JÖNKÖPING UNIVERSITY
School of Engineering

Licentiate Thesis

Developing Decision-Support Tools for Evaluation of Manufacturing Reshoring Decisions

Movin Sequeira

Jönköping University
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Dissertation Series No. 054 • 2020

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Licentiate Thesis in Production systems

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Published by
School of Engineering, Jönköping University
P.O. Box 1026
SE-551 11 Jönköping
Tel. +46 36 10 10 00
www.ju.se

Printed by Stema Specialtryck AB 2020

Trycksak
3041 0234

ISBN 978-91-87289-57-6

Abstract

During last three decades, companies have offshored their manufacturing activities across international borders in order to pursue lower manufacturing costs. Despite having accomplished their purpose, companies have also suffered from issues, especially poor quality of products and a poor response to customer demand. Therefore, companies consider relocating some of the manufacturing activities back to the home country, a process that is known as manufacturing reshoring. There is paucity of scholarly attention on how manufacturing reshoring decisions are evaluated and supported. Therefore, the purpose of this thesis is to develop decision-support tools to evaluate manufacturing reshoring decisions. In order to fulfil this, it is important to know how industry experts reason while making manufacturing reshoring decisions (RQ1), and how their reasoning can be modeled into decision-support tools (RQ2). Therefore, three studies were conducted including a multiple case study and two modeling studies. The multiple case study addressed the criteria that are considered by the industry experts in these decisions, while the two modeling studies, based on fuzzy logic and analytical hierarchy process (AHP), used a part of these criteria to develop decision-support tools. The findings indicate that a holistic set of criteria were considered by industry experts in arriving at a manufacturing reshoring decision. A large portion of these criteria occur within competitive priority category and among them, high importance is given to quality, while low importance to sustainability. Fuzzy logic modeling was used to model the criteria from the perspective of competitive priority at an overall level. Three fuzzy logic concepts were developed to capture industry experts' reasoning and facilitate modeling of manufacturing reshoring decisions. Furthermore, two configurations and sixteen settings were developed, of which, the best ones were identified. AHP-based tools were used to capture experts' reasoning of the competitive priority criteria by comparing the criteria. It was observed that fuzzy logic-based tools are able to better emulate industry experts' reasoning of manufacturing reshoring. This research contributes to theory with a holistic framework of reshoring decision criteria, and to practice with decision-support tools for evaluation of manufacturing reshoring decisions.

Keywords: Manufacturing reshoring, decision-making, support tools, fuzzy logic, AHP

Sammanfattning

Under de tre senaste decennierna har många företag flyttat sin produktion till lågkostnadsländer för att kunna utnyttja lägre lönekostnader. Många gånger har företagen genom denna åtgärd lyckats sänka sin tillverkningskostnad men samtidigt drabbats av oförutsedda problem kopplat till exempelvis produkt-kvalitet och möjligheten att kundanpassa produkter. Hanteringen av problemen har lett till ytterligare kostnader som många gånger överstigit besparingen i tillverkningskostnad. Detta har lett till att allt fler företag börjat flytta tillbaka sin produktion till hemlandet, så kallad reshoring. Reshoring är ett ungt område där det saknas forskning gällande bland annat hur den här typen av beslut på bästa sätt kan utvärderas och vilken typ av beslutstöd som kan underlätta den här typen av beslut. Därför är syftet med den här avhandlingen är att utveckla beslutsstödverktyg för utvärdering av reshoring beslut. För att uppfylla syftet har två forskningsfrågor formulerats. Den första frågan handlar om hur industriexperter resonerar kring reshoring beslut (RQ1) medan den andra frågan handlar om hur deras resonemang kan modelleras i beslutsstödverktyg (RQ2). Tre studier har genomförts för att besvara forskningsfrågorna, en fallstudie och två modelleringsstudier. Fallstudien fokuserar på att identifiera vilka kriterier som industriexperter beaktar medan modelleringsstudierna fokuserar på att utveckla beslutstödsverktyg där en del av dessa kriterier beaktas, med hjälp av fuzzy logic och analytical hierarchy process (AHP). Resultaten från forskningen visar att industriexperter bedömer reshoring beslut utifrån ett holistiskt perspektiv. En stor del av dessa beslutskriterier finns inom konkurrenskraft kategorin och inom dessa, har industriexperterna lagt högst vikt på kvalitet och lägst vikt på hållbarhet. Genom fuzzy logic modellering modellerades kriterierna på en övergripande nivå. Tre nya fuzzy logic koncept utvecklades för att fånga experternas resonemang. Dessutom utvecklades två konfigurationer med sexton olika inställningar, och de bästa identifierades. AHP-baserade verktyg utvecklades för att fånga experternas resonemang om kriterierna för konkurrenskraft prioriteringar. Fuzzy logic-baserade verktyg kan bättre fånga experternas resonemang kring reshoring beslut. Denna forskning bidrar till teori med en holistisk lista över beslutskriterier för reshoring beslut, och till praktik med beslutsstöd verktyg för utvärdering av reshoring beslut.

Nyckelord: Produktion, reshoring, beslutsstödverktyg, fuzzy logik, AHP

Acknowledgement

This thesis marks my journey of past two and half years. I am deeply thankful to all those who have supported and inspired me during this enriching journey of pursuit of knowledge.

Firstly, I owe a debt of gratitude to my main supervisor Per Hilletofth for discovering my potential and believing in me. Thank you for guiding and inspiring me during this journey. Your feedback has greatly enriched this thesis. I also thank my co-supervisor David Eriksson who guided and encouraged me in this journey. Your appreciation and positivity have greatly helped me in this journey. I also thank Anders Adlemo and Wendy Tate, who have co-authored in the appended papers.

I take this opportunity to thank the companies from Reshoring project, who provided empirical data for the thesis. Thank you for your valuable time and support. I also thank my department colleagues, from both Supply Chain and Operations Management, and Industrial Product, Production Development and Design, for supporting me in operations. I express my gratitude to the those who have supported me continuously in administrative matters from my admission as a doctoral student until now. I thank fellow doctoral students, for engaging discussions and arranging activities that helped me relax during this journey.

I am grateful to my parents for loving me as I grow up. Thank you, dad and mom, for your love. Next, I thank my sister for being supportive in this journey. I also thank my in-laws for their love and support. Sincere and heartfelt gratitude also goes to all my family and friends in India and Sweden for their support. In particular, I thank my friends who are like my family in Jönköping who have made my life all the more meaningful. Last, but most importantly, I thank my wife, Anvitha for being by my side throughout this journey.

Movin Sequeira

Jönköping, May 2020

List of appended papers

This thesis is based on the publications below.

Paper I

Sequeira, M., Hilletofth, P., Eriksson, D., (2020), "Criteria considered in a reshoring decision: a multiple case study", Manuscript submitted for review (under review).[1]

Paper II

Hilletofth, P., Sequeira, M., Adlemo, A., (2019), "Three novel fuzzy logic concepts applied to reshoring decision making", *Expert Systems with Application, 126*, 133-143.

Paper III

Hilletofth, P., Sequeira, M., Tate, W., (2020), "Feasibility of fuzzy logic in reshoring decision making", Manuscript submitted for review (under review).[2]

Paper IV

Sequeira, M., Hilletofth, P., Eriksson, D., (2020), "Feasibility of AHP support tools in reshoring decision making", Manuscript submitted for review (under review).[2]

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[1] An earlier version of this paper was submitted and accepted at the 9th Swedish Production Symposium (SPS), Jönköping, Sweden. 6-9 October 2020.
[2] An earlier version of this paper was presented at the 9th International Conference on Operations and Supply Chain Management (OSCM), Ho Chi Minh City, Vietnam. 15-18 December 2019.

Author’s contribution in the appended papers

The contribution of the author in the appended papers is described by roles in accordance with the CRediT taxonomy[3], as shown in Table 1.

Table 1 Author's contribution in appended papers

Contributor roles	Paper I			Paper II			Paper III			Paper IV		
	Sequeira, M.	Hilletofth, P.	Eriksson, D.	Hilletofth, P.	**Sequeira, M.**	Adlemo, A.	Hilletofth, P.	**Sequeira, M.**	Tate, W.	**Sequeira, M.**	Hilletofth, P.	Eriksson, D.
Conceptualization		X		X			X			X		
Data curation	X	X		X	X		X	X		X		
Formal Analysis	X	X	X	X	X	X	X	X		X		
Funding acquisition		X		X			X				X	
Investigation	X	X	X	X	X	X	X	X		X		
Methodology	X	X	X	X	X	X	X	X		X		
Project administration		X		X			X				X	
Resources	X	X		X	X	X	X	X		X		
Software					X	X		X				
Supervision		X	X	X			X					X
Validation	X	X	X	X	X	X	X	X	X	X	X	X
Visualization	X	X		X	X		X	X		X	X	X
Writing- original draft	X			X			X			X		
Writing- review & editing	X	X	X	X	X	X	X	X	X	X	X	X

[3] CRediT or Contributor Roles Taxonomy defines 14 roles of academic contribution which can be accessed at https://casrai.org/credit/

Contents

List of figures

List of tables

1. Introduction

This chapter addresses the current scenario of manufacturing relocation and the associated decision-making involved in these relocations. It proceeds with identifying the problem area, that then leads to specific purpose and research questions of this thesis. Next, the chapter defines the scope of this research before presenting an outline for this thesis.

1.1 Background

Towards the end of the 20th century, manufacturing companies began facing intense competition, fueled by globalization and the advancement of information technologies (Hilletofth, 2010). This has impelled these manufacturing companies to persistently focus on cost cutting measures or disaggregate their value chain activities (Farrell, 2005; Thomas and Griffin, 1996). This further led firms to retain core value chain activities and relocate manufacturing activities across international borders. The relocation of manufacturing activities from home country to another country in order to support domestic activities is termed as 'offshoring' (Lewin and Peeters, 2006; Ketokivi et al., 2017). Offshoring is considered as an important strategy for improving competitive advantage; most significant of them have been cost advantages in terms of labor cost, disintegration advantages in terms of resource allocation, and globalization advantages in terms of access to new markets (Kedia and Mukherjee, 2009). Evidently, the decision to offshore has been an economically motivated decision where manufacturing firms have particularly capitalized on low cost of labor and natural resources (Kedia and Mukherjee, 2009; Da Silveira, 2014).

Even though manufacturing firms still continue the practice of offshoring, they are fraught with several challenges due to a changing importance of factors that originally motivated their offshoring decision (Ellram et al., 2013). Some of these challenges include 'hidden' costs of offshoring, for example extra monitoring costs and coordination costs (Holweg et al., 2011; Stanczyk et al., 2017), poor quality of offshored products (Canham and Hamilton, 2013), reduced responsiveness (Fratocchi et al., 2016), consumer perception of offshoring (Grappi et al., 2015), and increasing customization, among others (Hartman et al., 2017). Hence, the offshoring decisions have been incomplete in their analysis when investigated from the perspective of total cost (Eriksson et al., 2018; Gylling et al., 2015). This failure of making a holistic analysis, coupled with the rapidly changing importance of factors, has led manufacturing companies to relocate their previously offshored manufacturing back to their home country, which is termed as 'reshoring' (Gray et al., 2013; Wiesmann et al., 2017). Manufacturing reshoring continues to attract debates on whether it is an act of correction of managerial mistake or a mere result of changing competitive strategy that has been rational (Kinkel and Maloca, 2009; Di Mauro et al., 2018).

Manufacturing reshoring is not a widespread phenomenon, although it has elicited growing attention from researchers, practitioners, and policy makers (De Backer et al., 2016; Dachs et al., 2019; Wiesmann et al., 2017). To put this in perspective, only 4% of 1700 German manufacturing companies have reshored (Dachs et al., 2019), which supports an earlier finding where only 2% of 1600 German manufacturing companies were found to be active in reshoring between 2010 and 2012 (Kinkel, 2014). Another recent survey indicated that 26% of 373 Swedish manufacturing firms were active in reshoring (Johansson and Olhager, 2018). Despite this small proportion, reshoring activities are expected to increase with adoption of new technologies such as Industry 4.0 (Dachs et al., 2019), motivated by many factors, some of which are grouped homogenously as cost-related (Gylling et al., 2015), quality-related (Stentoft et al., 2016), market-related (Bals et al., 2016), risk-related (Tate et al., 2014) and supply chain-related (Ellram et al., 2013). On the other hand, reshoring activities are also hindered by many factors, some of which include a global economy, access to labor, and lack of decision-support (Engström et al., 2018a; 2018b).

The phenomenon of manufacturing reshoring remains novel and so far, it has been largely covered with respect to its drivers and barriers. One aspect of manufacturing reshoring that has received little attention is the decision-making or 'how' manufacturing reshoring is implemented (Barbieri et al., 2018; Wiesmann et al, 2017). Several future research agendas have identified this as a high priority for research (Stentoft et al., 2016; Barbieri et al., 2018). There are several reasons as to why manufacturing reshoring decision-making may have suffered from lack of attention in research. One plausible reason is that manufacturing reshoring decision-making is a complex process (Boffelli et al., 2018). Despite this apparent complexity, there exists a potential for understanding manufacturing reshoring decision-making and investigating decision-making tools which enable managers to analyze the ex-ante and ex-post reshoring scenarios. One way to realize this is to compile a checklist so that the managers are aware of possible criteria that should be considered in a decision ex-ante, thus averting unpleasant surprises ex-post (Kinkel and Maloca, 2009). Other ways are to explore semantic techniques (Hilletofth et al., 2019b), or multi-criteria decision-making techniques (Pal et al., 2018), that help provide an evaluation for different reshoring scenarios.

1.2 Problem area

Oftentimes, manufacturing reshoring decisions are based on large amounts of vague and uncertain information, which make these decisions difficult to handle. Due to the complexity of these decisions, the decision-making process has not been sufficiently studied. The lack of understanding of manufacturing reshoring decision-making implies that manufacturing companies find it difficult to evaluate their relocation strategies in order to stay competitive (Engström et al., 2018a). There are several issues that contribute to the complexity of the manufacturing reshoring decision-making process. The first issue is that it includes both qualitative and quantitative types of criteria (Gylling et al., 2015). Another issue is the paucity of knowledge of 'how much' information regarding the criteria that needs to be considered during the decision-making process. Some have contended that a complete information of complexity of the criteria is required prior to arriving at the manufacturing reshoring decision (Hartman et al., 2017). However, others have argued that there is no need to wait for complete information on the criteria before making the manufacturing reshoring decision, since it would render the manufacturing reshoring decision-making process inefficient and tremendously slow (Boffelli et al., 2018). Another issue that exacerbates the complexity is the interference of emotions into the decision, termed as "emotional reshoring" (Boffelli et al., 2018, p. 125), which should be avoided. Therefore, there is a need to identify rational ways of handling complex manufacturing reshoring decisions.

Various decision frameworks have been developed in order to rationally handle manufacturing reshoring decision-making problems. The existing decision frameworks have identified both qualitative and quantitative type of criteria, which can lead to a push or pull effect on reshoring (Joubioux and Vanpoucke, 2016; Bals et al., 2016). These frameworks have been conceptual and theoretical that require time-consuming analysis. One of them takes the departure from analyzing firms' pull and push factors of relocations (Joubioux and Vanpoucke, 2016). The analysis of push and pull factors were used in reaching one of the three decision alternatives: further offshore, maintain or reshore (Joubioux and Vanpoucke, 2016). However, the drawback of this approach is the lack of understanding of how these factors lead to the decision alternatives. This suggests that the decision-making process is related to a black box, where the observer cannot see what is occurring with the selected push or pull factors leading to the decision alternative. Another conceptual framework was developed from offshoring and outsourcing literature (Bals et al., 2016). This generic conceptual framework stresses the need to conduct further research on manufacturing reshoring decision-making (Bals et al., 2016). Considering the current research within manufacturing reshoring decision-making that largely consists of conceptual, theoretical, generic and time-consuming models, a clear research gap exists in decision-making with respect to tools and managerial support. Thus, there is a need for decision-support tools that are practical, rapid, and resilient.

Large amounts of data from real cases are required in order to realize decision-support tool for reshoring. The data not only pertains to the involved qualitative and quantitative criteria, but also to 'how' the criteria were considered and 'how' it led to a manufacturing reshoring decision. Currently, there is paucity of this type of data on these decisions in particular, or the type of data is difficult to obtain. Some databases have been created (e.g., UniCLUB or European Reshoring Monitor); yet, they don't explain 'how' these decisions were taken, or the tools that were involved in the decision-making stage. This lack of data should not be a barrier in building tools that can support managers in making resilient manufacturing reshoring decisions. In this context, one of the decision-support tools was developed through modeling approaches from the perspective of total landed cost (Gray et al., 2017). In this tool, attention was given to more quantitative factors, and it was suggested that modeling qualitative factors such as quality or flexibility, would require a different set of heuristics. For that purpose, different decision-making tools need to be explored for manufacturing reshoring decisions, especially those that can incorporate qualitative factors and uncertainty, which are an intrinsic part of manufacturing reshoring decisions. In addition to the fact that managers would benefit greatly from a tool that provides an automatic and rapid evaluation of a manufacturing reshoring decision, developing a decision-making tool would contribute to building knowledge and skills within manufacturing reshoring decisions, given that this could be a success factor in future making relocation decisions (Hilletofth et al., 2019a; 2019b).

1.3 Purpose and research questions

As manufacturing reshoring is a rather novel topic, the body of literature produced is small, but quickly gaining momentum (Barbieri et al., 2018). The existing directions of reshoring research have not adequately covered the decision-making process, according to three recent reviews of the topic (Barbieri et al., 2018; Stentoft et al., 2016; Wiesmann et al., 2017), classifying manufacturing reshoring decision-making as a 'high-priority' research within the topic (Barbieri et al., 2018). Other researchers have argued the lack of tools is unable to support this type of decision (Kinkel, 2012; Wiesmann et al., 2017). Therefore, there is an urgent need to develop tools which can support these decisions, despite the lack of large amount of data in manufacturing reshoring decision-making. Developing manufacturing reshoring decision-support tools, that are resilient, will build knowledge and capabilities in reshoring and that is where the future research should focus on (Hilletofth et al., 2019a). Therefore, in order to address the shortcomings of reshoring research stated above, the overall purpose of this research is:

To develop decision-support tools for evaluation of manufacturing reshoring decisions.

In order to fulfill the purpose, two research questions have been formulated. The first research question (RQ1) explores how individuals in-charge of making important decisions in a manufacturing company (henceforth called industry experts) reason in manufacturing reshoring decision-making. The essence of this question is to capture the mind of an industry expert while making a manufacturing reshoring decision. The reasoning behind a manufacturing reshoring decision can be addressed with respect to two aspects. The first one is the content of manufacturing reshoring decision-making while the second one is its process. The content of manufacturing reshoring decision-making are those criteria that are considered in the decision, while the process of manufacturing reshoring decision-making are those activities that are undertaken to make a manufacturing reshoring decision. In this research, the focus will be on the content of the manufacturing reshoring decision-making (i.e., criteria), while in future it is desirable to cover the decision-making process. It is suggested that criteria should move away from traditional cost factors towards more holistic factors (Hartman et al., 2017). The need for such a question is to holistically cover the qualitative and quantitative criteria within manufacturing reshoring decision-making, that are considered by industry experts. Therefore, RQ1 is formulated as follows:

RQ1. How do industry experts reason while making manufacturing reshoring decisions?

Next, after learning the reasoning in the form of decision criteria, it is desirable to know how this reasoning behind manufacturing reshoring decisions can be modeled into a decision-support. The second research question (RQ2) is concerned with modeling the reasoning behind making a manufacturing reshoring decision. In order to do so, expert systems are selected to model that uses both facts and heuristics to evaluate complex manufacturing reshoring decision-making. In this research, fuzzy logic-based tools will be explored since they are able to handle uncertainties. Furthermore, modeling decision-support allows to understand how industry experts think around the relationship between the criteria and the manufacturing reshoring decision. Modeling of manufacturing reshoring decisions eventually leads to tools that support managers in manufacturing reshoring decision-making. These tools can be used to predict the manufacturing reshoring decision, which, in turn, increases the knowledge of decision-making within manufacturing firms, thus increasing competitiveness within relocation. Therefore, the RQ2 is formulated as follows:

RQ2. How can industry experts' reasoning in manufacturing reshoring decisions be modeled in decision-support tools?

The research questions seek to increase our understanding of the manufacturing reshoring decision-making process and the criteria that are taken into consideration during this process. RQ1 gives an overview of what criteria are considered by the industry experts, while RQ2 explores how industry experts' reasoning is modeled into decision-support tools. This will eventually lead to development of decision-support tools in order to evaluate manufacturing reshoring decisions. Fulfilling the overall purpose will have implications for both research and practice.

1.4 Scope of the research

Manufacturing relocation decision is a broad research domain and a much-debated issue. The choice of where manufacturing should be located is dynamic based on existing internationalization frameworks (Lewin and Peeters, 2006). Manufacturing relocations can be further distinguished into relocation to a far country, which refers to 'offshoring' (Ketokivi et al., 2017), relocation to a neighboring country, which is termed as 'nearshoring' (Ellram et al., 2013; Panova and Hilletofth, 2017) or a relocation back to the home country, known as 'reshoring' (Wiesmann et al., 2017; Barbieri et al., 2018). This research will only address reshoring to home country.

As in other relocations, the reshoring process can be divided into two phases: feasibility phase and implementation phase (Boffelli et al., 2018). The feasibility phase consists of feasibility analysis where information regarding the criteria is gathered and analyzed. This is followed by a manufacturing reshoring decision that is still considered to be within the feasibility phase. The manufacturing reshoring decision is followed by the implementation phase, which addresses the manner in which activities can be physically disintegrated from the location and re-integrated at the new location (Bals et al., 2016). This research will only focus on the feasibility stage, particularly decision-making. Within this stage, it is crucial to know how industry experts reason with regard to the criteria and how these criteria can be modeled into decision-support tools.

Furthermore, with increasing integration of services within manufacturing, scholars have positioned research depending on whether it is a manufacturing activity or a service that is reshored (Albertoni et al., 2017). Most research within reshoring addresses the former; however, there are instances where companies have reshored IT services as well. This research is delimited to physical products or manufacturing activities that are reshored. The entire scope of the research can be visualized following the black boxes illustrated in Figure 1.

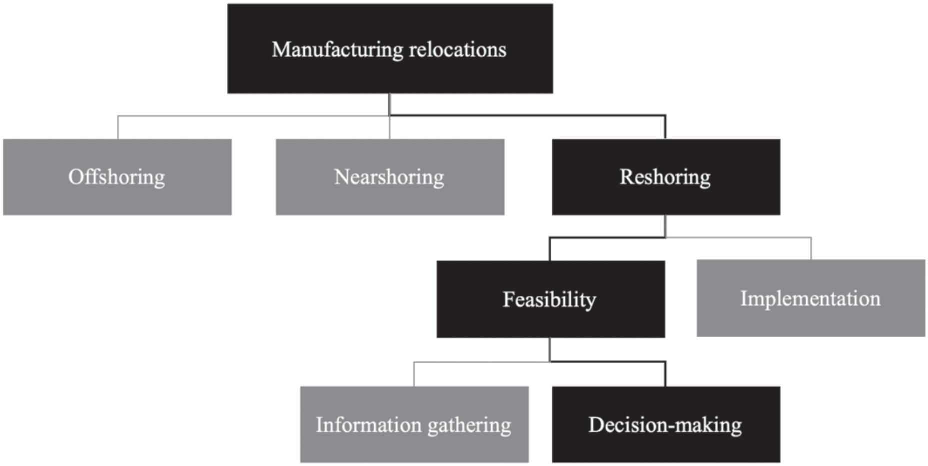

Figure 1 Scope of the research

1.5 Thesis outline

This thesis consists of six chapters and four appended papers. A brief description of each chapter is presented below:

Chapter 1: Introduction
This chapter addresses the current scenario of manufacturing relocation and decision-making involved for such relocations. The chapter proceeds with an identification of the problem area, that leads to specific purpose and research questions. Subsequently, it defines the scope of the research and presents an outline for this thesis.

Chapter 2: Literature review
This chapter describes the existing research within two umbrella topics based on which this thesis is developed: manufacturing reshoring and decision-support systems. Within the domain of manufacturing reshoring, the chapter begins with a definition of manufacturing reshoring, and is followed by a description of reshoring decision-making process, influencing factors and decision-support tools for a reshoring decision. Within the domain of

decision-support systems, the chapter addresses expert systems, followed by description of fuzzy logic-based and AHP-based decision-support.

Chapter 3: Research methods

This chapter describes the research process that was used to answer the research questions. In total, three studies were conducted, which are reported in four research papers. The chapter begins by connecting the purpose, research questions and the studies. This is followed by a description of the studies as well as the data collection and analysis procedures of each study. The chapter ends by discussing the research quality.

Chapter 4: Summary of papers

This chapter summarizes the main empirical and theoretical findings from the four appended papers. First, a summary of each paper is provided. Each paper presents the purpose, a short description of the research method and main findings. Next, the chapter summarizes how the findings from the appended papers have contributed to answering the research questions presented for this thesis.

Chapter 5: Discussion

This chapter discusses the findings from the research and appended papers in relation to the literature. The discussion commences with the results of the research by answering the research questions, followed by the contribution of the research to theory and industry. The chapter ends with a discussion on the limitations of the research methods and the research in its entirety.

Chapter 6: Conclusion

This chapter concludes the research by reflecting on purpose of the thesis and the process using which it was fulfilled. The chapter further shows way for future research, and the intended path towards the PhD dissertation.

2. Literature review

This chapter describes the existing research within two umbrella topics based on which this thesis is developed: manufacturing reshoring and decision-support systems. Within manufacturing reshoring, the chapter begins with a definition of manufacturing reshoring, which is then followed by a description of reshoring decision-making process, influencing factors and decision-support tools for a reshoring decision. Within decision-support systems, the chapter addresses expert systems, followed by description of fuzzy logic-based and AHP-based decision-support.

2.1. Manufacturing reshoring

Manufacturing reshoring refers to the process of bringing manufacturing back from a foreign country to home country, which is the opposite of offshoring. Since the phenomenon was quite novel in the beginning of this decade, reshoring had been addressed using many inconsistent terms (see e.g. Fratocchi et al., 2014; Wiesmann et al., 2017). However, as research progressed, a certain consensus has been reached around the terms. In particular, two of the terms, 'reshoring' and 'backshoring', have been most popular (Barbieri et al., 2018). In order to further understand reshoring, it is important to clarify its definition.

2.1.1. Defining manufacturing reshoring

The term 'reshoring' was used in a seminal work in this topic and defined as "fundamentally a location decision" (Gray et al., 2013, p. 28). This means that reshoring is only concerned with the location and not with ownership of manufacturing. Combining location and ownership dimensions, four different typologies of reshoring were proposed: in-house reshoring, reshoring for outsourcing, reshoring for insourcing, and outsourced reshoring (Gray et al., 2013). Meanwhile, the term 'backshoring' was used in the very first empirical study in a journal that shed light on the phenomenon by providing evidence from German manufacturing firms (Kinkel and Maloca, 2009). Backshoring is defined as "the re-concentration of parts of production from own foreign locations as well as from foreign suppliers to the domestic production site of the company" (Kinkel and Maloca, 2009, p. 155). This implies that backshoring may or may not result in a transfer of ownership. It was later argued that backshoring should only concern transfer of own activities, and not transfer of externally owned activities (Arlbjørn and Mikkelsen, 2014). However, the initial definitions have prevailed and the terms 'backshoring' and 'reshoring' are now being used interchangeably (Dachs et al., 2019).

2.1.2 Decision-making process

The manufacturing reshoring decision-making process is inherently complex. It consists of two phases: the feasibility phase and the decision-making phase (Boffelli et al., 2018). These two phases are separated by the point of decision. In the manufacturing reshoring decision-making process, the decision criteria impact both the phases. The criteria, which impacts the feasibility phase, include those criteria that are considered in pre-study and all the way until the decision. Similarly, the criteria impacting implementation phase include those that are considered after the point of decision (Figure 2).

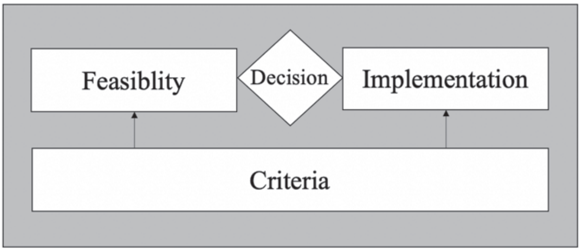

Figure 2 The manufacturing reshoring decision-making process

Several frameworks have been created in order to handle manufacturing reshoring decision-making in a systematic manner. Most of these frameworks have been theoretical and conceptual, implying that there is inadequate information on how these frameworks have been used in practice. One of the more advanced theoretical frameworks departs from the contingency theory by identifying contingency factors in the decision-making process (Benstead et al., 2017). The framework differentiates between the feasibility and implementation considerations in a manufacturing reshoring decision (Benstead et al., 2017). However, this approach lacks decision-support with respect to how the different considerations are to be tackled and arrive at a manufacturing reshoring decision. Another conceptual framework identifies the reshoring process as a series of eight procedures that were classified into two: a decision-making process (similar to feasibility) and a decision-implementation process (Bals et al., 2016). This framework shows reshoring as a linear process. However, this is debated as another framework develops further details of the manufacturing reshoring decision-making process as well as the decision-implementation process (Boffelli et al., 2018). This framework argues that the reshoring process is not linear, but cyclical or iterative. It also posits that there is no clear distinction between the manufacturing reshoring decision-making and implementation process (Boffelli et al., 2018). This further emphasizes the complexity of decision-making, and the need to develop different types of reshoring tools.

2.1.3 Influencing factors

Three kinds of factors are known to influence the manufacturing reshoring decision-making process: drivers, barriers, and enablers. Most of the existing research on reshoring has focused on reshoring drivers. A driver is defined as a factor that can cause a reshoring to occur (Kinkel and Maloca, 2009). Among the many drivers identified, the most relevant of them are increased flexibility in manufacturing due to growing demands from customers, lack of quality of offshored products, long delivery lead times for offshored products and hidden costs involved with offshoring due to excessive coordination and monitoring (Kinkel and Maloca, 2009; Dachs et al., 2019). The reshoring drivers are categorized into different theoretical frameworks that are popular within international business or strategic management domains (Fratocchi et al., 2016; Ancarani et al., 2015). The different frameworks emphasize on different drivers, since not all of the drivers clearly fit into these theoretically developed categories (Barbieri et al., 2018). Interestingly, many of the reshoring drivers have been empirically studied in a specific home country or regional contexts (Ellram et al., 2013). This is because it makes a greater contribution to theory and policy regarding these home countries. For example, evidence from Germany showed that quality and flexibility were the main drivers of reshoring activities (Kinkel and Maloca, 2009; Kinkel, 2014). Similarly, evidence from the Nordic countries showed that labor cost, quality, flexibility, access to knowledge, time to market and trade barriers were significant drivers of reshoring activities (Heikkilä et al., 2018). Additionally, evidence from the USA and Spain also show that quality and labor costs are significant drivers of reshoring activities (Zhai et al., 2016; Martinez-Mora and Merino, 2014).

Therefore, quality and cost are common drivers for reshoring, irrespective of the regional context.

Where drivers are treated as those factors that encourage reshoring, barriers are those factors that prevent reshoring. Like the drivers of reshoring, the barriers of reshoring have also been able to cut through theoretical frameworks (Engström et al., 2018a; 2018b; Wiesmann et al., 2017). The most frequently used framework for reshoring barriers classifies them into home country, host country, supply chain or firm level barriers. Only a few studies have covered the barriers and more research is needed on the topic (Bailey and De Propris, 2014a, Wiesmann et al., 2017). Surprisingly, labor cost is still considered significant in reference to barriers since some of the host countries have not increased their wages in comparison to home country (Bailey and De Propris, 2014a). Other barriers include issues with accessing skilled workforce and stringent regulations enforced in the home country (Bailey and De Propris, 2014a; 2014b). This could suggest that barriers may be specific to home or host-countries. However, with recent empirical evidence in the form of in-depth case studies, it is argued that most of the reshoring barriers were specific to the firm rather than home or host-country (Engström et al., 2018a; 2018b). For instance, barriers to reshoring identified included the lack of decision-support for reshoring and lack of established processes for making such decisions, which reinforces the urgency for this research (Arlbjørn and Mikkelsen, 2014; Wiesmann et al., 2017). In order to overcome some of the barriers, another group of factors called 'enablers' has been identified.

Another research area that is increasing in importance is the enablers of reshoring. An enabler refers to a factor that can assist the progress of reshoring. The majority of extant research has identified political incentives as enablers of reshoring. This is because governments have been primarily interested in enabling reshoring because it can create jobs and boost economy in the home country (Tate, 2014). For instance, "Made in America" slogans gained popularity as it was estimated that reshoring would create many jobs in the country (Vanchan et al., 2018). Consequently, the US government started providing tax incentives for enabling reshoring (Zhai et al., 2016) and releasing geography-wise reports of the number of jobs gained in every US state (Vanchan et al., 2018). There has also been a push for the UK to adopt some policies, similar to those in the US, in order to enable reshoring to the UK (Bailey and De Propris, 2014a). Some research has also identified manufacturing technologies acting as enablers of reshoring. For instance, it is proposed that additive manufacturing or 3D printing could propel reshoring activities (Fratocchi, 2018; Moradlou and Tate, 2018). Similarly, technologies related to automation can maintain jobs in the home country (Arlbjørn and Mikkelsen, 2014). Furthermore, the group of innovative manufacturing technologies labelled as 'Industry 4.0' technologies have been considered to affect manufacturing reshoring decisions with increasing diffusion of automation in manufacturing. However, the advantage of such technologies in the home country may be short-lived (Ancarani and Di Mauro, 2018). Continuous diffusion of innovative technologies into manufacturing would be required in order to enable reshoring for a long-term.

2.1.4 Decision-support tools

There is an overall lack of tools that support managerial decisions for reshoring; however, only a few of them have been explored. One of these decision-making tools incorporates two costing models to make a cost-based decision (Gylling et al., 2015). In one of the models, a total landed cost was evaluated, and in the other model, own manufacturing cost was compared against outsourced manufacturing cost using time-driven-activity-based-costing model. This led to the manufacturing reshoring decision in the case company (Gylling et al., 2015). Another tool makes use of the system dynamics model, making it only model in reshoring literature to be premised on heuristic decision-making (Gray et al., 2017). Heuristic decision-making consists of creating mental and simple rules, that often end up being rational amidst the prevailing uncertainty. It also holds true for manufacturing reshoring decision-making. According to the model, it is proposed that SMEs would more likely reshore if the competition is performance-based and not cost-based (Gray et al., 2017). This, in turn, suggests that decision-making based on other heuristics needs to be explored, which makes it possible to use performance factors.

2.2 Decision-support system

A decision-support system is an information system that supports managers in business or organizational decision-making activities. This information system is typically a computerized system that is able to compile available information and analyze data, before providing a recommendation on decisions (Power, 2016). Unlike managers without any support, a decision-support system enables managers to make better decisions (Sharda et al., 1988). The role of decision-support system is to support a human decision-maker in completing the task rather than replacing a decision-maker (Power, 2002). There is a great demand for more advanced decision-support systems in the reshoring domain (Boffelli et al., 2018; Hilletofth et al., 2019a; Wiesmann et al., 2017). A basic requirement for such decision-support systems is that they must not only be efficient and effective, but also provide pertinent, accurate, reliable and interpretable information, in order for the decision-maker to make a qualified decision (Hilletofth and Lättilä, 2012; Hilletofth et al., 2016).

Decision-support systems are traditionally classified in different ways (Power, 2002; Alter, 1980). One of the widely adopted classifications distinguishes decision-support into five types (Power, 2002): (1) data-driven, that analyzes large amounts of structured data; (2) model-driven, that use analytical models; (3) document-driven, that uses document or webpage page retrieval methods; (4) communication-driven, that supports communication between different users on the same task; and, (5) knowledge-driven, that uses domain expertise to suggest a decision. In the manufacturing industry, model-driven and knowledge-driven have been most widely used in recent years (Hasan et al., 2017). Due to growing interest in artificial intelligence (AI) techniques especially machine learning, data-driven decision-making is gaining prominence (e.g., Mourtzis et al., 2016; Sadati et al., 2018). However, there is a lack of large amounts of data in the manufacturing reshoring domain, which limits the use of data-driven decision-making. Therefore, knowledge-driven decision-support is feasible for manufacturing reshoring domain that can leverage on expert knowledge to make a decision. One of the AI techniques that enable knowledge-driven decision-support is expert systems (Power, 2016).

2.2.1 Expert systems

Expert systems are considered as an AI technique for decision-support since a computer is in charge of the decision-making process. These systems utilize the industry expert's specialized knowledge present to aid the decision-making process. This allows individuals with less expertise to use this knowledge and make better decisions (Benbasat and Nault, 1990). The knowledge of these experts is programmed into a series of if-then rules (heuristics), which is similar to how a human expert would reason. Therefore, logic is used to make a deductive decision, which offers certain advantages such as improved, faster and consistent decision-making, and improved productivity, among others (Rao and Miller, 2004). The motivation behind developing expert systems is that the knowledge of experts is scarce and consulting them is an expensive proposition. Thus, capturing this information can give unlimited access to the user of the system (Syberfeldt et al., 2016). A wide range of applications of expert systems has been identified in manufacturing, for example, efficient design of augmented reality devices in manufacturing (Elia et al., 2016; Syberfeldt et al., 2016) and improving designs of manufacturing processes (Sadati et al., 2018).

Expert systems consist of two components: a knowledge base and an inference engine (Figure 3). The knowledge base denotes a collection of rules. These rules can be created either manually or by interviewing industry experts. The inference engine provides the reasoning in the system by firing the relevant rules from the knowledge base and arriving at a decision automatically. In some cases, a user interface may be involved by which the system can interact with a human user. Semantic techniques can be used to build up expert systems. Some examples of these techniques which are used represent the domain expert's knowledge include frames, graphs, rules and logic (Sowa, 2000). Semantic techniques convert the knowledge into a human understandable form. These techniques explicate the underlying meaning behind objects and delineate the relationships between them (Domingue et al., 2011). These techniques enhance the interaction between the machine and the human. In order to handle the uncertainty in manufacturing reshoring decisions, fuzzy logic has been explored in this research. Expert systems are sometimes integrated with other AI techniques such as genetic algorithms, particle swarm optimization (Sadati et al., 2018), artificial neural networks (Ross, 2017), or analytical hierarchy process (AHP) (Elia et al., 2016).

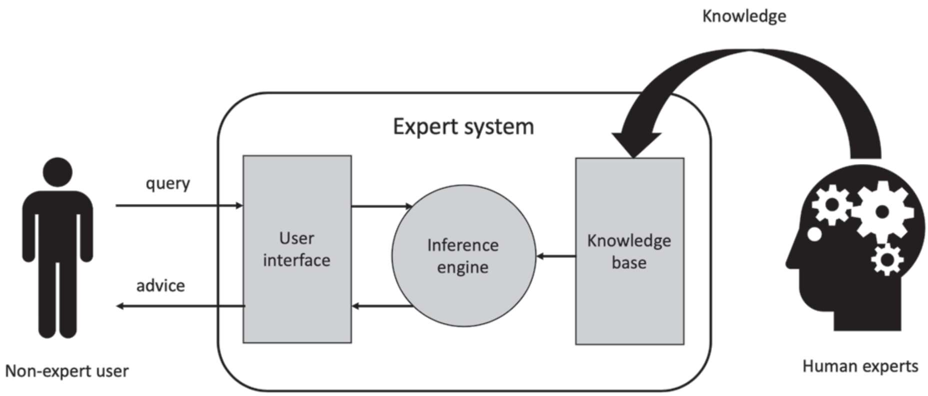

Figure 3 Parts of an expert system

2.2.2. Fuzzy logic-based decision-support

One of the decision-making supports that relies on rule-based heuristics is fuzzy logic. Founded in the branch of mathematics, fuzzy logic stems from fuzzy set theory (Zadeh, 1965). As the name suggests, fuzzy logic is an alternate for traditional Boolean logic, in which the former can have varying degrees of truth values (i.e., range of values from 0 to 1) unlike the latter, which depends upon only two values (i.e., 0 or 1). This makes fuzzy logic suitable for handling uncertainty in terms of fuzzy sets and numbers into decision-making. Uncertainty in decision-making can occur due to a number of reasons, such as presence of qualitative information, insufficient information, or ignorance (Ross, 2017). The process of decision-making can get increasingly complicated as the number of criteria grow. In many cases these criteria become conflicting towards the final goal of the decision. Furthermore, these criteria can be expressed either in qualitative and quantitative terms (Shaout and Trivedi, 2013). All of this can be handled by fuzzy logic since it uses human-like reasoning (Ross, 2017). The reasoning used within fuzzy logic is created by expert knowledge, which is why they are also known as expert systems. One important part of the expert knowledge is rules. A rule can be described as statements that have “IF p, THEN q” structure, where p is called the antecedent and q denotes the consequent. The expert can develop one or more of these rules depending on prior knowledge (Mendel, 2017). The decision-support tools implementing such rule-based structure have certain characteristics.

The characteristics of a decision-support tool based on fuzzy logic is that they need to be accurate, reliable, and interpretable. Usually, there exists a tradeoff between these characteristics. The most important tradeoff within fuzzy logic is between accuracy and interpretability (Cordón, 2011; Shukla and Tripathi, 2012). A fuzzy logic-based decision-support tool that is designed for high accuracy depends on a large rule base (i.e., large set of fuzzy rules). However, this increases the complexity of the tool and affects the readability of the rules. In order to tackle this issue, emphasis needs to be given to increasing interpretability of the tool, that relies on a small rule base (i.e., small set of fuzzy rules) (Casillas et al., 2013; Cpałka, 2017; Mencar and Fanelli, 2008). However, small rule bases also create further problems such as inconsistency-that is when same antecedents lead to dissimilar consequents, and redundancy-when overlapping antecedents result in the same consequent (Duţu et al., 2018; Gegov et al., 2017). Examples of both inconsistency and redundancy issues are depicted in Table 2. Improving the interpretability is not merely about reducing the number of the fuzzy rules, but also about reducing fuzzy sets, lowering the number of antecedents, or having a dynamic structure of fuzzy rules (Cpałka, 2017). Therefore, increasing interpretability without compromising the accuracy of a fuzzy logic-based support tool is a challenging task.

Table 2 Examples of inconsistency and redundancy issues in fuzzy rules

Inconsistency	`IF P is A1 AND Q is A2, THEN R` `IF P is A1 AND Q is A2, THEN S`	Rule 1 Rule 2
Redundancy	`IF P is A1 OR A2, THEN R` `IF P is A1, THEN R`	Rule 1 Rule 2

In order to develop a fuzzy logic-based tool with sufficient interpretability and accuracy, it is important to develop an understanding of the working of the 'fuzzy inference system'. A fuzzy inference system is a decision engine that employs fuzzy logic in order to transform multiple inputs into a single output (Jang, 1993). The fuzzy inference system typically consists of four functional blocks, as shown in Figure 4 (Lee, 1990; Pandian, 2017). The first block is called the fuzzification block and transforms the input data in crisp form into fuzzy data. This is done by mapping the crisp inputs to their corresponding grade of membership, which is a value between 0 and 1. The second block is known as the knowledge base. This consists of the knowledge from the application domain. In this study, the knowledge pertains to manufacturing reshoring decision, and a domain expert is used to construct the knowledge base. The knowledge base consists of two sub-blocks: the rule base and the membership functions. The rule base sub-block consists of fuzzy if-then rules that govern the decision-making. A domain expert in the application can be used to create such if-then rules; otherwise, a data-driven approach can be used to create the rules when large amounts of data are involved (Wu et al., 2001). The membership function sub-block consists of the type and shape of the mathematical function (such as triangular, trapezoidal or gaussian) that is used to describe the fuzzy set (Ross, 2017). This mathematical function does the mapping of elements of the set from 0 to 1. The third block is called the inference engine which selects appropriate rules from the knowledge base, before performing Boolean-like operations on them and then aggregating them to obtain a fuzzy output. The main feature of the inference engine is its ability to make decisions similar to human reasoning. The fourth block is called the defuzzification block. This transforms the resulting output, which is in a fuzzy form, into crisp values. Notably, this is done by mapping the fuzzy values onto a scale of corresponding crisp outputs. In recent years, many defuzzification methods have been proposed in the literature (Esogbue and Song, 2003; van Leekwijck and Kerre, 2001; Talon and Curt, 2017). The fuzzy inference system is an example of a grey box system, where the user can decipher its functionality, as opposed to black box systems where the user does not know what is happening within the system. This makes the fuzzy inference system applicable to various decision-making problems, such as those in operations management.

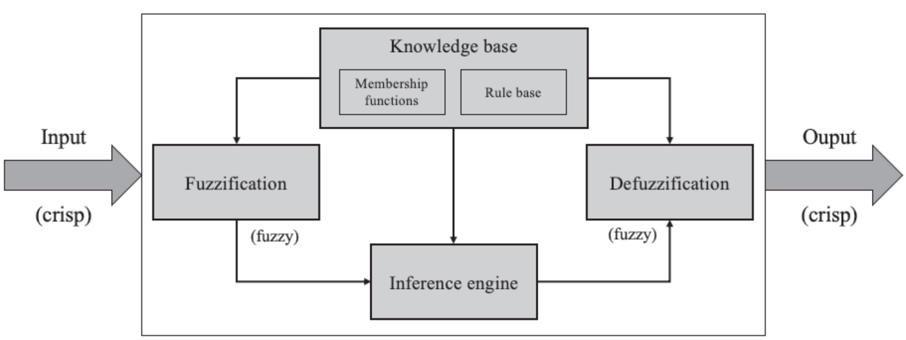

Figure 4 The fuzzy inference system (Jang, 1993)

Most other studies identified in the review have adopted the concept of fuzzy logic as a means to only rank the criteria and use them in an analytical hierarchy process (AHP)-based support (Azadegan et al., 2011).

2.2.3 Analytical hierarchy process-based decision-support

The analytical hierarchy process (AHP) is a multi-criteria decision-making approach based on structured comparison of criteria (Saaty, 1980; 2005). It is one of the most commonly used decision-support in operations management (Ho and Ma, 2018; Vaidya and Kumar, 2006). The AHP works by quantifying comparisons of criteria from the viewpoint of a decision-maker (Brunelli, 2015). The AHP employs crisp numbers to make an evaluation, which makes it difficult to model any uncertainties or fuzziness regarding the criteria comparison. Therefore, in order to handle the uncertainties, fuzzy extension of AHP was developed, called fuzzy-AHP (van Laarhoven and Pedrycz, 1983). The AHP uses a scale from 1-9 to compare two criteria, and the fuzzy equivalent of the scale is shown below (Table 3). In the latter, a triangular type of fuzzy sets is employed due to their computational simplicity.

Table 3. Scale of preference of two criteria

AHP scale	**Fuzzy scale**	**Verbal interpretation**
1	1,1,1	Equal preference
3	1,3,5	Moderate preference
5	3,5,7	Strong preference
7	5,7,9	Very strong preference
9	9,9,9	Extremely strong preference

The procedures for both AHP and fuzzy AHP entail three main parts: hierarchy construction, pairwise comparison and weights calculation (Figure 5). The first part is common for both the approaches. Under this step, a complicated problem is broken down in a layer of hierarchy comprising of decision criteria (Vaidya and Kumar, 2006). The second part departs from the use of two scales for pairwise comparison of the criteria. Depending on the choice of the scale, diverging procedures are followed. In the third part, the priority weights are calculated. For the AHP, this is done by directly calculating them from the normalized matrix. However, additional steps are required for the fuzzy-AHP (see e.g., Chang, 1996). These additional steps involve computation of the fuzzy synthetic sets and the degree of possibility. Next, the weights of the criteria are determined using the degrees of possibility. An advantage of the AHP is that it is possible to calculate the consistency among the comparisons (Brunelli, 2015).

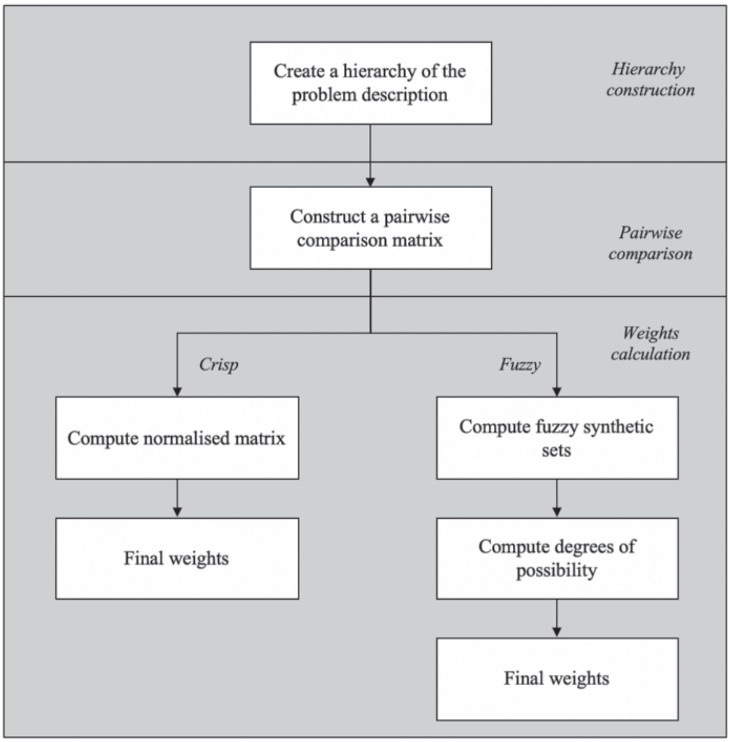

Figure 5 The procedure for AHP and fuzzy-AHP for calculation of criteria weights

Both AHP and fuzzy-AHP have been used for making relocation decisions. In one study, AHP was applied to 17 risk criteria that were structured in hierarchy of three groups: people, partner and environment. Among the criteria, cost received the first rank, while quality received the second rank (Schoenherr et al., 2008). Another study proposed an AHP decision-making model where 38 socio-environment criteria were used; out of which the social dimension of sustainability was highly ranked (Guarnieri and Trojan, 2019). Another study applied fuzzy-AHP and identified 12 criteria out of which, the availability of production capabilities was highly ranked (Pal et al., 2018). These studies within AHP and fuzzy-AHP have considered operations capabilities, of which cost and quality have been consistently important. However, some studies have separately focused on sustainability criteria (Guarnieri and Trojan, 2019). This reinstates the need to consider sustainability aspects in the relocation criteria.

3. Research methods

This chapter describes how this research is carried out, so that similar results can be reached if the research is repeated. The chapter begins with the research process which connects the research questions to the studies. Next, each of the studies is described with regard to research method, data collection, and analysis. Finally, research quality is assessed.

3.1 Research process

This research aims to develop support tools for evaluating manufacturing reshoring decisions. The research was conducted from January 2018 to May 2020. After starting the research process, the author joined an ongoing research project about manufacturing reshoring. The research started with exploring the literature on reshoring with regard to the decision criteria of manufacturing reshoring. Therefore, a literature review was performed within the topic of manufacturing reshoring. Then, a research gap within the literature of reshoring was identified, subsequent to which a research proposal was established to address this gap. The most critical parts of the research proposal are the purpose and research questions. The purpose has remained the same, while the research questions have been developing with the thesis. Three studies have been conducted to fulfil the purpose and answer the research questions. The connections between the research questions and studies are illustrated in Figure 6.

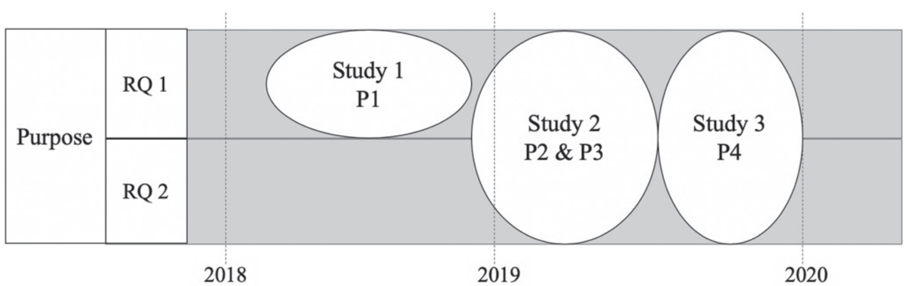

Figure 6 Connection between the research questions and the studies

The first study (Study 1) is aligned with the first research question (RQ1) regarding how industry experts reason while making manufacturing reshoring decisions. This study was a part of the research project, that provided the necessary empirical data for the study. The outcome of study 1 was an overview of the qualitative and quantitative criteria within manufacturing reshoring decision-making, in accordance with the views of industry experts. The Study 1 and the research project were concluded simultaneously.

After concluding the research project, the author was driven by relevance and his own interests to pursue modeling methods for developing support tools. This led to the second study (Study 2), that is mainly aligned with the second research question (RQ2) regarding how the reasoning of industry experts can be modeled into decision-support tools. During the course of this study, answer to RQ 1 was also partially identified. The developed tools are able to evaluate manufacturing reshoring scenarios and make recommendations for manufacturing reshoring decision with certain levels of accuracy.

The next step entailed an exploration of other types of support tools that could be feasible for manufacturing reshoring decision-making. This led to the third study (Study 3), which was also aligned with both RQ1 and RQ2, as these tools can capture industry experts' reasoning of manufacturing reshoring decisions while providing recommendations of manufacturing reshoring decision with certain levels of accuracy. The three consecutive studies are reported in four papers (i.e., P1, P2, P3 and P4).

3.2. Research studies

The three studies are described below. The research method, data collection and analysis methods are described for each of the study.

3.2.1. Study 1

Study 1 is used to answer the RQ1. The multiple case study is the main research method in this study. A multiple case study is used to investigate a contemporary phenomenon in a real-life context and allow for cross-case comparison where they may produce similar or contrasting results (Yin, 1994). Generally, multiple case studies can combine a variety of data collection techniques such as interviews, audio or video tapes, documents, surveys, field notes or other observations. For this study, the main sources of data were audio files from interviews and documents that were used during the manufacturing reshoring decision-making process.

In order to support the main research method, literature review was conducted by following a systematic search process. Literature review need to be systematic in order to ensure a degree of clarity, validity and auditability (Booth et al., 2016). In this process, clarity makes it easier for reviewers to judge validity in findings, avoids biases and auditability, and ensure transparency in research (Booth et al., 2016). The literature review was conducted based on Mayring' s process model (Mayring, 2000) which consists of four distinct steps: material collection, descriptive analysis, category selection, and material evaluation.

Semi-structured interviews and documents were used as the data collection techniques in the multiple case study. Semi-structured interview was conducted with industry experts, comprising of managers from different positions in the case companies, that, in turn were involved in the decision-making process related to manufacturing reshoring. Since multiple researchers were involved in the project, an interview protocol was strictly complied with. The data from the interviews was independently analyzed. All of the voice-recorded interviews were transcribed into a word processor, coded and finally categorized. The information related to the manufacturing reshoring criteria were used to answer the RQ1. The author validated the data at the final group workshop that witnessed the participation of all companies. All of the case companies operate in different types of industries (Table 4).

Table 4. Overview of case companies and data files

Firm name	No. of employees (2018)	Turnover MSEK (2018)	Products	Data collection files	Position of interviewees
ElecCo	23	70	Electric equipment	5 audio 5 documents	CEO; Purchasing manager; Marketing manager; Operative purchaser

PlastCo	135	380	Plastic equipment	2 audio 1 document	CEO
SpringCo	80	137	Industrial equipment	2 audio 1 document	CEO
AlumCo	35	65	Aluminum profiles	4 audio 1 document	General manager
OfficeCo	135	693	Office furniture	8 audio 17 documents	Managing director; Vice-president (Production); Quality manager; Supply chain manager

Data analysis techniques in the multiple case study involved qualitative data analysis. The semi-structured interviews and workshop discussions were recorded, transcribed and categorized (Williamson, 2002). The data analysis was undertaken in three phases in accordance with the methodology postulated by Miles and Huberman (1994). In the first phase, data was coded and categorized based on the categories developed in the literature review. In the second phase, the condensed data was tabulated and carefully examined to identify criteria for each case and cross case. In the third phase, the data was concluded by developing an extensive list of criteria that were taken into consideration and that needed to be implemented in developing decision-support tool for evaluating manufacturing reshoring decisions.

3.2.2. Study 2

Study 2 is used to answer both RQ1 and RQ2. The main research method in this study is modeling using fuzzy logic. As mentioned previously, fuzzy logic provides a powerful way of understanding, quantifying and handling numerous and uncertain data. Fuzzy logic modeling follows a systematic methodology (Emami et al., 1998) consisting of five steps:

(1) Defining linguistic variables,
(2) Defining linguistic labels,
(3) Defining membership functions,
(4) Defining fuzzy rules, and,
(5) Configuring the fuzzy logic system.

In the first step, the linguistic variables are defined that serve as the input to the fuzzy logic system. Due to modeling limitations, the most relevant linguistic variables were selected in this step. Meanwhile, linguistic labels are defined in the second step. These are the values for the variables, expressed in linguistic terms. In the third step, membership functions are defined. These membership functions map the linguistic labels to range of truth values. In the fourth step, fuzzy rules are defined. IF–THEN fuzzy rules are used that describe relationships between the variables (Emami et al., 1998). In the fifth step, the fuzzy logic system is configured. The fuzzy logic system was configured in two different ways to cover the two main fuzzy logic modeling approaches: a complete rule base configuration comprising of all possible combination of variables and labels; and, a reduced rule base configuration, which consists of only the most relevant rules.

The modeling is done together with a subset of industry experts who have previously made manufacturing reshoring decisions. For the study, the experts were purposively selected. The modeling is done on an overall criteria level while the sub-criteria were not taken into consideration owing to modeling limitations. Importantly, the choice to make use of only the criteria level could be considered a limitation.

Analysis of fuzzy logic-based tool is done using algebraic and graphical techniques by utilizing the MATLAB Fuzzy Logic Toolbox software. The algebraic techniques involve calculating an error between the output of the fuzzy logic system and an opinion of the experts' decision. The term mean absolute error (MAE) is used to calculate this error between the system and the expert (Eq.1). A low value of MAE is deemed desirable.

$$MAE = \frac{1}{n}\sum_{j=1}^{n} | y_j - \hat{y}_j | \qquad (1)$$

where: n denotes the number of decision scenarios
y_j represents the experts' opinion on the decision
$\hat{y}_j$ is the output from the fuzzy logic system

A rule-viewer in MATLAB is graphical technique used for analyzing the fuzzy logic system. This provides a visual representation of the fuzzy rules that are triggered for the particular query of decision scenarios, as shown by an example in the figure (Figure 7). In this example, the second rule is triggered for the given query of decision scenarios.

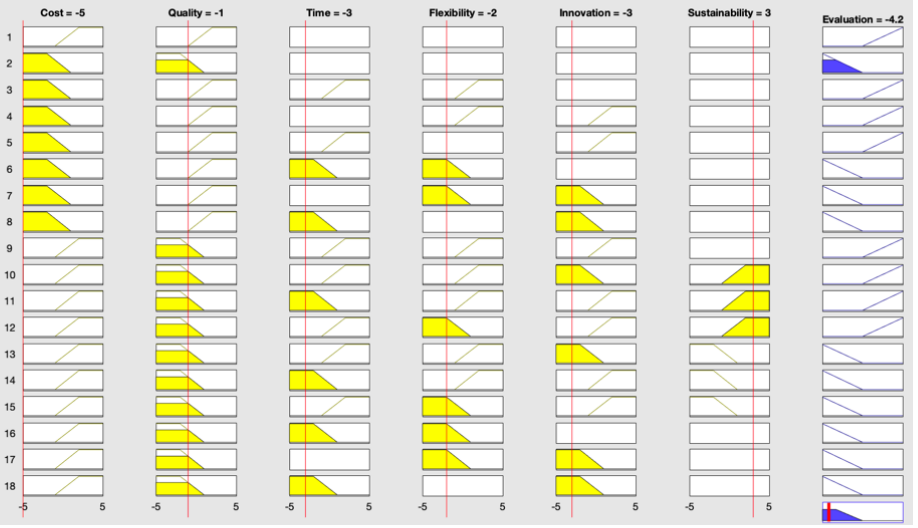

Figure 7. Rule viewer for decision scenarios indicating the fuzzy rules that are triggered

3.2.3. Study 3

Study 3 is used to answer both RQ1and RQ2. This study is about exploring other decision-support tools for manufacturing reshoring decisions. The main research method in this study is modeling that makes use of AHP and fuzzy-AHP. The AHP procedure consists of three main steps: hierarchy construction, pairwise priority analysis and consistency validation. In the first step, the decision-makers structure a complex problem consisting of numerous quantitative and qualitative criteria in the form of a simple hierarchy. In the next step, the decision makers compare each criterion in the same level in a pairwise manner with every other criterion using AHP and fuzzy-AHP scales (Saaty, 1980). This leads to a pairwise matrix (A) that is represented as:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}, \text{ and } a_{ij} = 1 \text{ if } i = j \qquad (2)$$

Subsequently, this matrix is normalized for *n* criteria and the resulting weighted normalized matrix (N) is given by the following equation:

$$\mathrm{N} = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}, \text{ where } w_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad (3)$$

The term $\sum_{i=1}^{n} a_{ij}$ is the sum of each column. Next, the weights w_i are calculated by taking the average of each row in the normalized matrix in order to construct the weighted matrix and w_i is represented by the equation:

$$w_i = \frac{\sum_{j=1}^{n} w_{ij}}{n} \quad (4)$$

Next, a consistency ratio (CR) of the pairwise comparisons is calculated as a ratio of consistency index (CI) to random index (RI), and is represented by the following equations:

$$\mathrm{CR} = \frac{\text{Consistency index (CI)}}{\text{Random index (RI)}} \quad (5)$$

$$\mathrm{CI} = \frac{\lambda_{max} - n}{n-1} \quad (6)$$

, where λ_{max} is the maximum eigenvalue of the matrix

The random index (RI) value is a standard value depending on the number of criteria and is obtained from the table below (Table 5).

Table 5. Average random inconsistency index based on number of criteria (Saaty, 1980; 2005)

Number of criteria (n)	1	2	3	4	5	6	7	8	9	10
Random inconsistency (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

The procedure of fuzzy-AHP is similar to that of AHP, with the exception that a fuzzy set is used for pairwise comparisons. After obtaining the weights, a weighted sum technique is used to arrive at output from the AHP and fuzzy-AHP using the following equation:

$$O_1 = \sum_{i=1}^{n} x_i w_i \quad (7)$$

where: O_1 denotes the output of either AHP or fuzzy-AHP
x_i signifies the value of the criteria in the decision scenario
w_i is the weight of the criteria from either AHP or fuzzy-AHP

3.3. Research quality

In order to ensure the quality of research, aspects that determine the quality is addressed for each of the research methods used in this thesis. The two methods are case study and modeling. After depicting an overview of research quality in Table 6, quality aspects for each method is discussed below.

Table 6. Overview of research quality

Quality criteria	Case study	Modeling
Internal validity	Converging results from different sources Checking empirical data provided by the participants	Selecting relevant variables for modeling Following guidelines according to MATLAB software documentation Repetition of trials
External validity/ generalizability	Comparing the results with the literature Selecting a variety of manufacturing companies in the sample	Checking outputs from the model with industry experts
Reliability	Stepwise documentation Interview protocols Keeping records of every step in the research process, starting from the initial “raw data”	Stepwise documentation Checking outputs from the model with industry experts

3.3.1 Case study

For the case study method, validity and reliability have traditionally been the important criteria in assessing the quality of research (Bell et al., 2018). Validity refers to “the extent to which a research instrument measures what it is designed to measure" (Williamson, 2002, p. 27), and is divided into two parts: internal and external. Internal validity refers to the credibility and authenticity of research results. In the current study, this is ensured through multiple techniques of data collection, such as semi-structured interviews and company documents. Additionally, multiple sources were used for interviewees in the same company. Furthermore, a seminar with interviewees was conducted where data analysis and results were presented. External validity is defined as the generalizability of the findings (Williamson, 2002) and is ensured by comparing the findings from the case study (i.e., reshoring criteria) with the previous theory.

Reliability is associated with getting consistent and stable research results (Williamson, 2002). A good reliability means that the study can be repeated and generate the same results even if another researcher conducts it. This can be achieved by thoroughly documenting the research. Guidelines and procedures of case studies were followed in this study (Williamson, 2002). Moreover, all the interviews were transcribed and coded in a systematic manner, which allows access to the raw data. The documents used during the decision-making process were reliable sources of information for such retrospective case studies.

3.3.2 Modeling

For the modeling research method, verification and validation of the model are important criteria to assess the quality of research (Schwer, 2009). Accordingly, verification must precede validation. Verification is related to the correctness of the model itself and entails code verification and calculation verification. The code verification is related to removing programming related errors. The code was checked for syntax errors using MALTAB guidelines for building a fuzzy logic model (MathWorks Inc, 2019). In addition, testing values that lie outside the range of the fuzzy logic model were entered, after which the system returned an error. The code was also verified by repeating the input values of decision scenarios, in order to produce consistent output. Each trial in calculating the output was documented and archived. Calculation verification is undertaken by comparing the results with fundamental equations in fuzzy logic and AHP approaches. On the other hand, validation is related to the model's predictive capability, which was done by comparing the results of the models with the real world. Construct validation was ensured by selecting only the relevant decision-making criteria in the model. Face validation is performed by comparing the outputs from the models with industry experts. Other types of validation, such as content and criterion validation will, in all means, be considered in future.

4. Summary of papers

This chapter summarizes the main empirical and theoretical findings from the four appended papers. First, a summary of each paper is provided. Each paper presents the purpose, a succinct elucidation of the research method, and main findings. Next, the chapter summarizes how the findings from the appended papers have contributed to answering the research questions presented for this thesis.

4.1 Paper I

The purpose of this paper was to identify the criteria that are considered in manufacturing reshoring decision. The purpose contributes to RQ1 which seeks to understand how industry experts reason while making manufacturing reshoring decisions. This paper commences with a review of the factors that influence the reshoring decision, found within the literature of reshoring drivers, enablers, and barriers. In the review, more than 100 decision criteria were identified and categorized into: (1) competitive priority criteria, (2) resource criteria, (3) strategy criteria, (4) global condition criteria, (5) preference criteria and (6) context criteria. These categories were visualized using a theoretical framework (Figure 8). Subsequently, a multiple case study methodology, consisting of five companies, was employed to further identify criteria that were potentially missed out on in the literature. Thereafter, the identified criteria in the multiple case study were mapped to those in the literature.

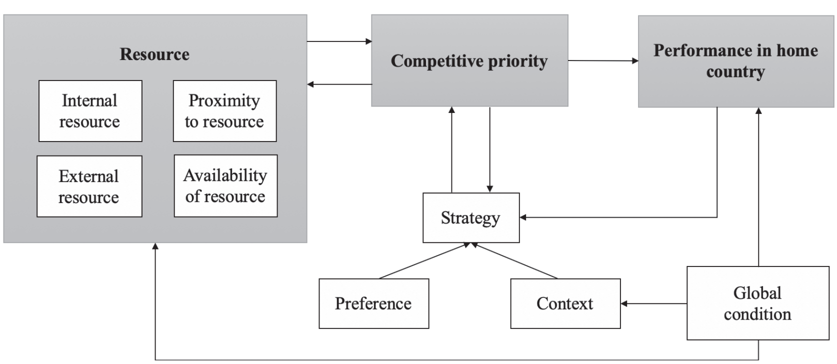

Figure 8. Theoretical framework of reshoring criteria

The first case company, ElecCo, reshored their manufacturing from a Polish supplier to a local supplier in Sweden. The experts at ElecCo identified 30 manufacturing reshoring decision criteria. Among them, delivery quality, delivery lead time, and supplier flexibility were important criteria considered in the manufacturing reshoring decision. The second case company, PlastCo, reshored their manufacturing from Denmark to its own facilities in Sweden. The experts at PlastCo identified 43 decision criteria, among which product quality and delivery quality were important criteria considered in the manufacturing reshoring decision. The third case company, SpringCo, reshored their manufacturing from China to its own facilities in Sweden. The experts at SpringCo identified 30 decision criteria. Among them, transportation cost and delivery lead time were important criteria considered in the manufacturing reshoring decision. The experts also had a personal preference to locate manufacturing within the home country. The fourth case company, AlumCo, reshored their manufacturing from China to its own facilities in Sweden. The experts at AlumCo identified 45 decision criteria, among which, quality and process efficiency were important criteria considered in the manufacturing reshoring decision. The final case company, OfficeCo, reshored its manufacturing from Lithuania to its own facilities in Sweden. The experts at OfficeCo identified 45 decision criteria and among them, total cost, volume flexibility in production and delivery lead times were important criteria considered in the manufacturing reshoring decision. The complete list of manufacturing reshoring decision-making criteria for all the case companies is shown Table 7.

Table 7. Reshoring criteria considered by case companies

	Criteria	**Elec-Co**	**Plast-Co**	**Spring-Co**	**Alum-Co**	**Office-Co**
Competitive priority criteria	Total cost	X	X	X	X	X
	Manufacturing cost				X	X
	Raw material cost	X			X	X
	Energy cost	X				
	Labor cost	X	X	X		X
	Distribution cost		X	X	X	X
	Warehousing cost		X		X	X
	Inventory holding cost	X	X	X	X	X
	Transportation cost	X	X	X	X	X
	Customs cost	X			X	
	Coordination cost				X	X
	Monitoring cost	X	X			X
	Switching cost	X	X	X	X	X

	Process efficiency				X	X
	Labor productivity			X		X
	Flow efficiency		X			X
	Product quality				X	X
	Process quality	X	X		X	
	Delivery dependability	X				X
	Supplier dependability	X	X			X
	Brand quality				X	
	Delivery lead time	X	X	X	X	X
	Delivery flexibility	X				X
	Volume flexibility		X		X	X
	Product mix flexibility				X	
	Supplier flexibility	X				
	Product flexibility				X	X
	Labor market flexibility		X			X
	Labor flexibility				X	X
	Product innovation					X
	Supply chain innovation					X
	Product sustainability				X	
	Process sustainability		X	X	X	
	Supply chain sustainability	X			X	
Resource criteria	Proximity to customers	X	X	X	X	X
	Proximity to suppliers	X	X		X	
	Proximity to R&D		X	X	X	
	Proximity to knowledge institutions		X			
	Proximity to industrial cluster				X	X
	Availability of labor		X	X	X	X
	Availability of suppliers	X	X		X	X
	Availability of raw material			X		
	Availability of manufacturing technology	X	X	X	X	X
	Availability of transportation infrastructure		X	X		
	Availability of production infrastructure		X		X	X
	Availability of energy infrastructure		X		X	
	Availability of information technology	X	X			X
	Availability of production capacity		X		X	X
	Process control	X		X	X	X
	Supply chain control	X			X	X
	Supply chain governance				X	X
	Government incentives			X		
	Evaluation process	X	X		X	
	IP and know-how			X		X
	Internal communication	X	X			
Stra tegy	Operations strategy	X	X			X
Context criteria	Industry practice		X	X		
	Product characteristics	X	X	X	X	
	Market characteristics		X	X	X	X
	Industry characteristics			X		X
	Regional culture	X	X	X	X	
	Company culture		X	X		

Preference criteria	Customer preference	X	X	X	X	
	Owner preference		X	X		
	Management preference		X			
	Emotional preference		X	X	X	X
Global condition criteria	Economic conditions and stability	X	X		X	X
	Exchange rate		X		X	X
	Government policies		X	X		X
	Labor union			X		
	Trade barriers				X	
	Supply chain disruption		X	X	X	X

According to the findings, the manufacturing reshoring decision criteria were considered across all of the categories of the theoretical framework. Among the companies, the highest number of criteria was found within the category of competitive priority. This category is the most relevant one as far as manufacturing reshoring decision-making is concerned. Within competitive priority, the most common criteria across all of the case companies were total cost, inventory holding cost, transportation cost, switching cost and delivery lead time. Next most relevant category is the resource category, where proximity to customers and availability of manufacturing technology were the most common criteria across all of the case companies.

This paper answers the RQ1 on how industry experts reason while making manufacturing reshoring decisions with respect to the aforementioned criteria. More than 100 criteria were identified in the literature, of which 72 of them were found in case companies. Empirical research shows that the criteria were considered across all of the categories. Therefore, manufacturing reshoring decisions are not merely based on costs, but also on a holistic set of criteria among which, delivery lead times, proximity to customers and availability of manufacturing technology are relevant. Among the holistic set of criteria, some of them were qualitative (for example, the preferences of the customer or the owner to move back) and therefore challenging to incorporate them into quantitative tools used by the case companies.

4.2 Paper II

The purpose of this paper was to demonstrate concepts that enable modeling manufacturing reshoring decisions based on fuzzy logic. This contributes to RQ1 and RQ2 by extracting experts' reasoning before capturing this reasoning. Three novel fuzzy logic concepts were developed to improve interpretability of the models when applied to manufacturing reshoring decision-making. Two main fuzzy logic modeling approaches were explored: a complete rule base configuration consisting of all possible combination of variables and labels; and, a reduced rule base configuration which only encompass the most relevant rules. The three novel concepts were used in both types of modeling approaches.

The first novel concept is relative linguistic labels. Unlike its rival concept of absolute labels, which give different messages for different decision makers, relative labels concept captures both positive and negative impacts. Examples of relative linguistic labels are *positive*, *neutral* and *negative* as opposed to absolute labels low, medium and high. For example, if absolute labels were used, then *high* quality and *low* cost are considered desirable for manufacturing reshoring decision. However, simultaneously using both *high* and *low* labels can cause confusion among decision makers, thus reducing the system's interpretability. Therefore, a relative label prevents these issues and was demonstrated in case of manufacturing reshoring decision-making. As a case in point, relative label *positive* means that the variable (cost or quality) has a positive impact on the decision (low cost or high quality). Therefore, the relative labels ensure consistent semantics among system users.

The second novel concept is that of high-level rules. High-level rules are those rules that are intuitive and obvious to the domain expert. The need for high-level rules is underscored by the fact that the total number of rules in a fuzzy logic system increase considerably with the number of linguistic labels and variables. To illustrate, a system with three linguistic labels (e.g., positive, negative and neutral) and six linguistic variables (e.g., six competitive priority) would require 3^6 (=729) rules in the system. This is extremely large for any expert to assign outputs. Therefore, high-level rules reduce the complexity of fuzzy logic system by ensuring a lower number of rules in the rule base.

The third and final novel concept is that of linguistic variable weights. This is used in the automatic design of a fuzzy rules in the complete rule base configuration, assigning an output to each rule is time-consuming for an expert. A range of values from [-5, 5] is assigned to the linguistic variables in antecedent part, the direction of which depends on the corresponding linguistic label. For example, when the quality is positive, a value of +5 is chosen. Similarly, a value of -5 is chosen when the quality is negative. The output of the rule is computed by summing all values of the antecedents of the rule. This, in turn, ensures a rapid creation of rule base. Therefore, linguistic variable weight reduces the complexity while working with complete rule base.

The three novel concepts were used in the two configurations, wherein ten hypothetical scenarios of reshoring were evaluated (Table 8). The outputs from the fuzzy logic system was then compared with an industry experts' opinion of the scenario using MAE.

Table 8. Output of the fuzzy logic system from both configurations (Hilletofth et al., 2019b)

Scenario	Criteria						Expert opinion	System output (Config 1)	System output (Config 2)	Decision	Conflict
	Cost	Quality	Time	Flexibility	Innovation	Sustainability					
1	-5	-1	-3	-2	-3	3	-5	-4.20	-4.20	Don´t evaluate	No
2	2	5	-1	3	4	1	4	5.00	4.20	Evaluate	No
3	-3	-4	-3	-1	4	-1	-4	-5.00	-4.20	Don´t evaluate	No
4	3	-4	-1	-3	-5	-3	-4	-5.00	-4.20	Don´t evaluate	No
5	-4	-2	5	-1	-1	5	-4	-5.00	-4.20	Don´t evaluate	No
6	4	2	-4	2	2	-5	4	5.00	5.00	Evaluate	No
7	-4	2	1	2	2	5	4	5.00	4.20	Evaluate	No
8	2	-1	3	-1	1	5	3	4.20	4.20	Evaluate	No
9	3	5	5	2	5	-3	5	5.00	5.00	Evaluate	No
10	-3	-5	3	-2	5	-2	-4	-5.00	-5.00	Don´t evaluate	No
							MAE	0.90	0.50		

According to the findings, there was no conflict in decisions between the fuzzy logic tool and the reshoring expert for all of the input scenarios based on competitive priority criteria. The difference between the tool and the experts' opinion was found to be low. Thus, it is evident that novel concepts have demonstrated advantages while modeling manufacturing reshoring decision-making in fuzzy logic. The configuration using linguistic variable weights performs better than using high-level rules.

This paper answers RQ1 with respect to how industry experts reason while making manufacturing reshoring decisions. The industry experts reason by focusing on the most relevant if-then rules during manufacturing reshoring decision-making. In addition, since some of the criteria are more important than others and the industry experts assign integer values to the criteria based on their significance in manufacturing reshoring decisions. The industry experts use relative ways to compare the criteria. Meanwhile, this paper also answers RQ2 with respect to how industry experts reasoning can be modeled into a decision-support tool. This is done using the three novel concepts for modeling into fuzzy logic-based support tools. Relative labels ensure consistent semantics for experts' reasoning of criteria in manufacturing reshoring decision-making. More specifically, high-level rules ensure a lower number of rules in manufacturing reshoring decision-making, whereas, linguistic variable weights reduce the complexity while creating a complete rule base.

4.3 Paper III

The purpose of this paper was to explore the feasibility of fuzzy logic as a tool for manufacturing reshoring decision-making. This aligns with RQ2, which seeks to understand how industry experts' reasoning of manufacturing reshoring decision be modeled in a decision-support tool. Another two fuzzy logic models were created using the three novel concepts developed in the previous paper. In this paper, the fuzzy logic model is advanced with respect to three aspects. First. the number of linguistic labels is increased to three (i.e., positive, neutral and negative). This, in turn, has increased the number of fuzzy rules to 3^6 (=729). Second, as many as sixteen settings were used in this model as compared to a single setting in the previous paper (Table 9).

Table 9. Settings in the fuzzy inference system

Setting	AND method	OR method	Implication method	Aggregation method	Defuzzification method
1	Min	Max	Min	Max	Centroid
2	Min	Max	Min	Max	Mom
3	Min	Max	Min	Sum	Centroid
4	Min	Max	Min	Sum	Mom
5	Min	Max	Prod	Max	Centroid
6	Min	Max	Prod	Max	Mom
7	Min	Max	Prod	Sum	Centroid
8	Min	Max	Prod	Sum	Mom
9	Prod	Max	Min	Max	Centroid

10	Prod	Max	Min	Max	Mom
11	Prod	Max	Min	Sum	Centroid
12	Prod	Max	Min	Sum	Mom
13	Prod	Max	Prod	Max	Centroid
14	Prod	Max	Prod	Max	Mom
15	Prod	Max	Prod	Sum	Centroid
16	Prod	Max	Prod	Sum	Mom

Third, the number of reshoring scenarios were doubled. A total of 20 scenarios were used, among which the first 10 are similar to the previous paper. Meanwhile, the latter 10 were developed to test the fuzzy logic system (Table 10). Each scenario was provided as inputs when the system was configured in each of the 16 settings, resulting in a total of 320 output values and output decisions.

Table 10 Manufacturing reshoring decision scenarios (based on Hilletofth et al., 2019b)

Scenario	Criteria					
	Cost	Quality	Time	Flexibility	Innovation	Sustainability
1	-5	-1	-3	-2	-3	3
2	2	5	-1	3	4	1
3	-3	-4	-3	0	4	-1
4	3	-4	0	-3	-5	-3
5	-4	-2	5	-1	0	5
6	4	2	-4	2	2	-5
7	-4	2	1	0	2	5
8	2	-1	3	0	1	5
9	3	5	5	2	5	-3
10	-3	-5	3	-2	5	-2
11	0	0	0	0	0	0
12	3	-4	2	-2	-2	2
13	-5	0	3	5	5	4
14	-5	4	2	-1	-4	3
15	-2	-5	-5	-2	-5	5
16	-3	5	5	3	5	-3
17	1	-5	1	1	1	-5
18	-5	1	-5	-5	-5	1
19	5	-1	5	5	5	-1
20	-1	5	-1	-1	-1	5

In the first support tool that used a complete rule base (Config 1), good alignment was found between decision of the expert and decision of the tool. For most of the settings, (i.e., 1, 2, 4, 5, 6, 9, 10, 11, 12, 13 and 14), no decision conflicts were observed in any of the scenarios. However, for the other settings (3, 7, 8, 15, and 16) decision conflicts were seen in two scenarios. This brings the total number of decision conflicts to 8 out of 320 output decisions, corresponding to a decision mismatch of 2.5%. The conflicts occurred in the latter half of the scenarios, which were designed to test the system. Setting 2 performed the best in terms of alignment between system output and experts' opinion. The alignment is measured as MAE whose value was 0.63 in Setting 2.

Meanwhile relatively mixed results were obtained in the second support tool that used a reduced rule base (Config 2). For some of the settings, good alignment was found between the decision of the expert and decision of the tool. This was found in settings 1, 2, 5, and 6. In fact, setting 2 in the reduced rule base performed much better than in the complete rule base. The alignment measured as MAE was found to be 0.48, thus implying better alignment between the expert and the tool (Figure 9). However, decision conflicts occurred in three of the reshoring scenarios on the other settings (i.e., 3, 4, and 7 to 16). In total, 24 out of 320 output decisions were incorrect, corresponding to a decision mismatch of 7.5%.

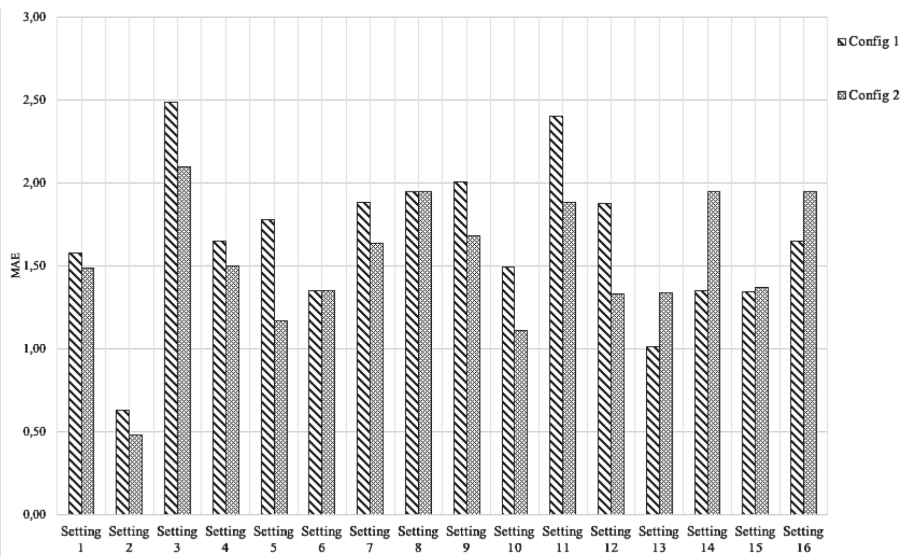

Figure 9. MAE comparisons of both fuzzy logic tools in all sixteen settings.

The findings show how manufacturing reshoring decision-making can be modeled into fuzzy logic-based tools. Among the different modeling approaches, the reduced rule base configuration was found to perform better than the complete rule base after choosing Setting 2 (Figure 9). While the fuzzy logic-based tools are suitable on an overall competitive priority level, they need to consider the sub-criteria in order to be more applicable.

This paper answers RQ2 with respect to how industry experts reasoning can be modeled into a decision-support tool. This is done by selecting appropriate settings and configuration required to model manufacturing reshoring decisions. The choice of the fuzzy inference settings affects the output of the fuzzy logic system. Setting 2 is deemed feasible since it has the least error in comparison to other settings and performs best with the reduced rule base.

4.4 Paper IV

The purpose of this paper is to investigate the feasibility of AHP and fuzzy-AHP decision-support tools for reshoring. This paper aligns with both RQ1 and RQ2. In this type of decision-support, a hierarchy of criteria was first created based on industry experts' reasoning of manufacturing reshoring decisions. Next, the experts were asked to compare the criteria in a pairwise manner before calculating the priority weights. The industry experts' involvement in these steps allows to explore how they reason while making manufacturing reshoring decisions and which criteria are important in decision-support for manufacturing reshoring decisions. Finally, the weights were applied to reshoring scenarios in a weighted sum technique, that mathematically evaluates manufacturing reshoring decisions from the reshoring scenarios. The output from AHP and fuzzy-AHP are then compared with each other and with the experts' opinion. Finally, the difference in outputs is determined by MAE values. This provides insights into how accurately industry experts' reasoning is modeled into AHP and fuzzy-AHP decision-support tool.

Crisp comparisons were used in the fuzzy-AHP support tool, while fuzzy comparisons were used in the fuzzy-AHP support tool. Both these tools provide an order of importance of the criteria and their priority weights. The most important criterion was quality, followed by cost. Meanwhile, time, flexibility and innovation received equal weights. The criterion sustainability received the least weight. When uncertainty is incorporated in the tool, it is found to increase the weight of more important criteria and suppress the weight of less important criteria, as illustrated in Table 11.

Table 11. Weights obtained in both support tools

Criteria	**AHP**	**Fuzzy-AHP**	Relative change in weights
Cost	**0.29**	**0.38**	+0.09
Quality	**0.41**	**0.41**	0
Time	**0.09**	**0.07**	-0.02
Flexibility	**0.09**	**0.07**	-0.02
Innovation	**0.09**	**0.07**	-0.02
Sustainability	**0.03**	**0**	-0.03

When the weights obtained from both the tools were applied to the same 20 scenarios, consistent decisions were obtained between outputs of the tool and the experts' opinion for 18 of the scenarios. The remaining two scenarios showed conflict between the tool's decision and the experts' opinion. In totality, both of these tools had a high value of MAE, 2.28 for AHP, and 2.23 for fuzzy-AHP. These values are considerably higher than that which are obtained in fuzzy logic-based decision-support. The high MAE values also indicate conflicts between the outputs of the tools and the experts' opinion (Table 12). In the AHP, four of its decisions were found to be conflicting with the expert. These decisions were found in the scenarios 12, 15, 18, and 19. Additionally, four of its decisions were in conflict with the experts' opinion in the fuzzy-AHP. These decisions were found in scenarios 7, 12, 15, and 18.

Table 12. Decision evaluation from AHP and fuzzy-AHP for the scenarios (based on Sequeira and Hilletofth, 2019a; 2019b)

Scenario	Criteria						Expert opinon	AHP output	AHP decision	Fuzzy -AHP output	Fuzzy-AHP decision	Absolute error
	Cost	Quality	Time	Flexibility	Innovation	Sustainability						
1	-5	-1	-3	-2	-3	3	-5	-2.49	Do not evaluate	-2.87	Do not evaluate	0.38
2	2	5	-1	3	4	1	4	3.21	Evaluate	3.22	Evaluate	0.01
3	-3	-4	-3	-1	4	-1	-4	-2.56	Do not evaluate	-2.75	Do not evaluate	0.19
4	3	-4	-1	-3	-5	-3	-4	-1.67	Do not evaluate	-1.14	Do not evaluate	0.53
5	-4	-2	5	-1	-1	5	-4	-1.57	Do not evaluate	-2.10	Do not evaluate	0.53
6	4	2	-4	2	2	-5	4	1.84	Evaluate	2.32	Evaluate	0.48
7	-4	2	1	2	2	5	4	0.26	Evaluate	-0.34[a]	Do not evaluate	0.60
8	2	-1	3	-1	1	5	3	0.58	Evaluate	0.57	Evaluate	0.01
9	3	5	5	2	5	-3	5	3.92	Evaluate	4.03	Evaluate	0.11
10	-3	-5	3	-2	5	-2	-4	-2.47	Do not evaluate	-2.73	Do not evaluate	0.26
11	-3	5	5	3	5	-3	4	2.26	Evaluate	1.84	Evaluate	0.42
12	1	-5	1	1	1	-5	3	-1.66[a]	Do not evaluate	-1.43[a]	Do not evaluate	0.23
13	-5	1	-5	-5	-5	1	-3	-2.34	Do not evaluate	-2.57	Do not evaluate	0.23
14	5	-1	5	5	5	-1	3	2.34	Evaluate	2.57	Evaluate	0.23
15	-1	5	-1	-1	-1	5	-3	1.66[a]	Evaluate	1.43[a]	Evaluate	0.23
16	0	0	0	0	0	0	-3	0.00	Do not evaluate	0.00	Do not evaluate	0.00
17	3	-4	2	-2	-2	2	-3	-0.90	Do not evaluate	-0.66	Do not evaluate	0.24
18	-5	0	3	5	5	4	3	-0.18[a]	Do not evaluate	-0.94[a]	Do not evaluate	0.76
19	-5	4	2	-1	-4	3	-3	0.03[a]	Evaluate	-0.48	Do not evaluate	0.51
20	-2	-5	-5	-2	-5	5	-5	-3.57	Do not evaluate	-3.65	Do not evaluate	0.08

[a] Conflict between output from the tool and the expert

The findings show that both AHP and fuzzy-AHP are suitable tools for manufacturing reshoring decision from competitive priority criteria since they provide a consistent evaluation for most of the manufacturing reshoring decision scenarios. In both these tools, the error in decision was found when the output values were low. Therefore, this tool's accuracy can be increased by incorporating more middle decisions that encompass these low output values. In the fuzzy-AHP tool, it was found that inducing uncertainty augments the weight of the important criteria and suppresses the weight of the less important criteria. This, in turn, has implications on less important criteria, for example, sustainability, given that they are taken for granted.

This paper answers both RQ1 and RQ2. When investigating how industry experts reason while making manufacturing decisions, the criteria are divided into three groups based on their importance in the decision-making process. The final priority weights that are obtained in both AHP and the fuzzy-AHP decision-support reveal that the criteria cost and quality are more important among the competitive priority in terms of manufacturing reshoring decision-making. The criterion sustainability is the least important of the competitive priority criteria in manufacturing reshoring decision-making. When investigating how the industry experts' reasoning is modeled in decision-support tool, implementing AHP and fuzzy-AHP to obtain priority weights and using it in a weighted sum technique is found to provide satisfactory evaluation in manufacturing reshoring decisions. Furthermore, the priority weights of the criteria get either augmented or suppressed after inducing uncertainty.

4.5 Contributions of the appended papers

The findings from the four papers have answered both RQ1 and RQ2. The correlation between these papers and the research questions in this thesis are presented in Table 13.

Table 13. Connection between the appended papers and the research questions

	RQ 1: *How do industry experts reason while making manufacturing reshoring decisions?*	**RQ 2:** *How the industry experts' reasoning of manufacturing reshoring decisions can be modeled in decision-support tools?*
Paper I	• A holistic set of criteria is considered in manufacturing reshoring decision-making. • The considered criteria are divided into competitive priority, strategy, resource, preference, context and global condition. • The largest category of considered criteria is the competitive priority.	
Paper II	• The industry experts use relative means such as "positive" or "negative" to reason for criteria • The industry experts reason through relevant if-then rules in the decision. • The industry experts reasoning by dividing the competitive priority criteria in three groups based on importance.	• The industry experts' reasoning is captured through the three novel concepts: relative linguistic labels, high-level rules, and linguistic variable weights. • The novel concepts improve interpretability and reduces complexity in modeling.
Paper III		• Two configurations and sixteen settings were explored in a fuzzy logic-based decision-support tool. • The reduced rule configuration and one of the settings performed best with a high level of decision accuracy

Paper IV	• The industry experts reason by dividing the competitive priority criteria in three groups based on importance (prior to pairwise comparison). • Some criteria such as quality and cost are more important, whereas sustainability is less important based on weights.	• The industry experts' reasoning is captured in AHP through pairwise comparison of criteria. The weights of the criteria are calculated. • The weights are used to compute the decision in weighted-sum manner. • Under uncertainty, the least prioritized criteria are further suppressed in importance.

This research fulfils the purpose "to develop decision-support tools for evaluation of manufacturing reshoring decisions" by first understanding how industry experts reason while making manufacturing reshoring decisions concerning the criteria that should be considered in manufacturing reshoring decisions. Further the industry experts' reason is captured through relative means, rules and criteria weights in evaluating manufacturing reshoring decisions. Subsequently, this research seeks to understand how the industry experts' reasoning can be modeled in decision-support tools. Paper 1 identified an extensive list of criteria considered by industry experts before dividing them into the following categories: competitive priority, resource, strategy, preference, context and global condition. Among them, the biggest category of competitive priority was selected for modeling purposes at an overall level. Meanwhile, Paper 2 demonstrates how three novel fuzzy logic concepts enable modeling of the selected category of criteria for manufacturing reshoring decisions. The fuzzy logic concepts were found to be relevant in emulating industry experts' reason while making manufacturing reshoring decisions. Similarly, Paper 3 identifies the best configuration as well as the best settings for fuzzy logic-based decision-support tool in reshoring decisions. Finally, Paper 4 investigates AHP-based decision-support in evaluating a manufacturing reshoring decision. The industry experts' reason is captured through a pairwise comparison of selected criteria that determines criteria weights and ranking on the basis of importance. The findings are discussed in greater detail in the next chapter.

5. Discussion

This chapter discusses the findings from the research and appended papers in relation to the literature. The discussion commences with the results of the research by answering the research questions, followed by the contribution of the research to theory and industry. The chapter ends with a discussion on the limitations of the research methods and the research in its entirety.

5.1 Results

This research is done to develop decision-support tools in order to evaluate manufacturing reshoring decisions. In order to do so, the first research question (RQ1) intends to find out how industry experts reason while making manufacturing reshoring decisions. The reasoning in manufacturing reshoring decisions can be addressed with respect to the criteria that are considered in these decisions (i.e., content). Industry experts have considered an extensive set of criteria in their decision. The criteria considered are both quantitative and qualitative. This is in alignment with the recommendations from researchers to not only base manufacturing reshoring decisions on cost factors, but also to adopt a holistic perspective on these decisions (Hartman et al., 2017; Engström et al., 2018a; 2018b). To put things into perspective, 72 criteria were identified by the industry experts. The criteria are grouped into categories such as competitive priority, resource, strategy, preference, context and global condition. The grouping of the criteria is similar to that of previous frameworks (e.g., Benstead et al., 2017; Srai and Ané, 2016). However, the preferences category, have not been sufficiently covered in earlier frameworks. The largest category in the list is the competitive priority category, which emphasizes the importance of this category in manufacturing reshoring decisions. This is also in alignment with previous frameworks that suggest a large share of competitive priority criteria (Benstead et al., 2017). Therefore, a competitive priority perspective is a relevant group to consider while modeling reshoring decisions. Due to the fact that no new criteria were identified by the industry experts, it is suggested that decision criteria are well-covered within the influencing factors present in the extant literature (Barbieri et al., 2018).

Another aspect of the first research question (RQ1) that dictates experts' reasoning of manufacturing reshoring decisions is the importance of criteria on an overall competitive priority level. The experts divide the criteria of competitive priority into three groups based on their importance. Industry experts reason that in manufacturing reshoring decisions, quality is the most important criterion, followed by cost. In their opinion, sustainability is the least important criterion in competitive priority. The same order of importance was captured in both fuzzy logic-based and AHP-based decision-support. It is interesting to observe that another AHP-based study found flexibility (the ability to respond to demand) as the most important criterion, followed by quality (Pal et al., 2018). One plausible reason for that is that sustainability is often taken for granted and hence, requires further attention (Pal et al., 2018). The experts use relative terms such as *positive*, *negative* or *neutral* to compare the criteria. These terms ensure that semantics are consistent among different experts. Furthermore, the experts did not consider the combination of all the criteria while reasoning. In fact, they used only those rules that are relevant to them in the decision-making.

The second research question (RQ2) intends to find out how industry experts' reasoning in manufacturing reshoring decisions can be modeled in decision-support tools. In order to model experts' reasoning in a decision-support tool, expert systems that considers facts and heuristics for evaluating complex manufacturing reshoring decision-making are used. As a starting point, the competitive priority category is selected for modeling on an overall level. The choice of competitive priority category is attributed to its higher share among the decision criteria. Three fuzzy logic concepts were developed to emulate the experts' reasoning. The first concept, relative linguistic variables, increases consistency during modeling. This helps avoid confusion that is caused by absolute labels, which may assign different meanings for different criteria. The second concept, high-level rules, simplifies the rule base. This considers only the if-then rules that are relevant for the experts. The third concept, linguistic variable weights assigns weights to the criteria according to the importance considered by the industry experts. The linguistic variable weights are used to automatically creates a complete rule base. Two main modeling types are addressed in order to further develop the decision-support tool. The first one used a complete rule base, while the second one incorporated a reduced rule base. In order to model industry experts' reasoning, the reduced rule base is preferred. Furthermore, one of the sixteen settings were found to perform significantly better and hence, is recommended for future modeling for manufacturing reshoring decision-making. Experts' reasoning is also captured using AHP support tools, and is modeled by calculating the decision output in a weighted-sum technique. Among the decision-support tools that have been developed in this research, the fuzzy logic-based tool performed better than the AHP-based support tools in emulating industry experts' reasoning.

5.2 Contribution

The research presented in this thesis contributes to theory and industry in several ways. The theoretical contribution of this thesis is the increased knowledge on manufacturing reshoring decisions. The manufacturing reshoring decision is based on an extensive list of criteria that is categorized into the following: competitive priority, resource, strategy, preference, context and global condition. Subsequently, it is developed into a theoretical framework that contributes towards understanding the content of the manufacturing reshoring decision and can be used by researchers for further development. Furthermore, it can be used as a starting point to conduct case-based empirical research. The developed theoretical framework includes soft factors in the form of stakeholders' preferences, which has not been addressed previously in any of the frameworks. While developing decision-support tools for reshoring, three fuzzy logic concepts were conceived: relative linguistic labels, high-level rules, and linguistic variable weights. The novel concepts make a significant contribution to the theory of fuzzy logic, and not manufacturing reshoring alone, since they are applicable to any manufacturing-related application. These concepts simplify the modeling process for researchers and system users alike and help improve interpretability-accuracy tradeoff in the fuzzy logic topic. While developing decision-support tools for reshoring, different settings were investigated. It was suggested that one of them outperformed the other. This contributes to theory in how manufacturing reshoring decisions can be modeled in fuzzy logic, and which setting (or settings) are appropriate for such applications.

This thesis also makes several contributions for the industry. First, it provides managers with a tool in the form of an extensive list of criteria, that can be used as a checklist. The managers may select the relevant criteria to be included in the manufacturing reshoring decision. Second, this thesis provides two kinds of decision-making tools: fuzzy logic-based and AHP-based. These tools are capable of suggesting whether or not a reshoring option should be further evaluated. Therefore, the developed support tools help managers to make timely and resilient manufacturing reshoring decisions. Third, within the fuzzy logic-based tools, the research shows that managers can choose between a complete or reduced rule base configuration, depending on the availability of information. Managers are often conflicted in either making a timely decision or obtaining complete information of the criteria. Fourth, these tools were based on competitive priority criteria, which were the most common group in theoretical and empirical findings. The criteria selected are holistic and are generic to firms belonging to the manufacturing industry. Fifth, the academic expert used in this study will help managers verify the criteria weights with those opined by the expert. Therefore, this research makes it easier for managers to make resilient manufacturing reshoring decisions.

5.3 Limitations

As in case with all research studies, this thesis also suffers from certain limitations. The limitations are identified for the specific papers and to modeling method that have been used in this research. The limitations in Paper 1 is that the selection of case companies was done through purposive sampling. This sampling technique was employed since the case companies formed part of a broader research project. The quality of this study may have improved if cases were selected randomly. The selected case companies were based in Sweden, which, in turn, poses a geographic limitation in terms of generalizing the findings of this study. Additionally, the data collected relied on recollection of past incidents, which is a drawback while conducting interviews. Had the reshoring project been ongoing, it would help to obtain a real-time understanding of how the reshoring criteria are chosen in the decision-making process. Meanwhile, the main limitation in Paper 2 was that the three novel concepts were not fully compared to rival fuzzy logic concepts already present in the extant literature, which would help improve the concepts' verifiability. On the other hand, the limitations in Paper 3 was the decision to use Gaussian-type membership functions, without exploring other types of membership functions. Finally, in Paper 4, one of the limitations was the use of weighted-sum technique, without exploring other techniques to arrive at the decision.

In general, the modeling method that uses fuzzy logic also poses several limitations. One of the limitations was the selection of only one of the categories of criteria (i.e., competitive priority) for modeling purposes. A large number of criteria further increases the complexity of modeling in fuzzy logic. Since this research explores feasibility, too many criteria were not included in order to avoid increasing the complexity. The selection was based on the fact that majority of criteria were found as competitive priority. Furthermore, in order to avoid increasing the complexity of the models, the selection of linguistic labels is limited. Another limitation is that only a subset of industrial experts was used throughout the research. It would have been more useful to include more experts both from the academia and the industry in a proportionate sample. However, the gathered data is considered highly valid due to the selected experts' knowledge and skill. Another limitation is that lack of models' validation. However, this limitation, by all means, will be addressed in future research. This requires more testing with the companies and involving more experts from academia as well as the industry.

6. Conclusion and further research

This chapter concludes the research by reflecting on the purpose and how it was fulfilled. Finally, the chapter ends with interesting avenues for future research in addition to the intended path to PhD dissertation.

6.1 Concluding remarks

Manufacturing relocation decisions have been relatively less studied with respect to decision-support tools. Therefore, the purpose of this thesis is: "to develop decision-support tools for evaluation of manufacturing reshoring decisions." The purpose was fulfilled by developing an extensive list of criteria and multiple decision-support tools. The extensive list of criteria can be used as a checklist to support managers on manufacturing reshoring decisions. The two decision-support tools were based on modeling using fuzzy logic and AHP. The fuzzy logic-based decision-support captures experts' reasoning in a semantic manner, while the AHP-based decision-support captures experts' reasoning in the weights of criteria and weighted-sum technique for decision evaluation. When used on an overall level of criteria, both types of decision-support tools were feasible. Reshoring decision-making is a complex process, and the mind of the decision-maker cannot be fathomed. Therefore, this research signifies a small effort on unfolding the labyrinth of the decision-making process. The research, however, remains in its nascent stages in order to reach a detailed conclusion. Therefore, more fuzzy logic-based concepts need to be developed and integrated with the existing concepts as a continuation of this research. In addition, more decision criteria need to be considered through multi-stage fuzzy logic systems in order to increase the applicability of decision-support.

6.2 Further research

In order for the research to continue, several future research avenues can be identified. This assumes significance because the decision-making aspect of manufacturing reshoring remains an underexplored topic. Therefore, this area needs further attention. Future research could explore the “right number” of criteria (amount) and type of data considered in these criteria. There is ambiguity in terms of how many criteria needs to be considered and balanced in order to make a timely manufacturing reshoring decisions, due to the dilemma on whether to take an early manufacturing reshoring decision or to wait for complete information of criteria, even though the former is suggested in certain industries (Boffelli et al., 2018). Thus, multiple case studies need to be conducted to capture the insights of those firms which have taken an early decision and those that have waited for complete information. Within the literature, there are relatively few single-case studies that have captured the decision-making process. These case studies could help capture the decision-making process in a detailed manner and the tools that were considered in this process. This research has only encompassed a few types of tools for manufacturing reshoring decision-making. Therefore, future research could also draw insights in various other tools that are available/developed for manufacturing reshoring decision-making as well as for different reshoring types.

In light of the 2020 coronavirus crisis, there is heightened uncertainty in the manufacturing sector. Furthermore, its impacts are likely to be far worse than the 2008 financial crisis (OECD, 2020). Future research will need to address how companies who find themselves in this crisis can relocate to the home country. With nations imposing lockdowns, the intensity of manufacturing relocations is likely to decrease, as an increasing number of companies are considering relocation back to home countries, as opposed to offshoring, which is similar to how the events unfolded in the aftermath of the 2008-financial crisis (Kinkel, 2012). Reshoring activities is expected to increase in future as manufacturing industries cut-off their dependence from globalization or uncertain supply chains (Bloom, 2020). Future research should investigate the reshoring intensity due to the impact of the 2020 coronavirus crisis. This crisis might lead to events where global condition category will be increasingly integrated in future decision-support tools. Future research should investigate how global conditions are taken into consideration in the manufacturing reshoring decision-making process. The tools developed in future research should incorporate scenario analysis, which also account for such rare and devastating events.

Some of the future research avenues will be continued towards the PhD dissertation. In this study, so far, only a subset of industry experts was involved. Therefore, as part of future studies, more experts, both from academia and the industry, will be involved. This will help increase the validity of the models. These models will include more criteria from different categories. For this purpose, multi-stage fuzzy logic systems will be investigated. The idea of combining multi-stage is to scale-up the performance of several single stage fuzzy inference systems. These multi-stage systems will be guided by both theoretical and empirical findings of this research. Given that the implementation of multi-stage systems would make it possible to incorporate more criteria, the number of fuzzy rules in the system will also increase correspondingly. Therefore, automatic generation of fuzzy rules must be explored in future, not only using the concepts demonstrated in this research, but also leveraging other techniques such as c-means clustering (Gou et al., 2015).

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Developing Decision-Support Tools for Evaluation of Manufacturing Reshoring Decisions

During last three decades, companies have offshored their manufacturing activities across international borders in order to pursue lower manufacturing costs. Despite having accomplished their purpose, companies have also suffered from issues, especially poor quality of products and a poor response to customer demand. Therefore, companies consider relocating some of the manufacturing activities back to the home country, a process that is known as manufacturing reshoring. There is paucity of scholarly attention on how manufacturing reshoring decisions are evaluated and supported. Therefore, the purpose of this thesis is to develop decision-support tools to evaluate manufacturing reshoring decisions. In order to fulfil this, it is important to know how industry experts reason while making manufacturing reshoring decisions (RQ1), and how their reasoning can be modelled into decision-support tools (RQ2). Therefore, three studies were conducted including a multiple case study and two modeling studies. The multiple case study addressed the criteria that are considered by the industry experts in these decisions, while the two modeling studies, based on fuzzy logic and analytical hierarchy process (AHP), used a part of these criteria to develop decision-support tools. The findings indicate that a holistic set of criteria were considered by industry experts in arriving at a manufacturing reshoring decision. A large portion of these criteria occur within competitive priority category and among them, high importance is given to quality, while low importance to sustainability. Fuzzy logic modeling was used to model the criteria from the perspective of competitive priority at an overall level. Three fuzzy logic concepts were developed to capture industry experts' reasoning and facilitate modeling of manufacturing reshoring decisions. Furthermore, two configurations and sixteen settings were developed, of which, the best ones were identified. AHP-based tools were used to capture experts' reasoning of the competitive priority criteria by comparing the criteria. It was observed that fuzzy logic-based tools are able to better emulate industry experts' reasoning of manufacturing reshoring. This research contributes to theory with a holistic framework of reshoring decision criteria, and to practice with decision-support tools for manufacturing reshoring decision.

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ISBN 978-91-87289-57-6