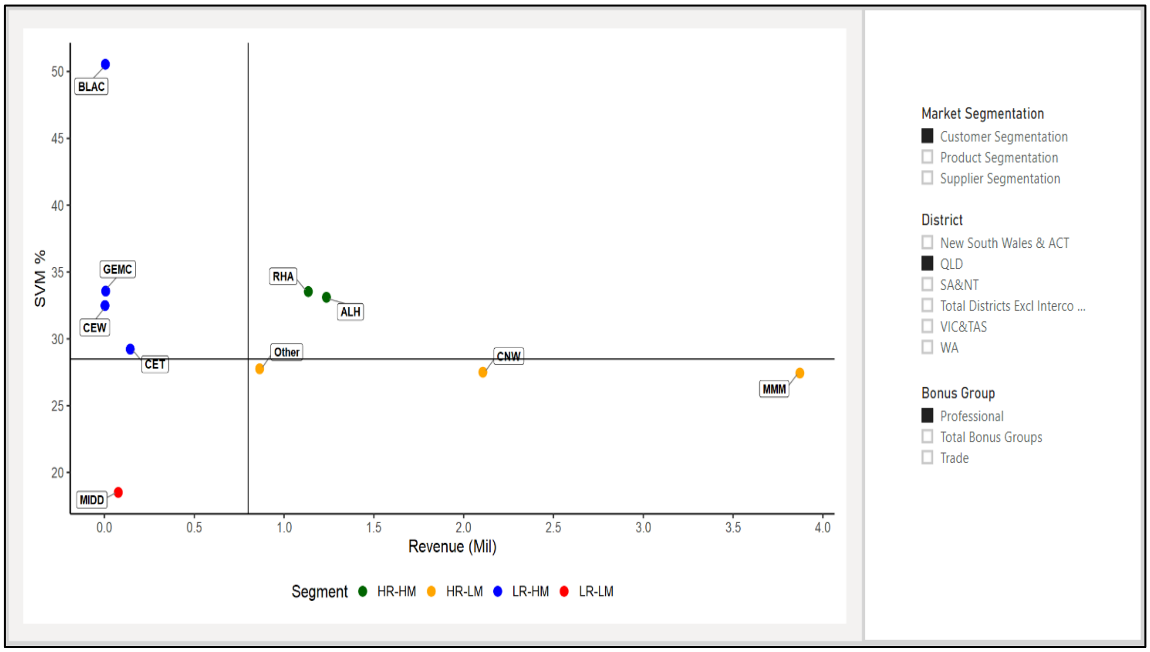

Figure 28 Downstream customer market segmentation screen

The remainder of the screens can be viewed in Appendix C.

5.4.1 Market segmentation options

The available options for the visualisation of the market segmentation are accessible from the right-hand side of the visualisation. These options allow users to select the different segments of the supply chain and features. The following are the features available:

- **Market Segmentation:** enables the user to switch between the three different sections of the supply chain. (Upstream, Internal, Downstream). Refer to Appendix C for the views of the different sections of the supply chain

- **District:** This allows users to view the selected supply chain section by a specific district or national level.
- **Bonus Group:** provides the user options to view the visualisation by a specific product group.
- **X-axis:** The x-axis is the horizontal line in the visualization that runs left to right. It is a dynamic reference that provides the average SVM% based on the options the user selects.
- **Y-axis:** This is the vertical line on the visualisation that provides the average revenue based on the user's selections.
- **Segment key:** The key identifies the quadrant based on the colour scheme of the plotted data. The following are the four quadrants in the visualisation tool:

    - HR-HM: High Revenue - High Margin
    - HR-LM: High Revenue - Low Margin
    - LR-HM: Low Revenue - High Margin
    - LR-LM: Low Revenue - Low Margin

5.5 Market Intelligence Tool

Market intelligence (MI) helps the organisation keep track of their competitors and the industry's general state. Market intelligence is defined as a process designed to constantly produce knowledge for organisations from dispersed data and information for strategic market positioning (Jamil, 2013). The MI tool is part of addressing the following user story "As a category manager, I want to know the price of competitor products so that I can make informed decisions" in forecasting uncertain product demand. In particular, it addresses the user story "As a category manager, I want access to more market intelligence data so that we can make decisions with a complete set of data". Following the field study and feedback received from the business, a tool was required to monitor and analyse competitor products imported into the Australian market. The MI tool allows users to navigate and analyse competitor products including quantity being imported and the cost. This provides the business with the capability of determining the sale price once additional costs and margin are added. Further to this the market intelligence tool provides insights into the luminaire market and helps identify any trend. This information helps managers in forecasting any potential changes occurring in the market.

The technologies used for the MI tool are SQL server, Wherescape Red, Python and Microsoft Power BI. The MI tool's overall architecture comprises three sections as depicted in Figure 29, data source, data aggregation/translation, and visualisation.

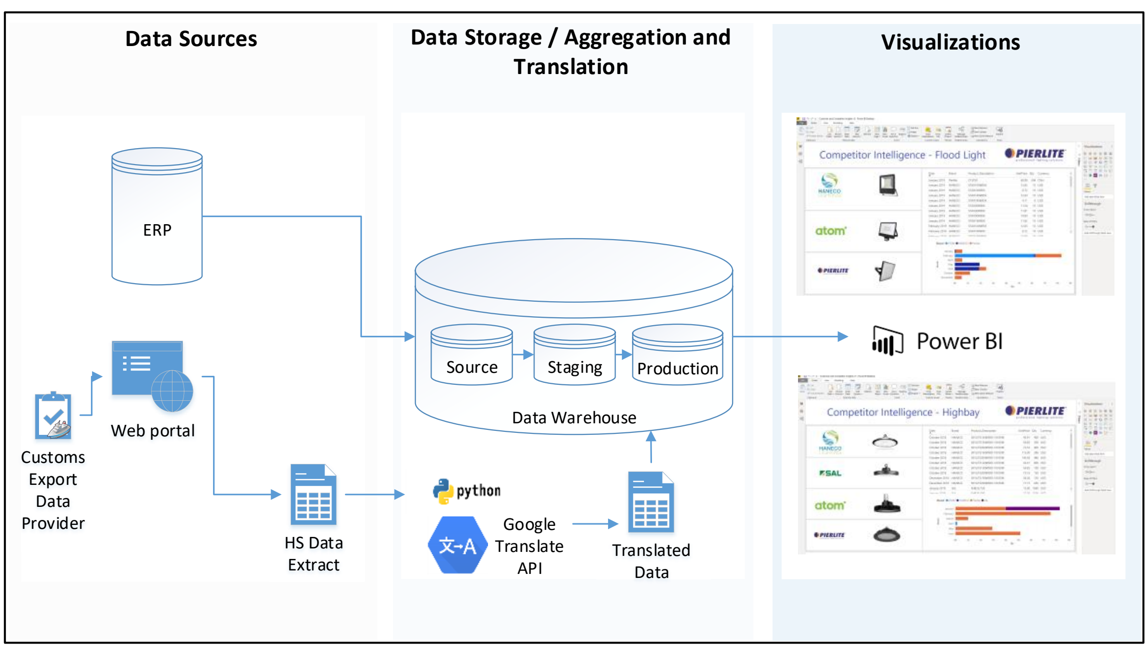

Figure 29 Market intelligence architecture

Data Sources: The data sources section contains the required system that would provide the data for the tool. There are two sources of data; the ERP system and the Customer Export data portal.

Data Aggregation and Translation: This section enables the raw data preparation process for cleansing, aggregation, and storage within the data warehouse. The data is transferred into the source tables, where the original data is stored before any transformation occurs. The staging area is then used to prepare the data by cleaning, transforming and reconciling the data. The customs export data was obtained in the mandarin language, Figure 30 depicts a sample of the data. This data was translated into English by passing the data through google translate via a python script. The validity of Google translation was checked by two external colleagues who were bilingual in English and mandarin. They randomly selected several records and checked the accuracy of the translation. It was found that the translation accuracy for the field required was adequate for the tool. Both the mandarin and English data are stored in the data warehouse to eliminate the need to reprocess the same translations in the future.

<table>
<tr><th>出口</th><th>目的国</th><th>商品编码</th><th>产品名称</th><th>产品型号</th><th>成交方式</th><th>美元单价</th><th>美元总价</th><th>法定重量</th><th>目的国_E</th><th>区域</th><th>品名</th><th>产品类别</th></tr>
<tr><td>深圳海关</td><td>澳大利亚</td><td>94051000</td><td>工矿灯</td><td>工厂内部安装在墙壁上或天花板上照明用|无牌|无型号</td><td>FOB</td><td>2.9</td><td>58</td><td>20</td><td>Australia</td><td>AU</td><td>工矿灯</td><td>灯具</td></tr>
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<tr><td>宁波关区</td><td>新西兰</td><td>94051000</td><td>LED高棚灯</td><td>户外灯具|户外照明|无牌</td><td>FOB</td><td>31.12</td><td>19666</td><td>632</td><td>New Zeala</td><td>AU</td><td>工矿灯</td><td>灯具</td></tr>
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<tr><td>深圳海关</td><td>澳大利亚</td><td>94051000</td><td>LED支架灯</td><td>室内灯|照明用|CLA牌</td><td>FOB</td><td>3.5</td><td>6650</td><td>1900</td><td>Australia</td><td>AU</td><td>支架灯</td><td>灯具</td></tr>
<tr><td>深圳海关</td><td>澳大利亚</td><td>94051000</td><td>壁灯</td><td>壁灯|照明用|无牌</td><td>FOB</td><td>22.61</td><td>2600</td><td>115</td><td>Australia</td><td>AU</td><td>壁灯</td><td>灯具</td></tr>
<tr><td>深圳海关</td><td>澳大利亚</td><td>94051000</td><td>吊灯</td><td>吊灯|照明用|无牌</td><td>FOB</td><td>176.77</td><td>32526</td><td>184</td><td>Australia</td><td>AU</td><td>吊灯</td><td>灯具</td></tr>
</table>

Figure 30 Sample customs export data

The data warehouse's staging area is also used for testing purposes before promoting to the production area.

Visualisation: The visualisation of the market intelligence tool is the presentation layer to the stakeholders. Figure 31 depicts a screen the users display when selecting LED Flood Lighting from the main user interface (chapter 5.3.4).

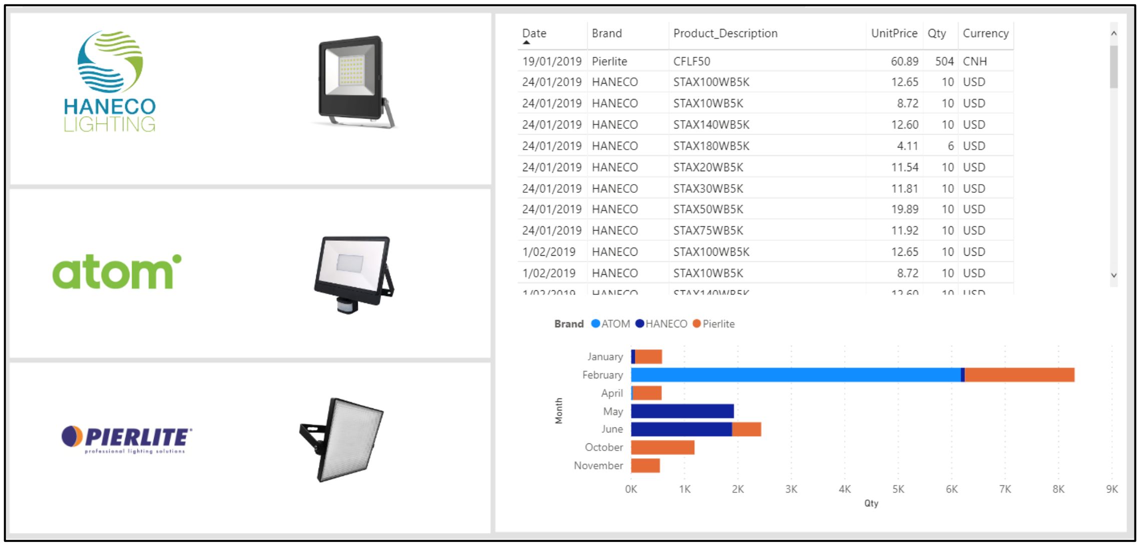


Figure 31 Market intelligence screen

The market intelligence screen presents the user with competitor import information such as the date, brand, product description, unit price, quantity and currency.

The following describes the information presented:

Date: This presents the user with the date of product importation into Australia from China.

Brand: This enables the user to identify the brand of the product being imported. This is also typically the company the product belongs to.

Product Description: enables the user to identify the product being imported into the market.

Unit Price: the total value the product is known to be purchased for.

Quantity: the total quantity of products being imported into the country.

Currency: the currency the products have been purchased for from the supplier.

5.5.1 Market intelligence options

There were no options available for the market intelligence tool other than selecting a product grouping from the main menu screen. However, having received feedback from the tool's evaluation during the evaluation phase (Chapter 6) a change was made to the tool after the stakeholders' evaluation. Feedback was received on users wanting to have the ability to view the specifications of products so that the products can be compared like for like. This resulted in enabling users to select the product photo and the specifications displayed on the screen (See appendix C).

5.6 Collaborative Forecasting Model

The collaborative forecasting model (CFM) provides a tool that allows users to input and reconcile forecast information, enabling the process of collecting and reconciling product forecasts in the organisation. The tool's primary role is to provide the organisation with a single unified forecast where forecasting can be carried out at multiple levels. The CFM contains four levels of the forecast, three of which are user derived and one that is derived by the system. The three-level forecasts are as follows:

Business Chain Forecast: This forecast consists of analysing sales by customers and inputting the forecast at the business chain level. In collaboration with the leadership team, the regional manager is responsible for completing the forecast at this level.

Light Source Forecast: This forecast represents a grouping of similar products combined to form a light source, i.e. (LED, Traditional). The total forecast aggregates up to equal to the total business chain forecast

Product Forecast: This is the detailed level forecast and specific to the stock-keeping unit (SKU). This forecast aggregates up to the light source forecast, which then aggregates to the total business chain level.

Bill of Material Forecast (BOM): The BOM is a system derived forecast based on the users' product forecast. This forecast determines the components required to manufacture the products the users have forecast.

The major benefit of the CFM is the ability to reconcile differing user views of the product demand. The CFM (See Figure 32) has been constructed based on four tiers, the data sources, data warehouse, forecasting and visualisations.

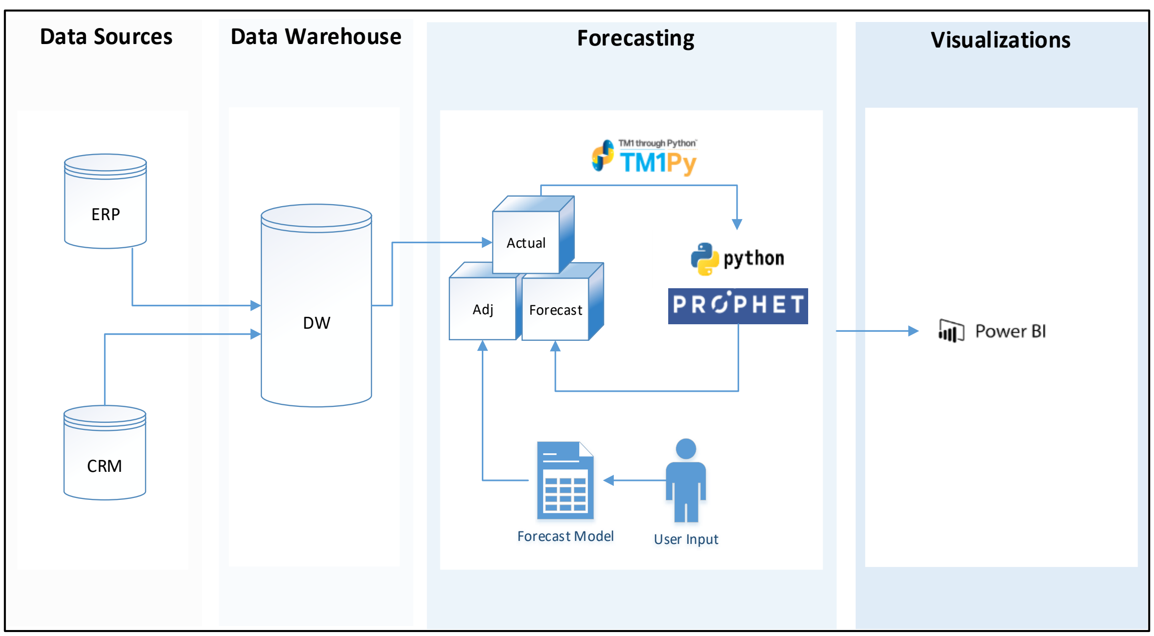


Figure 32 CFM system tiers

Each tier aims to allow the solution to be constructed with different components that are interoperable and flexible for implementation and allow for any additional modifications that the organisation may require. The following describes and purpose of each tier:

Data Sources: Contains all the relevant data necessary for the tool to function as intended. This layer includes the enterprise resource planning (ERP) and customer relationship management system (CRM). Both these systems provide significant amounts of data, i.e. (Sales data records, customer orders, quotes and invoices).

Data Warehouse: The data warehouse layer allows integrating the data from the ERP and CRM systems. This is also the central repository where the forecasting model extracts the required data.

Forecasting: This layer comprises four components (Tm1py, Planning Analytics, Python, Excel) used to develop the overall forecasting engine for the CFM. The following describes each component:

> **TM1Py:** Allows the Python package to wrap around the TM1 planning analytics representational state transfer application programming interface (REST API) while providing a library of functions to use. The REST API supports the python package to access the data stored in the TM1 planning analytics model.
>
> **TM1 Planning Analytics:** This platform enables the CFM development using in-memory multidimensional online analytical processing (OLAP) cubes. The cubes are built with dimensional hierarchies, which allow aggregation to take place. The TM1 TurboIntegrator is used to extract, transform, and load (ETL) data from the data warehouse. The TM1 TurboIntegrator is a programming/scripting tool that allows for the automation of data loading and metadata management. The CFM stores its data against multiple dimensions within a cube.
>
> **Python:** Python is a language used for developing applications, websites, or other applications' functionality to perform common tasks. The CFM uses python scripting

to run a time series forecasting procedure, retrieving actual data from the TM1 planning analytics cube to return a forecast based on the procedure.

TM1 Excel Add-in: The TM1 excel add-in component provides worksheet functions that allow users to interact with the CFM model. The interaction that users have with the model is not limited to obtaining the actual values and inputting the forecast.

Visualisations: This layer provides users with the reporting and understanding of the forecast data by utilising visual representations to the data. Multiple visualisations have been created to form part of the CFM tool these are as follows:

Decision making framework: this framework guides the decision making process that users of the CFM are making when adjusting the forecast. The framework is accessible from the main user interface (chapter 5.3.4). The framework was developed as part of the systematic literature review (chapter 2.4.3).

Judgemental Adjustment Review: enables stakeholders of the system to visualise the adjustments made to the different levels of the forecast. The user can identify any adjustments made, who adjusted it, when it was adjusted, the reason chosen for adjusting, and any comments entered.

Forecast Accuracy: this enables the users to view the accuracy of the user derived forecast. The forecast accuracy is based on prior actual periods that have occurred and are measured against what was forecasted. The period is adjustable and may be selected by the user.

5.6.1 CFM options

The CFM provides several options for users of the tool. The model is built to work for future years and multiple months and forecast version. The system administrator of the tool maintains these configurations. Figure 33 depicts the menu presented and options available when logging into the CFM.

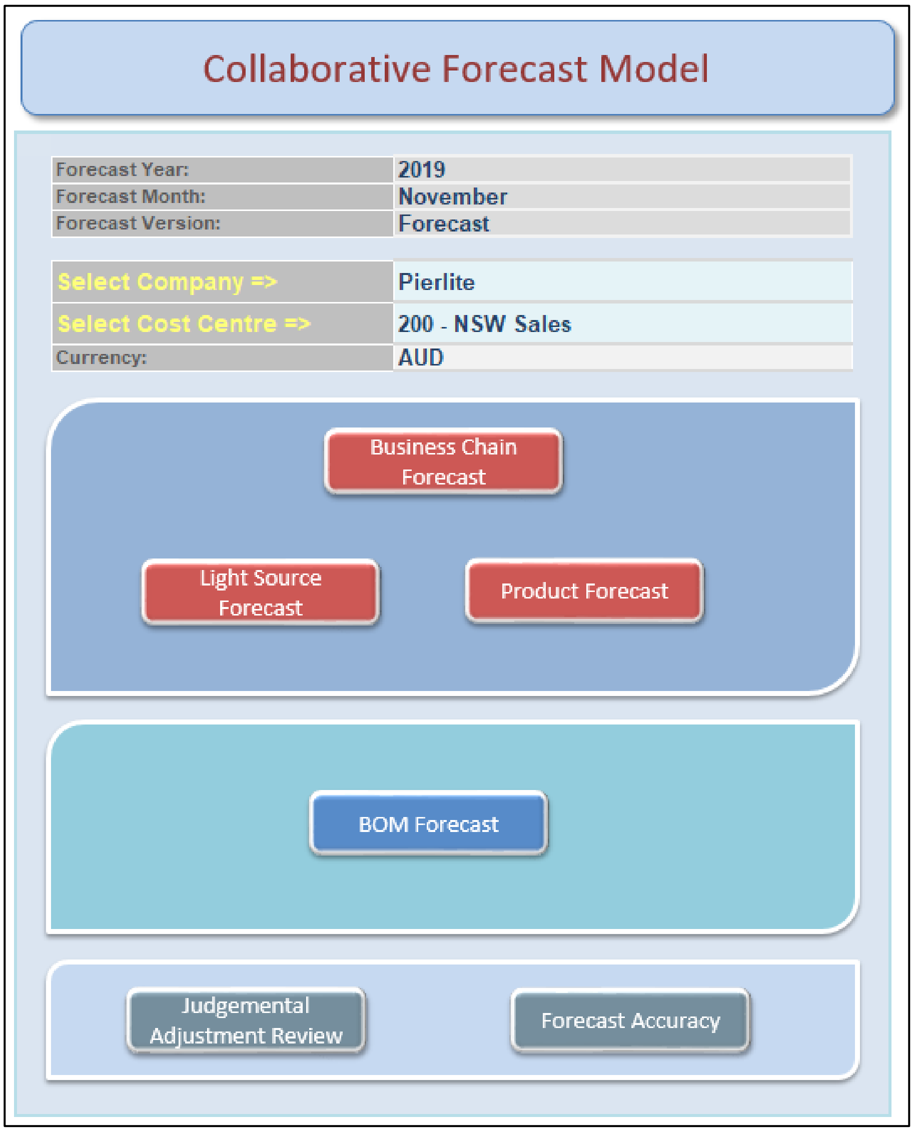


Figure 33 CFM Menu

Below is an explanation of the options available:

Company: This option enables users of the tool to forecast for different companies of the organisation. Each company can have an individual forecast at different levels.

Cost Centre: This enables users to select a specific cost centre to forecast, i.e 200 – Sydney, 300- Melbourne etc.

Currency: This option works with the company selection; if a foreign company is selected such as NZ, the currency will automatically change to New Zealand dollars.

Red Forecast buttons: These enable users to select a specific forecast level to make adjustments to the forecast. These options only work once the above selections have been made. The three-level user derived forecast is discussed in chapter 5.6.

BOM Forecast button: This enables users to view the system generated forecast once the user derived forecast is complete. The bill of materials forecast determines the components required to manufacture forecast derived by the users.

Grey Forecast buttons: These options provide users with the capability of reviewing the forecast adjustments made and the forecast accuracy.

5.7 Toolkit in Action

The following section provides an overall walkthrough of the forecasting tool usage's functionality and features in the Australian Luminaire Manufacturer organisation. Although not all the features and screens are demonstrated, this section provides an overview of the general steps taken by users of the tool to forecast product demand. The below illustration has been divided into three simple stages being 1) Insights – Exploring data by running the marketing intelligence and market segmentation tools for quickly gaining a valuable understanding of the competitive market and the performance of the market segments, 2) Forecasting – Analysis of historical data, exploring and adjusting the forecast, and 3) Presentation - production of the results of the forecast.

5.7.1 Insights

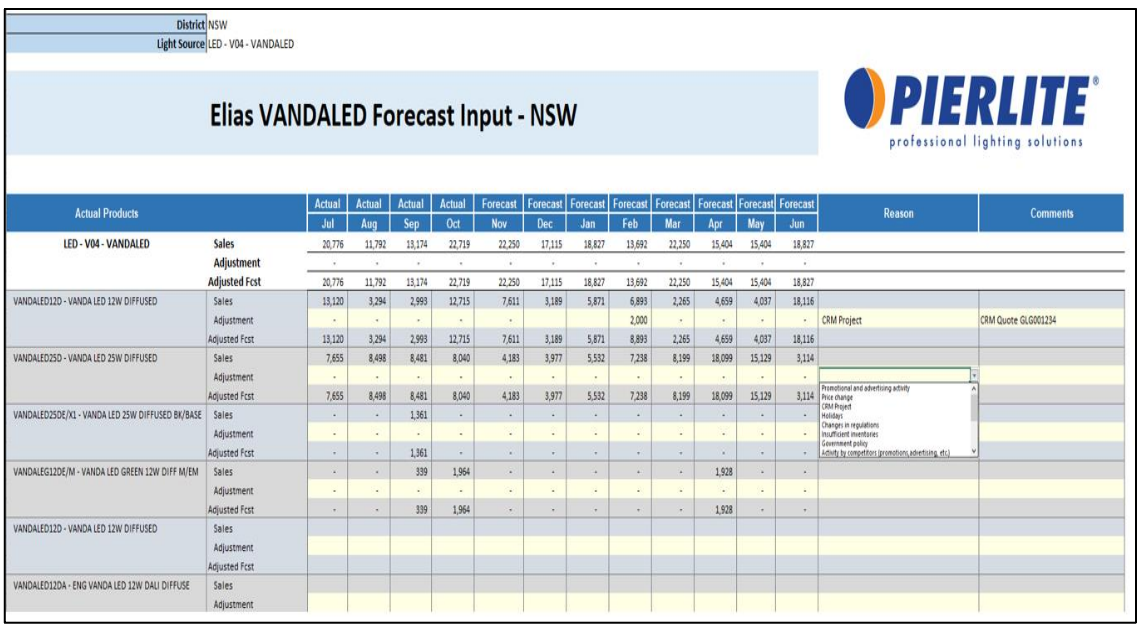
The first step of the new forecasting tool is for the participating users to log into the power BI system. The users will receive a main user interface menu; as depicted in chapter 5.3.4, the analyst can then navigate to the required functionality. The market intelligence and market segmentation will both be available for users. It is important to note that the users' data security has not been enabled for this research demonstration. The intention for the market segmentation is that sales representatives and regional managers will only have access to the states they are responsible for. The national manager and the executive leadership team will have access to all states. Appendix B presents the additional screens available to users.

The market intelligence is intended to be provided to all users of the systems with no security exceptions. For this demonstration, Figure 31 depicts the LED Flood light market intelligence. Market intelligence intends to present the largest competitors in the industry. The data for most of the organisations' competitors can be viewed, however, it was decided that the competitors with the highest import value are to be shown. There are further options that users can view; these include market intelligence for LED Highbay, LED Strip lighting and LED Panel. However, they are not illustrated in this demonstration (see Appendix C). The user can remain logged in to the system while moving on to the next step, the collaborative forecasting model.

5.7.2 Forecasting

The next step in the forecasting tool is where users log in to the planning analytics model via the excel TM1 add-in ribbon and are presented with a menu of the forecast's different levels (chapter 5.6.1).

The users participating in the forecasting make their way through reviewing the historical sales and forecast generated by the time series algorithm. Considering the market intelligence, market segmentation and any other sources of information the user is able to make the necessary adjustments to the forecast. Figure 34 depicts the product level forecasting screen that has been started.



District NSW
Light Source LED - V04 - VANDALED

Elias VANDALED Forecast Input - NSW

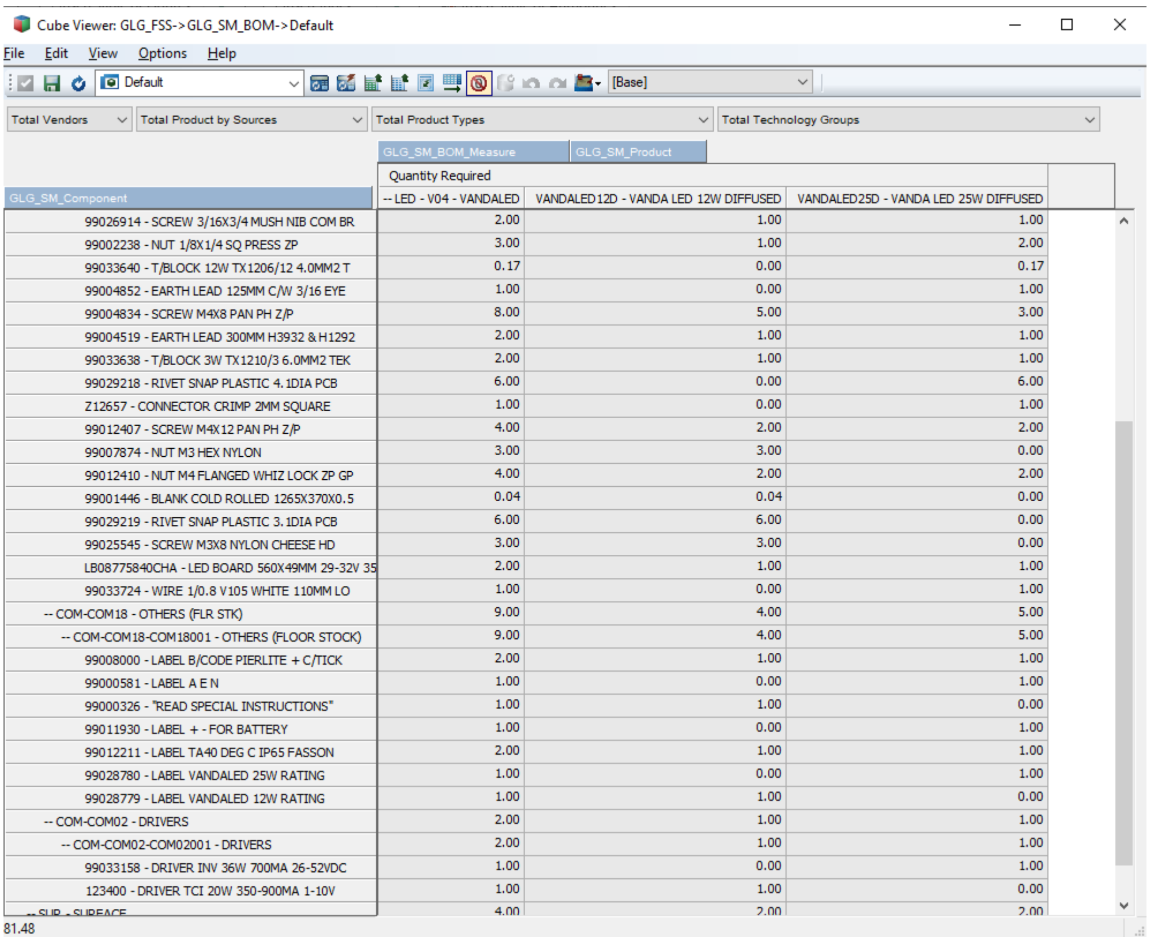
PIERLITE professional lighting solutions

Actual Products		Actual Jul	Actual Aug	Actual Sep	Actual Oct	Forecast Nov	Forecast Dec	Forecast Jan	Forecast Feb	Forecast Mar	Forecast Apr	Forecast May	Forecast Jun	Reason	Comments
LED - V04 - VANDALED	Sales	20,776	11,792	13,174	22,719	22,250	17,115	18,827	13,692	22,250	15,404	15,404	18,827		
	Adjustment	-	-	-	-	-	-	-	-	-	-	-	-		
	Adjusted Fcst	20,776	11,792	13,174	22,719	22,250	17,115	18,827	13,692	22,250	15,404	15,404	18,827		
VANDALED12D - VANDA LED 12W DIFFUSED	Sales	13,120	3,294	2,993	12,715	7,611	3,189	5,871	6,893	2,265	4,659	4,037	18,116		
	Adjustment	-	-	-	-	-			2,000	-	-	-	-	CRM Project	CRM Quote GLG001234
	Adjusted Fcst	13,120	3,294	2,993	12,715	7,611	3,189	5,871	8,893	2,265	4,659	4,037	18,116		
VANDALED25D - VANDA LED 25W DIFFUSED	Sales	7,655	8,498	8,481	8,040	4,183	3,977	5,532	7,238	8,199	18,099	15,129	3,114		
	Adjustment	-	-	-	-	-	-	-	-	-	-	-	-		
	Adjusted Fcst	7,655	8,498	8,481	8,040	4,183	3,977	5,532	7,238	8,199	18,099	15,129	3,114		
VANDALED25DE/X1 - VANDA LED 25W DIFFUSED BK/BASE	Sales	-	-	1,361	-	-	-	-	-	-	-	-	-		
	Adjustment	-	-	-	-	-	-	-	-	-	-	-	-		
	Adjusted Fcst	-	-	1,361	-	-	-	-	-	-	-	-	-		
VANDALEG12DE/M - VANDA LED GREEN 12W DIFF M/EM	Sales	-	-	339	1,964	-	-	-	-	-	1,928	-	-		
	Adjustment	-	-	-	-	-	-	-	-	-	-	-	-		
	Adjusted Fcst	-	-	339	1,964	-	-	-	-	-	1,928	-	-		
VANDALED12D - VANDA LED 12W DIFFUSED	Sales														
	Adjustment														
	Adjusted Fcst														
VANDALED12DA - ENG VANDA LED 12W DALI DIFFUSE	Sales														
	Adjustment														

Figure 34 Product level forecast

We can see that there is the capability of adjusting the forecast and selecting a reason for the adjustment via a dropdown list; these reasons were derived from the literature review and field study. However, it is noteworthy to note that during the validation phase stakeholders provided feedback after using the CFM and suggested that the user should have the capability to add multiple reasons for an adjustment to the forecast. This feedback was considered and a new screen was constructed to enable users to provide multiple reasons for an adjustment made. Appendix D contains the screen for the reasons an adjustment is made to the forecast.

When the participants complete the forecast, the data is automatically stored in the CFM. This task is repeated for the different levels of the forecast. The information that has been generated is then used to produce a bill of material forecast automatically. The bill of materials cube (Figure 35) is used to determine the components required to meet the forecast demand.



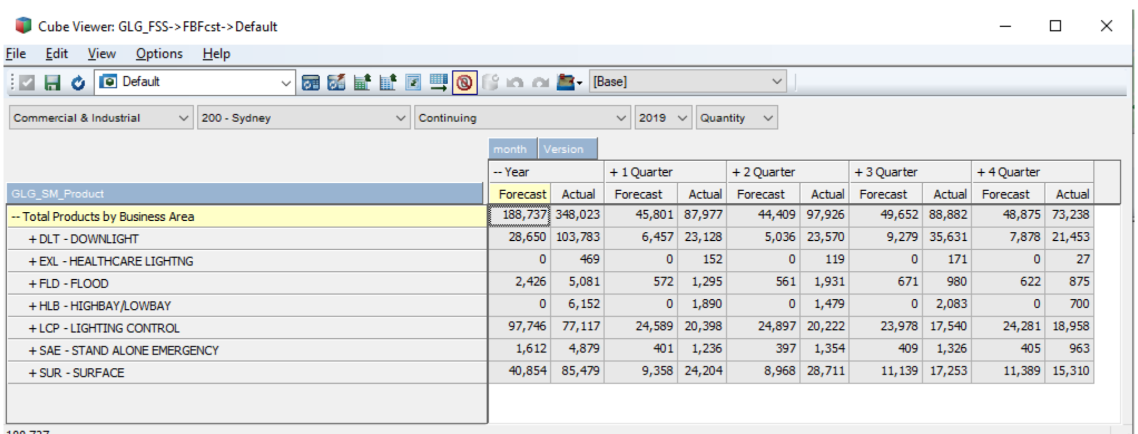
GLG_SM_Component	-- LED - V04 - VANDALED	VANDALED12D - VANDA LED 12W DIFFUSED	VANDALED25D - VANDA LED 25W DIFFUSED
99026914 - SCREW 3/16X3/4 MUSH NIB COM BR	2.00	1.00	1.00
99002238 - NUT 1/8X1/4 SQ PRESS ZP	3.00	1.00	2.00
99033640 - T/BLOCK 12W TX1206/12 4.0MM2 T	0.17	0.00	0.17
99004852 - EARTH LEAD 125MM C/W 3/16 EYE	1.00	0.00	1.00
99004834 - SCREW M4X8 PAN PH Z/P	8.00	5.00	3.00
99004519 - EARTH LEAD 300MM H3932 & H1292	2.00	1.00	1.00
99033638 - T/BLOCK 3W TX1210/3 6.0MM2 TEK	2.00	1.00	1.00
99029218 - RIVET SNAP PLASTIC 4.1DIA PCB	6.00	0.00	6.00
Z12657 - CONNECTOR CRIMP 2MM SQUARE	1.00	0.00	1.00
99012407 - SCREW M4X12 PAN PH Z/P	4.00	2.00	2.00
99007874 - NUT M3 HEX NYLON	3.00	3.00	0.00
99012410 - NUT M4 FLANGED WHIZ LOCK ZP GP	4.00	2.00	2.00
99001446 - BLANK COLD ROLLED 1265X370X0.5	0.04	0.04	0.00
99029219 - RIVET SNAP PLASTIC 3.1DIA PCB	6.00	6.00	0.00
99025545 - SCREW M3X8 NYLON CHEESE HD	3.00	3.00	0.00
LB08775840CHA - LED BOARD 560X49MM 29-32V 35	2.00	1.00	1.00
99033724 - WIRE 1/0.8 V105 WHITE 110MM LO	1.00	0.00	1.00
-- COM-COM18 - OTHERS (FLR STK)	9.00	4.00	5.00
-- COM-COM18-COM18001 - OTHERS (FLOOR STOCK)	9.00	4.00	5.00
99008000 - LABEL B/CODE PIERLITE + C/TICK	2.00	1.00	1.00
99000581 - LABEL A E N	1.00	0.00	1.00
99000326 - "READ SPECIAL INSTRUCTIONS"	1.00	1.00	0.00
99011930 - LABEL + - FOR BATTERY	1.00	0.00	1.00
99012211 - LABEL TA40 DEG C IP65 FASSON	2.00	1.00	1.00
99028780 - LABEL VANDALED 25W RATING	1.00	0.00	1.00
99028779 - LABEL VANDALED 12W RATING	1.00	1.00	0.00
-- COM-COM02 - DRIVERS	2.00	1.00	1.00
-- COM-COM02-COM02001 - DRIVERS	2.00	1.00	1.00
99033158 - DRIVER INV 36W 700MA 26-52VDC	1.00	0.00	1.00
123400 - DRIVER TCI 20W 350-900MA 1-10V	1.00	1.00	0.00
-- SUR - SURFACE	4.00	2.00	2.00

Figure 35 BOM cube showing the vandaled components required

At this point in the forecast process, the information is ready for the presentation phase as described below.

5.7.3 Presentation

Once the system users have entered the forecast at the various levels, the information can be reviewed collaboratively, or individually by management, or relevant stakeholders in the organisation. At this stage, the forecast is locked and no further user input is possible. For the walkthrough, the data used in the reporting presented is fictitious. The overall reporting available for users is depicted in (chapter 5.6.1). It is noteworthy that as the users complete the forecast and adjustments, the user details are captured to ensure management knows who is making adjustments to the forecast. The reporting is available both in the CFM via excel and through the Power BI menu, the reason for this is so that executive management can view the output through the main user interface. Also, using the OLAP system to develop the CFM, stakeholders can slice and dice the forecasting cube at various layers and intersections to view the data as they please. Figure 36 depicts the cube view that shows the forecast versus the actual for the Sydney cost centre.



GLG_SM_Product	-- Year		+ 1 Quarter		+ 2 Quarter		+ 3 Quarter		+ 4 Quarter	
	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual	Forecast	Actual
-- Total Products by Business Area	188,737	348,023	45,801	87,977	44,409	97,926	49,652	88,882	48,875	73,238
+ DLT - DOWNLIGHT	28,650	103,783	6,457	23,128	5,036	23,570	9,279	35,631	7,878	21,453
+ EXL - HEALTHCARE LIGHTNG	0	469	0	152	0	119	0	171	0	27
+ FLD - FLOOD	2,426	5,081	572	1,295	561	1,931	671	980	622	875
+ HLB - HIGHBAY/LOWBAY	0	6,152	0	1,890	0	1,479	0	2,083	0	700
+ LCP - LIGHTING CONTROL	97,746	77,117	24,589	20,398	24,897	20,222	23,978	17,540	24,281	18,958
+ SAE - STAND ALONE EMERGENCY	1,612	4,879	401	1,236	397	1,354	409	1,326	405	963
+ SUR - SURFACE	40,854	85,479	9,358	24,204	8,968	28,711	11,139	17,253	11,389	15,310

Figure 36 Forecast cube view

System users can either select a single value or multiple values from the cube dimensions, to create a new view with a particular subset of the data required.

5.8 Discussion

Several additional features were considered for the forecasting tools, including embedding product quote information, customer opportunity information, and additional statistical forecast options; however, these were not implemented as part of the CFM solution. The reason for excluding these features is mainly due to the value they provide compared to the overall goal of the industry research project. Additional features were considered valuable to have; however, they were considered to be rather out of scope with the toolkit's overall focus and objective. These features include use of workflows to manage the timing and completion of the different levels of the forecast. Also considered were features such as automating the accessibility of values based on the user's role and automating the reporting. However, these were only partially developed as they require considerable effort and time to implement and evaluate to an adequate level that would enhance the overall research project results.

The use of the organisations' available platforms and technologies in the toolkit development has given us and the organisation several important advantages, including developing the toolkit cost-effectively by eliminating the need to build specific applications from scratch. It has provided an opportunity for scalability, where the business can modify their processes or systems easily and effectively. It has also lowered the learning curve, as stakeholders of the toolkit are experienced with the existing systems.

Furthermore, in addition to addressing the user stories and providing the tool to address the issues often experienced in the organisation with forecasting uncertain product demand, the tool allows users to communicate openly, access critical forecasting information that is central, traceable and reportable. In effect, the tool allows the stakeholders to be actively engaged in the forecast, thereby encouraging accountability, ownership, and stakeholders' commitment. The tool overcomes a major limitation of many forecasting systems where non-time series information is typically not formally handled by decision support systems devoted to forecasting – a so-called forecasting support system (Webby et al.'s, 2005). The tool developed not only provide market intelligence and market segmentation; it provides a platform for forecasting that also allows users to incorporate judgemental adjustments and encourages the use of contextual reasons for these adjustments. The solutions better inform forecasters by providing systematic guidance that can be utilised to inform and/or train the judgment. To achieve this, we have endeavoured to use the tool as flexible and configurable as possible while still providing an appropriately structured and rigorous foundation for forecasting uncertain product demand and constructivist learning.

5.9 Chapter Summary

The dominant paradigm in time series forecasting is that statistical methods are more accurate than a judgemental approach. Several forecast support systems are available that promote advanced statistical methods, increased forecast accuracy, and useable interface (Yurkiewicz, 2003, Tashman and Hoover, 2001). However, it appears that non-time series information is a significant factor in determining the final forecast (Webby et al.'s, 2005). Studies have shown that people prefer judgemental forecasting methods (Lawrence et al.'s, 2000, Winklhofer and Diamantopoulos, 2003). It provides an essential and vital part in developing the forecasting tool's solution and features through direct interactions with forecasting stakeholders and the organisational context.

The most relevant and important aspect of the tool constructed is that the tool does not necessarily require significant expertise or substantial experience, nor depends on the selection and implementation of any other process. As a result, we believe that the tool can be applied in various organisations and not only in the electrical industry. Also the tool is particularly suited to novice analysts and those organisations lacking forecasting expertise. However, the forecasting tool's acceptance and adoption is also heavily dependent on the ease of learning and its appropriateness to the organisation. These and other aspects related to the forecasting tool will be tested through evaluation in the following chapter.

6 Evaluation

6.1 Chapter Overview

In the previous chapter, we described the design and development of the toolkit comprising of three tools, (1) Market Segmentation (chapter 5.4), (2) Market Intelligence (chapter 5.5), and (3) the Collaborative Forecasting Model (chapter 5.6). This chapter will develop our evaluation framework, describe our evaluation methods, and present the results of the evaluations for the developed toolkit. The ethical considerations detailed in chapter 3.5 of this thesis were also applied to the planning, preparation, and evaluation analysis. A range of different methods and techniques can be applied in design science research to build, evaluate, and improve artifacts, including benchmarking, surveys, interviews prototypes, and simulations (Sonnenberg and Brocke, 2012, Helfert et al.'s, 2012, Hevner et al.'s, 2004). Researchers have known that incorporating components of several methods enhances the viability and fidelity of evaluations (Bledsoe and Graham, 2005). Our evaluation involves a focus group (chapter 6.5.2), system testing (chapter 6.5.1), and a questionnaire (chapter 6.5.3). The incorporation of multiple evaluation methods can help better understand the needs of stakeholders and the end-users (Bledsoe and Graham, 2005). This will be followed by the discussion (chapter 6.7) and a summary of the entire chapter (chapter 6.8).

6.2 Evaluation Purpose

The purpose of the evaluations described in this chapter was to provide empirical evidence as to the performance of the toolkit for forecasting uncertain product demand. Also to directly address our Research Goal 4, in terms of how useable the toolkit is in improving transparency (RQ7), how efficient the toolkit is (RQ8), how effective it is (RQ9) and how useable the toolkit is (RQ10). Without evaluation, our design science research outcomes are an unsubstantiated assertation that the implemented artefact will achieve its purpose.

Transparency refers to the information that flows amongst stakeholders to inform informed decision-making and take the right action (Hosseini et al.'s, 2018). DiPiazza Jr and Eccles (2002) refer to transparency as the obligation to willingly provide stakeholders with the information needed to make decisions. Hence transparency depends on the availability of information, the conditions of its accessibility and how the information, which has been made transparent, may pragmatically support the user's decision-making process (Turilli and Floridi, 2009). Concerning the toolkit's transparency, the measurement we have chosen is the overall level of detail available in the toolkit, that is, the information available for users to make informed decisions (e.g. market intelligence by product segmentation, market segmentation by customer grouping and detailed forecasting). This measurement was selected because it relates directly to the availability of information during the digital toolkit and the information available from the toolkit output.

Efficiency refers to the resources (such as time or effort) expended with the speed with which users can achieve goals (Standardization, 2013). It can be measured by using indicators such as the time users take to complete a task and the user's rate of input, for example, using a mouse or keyboard (Frøkjær et al.'s, 2000). Concerning our toolkit's efficiency, the measurement we have chosen is the response time of the toolkit, meaning the overall time it takes to respond to a user's request (e.g. inputting a forecast, retrieving judgemental adjustments, and reporting). This measurement was selected because it relates directly to the speed of the effort expended during the use of the toolkit and it is relatively easy to identify, count, and compare.

Effectiveness refers to the accuracy and completeness with which users can achieve specified goals (Standardization, 2013). It can be measured using indicators such as the results' quality (Frøkjær et al.'s, 2000). As a result, and concerning our toolkit's effectiveness, the measurement chosen is the quality of the results and if the results are useful to the user (e.g. toolkit results help to achieve goals, helps in the decision-making process, and results are practical for use). This measurement was selected because it relates directly to the amount of effort expended and the completeness of information extracted from toolkits.

Useability The International Organisation for Standardization (ISO) defines useability as “the extent to which a system, product or service can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use” (Standardization, 2013). As a result, and concerning our toolkit's useability, the measurement chosen is how user-friendliness the toolkit is to achieve a task. This measurement was selected because it directly relates to users experiences with the toolkit developed.

We performed a focus group and questionnaire to cover the different aspects of effectiveness, efficiency, useability, and satisfaction (i.e. the users’ comfort with, and positive attitudes towards using the toolkit) (Frøkjær et al.'s, 2000). Using both the questionnaire (chapter 6.5.3) and focus group (chapter 6.5.2) methods for the evaluation enables us to compare the focus group discussion and questionnaire results. Our questionnaire was based primarily on system usability scale (SUS) (Brooke, 1996) questions as this method allows for low-cost assessments of useability in industrial systems evaluation and is widely regarded and commonly used in research and practice (e.g. (Sauro and Kindlund, 2005, Igwe, 2004)). The focus group was based on using stimulus materials, such as the use of the artefact prototype and questionnaire, this encouraged dialogue among the participants (Oates and Alevizou, 2017)

6.3 Evaluation Framework

As described later in this section, we endeavoured to develop a structured and rigorous evaluation strategy for the toolkit with respect to the research goals, the time available on the industry research project, and resources accessible from the Australian Luminaire Manufacturer (ALM). We use the design science research evaluation method selection framework (Figure 16) described in (chapter 3.3.3) to present our evaluation strategy (Figure 37).

DSR Evaluation Method Selection	**Ex Ante**	**Ex Post**
Naturalistic	**6.4.1** - Executive Leadership Feedback **6.4.2** - Testing partial system design	**6.5.1** - System testing **6.5.2** - Focus Group **6.5.3** - Questionnaire (qualitative and quantitative)
Artificial	• Not used	**6.6.1** - Role playing simulation **6.6.2** - User role play system testing (end user testing)

Figure 37 Design science research evaluation methods selected

A combination of naturalistic and artificial evaluation was used. It has been noted that picking a single box may not be the best strategy; rather a hybrid strategy where picking more than one quadrant is used to resolve conflicting goals (Venable et al.'s, 2012a). The specific methods were chosen for each quadrant that fit the ALM resources and time available for the industry research project. The Ex ante artificial evaluation was not used as the organisation was not interested in evaluating an uninstantiated artifact. The researcher and the organisation in questions here are also familiar with these methods. It is important to note that the Ex ante evaluation will precede Ex post evaluation (Samset and Christensen, 2017), however, more than one evaluation may be performed and more than one method can be used at one time. The following sections will describe each of the selected methods from each quadrant.

6.4 Ex ante naturalistic evaluation methods

The research artefact is designed in an iterative process (discussed in chapter 1.8). The iterative design process allowed the collection of stakeholder feedback and validation testing which help form our design rationale over multiple development sprints.

6.4.1 Stakeholder feedback

Stakeholder feedback permitted the continuous evaluation of the partial toolkit design by receiving feedback and performing testing over each iteration. As part of this research, when major milestones were completed (i.e. design and development of market intelligence component) updates on the working components of the toolkit were presented to the ALM stakeholders, this ensured that an overall evaluation of the project was undertaken as the research progressed. The feedback received from stakeholders and incorporated at the early stage of the research project limits the danger of an inherent bias from the researcher

(Anderson, 2010). The numerous times' stakeholders were involved throughout the development for feedback also ensures that the risk of useability problems are minimised (Holzinger, 2005).

6.4.2 Validation test

We performed problem discovery useability testing during the iterative development process throughout the design science research cycle. Usability testing is also known as a validation test that early in development tends to be exploratory and tests early design concepts (Lazar et al.'s, 2017). The goal of problem discovery useability testing is to uncover as many useability problems as possible (Tullis and Albert, 2013). Also to verify/validate the quality and compliance with the requirements.

The researcher was involved in all lifecycle stages of the development of the tool including testing. Once the final artefact development sprints were completed any further validation moved towards ex post, ending with the final toolkit design.

6.5 Ex post naturalistic and artificial evaluation methods

This quadrant was followed after the ex-ante and consisted of five evaluation methods as shown in Figure 37. These methods have both naturalistic and artificial settings and will be discussed below.

6.5.1 System Testing

Functional testing was carried out by the researcher at the end of each development sprint. Functional testing aims to validate the correct operation of a digital system concerning its expected functionality (Kwok-Woon and Siewiorek, 1983). Since the toolkit developed is considered a proof of concept prototype for ALM, testing is limited and informal, i.e. not documented in this thesis. Formal testing would have to be planned and carried out to convert the toolkit prototype into a production environment.

6.5.2 Focus Group

A focus group is a qualitative research technique to discuss ideas with a group of participants (Morgan, 1988). The discussion is kind of a group interview, with the session lasting not more than two hours. The session involves not more than 12 participants and is based on a particular topic of interest directed by a moderator (Morgan, 1988). Focus groups typically use stimulus materials such as prototypes or questionnaires to encourage dialogue among the participants (Oates and Alevizou, 2017). The focus group participants are encouraged to express their opinions about the topic of interest and enrich each other's views and elicit important opinions and perceptions about the artefact.

Stewart and Shamdasani (2014) give several reasons that focus groups are an appropriate evaluation technique for design science research:

- Allows direct interaction with participants who are the domain experts and the potential users of the artefact. The researcher can also clarify the design artefact.
- Provides the flexibility for an open format and the ability to deal with a wide range of design ideas.
- Produces a large amount of information allowing researcher designers to obtain a good view of the artefact design and any other organisation issues that may impact the design.
- Provides a good setting to acquire new design ideas, opinions or problems that may not be covered in individual interviews.

6.5.2.1 Planning the focus group

The focus group's goal was to collect users' opinion and their evaluation of the artefact developed in terms of four criteria: transparency, effectiveness, efficiency, and useability. For design science research, the focus group participants should be from a population familiar with the application environment for which the artefact is designed so they can adequately inform the refinement and evaluation of the artefact (Tremblay et al.'s, 2010). The participants' recruitment was from the ALM organisation and was not random but rather based on the participants' experience, position, and knowledge concerning the artefact being discussed. The participants selected were also potential users of the proposed artefact. The characteristics used to select the participants ensured that we maximise the opportunity to capture different valuable perceptions. There were nine participants in total, they represented five departments (sales, category, finance, IT and operations). This combination of participants' objective was to decrease the threat to validity and increase the rigour and relevance of the evaluation. The participants had an average experience of 4 years working at ALM. The researcher acted the role of the focus group moderator.

6.5.2.2 The running of the focus group

A detailed agenda for the focus group was organized before the commencement of the focus group. The focus group commenced with the moderator greeting the participants as they entered. The participants were seated in a U-shape arrangement known to encourage collaboration (Krueger, 2014). The focus group started by first requesting consent for the focus group to be recorded. The focus group was recorded to capture the discussion accurately. The focus group began with a one-hour PowerPoint presentation describing the overall research, presenting the high-level user stories and each digital tool that addresses the user stories. During the presentation, oral discussions were also allowed and the moderator provided clarification when required.

The moderator asked several questions during the focus group, these questions were divided into four groups: design, navigation, structure and best/worst features. The questions were answered in a collaborative approach where each participant did not need to wait to be asked. This was done as different participants had more to say on some items and less on others. Hence, the participants did not need to wait for others to finish and a group discussion was able to take place. The moderator encouraged all participants to contribute their opinion on the digital toolkit presented. For the best/worst features of the group of questions, participants were asked to mention what they thought were the best and worst characteristics of the toolkit presented. Table 10 identifies the best and worst features that the participants mentioned. Further to this, the features identified were also voted on during the focus group and recorded.

Table 10 Best and worst features from focus group discussion

Feature	Best / Worst	Voting
Multi-level forecasting	best	consensus
Competitor Intelligence does not include ALM product import	worst	5 participants
Automated bill of materials (BOM) forecasting	best	6 participants
Retrieval of the forecast is simplified	best	consensus
Lack of ability to add more than one comment for a judgemental adjustment	worst	consensus
Human input is still required to achieve the desired result	worst	2 participants
Ability to report on judgemental adjustments	best	7 participants
Measurable judgemental adjustment reasons	best	5 participants

The voting results were immediately discussed with the group. The session then continued with a demonstration of the toolkit. The moderator performed a role-playing simulation on how the toolkit could be used in the organisation (chapter 6.6.1) and participants were able to observe and ask for clarification. The session ended with the moderator providing details about how the participants can access the toolkit for their use and evaluation. A questionnaire (chapter 6.5.3) was also provided at the end of the session to gather further evaluation after using the toolkit.

6.5.2.3 Observation Notes

During the focus group session, most participants were quiet at the start. However, as the session progressed and the moderator asked open-ended questions the groups' interest level increased and participants became more involved and confident in the discussion.

It was noticed that during the session if one or two participants were highly engaged in the discussion then this had an overall significant and positive impact on the other participants' engagement in the discussion. It was also observed that the role-play simulation of the digital toolkit reaffirmed the presentation and participants further questioned and sought clarifications on their understanding and view of the digital toolkit.

6.5.3 Questionnaire

At the end of the focus group, all participants were given a questionnaire (see Appendix D: The Questionnaire) to complete. The questions were derived based on the evaluation of the toolkit's performance (**Research Goal 4**). Participants were given 10 business days to complete the questionnaire and return it to the researcher. In accordance with subsequent Ethics Approval (see Appendix A) we have not identified the participants by name. Some participants asked for extra time to complete the questionnaire, however, the time needed was for the participants to test the toolkit developed before completing the questionnaire. None of the participants contacted the researcher for assistance or advice regarding the questionnaire. The anecdotal feedback received from participants was that the questionnaire was certainly understandable

The questionnaire was used to collect feedback about the participants' opinions and experience using the digital toolkit they had used (chapter 6.6.2). The questionnaire contained 10 questions, however, in addition to the questionnaire additional information was sought through email to reduce the amount of time to transcribe. These questions have been added to form part of the questionnaire and forms part of our continuous feedback loop in our agile development approach. The results were consolidated into a single spreadsheet where the scores for each Likert scale were combined and calculated. The calculation is based on frequency analysis and a points system whereby each 'Strongly Agree, was worth + 2 points, each 'Agree' +1, each 'Neutral' 0, each 'Disagree' -1, and each 'Strongly disagree' was worth -2, in accordance with the research methods knowledge base (Trochim, 2020). As there were 9 responses to the questionnaire in total, each statement had a maximum (highest) a possible total of + 18 if all participants strongly agreed and a minimum (lowest) possible total of -18 if all participants strongly disagreed.

As shown in Table 11 below, the highest marked statements have a score of +14 out of a possible maximum of +18. These were the statements that the participants most strongly agreed with; the toolkit helped me be more productive (S04), the toolkit is effective to use (S07) (i.e. users ability to achieve a goal), and I would find it easy to get the forecasting model to do what I want it to do (S10). Overall each category had at least one statement with the highest mark except for the transparency category.

Table 11 Summary of questionnaire results

Statement	**Strongly Agree (+2)**	**Agree (+1)**	**Neutral (0)**	**Disagree (-1)**	**Strongly disagree (-2)**	**Total Score**
(S01) Overall there is a sufficient level of detail in the forecasting model	5		3	1		+9
(S02) My interaction with the forecasting model would be clear and understandable	5		3	1		+9
(S03) The forecasting model provides data integrity and completeness	4	2	3			+10
Transparency:						+28
(S04) The toolkit helps me be more productive	6	2	1			+14
(S05) The response time of the toolkit is good	2	4	3			+8
(S06) The solution is consistent and fits well within the organisation	5		4			+10
Efficiency:						+32
(S07) The toolkit is effective to use	6	2	1			+14
(S08) The results of the toolkit are useful	5	2	2			+12
(S09) The results of the toolkit are of good quality	5	1	3			+11
Effectiveness:						+37
(S10) I would find it easy to get the forecasting model to do what I want it to do	7		2			+14
(S11) Learning to operate the digital solutions would be easy for me	6		3			+12
(S12) The tool was easy to navigate	6	1	2			+13
Useability:						+39

Out of a possible maximum total of +54 the highest-ranked category was useability with a score of + 39 closely followed by Effectiveness with a score of +37. These results suggest that the participants felt strongly that the toolkit is effective while also being simple to navigate and use. The results also show that the lowest marked statement with a score of +8 out of a possible +18 was the response time of the toolkit is good, meaning this was the least strongest statement the participants agreed with.

Two of the three lowest marked statements with a score of +9 each out of a possible maximum of +18 was that the overall toolkit had a sufficient level of detail in the forecasting model. The interaction with the forecasting model would be clear and understandable. Therefore, it is foreseeable that the tool's transparency was the lowest ranking category of statements with a score of +28 out of a possible maximum score of +54. However, it is noteworthy that many neutral responses in the category may be attributed to the fact that participants were not in a state to confirm their statements. This may have been a result of their lack of experience with the toolkit.

At the end of the questionnaire, participants were asked to give their opinion of the toolkit's most positive and negative aspects. For the positive opinions, three of the nine participants mentioned that the toolkit was easy to use and understand. One participant mentioned “It is systematic, easy to retrieve records for analysis and decision making”, another participant stated “clear indicator and easy to understand” and thirdly “enables alignment of functions and easy to use”. While three other participants suggested that the toolkit provides the required level of details. A participant stated, “very detailed and provides good insights” a second participant stated “users can dig into details and focus on more of the important items” thirdly “provides the required level of the detail with the ability to drill down into the forecast numbers”. Two of the participants stated that the visualisations and visibility of information the toolkit provides are very useful. Stating; “the visibility of information - it enables key personnel to engage in discussions to make clear business decisions” secondly, “The availability of the reports to everyone is easy to access and the visualisation is valuable as it shows what the future would look like". Finally, one participant cited that "the toolkit improves the overall forecasting process and minimises human error".

When participants were asked to provide their opinion on the most negative aspects of the toolkit, opinions received from the participants included; three participants suggested that to make judgemental adjustments, the toolkit should enable users to select more than one reason for the judgemental adjustment. Two participants suggested a clear training and responsibilities is established for the collaborative forecasting model to avoid misuse and misunderstanding. One participant suggested that the toolkit should be connected to the customer relationship management (CRM) system data in the future. One participant stated human input is still required to achieve a more accurate result. The remaining participants did not provide any negative aspects.

Although this data alone has limited analysis value, the cross-analysis of this data with the evaluation from the focus group results was used to later draw some useful conclusions (chapter 6.7) on the transparency, efficiency, effectiveness and useability of the digital tool.

6.6 Ex post artificial evaluation methods

This quadrant consisted of two evaluation methods as shown in Figure 37. These methods have both artificial settings (i.e simulated values) and will be discussed in the below section

6.6.1 Role-play based simulation

The general concept of a role-play based simulation is an imitation of how a system would work (Goldsman, 2007). It can be a particularly effective technique for providing a concrete basis for discussion by illustrating an artifact's major principles and arousing interest (Freeman, 2020). Simulations are known to be used for several applications, such as training users of new systems and supporting arguments to justify going ahead with system development (Council, 1998). A role-play simulation was performed at ALM as part of the focus group to verify that the toolkit performs satisfactorily. In this scenario, ALM can be considered a form of a thought experiment where a toolkit is carried out in an artificial setting with simulated values. This allowed the researcher to experiment and demonstrate the artefact to participants with various forms of multi-actor users such as a category manager, sales representative, operations stakeholder and management. The reactions from the participants were explored and noted. It is noteworthy that the artefact evaluation should not be limited to the role-play simulation, therefore we allow for further end user testing to take place, experts performed an evaluation by using the toolkit prior to completing the questionnaire (chapter 6.5.3). The experts' evaluation will be described in the section below.

6.6.2 End-user testing

The end-user testing allowed participants to have firsthand experience with the final toolkit prototype for their evaluation. The researcher prepared one single testing environment for the toolkit and used for all participants to ensure they all had the same conditions. The test environment allowed participants to "play" with the toolkit to explore and understand how the toolkit works. Users had free will to choose which functionality to use or tasks they would like to complete in the toolkit. Participants were not limited to only try certain functionality based on their roles, the features and functions of the toolkit were accessible by all participants. All participants were presented with the same simulated values for the forecast and they were able to make adjustments at the different forecast levels available. After testing the toolkit, participants had the opportunity to provide valuable feedback in the questionnaire (chapter 6.5.3), particularly the useability and most negative/positive aspects of the toolkit.

6.7 Discussion

The digital toolkit evaluation consisted of several phases (functionality testing, focus group discussion, role-play simulation, end-user testing and questionnaire evaluation). Thus it was also possible to compare the results gained by the different methods used. The use of multiple evaluation methods has strengthened the validity and reliability of the results. The results of the evaluation were used to refine the design and build of the digital toolkit. The focus group discussion allowed for in-depth exploration of why the participants think the way they do whereas questionnaire results reveal usually only what people think, not why (Shull et al.'s, 2007). The end-user testing produced a more detailed analysis of usability although the most severe problems were found already in the focus group discussions. As compared to the questionnaire, the focus group provided information on more detailed issues since there was time to ask and discuss more questions. The various evaluation methods allowed us to make changes to the toolkit, such as the inclusion of ALM product import information into the market intelligence solution and allowed for the ability for users to add multiple comments for a judgemental adjustment.

From the evaluations' results, we can see that the useability received the most positive feedback from participants. Given the tool was developed using existing technologies (i.e. TM1, PowerBi) that the participants were familiar with and used daily in their usual tasks, this may be a factor in the high positive result. Overall the digital toolkit developed received high results in useability, effectiveness and efficiency, indicating that the participants themselves found the tool easy to understand, learn, and, more importantly, use. Of the main categories in the questionnaire, transparency recorded the lowest total points in the questionnaire. This may well be a product of confusion with the questionnaire's statements or the participants understanding of transparency (i.e. insufficient explanations of the category provided), rather than an accurate impression of the results produced. However it is noteworthy that in group situations, where participants are known to each other, their point of view may be influenced by others due to social acceptability, or participants may provide the wrong information to prevent disagreements to take place (Sim and Waterfield, 2019). It is therefore a category that may well need to be further evaluated.

6.8 Chapter Summary

The use of multiple evaluation methods within the design science research framework (Pries-Heje et al.'s, 2008a) presented in this chapter provides several potential benefits. Ex ante evaluation methods helped shape our decisions on developing the digital toolkit and limit the danger of an inherent bias from the researcher. The Ex post evaluation methods provide us with the assessment of the value created from the digital toolkit. Although existing literature assumes that only one kind of evaluation will be necessary to demonstrate both the artefact's utility, fitness, or usefulness (Gill and Hevner, 2013). We recommend combining two or more methods in evaluating an artefacts transparency, effectiveness, efficiency and usability.

Through the evaluations presented in this chapter, we were able first to establish that cyclic feedback and testing are useful methods for the early stages of designing and developing an artefact. Furthermore, the toolkit's development in an agile and iterative approach with the continuous evaluation proved that using the digital toolkit goals was successful as they improved overall effectiveness, efficiency, and transparency concerning forecasting uncertain product demand at ALM. Although the findings were proven within only one organisation with real stakeholders, the overall findings from the various evaluation methods used were consistent, and therefore comparable.

It was also imperative that the evaluation participants match the intended audience and users of the digital toolkit. We were able to maintain very high construct validity and reliability for all of the evaluations by comparing the results from the different evaluation methods. Although the researcher was actively involved in the focus group and the data collection and analysis. This potential bias risk was minimized by the use of both qualitative and quantitative metrics from multiple data sources (i.e. questionnaire, focus group, simulation) for evaluation including the use of an anonymous questionnaire feedback

7 Conclusion

7.1 Introduction

The problem being investigated in this thesis is faced in different industries; however, each industry presents unique parameters. For example, in the pharmaceutical industry, the packaging and labelling standards (Shah, 2004). This thesis investigated the barriers in forecasting uncertain product demand in the Australian Luminaire Manufacturer organisation. The luminaire industry has distinctive features. We developed and evaluated a digital toolkit to support practitioners in forecasting uncertain product demand. The research has been carried out and presented in three phases according to the research design. Phase 1 presented the investigation of the environment and scoping the industry research problem. This phase was described in Chapters 1, 2 and 4 to present the industry problem, the literature review and qualitative field study for investigating the barriers of forecasting uncertain product demand in the supply chain respectively. Phase 2 presented the solution design and development of a digital toolkit in Chapter 5. The solution design involved elicitation of high-level requirements from the qualitative field study followed by requirements' prioritization. The toolkit developed comprises three tools, market segmentation tool, market intelligence tool and collaborative forecasting model. Phase 3 consisted of Chapter 6 that described an evaluation framework, the evaluation methods used, and the evaluation results for the developed toolkit. In this chapter, the thesis goals and contributions are revisited and the implications of the contributions are presented. Finally, the future research directions, limitations and personal reflections are presented.

7.2 Research Goals

The research was conducted using Hevner et al.'s (2004) design science research methodology to achieve our goals that are revisited as follows:

Research Goal 1: Review and critically analyse the existing state-of-the-art in forecasting uncertain product demand in the supply chain from empirical literature, including the existing methods, barriers, and solutions.

To achieve Goal 1, a review and critical analysis of the existing literature was performed. Chapter 2 thoroughly addressed the following three questions:

Research question 1: **What methods are used in forecasting uncertain product demand in the supply chain?**

The identification of methods (section 2.3.1) used in forecasting uncertain product demand revealed 38 methods that attempted to address some of the barriers in forecasting uncertain demand. Our analysis of these methods did not reveal if there is one best method to overcome the barriers. Following are the top 10 frequently used methods from the literature:

1. *Single/Simple Exponential Smoothing*
2. *Syntetos-Boylan Approximation (SBA)*
3. *Average of statistical and judgmental*
4. *Judgmental adjustment alone*
5. *Statistical forecast judgmentally adjusted*
6. *Croston's*
7. *Naïve*

8. *Bootstrap*
9. *Holt's Exponential Smoothing (Holt)*
10. *Autoregressive AR (1)*

Research question 2: **What are the barriers faced in forecasting uncertain product demand in the supply chain?**

Section 2.3.2 identified 31 barriers faced in forecasting uncertain product demand grouped into internal or external categories. Overall the highest barrier mentioned in the studies is the judgmental adjustments from the internal category that belongs to the communication dimension, which causes bias and reduces the forecast accuracy.

Research question 3: **What solutions have been adopted to address the barriers in forecasting uncertain product demand in the supply chain?**

In section 2.3.3 we identified 16 solutions used to address barriers in forecasting uncertain product demand. We grouped the solutions into internal or external categories. The top occurring internal solution identified was the use of judgmental adjustment which belongs to the communication dimension. In hindsight, this also was the most occurring barrier faced in the studies. The most frequently occurring solution for the external category was information sharing which belonged to the technology dimension, sharing information between supply chain stakeholders provides a better outcome in forecasting demand.

Research Goal 2: Investigate and survey the current state-of-the-practice in forecasting uncertain product demand in Australian Luminaire Manufacturer.

To achieve Research Goal 2, a qualitative field study was performed to investigate and survey the current state-of-the-practice presented in chapter 4. The following main research question guided the goal:

Research question 4: **What do supply chain stakeholders from the Australian Luminaire Manufacturer perceive as state-of-the-practice in forecasting uncertain product demand?**

In section 4.4, the qualitative field study findings with practitioners from ALM revealed each business group interviewed has a different set of their top 5 barriers faced in forecasting uncertain product demand. The following are the overall top 5 frequently mentioned barriers extracted from the interview study:

1. *Lack of commitment*
2. *Poor Communication*
3. *Lack of data governance*
4. *Seasonality*
5. *Difficult to understand the market*

Research question 5: **What are the high-level requirements from the Australian Luminaire Manufacturer to address the barriers of forecasting uncertain product demand?**

In section 5.3.1 a detailed list of all the high-level requirements (user stories) was extracted from the stakeholders' interviews and presented. Furthermore, the prioritised set of user stories were provided in section 4.5 was developed by performing a card sorting exercise. The user stories with the highest priorities and most consensus from management were used to form the requirements to forecast uncertain product demand barriers.

Research Goal 3: Design a toolkit to support the organisation in forecasting uncertain product demand.

We designed and implemented a toolkit to achieve Goal 3 and the results were presented in chapter 5 that was guided by the following research question:

Research question 6: **Can the identified high-level requirements be used to design and implement a toolkit to support the organisation in forecasting uncertain product demand?**

Chapter 5 presents the details of the digital toolkit solution's design and development based on the design science methodology. The digital toolkit is developed to satisfy the requirements extracted from the field study and prioritised.

Research Goal 4: Evaluate the toolkit's performance for supporting forecasting uncertain product demand in terms of improvements in transparency, efficiency, effectiveness and useability.

The evaluation phase aimed to assess the toolkit's performance and was completed as described in chapter 6. Goal 4 was guided by the following research questions:

Research question 7: **How transparent is the toolkit in the process and results of forecasting uncertain product demand?**

Both Ex Ante (before artefact construction) and Ex Post evaluation (after artefact construction) were used in chapter 6 to evaluate the transparency of the digital toolkit designed. The results revealed that the digital toolkit enables greater transparency in forecasting and collaboration between supply chain stakeholders. The digital toolkit provides details, which is information that flows amongst stakeholders for informed decision-making and taking the right action (Hosseini et al.'s, 2018). DiPiazza Jr and Eccles (2002) .

Research question 8: **How efficient is the toolkit in improving the process of forecasting uncertain product demand?**

Both the focus group and questionnaire show that the digital toolkit is efficient in the overall time it takes to respond to a user's request. The results revealed that the overall time it takes for users requests such as reporting or retrieving judgemental adjustments from the toolkit is with a minimum amount of wasted effort and expense.

Research question 9: **How effective is the toolkit in improving the process of forecasting uncertain product demand?**

The results revealed that the toolkit produces useful results for the users. The participants felt strongly that the toolkit is effective while also being simple to navigate and use. The effectiveness of the toolkit enabled users to achieve specified goals (Standardization, 2013). The results of the effectiveness of the toolkit produced the second-highest score in the questionnaire results.

Research question 10: **How useable is the toolkit in improving the process of forecasting uncertain product demand?**

The end-user testing and validation testing produced a detailed analysis of the usability of the toolkit. The results revealed that the toolkit enabled ease of navigation, accessibility of information and simplicity to learn the toolkit. This has resulted in the highest score for the useability of the toolkit in the questionnaire.

7.3 Research and Industry contributions

The research presented in this thesis provides 5 significant and valuable contributions to the body of knowledge as listed below:

7.3.1 Contributions to the Body of Knowledge

1. A detailed systematic literature review and analysis of the current state-of-the-art in forecasting uncertain product demand (chapter 2), including the barriers (section 2.3.2), methods (section 2.3.1) and solutions adopted section (2.3.3) to address the barriers.

2. A novel decision-making framework helps practitioners make judgmental adjustments to a forecast through a repeatable and clear decision-making approach (section 2.4.3).

3. A qualitative field study (chapter 4) covers the end-to-end barriers (section 4.4) in forecasting uncertain product demand in the ALM organisation's supply chain.

4. Novel digital toolkit (chapter 5) supports the supply chain management process and overcome some of the barriers in forecasting uncertain product demand in the ALM organisation.

5. Empirical evidence (chapter 6) defines the toolkit's performance for forecasting uncertain product demand, with respect to transparency, efficiency, effectiveness, and usability.

7.3.2 Solutions to Problems in Practice

Also, the research presented in this thesis provides several helpful solutions to the problems in the Australian Luminaire Manufacturer including:

1. Directly addressing the area of judgmental adjustment by developing a decision making framework (section 2.4.3) and embedding it into the collaborative forecasting model through reporting (appendix C).

2. Using the presented digital toolkit for forecasting, this thesis demonstrates (section 6.5) that practitioners will manage detailed level forecasts and have greater transparency and effectiveness in the forecasting process.

3. The digital toolkit presented in the thesis also addresses the lack of market intelligence (section 5.5) and segmentation (section 5.4); the tool enables practitioners to visualize and reference large amounts of information effortlessly.

7.4 Implications for industry

This study provides interesting insights for managers contemplating investing in improving accuracy in forecasting uncertain product demand in the supply chain. In particular, the study offers several useful directions to managers involved in forecasting product demand in the supply chain. First, this study's results can be used to understand the barriers organisations face internally and externally in forecasting uncertain product demand (RQ2) and the solutions adopted to address these barriers (RQ3). Secondly, this study highlights the methods used across multiple supply chain industries (RQ1) and the importance of judgmental adjustments in the forecasting process. The success of judgmental adjustment in the forecast depends on the commitment of managers and the maturity of the process. A framework has been developed to help forecasters make judgmental adjustments through a repeatable and clear decision-making method. Our study uses empirical results from literature review across multiple supply chain industries, which may offer guidance to organisations and their top managers

One of the major criticisms of the research community is about the validity of the problem and acceptance and applicability of the solution in real world or industry (Davis and Hickey, 2002, Wieringa, 2005). A richer picture could have been painted if more stakeholders were interviewed. However, to reduce the threat of validity, I ensured that when analysing the transcripts of the interviews, when I did not see any new insights coming out, I had reached saturation point, and no new information was received.

The biggest threat to validity is my own bias that could have impacted some of my decisions or results. This threat has been mitigated by checking the results with my supervisor, who is an independent person.

Finally, the extraction of high-level requirements resulting from an interview study and the development of a digital toolkit bridges the gap between the literature and the knowledge from expert practitioners in the industry.

7.5 Implications for research

This research has significant implications on theory and the body of knowledge in the following three ways:

1. Regarding the environment (problem space), an increased general understanding and knowledge gained in the field of supply chain, in particular, the forecasting of uncertain product demand. This is as a result of both the literature review (chapter 2) and survey of practice (chapter 4).

2. As part of the research, the design and development of a digital toolkit in the solution space (chapter 5) provides a foundation for other researchers to develop further additional support for forecasting uncertain product demand.

3. The successful demonstration of the evaluation (chapter 6) of the digital toolkit use specifically for forecasting uncertain product demand in ALM provides guidance in using a multi-faceted evaluation approach.

7.6 Future research directions

This study provides both theories and practice with several valuable and much-needed contributions. Several opportunities exist for the development of future work to enhance the results and extend their implications.

Considering the environment phase, more participants for the qualitative field study would have naturally provided more data on state-of-the-practice, particularly from the external stakeholders, such as the supplier and customer. This would arguably present a more complete picture of opinions and attitudes on the barriers faced in forecasting uncertain product demand.

Further development of some of the partially implemented (e.g. Judgemental adjustment rules and reporting) and out of scope features (e.g. Forecast accuracy) would provide the toolkit users greater functionality and confidence. Given judgemental adjustments is the highest mentioned barrier. Also, one of the solutions that may be adopted to overcome the barriers in forecasting uncertain product demand, further exploration, and research on judgment adjustment is an important exploration in future research.

It will also be useful to explore the possibilities of using the toolkit designed in other industries and observe its performance. However, processes and human factors need to be considered as each organisations sales and operations planning process will be unique. In addition to this, human factors such as toolkit adoption forecasting users will also need to be considered.

7.7 Limitations

This section discusses the limitation of the industry research project. First, although we have consistently followed a stringent search and selection following the guidelines of evidence-based paradigm to ensure our sample's completeness in the systematic literature review, there may be some further articles that have not been included in our data collection that we are not aware of. When we were forming our search string, using our pilot search, and testing, we did not use all alternate terms for ‘‘uncertain’’ demand. We discovered this later in the data extraction stage. By performing a thorough secondary search strategy, we believe that we have successfully compensated for this limitation. However, we acknowledge that there may have been some papers that could have been added to our sample should we have used these additional terms. Secondly, we were only interested in empirical studies investigating forecasting uncertain product demand, so perhaps we may have undervalued the present state of research. However, to minimize this limitation, we reviewed some of the papers that were not empirical and found that these studies provide the same insights that we have obtained from the empirical studies, for example, Du et al.'s (2008) and Li et al.'s (2012) find that lead times impact uncertainty in the supply chain and the increase in the lead time can to a certain extent decrease supply risk. Other studies claim that the introduction of information systems or models such as the use of a variance-retentive stochastic dynamic programming algorithm in decision support systems (Basu and Nair, 2014), Grey Jump models (Lin et al.'s, 2008) and improved Holt-Winters (HW) model (Ferbar Tratar, 2015) help in forecasting short life span products and uncertain product demand.

Thirdly, the papers that were screened are based on our inclusion, and exclusion criteria and the data extracted from the included studies were based on our research questions. Hence, the results of the selected papers, together with data analysis, were subjective. However, to ensure research quality, the chosen papers have been reviewed and evaluated by PhD supervisor randomly selecting and reviewing some papers from the data sample. The findings reveal a high degree of consistency in the papers selected among the two authors.

Finally, there are inherent limitations to the research design. The qualitative approach is more concerned with the ALM organisations supply chain than the general population's representation. In other words, in the luminaire industry, it is challenging to claim overall generalizability; hence our results may not be applicable in all contexts. This research is not claiming generalizability in the larger sense. However, for any organisations with similar characteristics described in this thesis, generalizability can be applied. We further concede that there are inherent limitations in evaluating the model in the real world. However, the research design has been explained in enough details so that others can repeat or perform similar studies in different contexts. There is also a possibility that there may have been some unconscious bias as the researcher is an ALM organization employee. However, this was limited as each group of participants were asked the same questions. The interviews were also recorded so that the researcher did not need to rely on his memory.

There are also limitations in the data collection, namely the semi-structured interview questions. As participants were asked to answer semi-structured questions, participants' responses are based on their experience, perception and memory. Respondents might have overlooked certain barriers that do not impact them or have decided to report on more desirable barriers and do not directly impact their positions in the organisation, hence the number of barriers reported is likely to be underestimated. It is also possible that respondents did not describe what is happening in the organisation.

7.8 Reflections

Reflecting on the research work performed in this thesis, we can analyse our research experience and journey. Having been given an industry problem by ALM, this was the basis of the research. The exploration of the state-of-the-art and state-of-the-practice environment was critical as it provided us with deep knowledge and understanding of the industry problem. The systematic literature review and qualitative field study were extremely useful methods to critically analyse existing research and our industry knowledge.

Reflecting on some of the challenges experienced in performing an industry research project is the continuous change in the business model at ALM. This also brought a human dimension where several vital stakeholders left the business during this study, and new employees joined. It was important to ensure the research project remained on track by providing regular feedback to the executive leadership team.

Although the design, development and evaluation of the digital toolkit was for the ALM, it would have been interesting to examine how the tool could be used, and its performance observed in other domains.

I appreciate that this research was industry-based, where an industry problem was investigated and a digital toolkit solution was designed and developed to address the organisation's main barriers in forecasting uncertain product demand. We hope that as a result of this research, future researchers and practitioners will be better informed and have the resources to develop further effective and sophisticated digital tools for forecasting uncertain product demand in the supply chain.

Appendix A: Ethics Approval from HREC UTS

HREC Approval Granted - ETH17-2021

Research.Ethics@uts.edu.au

Sent: Wed, Mar 21, 2018, 4:28 PM
To: Didar.Zowghi, Elias.AbouMaroun, Research.Ethics

Dear Applicant

Thank you for your response to the Committee's comments for your project titled, "……. supply chain improvement". Your response satisfactorily addresses the concerns and questions raised by the Committee who agreed that the application now meets the requirements of the NHMRC National Statement on Ethical Conduct in Human Research (2007). I am pleased to inform you that ethics approval is now granted.

Your approval number is UTS HREC REF NO. ETH17-2021.

Approval will be for a period of five (5) years from the date of this correspondence subject to the provision of annual reports.

Your approval number must be included in all participant material and advertisements. Any advertisements on the UTS Staff Connect without an approval number will be removed.

Please note that the ethical conduct of research is an on-going process. The National Statement on Ethical Conduct in Research Involving Humans requires us to obtain a report about the progress of the research, and in particular about any changes to the research which may have ethical implications. This report form must be completed at least annually from the date of approval, and at the end of the project (if it takes more than a year). The Ethics Secretariat will contact you when it is time to complete your first report.

I also refer you to the AVCC guidelines relating to the storage of data, which require that data be kept for a minimum of 5 years after publication of research. However, in NSW, longer retention requirements are required for research on human subjects with potential long-term effects, research with long-term environmental effects, or research considered of national or international significance, importance, or controversy. If the data from this research project falls into one of these categories, contact University Records for advice on long-term retention.

You should consider this your official letter of approval. If you require a hardcopy please contact Research.Ethics@uts.edu.au.

To access this application, please follow the URLs below:

* if accessing within the UTS network: https://rm.uts.edu.au
* if accessing outside of UTS network: https://remote.uts.edu.au , and click on "RM6 - ResearchMaster Enterprise" after logging in.

We value your feedback on the online ethics process. If you would like to provide feedback please go to http://surveys.uts.edu.au/surveys/onlineethics/index.cfm

If you have any queries about your ethics approval or require any amendments to your research in the future, please do not hesitate to contact Research.Ethics@uts.edu.au.

Yours sincerely,

Associate Professor Beata Bajorek
Chairperson
UTS Human Research Ethics Committee
C/- Research & Innovation Office
University of Technology, Sydney
E: Research.Ethics@uts.edu.au
I:https://staff.uts.edu.au/topichub/Pages/Researching/Research%20Ethics%20and%20Integrity/Human%20research%20ethics/human-research-ethics.aspx

INVITATION LETTER

FORECASTING UNCERTAIN PRODUCT DEMAND

IN SUPPLY CHAIN

Dear ___________

My name is Professor Didar Zowghi. I am an academic at the University of Technology Sydney.

My PhD student Mr Elias Abou Maroun and I are conducting research into forecasting unknown product demand and would welcome your assistance. The research will involve an interview conducted at ………… by Elias and should take no more than 60 minutes of your time. I have asked you to participate because you have expertise and/or involved in the forecasting of product demand at ……...

You are under no obligation to participate in this research and you are rest assured that your participation will have no impact on your employment or relationship with ………….

Your contribution will be valuable to this research. If you are willing to assist us, please email Elias (emaroun@...........com.au) within one week of the date you receive this invitation.

Yours sincerely,

Production Note:
Signature removed
prior to publication.

Professor Didar Zowghi
Faculty of Engineering and Information Technology
University of Technology, Sydney (UTS)
didar.zowghi@uts.edu.au
Phone: +61 2 9514 1860

NOTE:

This study has been approved by the University of Technology, Sydney Human Research Ethics Committee. If you have any complaints or reservations about any aspect of your participation in this research that you cannot resolve with the researcher, you may contact the Ethics Committee through the Research Ethics Officer (ph: +61 2 9514 2478 Research.Ethics@uts.edu.au), and quote the UTS HREC reference number. Any complaint you make will be treated in confidence and investigated fully and you will be informed of the outcome.

PARTICIPANT INFORMATION SHEET

FORECASTING UNCERTAIN PRODUCT DEMAND IN SUPPLY CHAIN
UTS HREC ETH17-2021

WHO IS DOING THE RESEARCH?

My name is Elias Maroun and I am a student at UTS. My supervisor is Professor Didar Zowghi from UTS (didar.zowghi@uts.edu.au)

WHAT IS THIS RESEARCH ABOUT?

This research is to find out about stochastic (unknown) demand of products. The variable demand for such products leads to unexpected inefficiencies across all the supply chain, creating sub-optimal use of capital and bottlenecks in the manufacturing process, delays in delivery and customer dissatisfaction. As products in this category vary significantly, a higher level of communication is required between the various points in the supply chain to offset unexpected delays, variations in customer requirements and/or suppliers service delivery.

WHY HAVE I BEEN ASKED?

You have been invited to participate in this study because you have the expertise and/or involved in forecasting demand at ……….. Your contact details were obtained by Elias Maroun from ……….

IF I SAY YES, WHAT WILL IT INVOLVE?

If you decide to participate, I will invite you to a semi-structured interview conducted at ………. by Elias Maroun and should take no more than 60 minutes of your time.

The interview will also be recorded and transcribed for this research study.

ARE THERE ANY RISKS/INCONVENIENCE?

Yes, there are some risks/inconvenience.

The interview may go longer than the 60 minutes allocated.

You may feel emotionally distressed with the data being collected via note-taking or recording during the interview.

There may be a risk of potentially being identified based on your response.

This risk is mitigated by carefully de-identifying the interview transcripts, and give a code name to each interview. The list of interviewees and their corresponding code will be kept in a secure locked location that is only accessible to Elias.

DO I HAVE TO SAY YES?

Participation in this study is voluntary. It is completely up to you whether or not you decide to take part.

WHAT WILL HAPPEN IF I SAY NO?

If you decide not to participate, it will not affect your relationship with the researchers or ……. Lighting. If you wish to withdraw from the study once it has started, you can do so at any time without having to give a reason, by contacting Elias Maroun at (emaroun@............com.au)

If you withdraw from the study, any interview that has been recorded or transcripts will be destroyed.

CONFIDENTIALITY

By signing the consent form, you consent to the research team collecting and using personal information about you for the research project. All this information will be treated confidentially. All interview recordings and transcripts taken will be stored in a lockable draw and accessible only by the research team. Your information will only be used for this research project.

In any publication, the information will be provided in such a way that you cannot be identified.

WHAT IF I HAVE CONCERNS OR A COMPLAINT?

If you have concerns about the research that you think I can help you with, please feel free to contact me at emaroun@............com.au

You will be given a copy of this form to keep.

NOTE:

This study has been approved by the University of Technology Sydney Human Research Ethics Committee [UTS HREC]. If you have any concerns or complaints about any aspect of the conduct of this research, please contact the Ethics Secretariat on ph.: +61 2 9514 2478 or email: Research.Ethics@uts.edu.au], and quote the UTS HREC reference number. Any matter raised will be treated confidentially, investigated and you will be informed of the outcome.

CONSENT FORM
FORECASTING UNCERTAIN PRODUCT DEMAND
IN SUPPLY CHAIN
UTS HREC ETH17-2021

I ____________________ agree to participate in the research of forecasting uncertain product demand in supply chain UTS HREC ETH17-2021 being conducted by Elias Maroun, University of Technology, Sydney (UTS), emaroun@...........com.au.
I have read the Participant Information Sheet or someone has read it to me in a language that I understand.

I understand the purposes, procedures and risks of the research as described in the Participant Information Sheet.

I have had an opportunity to ask questions and I am satisfied with the answers I have received.

I freely agree to participate in this research project as described and understand that I am free to withdraw at any time without affecting my relationship with the researchers or the University of Technology Sydney.

I understand that I will be given a signed copy of this document to keep.

I agree to be:

☐ Audio recorded

I agree that the research data gathered from this project may be published in a form that:

☐ Does not identify me in any way
☐
May be used for future research purposes

I am aware that I can contact Elias Maroun if I have any concerns about the research.

____/____/____

____
Name and Signature [participant] Date

____ ____/____/____
Name and Signature [researcher or delegate] Date

Appendix B: Industry User Stories

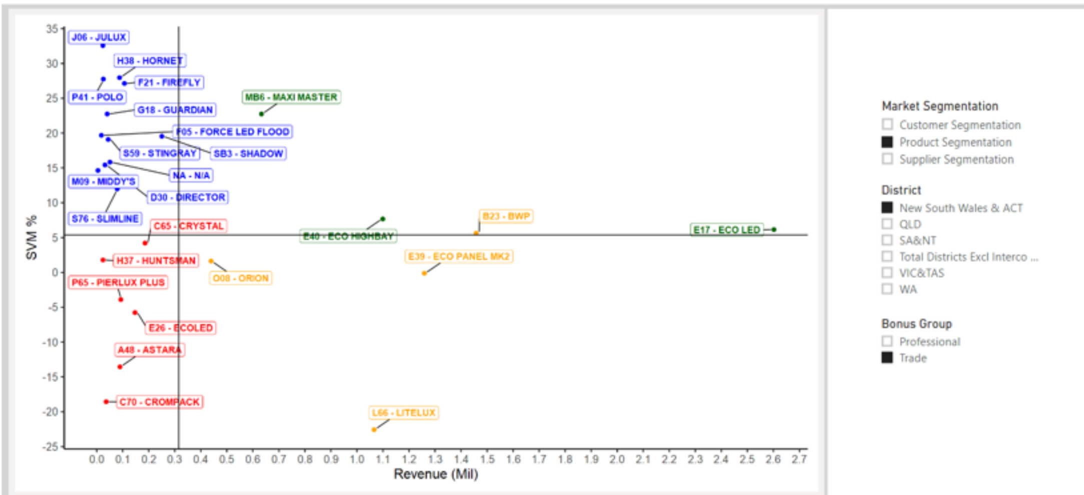
Card No #	User Story	Category	Who
1	As a sales representative, I want supply chain traceability of the products my customers have ordered so that I am promptly aware of any delays.	culture	sales representative
2	As a product engineer, I want a commitment on the product specifications so that we can plan more accurately.	culture	product engineer
3	As a supplier, I want the business to provide and commit to a forecast so that we can provide competitive pricing.	culture	supplier
4	As a sales manager, I want my sales representatives forecast to be trusted so that they are encouraged to use the system.	culture	Sales manager
5	As a supply chain stakeholder, I want to know the lifecycle of the product so that we can manage demand.	Product	Supply chain stakeholder
6	As a sales representative, I want details of new products available so that I am knowledgeable.	Product	sales representative
7	As a category manager, I want to know the price of competitor products so that I can make informed decisions.	Product	Category manager
8	As a finance manager, I want simplified SKU structures across the product range, so I can make quick decisions.	Product	Finance Manager
9	As a supply chain stakeholder, I want consistency in the data used so that we can overcome repeating tasks.	Technology	Supply chain stakeholder
10	As a supply chain stakeholder, I want accuracy of the data so that we can make informed decisions.	Technology	Supply chain stakeholder
11	As a category manager, I want access to more market intelligence data so that we can make decisions with a complete set of data.	Technology	Category manager
12	As a sales representative manager, I want better data integrity in the system so that I can manage outcomes better.	Technology	sales representative

13	As a sales representative manager, I want better communication on product availability during the holiday periods so that I can communicate better with our customers.	Communication	sales representative
14	As a product engineer, I want visibility on changing the bill of materials of product development requests so that we can plan better.	Communication	product engineer
15	As a supply chain stakeholder, I want better training across all the departments so that communication is uniform.	Communication	Supply chain stakeholder
16	As product engineer, we need to produce products that fulfil multiple customer requirements to reduce the number of SKU.	Product	product engineer
17	As supply chain stakeholder, we need to understand our sell-in and sell-through to keep new stock flowing through the channel.	customer	Supply chain stakeholder
18	As a sales representative manager, we need to reduce our product launch time to market to increase market share.	Product	Sales manager
19	As a supply chain stakeholder, we need to restrict the customer exchange policy, so we don't get caught up with old stock.	culture	Supply chain stakeholder
20	As a sales representative, I want simpler pricing structures so that I can work more effectively with my customers.	Product	sales representative
21	As category manager, we need to manage our suppliers' minimum order quantity (MoQ) so that we don't have to over order.	Suppliers	Category manager
22	As a supply chain stakeholder, we need transparency and visibility on the transitioning of components to newer versions.	Product	Supply chain stakeholder
23	As a finance manager, we need to do detailed forecasts, so we can better measure the business performance.	Product	Finance Manager
24	As a sales representative manager, we need to communicate the introduction of next-generation products to the market, so our customer's systems are up to date.	Communication	Sales manager

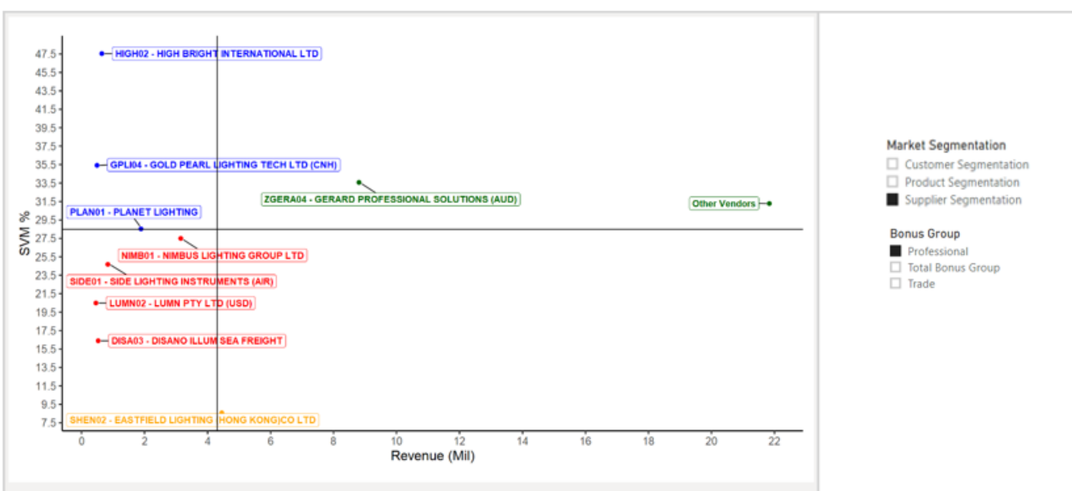
25	As a supply chain stakeholder, we need visibility of the timing of phase-in and phase-out of products.	Communication	Supply chain stakeholder
26	Blank		
27	Blank		
28	Blank		

Appendix C: Digital Toolkit solution screens

Product Segmentation

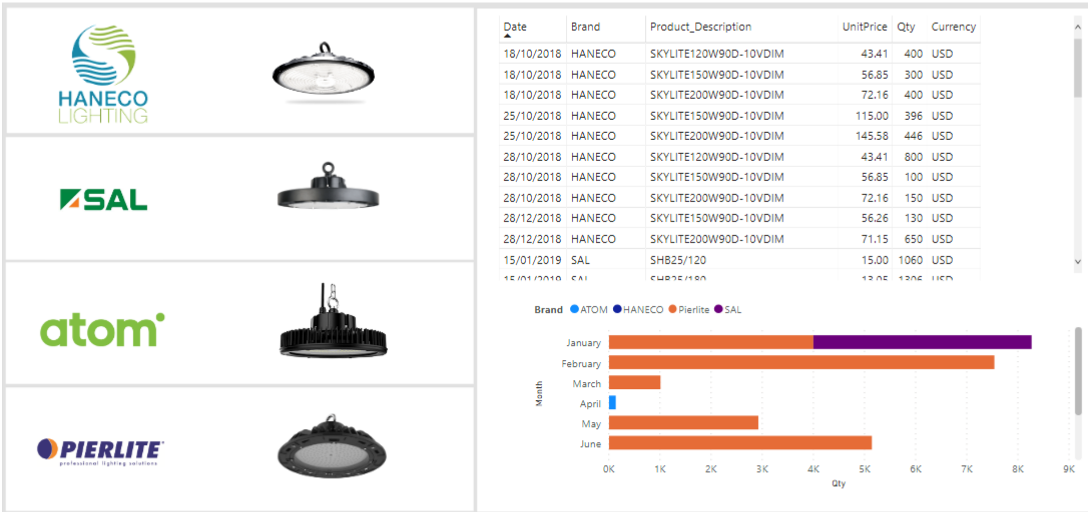


Supplier Segmentation



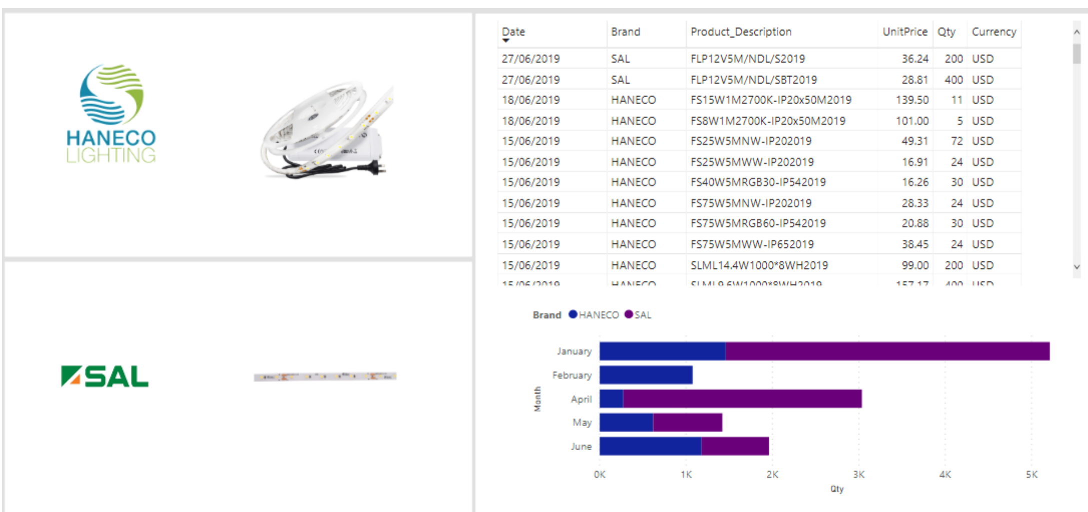
Market Intelligence Screens

Highbay Lighting



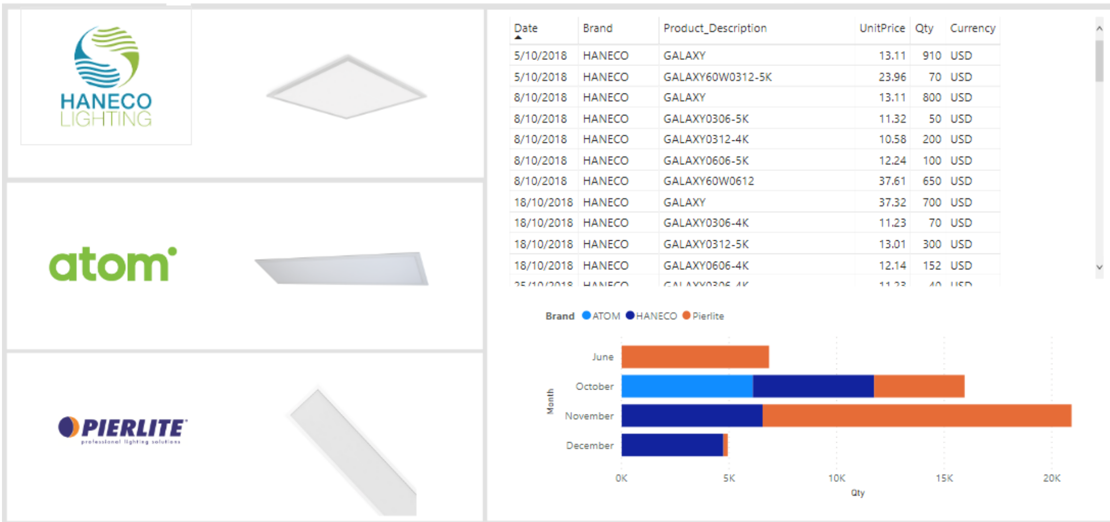
Date	Brand	Product_Description	UnitPrice	Qty	Currency
18/10/2018	HANECO	SKYLITE120W90D-10VDIM	43.41	400	USD
18/10/2018	HANECO	SKYLITE150W90D-10VDIM	56.85	300	USD
18/10/2018	HANECO	SKYLITE200W90D-10VDIM	72.16	400	USD
25/10/2018	HANECO	SKYLITE150W90D-10VDIM	115.00	396	USD
25/10/2018	HANECO	SKYLITE200W90D-10VDIM	145.58	446	USD
28/10/2018	HANECO	SKYLITE120W90D-10VDIM	43.41	800	USD
28/10/2018	HANECO	SKYLITE150W90D-10VDIM	56.85	100	USD
28/10/2018	HANECO	SKYLITE200W90D-10VDIM	72.16	150	USD
28/12/2018	HANECO	SKYLITE150W90D-10VDIM	56.26	130	USD
28/12/2018	HANECO	SKYLITE200W90D-10VDIM	71.15	650	USD
15/01/2019	SAL	SHB25/120	15.00	1060	USD

LED Strip Lighting

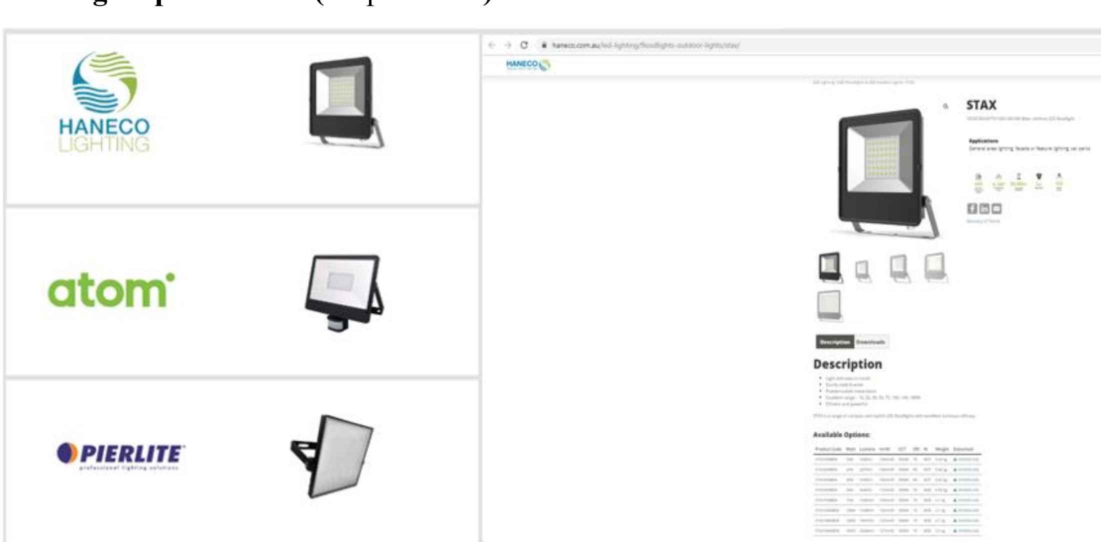


Date	Brand	Product_Description	UnitPrice	Qty	Currency
27/06/2019	SAL	FLP12V5M/NDL/S2019	36.24	200	USD
27/06/2019	SAL	FLP12V5M/NDL/SBT2019	28.81	400	USD
18/06/2019	HANECO	FS15W1M2700K-IP20x50M2019	139.50	11	USD
18/06/2019	HANECO	FS8W1M2700K-IP20x50M2019	101.00	5	USD
15/06/2019	HANECO	FS25W5MNW-IP202019	49.31	72	USD
15/06/2019	HANECO	FS25W5MWW-IP202019	16.91	24	USD
15/06/2019	HANECO	FS40W5MRGB30-IP542019	16.26	30	USD
15/06/2019	HANECO	FS75W5MNW-IP202019	28.33	24	USD
15/06/2019	HANECO	FS75W5MRGB60-IP542019	20.88	30	USD
15/06/2019	HANECO	FS75W5MWW-IP652019	38.45	24	USD
15/06/2019	HANECO	SLML14.4W1000*8WH2019	99.00	200	USD

LED Panel Lighting



Flood Light specification (chapter 5.5.1)



Collaborative forecasting model

Judgmental Adjustments due to competitor activities

District	300 - Melbourne
Business Chain	SUR - SURFACE
Judgemental Adjustment Reason	Competitor Activities

300 - Melbourne Competitor Activities

PIERLITE professional lighting solutions

SUR - SURFACE Products		Forecast Dec	Forecast Jan	Forecast Feb	Forecast Mar	Forecast Apr	Forecast May	Forecast Jun	Sales Rep	Comments
SUR - SURFACE	**Sales**	137,629	141,839	146,576	151,771	152,617	159,588	161,087		
	Adjustment	- 5,000	- 5,000	500	-	-	-	- 2,000		
	Adjusted Fcst	132,629	136,839	147,076	151,771	152,617	159,588	159,087		
JL100 - GLS ES JULUX CLEAR	Sales	20	30	200	350	200	50	55		
	Adjustment	-	-	500	800	-	-	-	Damien Allaire	JBG out of stock for nex three months
	Adjustment	-	-	200	1,000	200	200	-	Stuart Pair	ALH Elec closing down
	Adjusted Fcst	20	30	900	2,150	400	250	55		
JULUXLED2 - JULUX LED 2 BLK BASE PRIS VISO	Sales	450	845	1,185	2,265	1,545	4,852	3,545		
	Adjustment	- 200	- 400	- 500	- 500	- 500	- 500	- 2,000	Ryan Page	Cheaper alternative product available. Average 30% cheaper then our min sell price
	Adjusted Fcst	250	445	685	1,765	1,045	4,352	1,545		
CBL6485 - ACROMPTON OSTRO SURFACE MNT 14	Sales	535	557	579	601	623	645	666		
	Adjustment	- 250	- 250	- 250	- 300	- 300	- 300	- 300	Brad Hirsh	Lite House offering 50% on this product - run out sale
	Adjusted Fcst	285	307	329	301	323	345	366		
ECOBAT404E4 - AECO LED BATTEN 40W 1200MM ELE	Sales	83,944	89,179	94,588	99,996	105,231	110,640	115,874		
	Adjustment	20,000	20,000	20,000	20,000	20,000	20,000	20,000	Stuart Pair	ALH Elec closing down
	Adjusted Fcst	103,944	109,179	114,588	119,996	125,231	130,640	135,874		
ORN16W3/4/6K - ORION COLOUR SELECT OYSTER NON	Sales	6,940	6,872	6,802	6,731	6,663	6,592	6,524		
	Adjustment	1,200	1,200	1,200	1,200	12,000	1,200	1,200	Stuart Pair	ALH Elec closing down
	Adjusted Fcst	8,140	8,072	8,002	7,931	18,663	7,792	7,724		

Appendix D: The Questionnaire

Card #	User Story	Digital Solution
4	As a regional manager, I want my sales representatives forecast to be trusted so that they are encouraged to use the system.	Facebook Prophet + Judgemental Adjustments
10	As a supply chain stakeholder, I want accuracy of the data so that we can make informed decisions.	Facebook Prophet + Judgemental Adjustments
11	As a category manager, I want access to more market intelligence data so that we can make decisions with a complete set of data.	Market Intelligence + Customer/ Product Segmentation
12	As a regional manager, I want better data integrity in the system so that I can manage outcomes better.	Market Intelligence + Customer/ Product Segmentation
23	As a finance manager, we need to do detailed forecasts, so we can better measure the business performance.	Facebook Prophet + Judgemental Adjustments

1. **Business Unit** (circle one below)

   Sales/Category Finance/IT Operations

2. **ALM Experience**

   Less than 1 year b. 2-4 years c. 5-7 years d. More than 7years

3. **Learning to operate the digital solutions would be easy for me?**
   Strongly agree neutral strongly disagree
   1 2 3 4 5

4. **I would find it easy to get the forecasting model to do what I want it to do?**
   Strongly agree neutral strongly disagree
   1 2 3 4 5

   In your opinion does the forecasting model provide data integrity and completeness?
   Strongly agree neutral strongly disagree
   1 2 3 4 5

5. **My interaction with the forecasting model would be clear and understandable.**
   Strongly agree neutral strongly disagree

1 2 3 4 5

6. **Overall there is sufficient level of detail in the forecasting model**
   Strongly agree neutral strongly disagree
   1 2 3 4 5
7. **The solution is consistent and fits well within the organisation**
   Strongly agree neutral strongly disagree
   1 2 3 4 5

8. **In your opinion, what is the most negative aspect of the digitisation of the solution**

9. **In your opinion, what is the most positive aspect of the digital solution?**

10. **If you have any additional comments or questions about the editor functionality, please feel free to write them here**

Appendix E: Interview Questions

#	Question	In Study
General Interview Questions		
1	What are the steps that you take to forecast unknown product demand?	**Yes**
2	What type of data is used to forecast these unknown product demands?	**Yes**
3	What challenges do you face in achieving a more accurate forecast?	**Yes**
4	Why are these challenges occurring?	**Yes**
5	How do you think these challenges can be addressed?	**No**
6	What internal organisation challenges do you face in forecasting unknown product demand?	**Yes**
7	Do you think the ability to visualise data in forecasting demand could help address some of these challenges?	**No**
8	What specific data visualisation do you think can help?	**No**
Operations		
1	How long does a product development request (PDR) process take and what are the challenges faced? Why? Can this be improved, How?	**No**
2	When purchasing is turned off what happens to the safety stock and forecast?	**No**
3	Is there any seasonality for products and how is this treated with the forecasting?	**Yes**
4	What is the product lifecycle of products and how is this managed regarding forecasting?	**Yes**
Sales and Category		
1	How do you go about preparing the business for a potential opportunity	**Yes**
2	What are some of the challenges that you may face from a customer or project point of view with forecasting the product demand?	**Yes**

Appendix F: Systematic Literature Review Protocol

A Systematic Literature Review Protocol for Forecasting Product Demand in Supply Chain

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Abstract

Context

Australian businesses often rely on Business Construction and Infrastructure (BCI) data to monitor construction projects across the country which generates a stream of prospective business opportunities as they arise. BCI is a commercial data provider that various manufacturers and businesses in Australia purchase access to. Each project indexed by BCI generates several manufacturing and construction projects. The size of the data maintained by BCI is large and is continuously changing. This research project is to develop an intelligent decision support system to identify the most promising leads to a given manufacturing context to be used within forecasting and sales and operations planning.

Supply chain planning is an important process that is carried out within the supply chain management framework, it can have many impacts on an organisations success or failure in the industry. The forecasting or prediction of product demand in an organisation requires many aspects to be considered, such as inventory, transportation, warehousing capacity, revenue, and cash flow. Managing the product item supply and demand uncertainties is difficult due to the consequences that arise from unknown demand fluctuations such as the reduction of customer satisfaction, financial loss, the loss of market share and reputation damage. The setting of a sales goal for the sales team helps in motivating the salespeople to exceed those. However, concerns are raised if the demand estimate is not as accurate as it could be. This sales forecast is used by finance to project the costs, capital needs, and expected profit levels.

The overall research conducted as part of the thesis requirement is designed to achieve the following specific aims:

A. Explore the approach organisations have taken to reduce unknown product demand fluctuation and the impact this has had on the organisation.
B. Identify and investigate the tools and methods used to provide a better demand forecast for fluctuating demand.
C. Develop and test a scalable model or process that improves forecasts against fluctuating demand of products due to uncertainty in projects.

Objective

Following the Evidence-Based Research Paradigm guidelines, the objective of this Systematic Literature Review (SLR) is to gather all the published empirical evidence about intelligent decision support systems and forecasting of unknown customer product demand (2007 – 2017).

The SLR aims to aggregate and explore empirical studies on forecasting unknown product demand in the supply chain. This SLR specifically focuses on unknown product demand.

Method

The Systematic Literature Review (SLR) adopts guidelines from an Evidence-Based Software Engineering and Systematic Reviews, principally using the SLR guidelines from [1]. We will be carrying out all the steps outlined in the guidelines for performing systematic literature reviews in software engineering.

Expected Outcomes

From the systematic review results, we hope to gain answers to the research questions and find any gaps that have not yet been explored or that may be under-explored. We aim to enhance our understanding to develop a solution to improve the organisations forecasting capabilities for product demand and provide better visualisation.

KEYWORDS

1. Forecasting | Forecast | Prediction | Predict | Predicting
2. Product | Products | Stock Keeping Unit | SKU | Market
3. Demand| Order | Sales |Availability |Stochastic
4. Supply Chain | Planning | Procurement | Manufacturing | Inventory

INTRODUCTION

Customer's demand set organisations entire supply chain in motion. It generates a course of actions that organisations need to respond to such demand by ensuring the necessary components and products are in place to satisfy the customer's order [2]. The uncertainty of customer demand is a challenging problem in manufacturing organisations that leads to poor business performance and dissatisfied customers. If the customer's demand were constant or known with certainty well in advance, then a supply chain operation would be a straightforward exercise of ordering goods [2]. However, as the demand for products is not known for projects thus a forecast is required. The use of forecasting needs to apply to the regular consuming items and the irregular products that fluctuate and have a nonlinear sales trend [6]. Forecasting aims to predict the demand for a specific item in the future and reserve the amount of item based on the forecasting results [3]. Forecasting is important for all decision tasks from, inventory management, sales and operations planning and strategic management [4]. Since excess inventory leads to high holding costs and stockouts can greatly impact operations performance, there is a great need for accurate demand forecasting [5].

The adoption of technology within organisations and consumers is rapidly occurring, the speed at which consumers are expecting goods and services to be supplied is also shrinking. Organisations are competing on a global stage due to the speed of transactions occurring worldwide and freight and transportation efficiencies. This adds strain on the organisation that doesn't have a lean and agile supply chain that can forecast the consumer's needs. Consequently, we need to research the use of forecasting to cater for unknown consumer demand.

BACKGROUND AND MOTIVATION

Efficient replenishment planning is a very important problem for industry [7]. The accurate replenishment of products during any period may be impossible for some products due to a stochastic demand [8]. The focus of this study is on cost-saving opportunities in the delivery of products impacted by cavitation demand also known as noisy demand[9]. The variable demand for such products leads to unexpected inefficiencies across all the supply chain (SC), creating sub-optimal use of capital and bottlenecks in the manufacturing process, delays in delivery and customer dissatisfaction. As products in this category vary significantly, a higher level of communication is required between the various points in the supply chain to offset unexpected delays, variations in customer requirements and/or suppliers service delivery. Inventory related decisions are crucial for increasing efficiency and improving customer service level. Demand forecasting and stock control both contribute equally towards a decision making process [9]. The study will deliver cost savings by reducing communication problems and adding intelligence to the supply chain, where problems are recurring. The intelligence will support communication in newly created communication channels and enhance the forecasting capacity of the organisation.

RESEARCH QUESTIONS

This study is guided by the following question: "How can organisations better forecast stochastic demand for products that are used in projects and reduce the gap between the forecast and actual sales". Though this research question guides the wider study, it is multi-disciplinary and too broad to shape a SLR, instead the authors propose the following narrower questions:

> **RQ1** In studies of demand planning in the supply chain, what forecasting technique are the most frequently analysed in the empirical literature**.**
>
> **RQ2** In studies of demand planning in the supply chain, what are the challenges being faced in forecasting stochastic product demand
>
> **RQ3** In studies of demand planning in the supply chain, what research methods are used for forecasting stochastic product demand.

SEARCH STRATEGY

The following steps will be performed to search for the relevant studies.

1. We will derive major search terms from the Research Question(s).
2. List the keywords found in the article and identify relevant synonyms and alternative words that are used in published literature. The resulting terms will be connected using Boolean OR to incorporate alternative synonyms and Boolean AND operators to link major terms to construct a complete search string.
3. We will select a range of A-rated conference/journal proceedings in online databases for searching. The search string will be customized for the online databases' interfaces. The string will be applied to the title and abstracts. The searches will be open for date range between (2007 and 2017).
4. We will store the results (citations and abstracts) using Endnote[8] and Excel[9]. For every database, we will maintain a separate library. For sharing the final set of included papers we will be using google drive[10] online.

Major Search Terms

Based on our research questions, we have the following four major search terms:

1. Forecasting
2. Product
3. Demand
4. Supply Chain

[8] www.endnote.com

[2] https://office.live.com/start/Excel.aspx

[3] www.google.com.au/drive/

Search String

From the major search terms, we have identified the following alternative terms to construct our search string:

1	2	3	4
Forecasting Forecast Predicting Predict	Product/s Stock Keeping Unit SKU	Demand Availability Sales stochastic demand Noisy demand	Supply Chain Planning Procurement Inventory Order/s

By concatenating the terms, we get the following search string:

((“Forecast” OR “Predict*”) AND (“Product”* OR SKU” OR “Stock Keeping Unit”) AND (“Demand” OR “Availability” OR “Sales” OR “Stochastic” OR “Noisy”) AND (“Supply Chain” OR “Procurement” OR “Inventory” OR “Order”, OR “Planning”))*

The search string will be modified for different online databases as per requirement while keeping the logical order consistent.

Online Databases

We will apply the search string on a range of online databases to ensure that we do not miss any related study.

- Google Scholar (http://scholar.google.com.au)
- ProQuest (http://www.proquest.com)
- IEEE Explore (http://ieeexplore.ieee.org/Xplore
- Springerlink (http://www.springerlink.com)
- Business Source Complete EBSCO (https://www.ebscohost.com)
- Emerald (http://www.emeraldinsight.com)
- Science Direct (http://www.sciencedirect.com)
- Trove (http://trove.nla.gov.au)
- ACM Digital Library (http://dl.acm.org)
- Sage Journal (http://online.sagepub.com)
- JSTOR (http://www.jstor.org)
- Scopus (https://www.elsevier.com)
- Taylor and Francis Online (http://www.tandfonline.com)

All papers will be given a unique identification number based on the database from which it was retried. These unique identification numbers will be used to create a trace among various documents.

Specific conferences and journals

Given Forecasting product demand is a common problem within multiple industries, significant research into the field may be found in conference publications that may not be available in the above databases. The below specific conferences and journals are also suggested for inclusion in the research.

Conferences

- *IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI)*

Journals

- *European Journal of Operational Research*
- *International Journal of Production Economics*
- *Journal of Management*
- *Journal of Operations Management*
- *Journal of Forecasting*

- *International Journal of Project Management*
- *Journal of International Management*
- *Decision Support Systems*

STUDY SELECTION CRITERIA

Once all the results are obtained from all selected sources, we will apply the selection criteria to filter out the irrelevant studies. The Primary Reviewer will apply criteria on all papers and the Secondary Reviewer will randomly check among the results to reduce any selection bias. Any issues related to the selection of a paper will be resolved by discussion.

The following criteria will be applied in steps;

1. *IF ('the result is a thesis/general article/editorial/book review/') THEN EXCLUDE ELSE GOTO step 2*
2. *IF ('the study is investigating forecasting product demand and/or stochastic demand in the supply chain') THEN GOTO step 3 ELSE EXCLUDE*
3. *IF ('the paper is giving results based on EMPIRICAL investigation and not on personal opinions, theory or conceptual work and general surveys') THEN INCLUDE ELSE EXCLUDE*

Any duplicate citations (papers) will be discarded before applying the selection filter. Research papers retrieved from all search engines will be given an identification number from which it was retrieved. If more than one paper is using/describing results from the same study or is in multiple publications from one study for a conference and extended journal versions, they will be treated as one study.

Based on the retrieved results, we will perform secondary searches by scanning and reviewing the references and citations at the end of the papers. Those papers that would stand eligible for consideration will be treated with the same inclusion/exclusion criteria set for primary search selection. The resultant studies will be associated with the parent paper for trace from which it was retrieved.

Once the selection process is complete, new final identification numbers would be given to the included studies.

QUALITY ASSESSMENT CRITERIA

The quality of the study will be based on the research methodology adopted to produce empirical results. Primary Reviewer will apply the quality checklist on the selected studies and the secondary reviewer will check randomly and apply the criteria and evaluate if any differences arise. The differences will be solved after the discussion.

We are expecting the following different kinds of studies in our results:

1. Case studies
2. Interviews
3. Experience reports
4. Action research
5. Experiments
6. Design science research
7. Field Study
8. Survey

Quality Checklist	
Generic	
Are the aims clearly stated?	YES/NO
Are the study participants or observational units adequately described?	YES/NO/PARTIAL
Was the study design appropriate to the research aim?	YES/NO/PARTIAL
Are the data collection methods adequately described?	YES/NO/PARTIAL
Are the statistical methods justified by the author?	YES/NO
Are the statistical methods used to analyze the data properly described and referenced?	YES/NO
Are negative findings presented?	YES/NO/PARTIAL
Are all the study questions answered?	YES/NO
Do the researchers explain future implications?	YES/NO
Survey	
Was the denominator (i.e. the population size) reported?	YES/NO
Did the author justify the sample size?	YES/NO
Is the sample representative of the population to which the results will generalize?	YES/NO
Have “dropouts” introduced biases on result limitation?	YES/NO/NOT APPLICABLE
Experiment	

Quality Checklist	
Generic	
Were treatments randomly allocated?	YES/NO
If there is a control group, are participants similar to the treatment group participants in terms of variables that may affect study outcomes?	YES/NO
Could the lack of blinding introduce bias?	YES/NO
Are the variables used in the study adequately measured (i.e. are the variables likely to be valid and reliable)?	YES/NO
Case Study	
Is a case study context defined?	YES/NO
Are sufficient raw data presented to provide an understanding of the case?	YES/NO
Is the case study based on theory and linked to existing literature?	YES/NO
Are ethical issues addressed properly (personal intentions, integrity issues, consent, review board approval)?	YES/NO
Is a clear Chain of evidence established from observations to conclusions?	YES/NO/PARTIAL
Experience Report	
Is the focus of the study reported?	YES/NO
Does the author report personal observation?	YES/NO
Is there a link between data, interpretation and conclusion?	YES/NO/PARTIAL
Does the study report multiple experiences?	YES/NO

Some of the checklist items will be graded on yes/no and a few with partially. Scores will also be assigned according to the grades, 1 for Yes, 0 for No and 0.5 for Partial. The total sum of the scores will be used for the quality assessment of studies.

The decision about the ranking of the studies based on the quality score will be taken after we get the results. We wish to include all selected papers for analysis, as a part of our exploratory research. But we would check for the significance of the difference that low-quality papers are making on the overall analysis. Also, the quality of the conference/journal where the paper is published would be considered if we have to decide for including a low-quality paper.

DATA EXTRACTION

We will design data extraction forms in MS Excel to input the information we require from the papers to answer our research questions. There will be two forms, one for generic information and the other would be for specific information.

Following data will be extracted for generic form;

1. Title
2. Authors
3. Journal or conference
4. Name of journal or conference
5. Type of conference or journal
6. Publication year
7. Full citation
8. The geographical location (where the study was conducted)
9. Type of study (research method)

Following data will be extracted for the specific form to answer our research questions;

RQ1 In studies of demand planning in the supply chain, what forecasting technique are the most frequently analysed in the empirical literature.	• What was the **technique** used in stochastic product demand planning? (E.g. statistical distribution, decision support tree, etc)
RQ2 In studies of demand planning in the supply chain, what are the challenges being faced in forecasting stochastic product demand	• What **challenges** are being faced? • How was the **challenge** addressed? • What **outcomes** were reported? (e.g. positive/negative/neutral/other) who were the outcomes directed towards (e.g. researchers, industry, both) *and* what type of outcomes?
RQ3 In studies of demand planning in the supply chain, what research methods are used for forecasting stochastic product demand.	• What **methodologies** were used? (e.g. Case study, action research, survey, observations, design science etc.)

	• To what extent and how were these **methods empirically evaluated**? (% of studies that state how the method was empirically chosen or evaluated e.g. "only 20% of studies evaluated the method they were using")

DATA SYNTHESIS AND ANALYSIS

After completion of data extraction, we will aggregate the results to make them ready for further analysis. There will be two kinds of analysis we would perform; general and specific. For general analysis we would find out the following patterns in our results;

1. Frequency of publication in the following periods to assess the trend of investigation over the past 10 years (2008 – 2018)
2. Frequency of type of study (Research Methodology)

We do not have any prior plan for the type of analysis that we will apply to the results from diverse studies in our results. It is due to the fact that we are performing this Systematic Review for exploration. Therefore, the specific analysis technique will be decided once we have all the results available.

SLR ACTIVITY TIMELINE

Sr#	**Activity**		**Dates**	**Roles of Members**	**Status**
1	Protocol Development		October	Elias: Protocol Development Didar: Protocol Development and Review	completed
2	Protocol Review and updates		February	Didar: Final Review Mauneera Bano: External Review	completed
3	Protocol Review and Updates		February	Elias: test search string and modify for each search engine	completed
4	Execution	Primary Searches	To be decided	Elias: print off abstracts for primary searches	completed
		Study selection	To be decided		
		Secondary Searches	To be decided		
		Data Extraction	To be decided		
		Quality Assessment	To be decided		
		Conflict Resolution	To be decided		

		Data Synthesis	To be decided		
4	Reporting (Technical Report and conference/journal Paper)		To be decided		
			To be decided		

PILOT TESTING

Journal/Conference	**Search Through**	**Publisher**	**Results**
European Journal of Operational Research	Abstract / Title	Elsevier	100
International Journal of Production Economics	Abstract / Title	Elsevier	37
Journal of Management	Abstract / Title	Sage Publications	24
Journal of Operations Management	Abstract / Title	Elsevier	10
Journal of Forecasting	Abstract / Title	John Wiley & Sons, Inc.	25
International Journal of Project Management	Abstract / Title	Elsevier	7
Journal of International Management	Abstract / Title	Elsevier	8
Decision Support Systems	Abstract / Title	Elsevier	57
IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI)	Abstract / Title	IEEE	70
		Total Results	**338**

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GLOSSARY

Noisy Demand: Unpredictable demand patterns expressed in probabilities

Stochastic: Having a random probability distribution or pattern that may be analysed statistically but may not be predicted precisely.

Cavitation: The formation of empty space or voids

Quality assessment criteria

The scoring on the quality assessment checklist was based on three possible answers to the questions; yes = 1, partial = 0.5 and no = 0. If any of the criteria did not apply to any study then it was excluded from evaluation. The studies that scored less than 50% in the quality assessment were excluded as they were not providing adequate information on the studies research methodology.

Generic Assessment		
No	**Question**	**Possible Answer**
Q1	Are the aims clearly stated?	Yes/No
Q2	Are the study participants or observational units adequately described?	Yes/No/Partial
Q3	Was the study design appropriate for the research aim?	Yes/No/Partial
Q4	Are the data collection methods adequately described?	Yes/No/Partial
Q5	Are the statistical methods used to analyze the data properly described and referenced?	Yes/No
Q6	Are the statistical methods justified by the author?	Yes/No
Q7	Are negative findings presented?	Yes/No/Partial
Q8	Are all the study questions answered?	Yes/No
Q9	Do the researchers explain future implications?	Yes/No
Survey		
Q1	Was the denominator (i.e. the population size) reported?	Yes/No
Q2	Did the author justify the sample size?	Yes/No
Q3	Is the sample representative of the population to which the results will generalize?	Yes/No
Q4	Have “dropouts” introduced biases on result limitation?	Yes/No/Partial
Experiment		
Q1	Were treatments randomly allocated?	Yes/No
Q2	If there is a control group, are participants similar to the treatment group participants in terms of variables that may affect study outcomes?	Yes/No
Q3	Could the lack of blinding introduce bias?	Yes/No
Q4	Are the variables used in the study adequately measured (i.e. are the variables likely to be valid and reliable)?	Yes/No
Case Study		
Q1	Is the case study context defined?	Yes/No
Q2	Are sufficient raw data presented to provide an understanding of the case?	Yes/No
Q3	Is the case study based on theory and linked to existing literature?	Yes/No
Q4	Are ethical issues addressed properly (personal intentions, integrity issues, consent, review board approval)?	Yes/No
Q5	Is a clear Chain of evidence established from observations to conclusions?	Yes/No/Partial

Appendix G. Systematic Literature Review Details

According to the SLR guidelines, it is necessary to explicitly explain the planning and execution procedure of SLR to display the transparency and rigour of the process and make the results reliable and repeatable. In this appendix, the planning and execution of the systematic review are given for further information.

G1. Systematic Literature Review Execution

From our research question, we derived four major terms to be used for our search process: which included the following search words as shown in brackets: Forecasting (Forecast; Predicting; Predict), Product (Products; Stock Keeping Unit; SKU), Demand (Availability; Sales; Stochastic; Unknown; Noisy; Uncertain) and Supply Chain (Planning; Procurement; Inventory; Order; Orders). The first step in the execution of our method depicted in Figure 38 was performing a pilot search on Google scholar using our major terms. We retrieved a total of 303 papers in our step 1 results. The papers were scanned, and any relevant new terms were derived. We then derived our search string using Boolean AND/OR operators with our major and alternative terms.

> ON ABSTRACT *((“Forecast*” OR “Predict*”) AND (“Product*” OR SKU” OR “Stock Keeping Unit”) AND (“Demand” OR “Availability” OR “Sales” OR “Stochastic” OR “Noisy” OR “Unknown” OR “Uncertain”) AND (“Supply Chain” OR “Procurement” OR “Inventory” OR “Order*”, OR “Planning”))*

The search string was used on relevant high ranked journals and conference proceedings[11] for searching. The third author who is considered an expert in SCM supplied a list of top-ranked SCM Journals. For the primary search we executed the search string on selected specific resources, we retried a total of 338 papers in our results from step 2. We also applied a limit on the year during this primary search, we posed the limit between 2007 and 2018 to ensure we capture the most recent works on forecasting demand in the supply chain. Irrelevant papers that had been retrieved due to a poor search execution by online search engines were filtered out at step 3 of the SLR process. Any papers not in the English language and papers that were published before 2007 were excluded. We were left with 178 relevant papers.

[11] Based on Australian CORE ranking core.edu.au

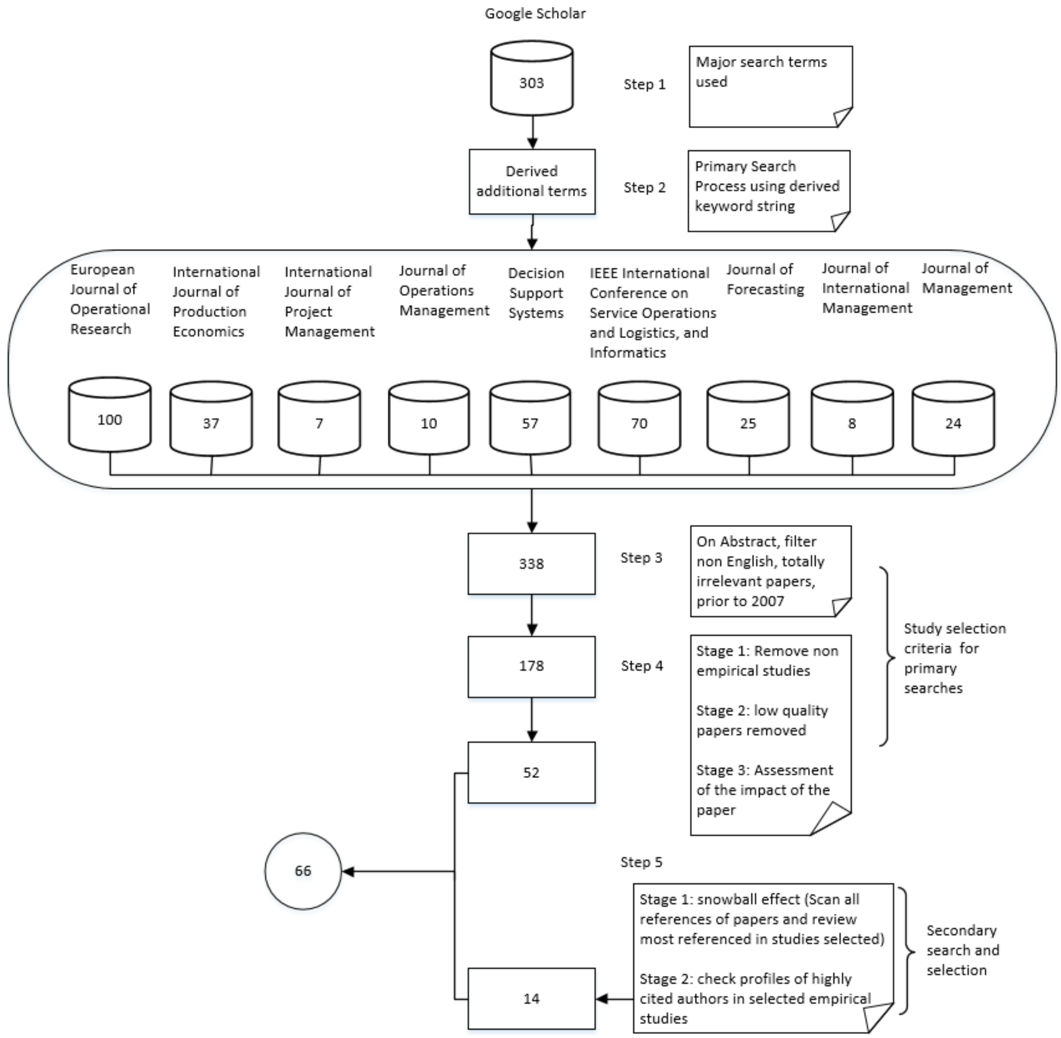

Figure 38 SLR process execution

In step 4 we read the full short-listed papers and performed a three-step quality assessment as follows:

Step 4.1: Quality of the study – The studies that have utilised poorly described research methods or have not used real data from the industry were filtered out. A decision was also made that any paper which used simulation with random data (not based on real data) did not meet the selection criteria and was excluded. Duplicate studies or studies that were not relevant to the supply chain or were Literature reviews, PhD or Masters theses were also excluded. We used the quality assessment checklist from SLR guidelines (see Appendix F). The quality assessment was not used for scoring or ranking but rather to filter out low-quality publications at the time of data extraction. All the papers that scored more than 50% were included in our review and all the others were excluded. For any differences, we had in selecting the appropriate literature the decision of the second author (Supervisor) was considered final.

Step 4.2: Quality of the publication outlet – For evaluating the quality of the outlet where the papers have been published, we utilized the ABDC (Australian Business Deans Council) ranking of 2016[12]. ABDC is committed to review and ensure the quality list rankings of journals. The outlets where the selected papers were published may not necessarily indicate the quality of the paper itself. To ensure the quality of the included papers, we already have assessed them through the quality checklist as described above and provided in Appendix F.

Step 4.3: Assessment of the impact of the paper – To assess the impact of the published papers, we checked their citations through Google Scholar. Out of 178 relevant papers, 54 remained, and 2 were excluded based on their low quality when evaluated against our quality assessment checklist (Appendix F). We were left with 52 empirical studies in Step 4. We then performed step 5 where we devised a secondary search strategy which included two steps to ensure that we do not miss any of the relevant studies. The secondary search strategy ensured the completeness of our results.

As part of Step 5 we performed a two-step secondary search and selection of studies as follows:

Step 5.1 of our secondary search was to complete a snowball scan on all the references in our selected studies. We scanned and reviewed all references that were cited greater than four times in our included studies. Using this snowballing approach, twelve articles were identified and added. The selected studies were applied to the same inclusion/exclusion criteria. However, in the screening process, they were found to be published before 2007 and had not provided any new and noteworthy insights that were not included in the selected studies of the last 10 years.

Step 5.2 of our secondary search had a selection criterion to check the publication profiles of four authors who were cited in our selected studies 10 or more times for their work on forecasting uncertain demand. These authors are: Fildes, R, Syntetos, A. A, Gardner, E. S, and, Cachon, G.P. We scanned all their published papers (from 2007 onwards) and those that were eligible for consideration were treated with the same two-step study selection criteria described above. We retrieved a further 14 studies that were relevant and were not included in our primary search results, these studies were included in the final list. At the end of these two steps of secondary search strategy, we ended up with a total of 66 papers for our final inclusion.

G2. Results from Systematic Literature Review

As part of the research methodology phase 3 of reporting results, in this section, we describe the quality characteristics extracted from the 66 empirical studies. Out of the 66 studies, 49 are from A* ranked journals from ABDC, which indicates we have an overall high-quality set of result. All the papers that have been included in our review were those that contained

[12] www.abdc.edu.au/master-journal-list.php

sufficient information about the research method used and hence they scored above 50% in the quality assessment checklist provided in Appendix F.

Out of the 66 papers, the average number of papers per years is 5.5 papers for the period chosen. The highest studies found were in 2015 followed by 2014 and 2007. Figure *39* shows an overall summary of the resultant studies by journal and year.

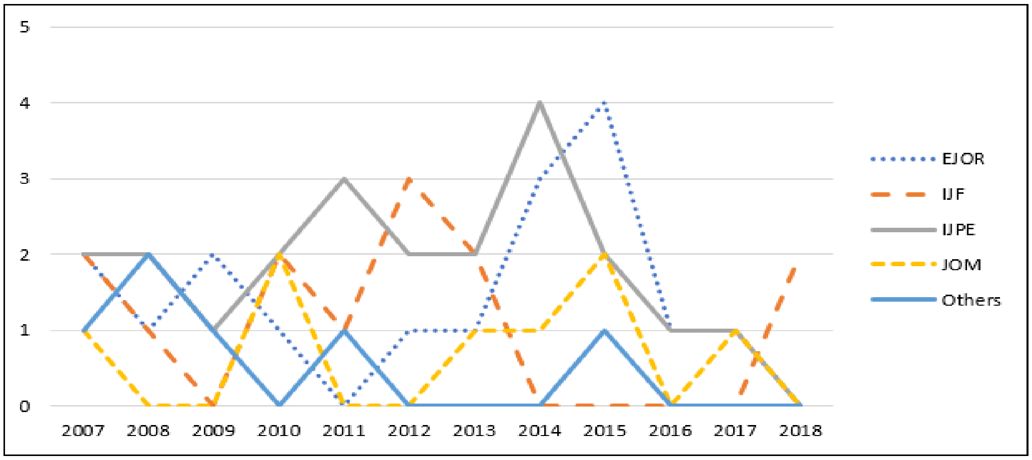

Figure 39 ***Publication by journal and year of resultant studies***

It is important to note that 60 of the included studies (22 from Journal of Production Economics, 17 from the European Journal of Operational research, 13 from International Journal of Forecasting and 8 from Journal of Operations management), are published in high ranked outlets with highest impact factors for many years. Our collection of the 66 empirical studies contains 37 experiments, 14 case studies and 15 surveys, 35 have used a statistical method in the research method (Figure 40).

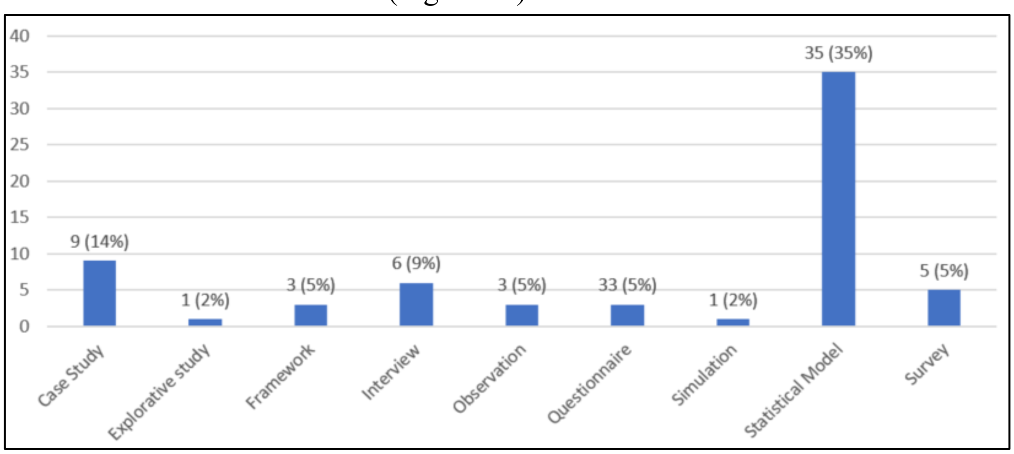

Figure 40 Research methodologies used in resultant studies

The percentages of research methods utilized in the included studies are experiments 56%, case studies 23%, survey 21%. From 2008 through to 2018 there is an average of 3 studies that are using a mathematical method and almost all of them are of very high quality and are published in A+ ranked journals.

One-third of the 66 studies are from the United Kingdom (

Figure 41). Other countries with the most studies are the USA, France and the Netherlands.

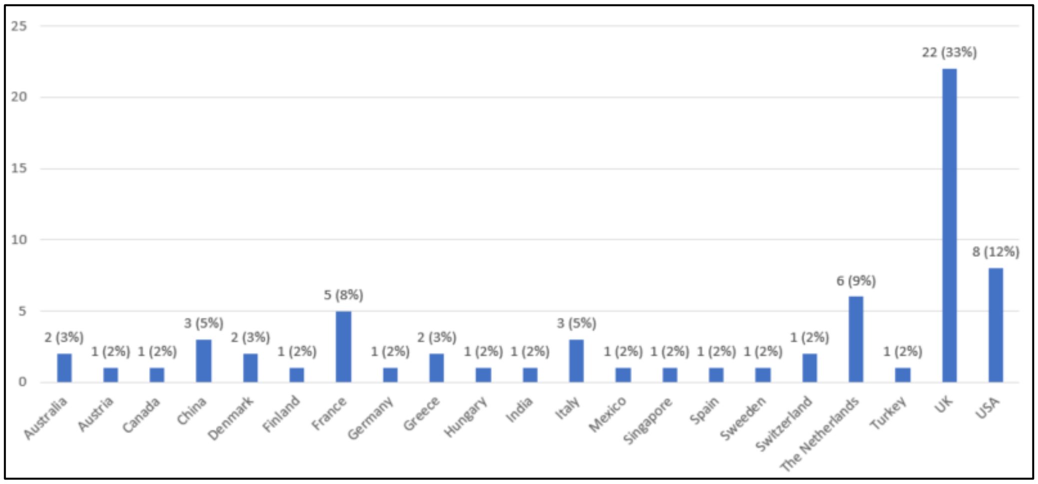

Figure 41 Primary geographic location of resultant studies

ANALYSIS

Based on the 3-phase SLR research methodology discussed in chapter 3, we now provide our findings to answer the research questions based on the data extraction from our set of 66 studies and their analysis. We used Excel for coding, syntheses and analysis of the studies. First, we extracted all the forecasting methods, barriers in forecasting and the solutions adopted to address the barriers which were later used for classification and cross-analysis. Thematic coding was used for the barriers in forecasting and the solutions adopted to address these barriers to identify common themes. Firstly, internal and external categories were derived, and the barriers and solutions extracted from the studies were coded against them. We then further identified multiple themes focusing on internal and external classifications of barriers. Similar themes identified were synthesized and dimensions of the results were created to provide further depth of barriers by incrementally creating several dimensions. Dimensions are generally categorical data and have also been called a variable (Nickerson et al.'s, 2013). In this paper, we define our dimensions as the characteristics of the barriers faced and solutions adopted in forecasting uncertain product demand. We created 6 dimensions for internal barriers and 5 for external, there was only one common dimension between the two categories which is “technology”. All the barriers and solutions derived from the studies were then classified against a dimension.

The identification number of the studies were captured against each barrier, solution and method extracted, frequency analysis was then carried out against this coding. Data was extracted in excel on the methods supporting a solution and which barriers were addressed by the solutions extracted. This analysis allowed us to produce the relationships between the barriers, solutions and methods (chapter 2.4.1), as well as in coming up with the decision-making framework (chapter 2.4.3)

Appendix H. Results from Card sorting exercise

The card sorting exercise was completed by all participants within the scheduled meeting. 36 cards were placed against the high priority, 24 medium and 15 low. The three blank cards provided were not used by any participants.

CRITERIA AND PRIORITIES

The participants were not given specific criteria to priorities the cards, the participants were only instructed to place the cards into one of the three priorities provided (high, medium & low priority). As depicted in Fig 3. the most used priority category by the participants (48%) was a high priority.

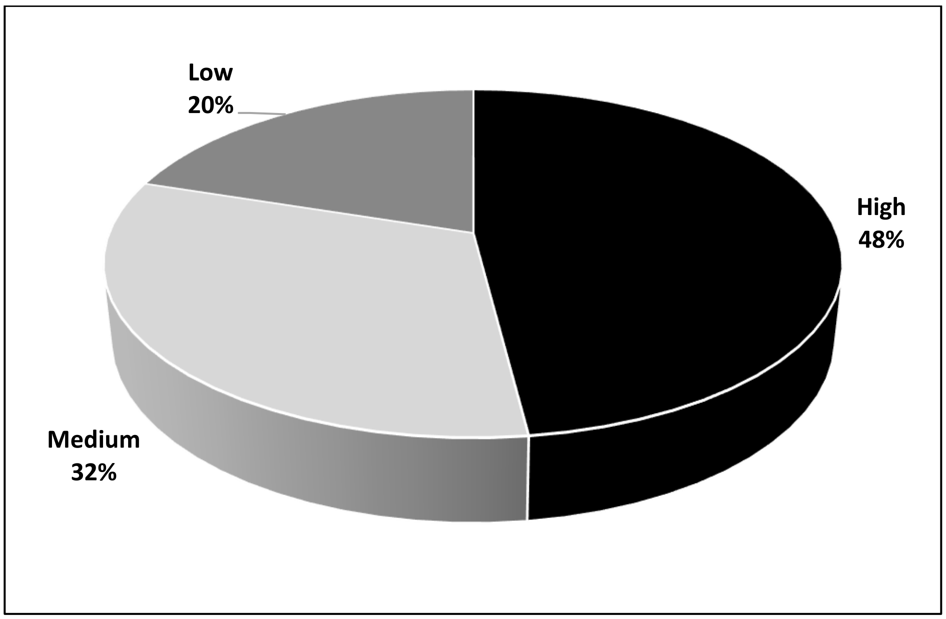

Fig. 3. Percentage of cards sorted against priority

Out of the 25 cards provided, 23 had at least one participant placing it in the high priority. Both cards number 13 “As a sales representative manager, I want better communication on product availability during the holiday periods so that I can communicate better with our customers.” and card number 19 “As a supply chain stakeholder, we need to restrict the customer exchange policy, so we don’t get caught up with old stock.” had no participants placing them in high priority. Using the unique number for each user story, Fig 4. Illustrates the total number of unique cards placed in each priority.

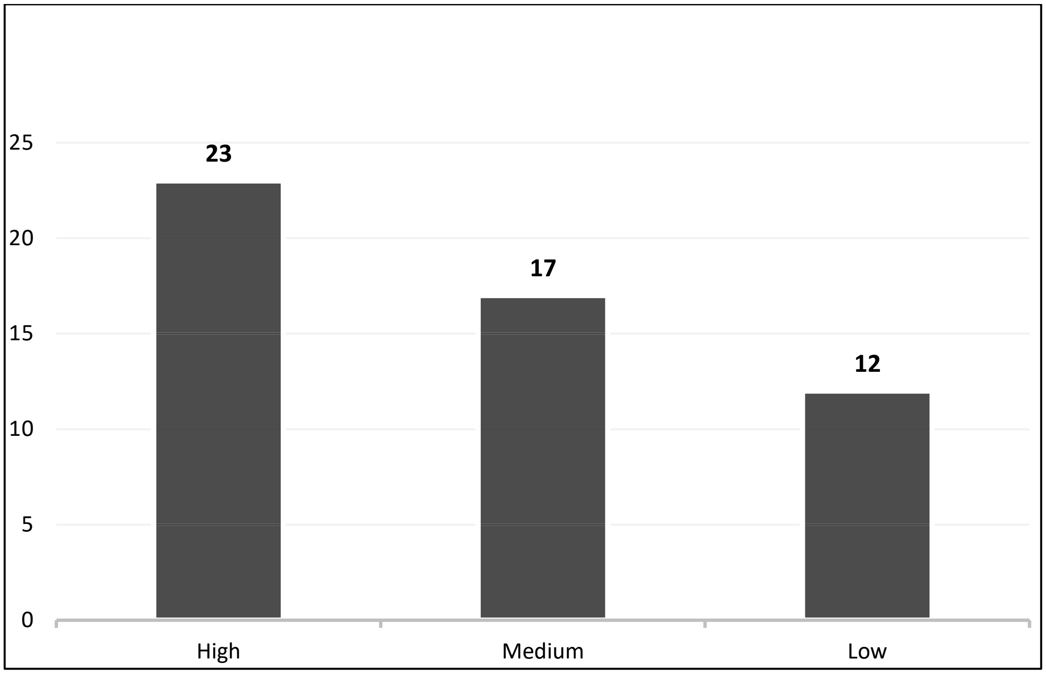

Fig. 4. Number of unique cards placed in each priority

The following is the results of our analysis on the user story stakeholders that have been categorised against a priority (H= High, M= Medium, L= Low). From the 25 user stories, there were a total of 7 user story stakeholders. Only two of the stakeholders (Sales representative and Supply chain stakeholder) had cards placed against all priorities, this may be due to them having the greatest number of cards. The remaining stakeholders either have a priority of High/Low or High/Medium. The participant's distribution of priority by user story stakeholder is presented in Table 1.

User Story Stakeholder	**# of cards with Stakeholder**	**Possible Combinations**	**H**	**M**	**L**
Supply chain stakeholder	8	24	10	10	4
Sales manager	3	9	6	3	0
Category manager	3	9	5	4	0
Product engineer	3	9	5	0	4
Sales representative	5	15	5	4	6
Finance manager	2	6	3	3	0
Supplier	1	3	2	0	1
Total	**25**	**75**	**36**	**24**	**15**

Table. 1. List of priorities by user story stakeholder

The results of the prioritization of requirements also demonstrate the difference in importance between the participants. Table 2 demonstrates the lack of consensus among the participants and that not all the requirements are equally important. There were 3 cards that had consensus among the participants, 2 cards (#4, #16) having all 3 participants categorizing them with high priority and 1 card (#19) with medium priority.

Card #	**H**	**M**	**L**
4	3	-	-
16	3	-	-
19	-	3	-
Total Consensus	2	1	-

Table. 2 Total number of cards that had consensus

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