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ScienceDirect

Procedia Computer Science 180 (2021) 696–705

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Industry 4.0 and Smart Manufacturing

CLUSTERING AND CLASSIFICATION OF MANUFACTURING ENTERPRISES REGARDING THEIR INDUSTRY 4.0 RESHORING INCENTIVES

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Abstract

Due to drivers like Industry 4.0, reshoring recently receives more attention. In order to increase understanding, in this novel field of research, k-means clustering is performed to find groups of enterprises, which differ regarding their reshoring incentives. Based on these clusters, manufacturing enterprises are classified by the combination of an intra variance analysis and prior knowledge. Therefore, an own enlarged sample, encompassing 94 German industrial enterprises with global sourcing and production activities is used. It is investigated that five clusters segment the sample optimally and that the importance of innovation as well as trust and sustainability are decisive for the classification of German manufacturing enterprises regarding their reshoring incentives. These findings contribute to the body of knowledge about reshoring incentives in terms of methodology and content, since unsupervised learning is used for the first time within that context and enables insight into previously unexplored structures of the reshoring phenomenon.

Keywords: Reshoring; Industry 4.0; Unsupervised Learning; K-Means Clustering

1. Introduction

The decision where to locate and relocate manufacturing activities has been an important topic within strategic operations management [1], [2]. Especially until about 20 years ago, there was a general trend to offshore manufacturing activities from the US to Middle America and Asia, and from Western Europe to Eastern Europe and

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1877-0509
10.1016/j.procs.2021.01.292

Asia. This was due to lower labor costs while transport costs in international container shipping were comparability low [3], [4], [5], [6].

In recent years, the manufacturing offshoring trend has been losing its speed, supported by national initiatives to bring manufacturing back to home countries and rising wages in countries such as China [7], [8]. Further, several risks are associated with production relocation abroad [9], [8], such as lower quality, local conflicts, long supply chains with high reaction times, or skill shortages. A further potential risk of global value chains is especially highlighted through the Covid-19 pandemic [10].

Cost advantages are the main reason for manufacturing enterprises to offshore. However, within the scientific discussion about offshoring, the financial perspective is seen as limited and further aspects should be taken into account when deciding on a location [11]. In this context, the productivity increases in Germany through Industry 4.0 and the higher flexibility requirements illustrate relocation factors that go beyond the financial perspective and represent incentives for bringing production back to the home country. This reshoring phenomenon has recently been noticed and the scientific contributions are limited in amount and to specific topics [12], [7], [13]. Therefore, this paper aims to explore which reshoring incentives are essential for different groups of German manufacturing enterprises. In order to meet this requirement as objective as possible, data-driven clustering and classification are performed through a k-means algorithm and an intra class variance analysis. Therefore, a questioner that surveys the reshoring incentives of 94 German manufacturing enterprises in the context of Industry 4.0 is raised. Since there exist no prior research that uses unsupervised learning within the reshoring context, this paper offers a novel approach how German industrial enterprises are clustered and further classified in regard to their reshoring incentive.

The remainder of this paper is structured as follows: Section 2 outlines the theoretical background behind Industry 4.0, reshoring, and prior work. Section 3 describes the approach based on the empirical sample and the clustering approach. Section 4 presents the clustering as well as classification results, which are discussed in section 5. Section 6 concludes the paper with limitations and suggestions for future research.

2. Theoretical Background

The following sections define the concepts of Industry 4.0 (section 2.1) and reshoring (section 2.2) as well as the current state of research, deriving the research question for this paper.

2.1. Industry 4.0

The concept of Industry 4.0, relating to the idea of a fourth industrial revolution, is an intensively discussed topic since the German federal government introduced the term as part of the country's high-tech strategy in 2011. Industry 4.0 is based on the idea of merging the physical and virtual worlds through Cyber-Physical Systems, and interconnecting humans, machines and devices through the Internet of Things (IoT). This horizontal and vertical interconnection across entire value chains, from customer to supplier, across the entire product lifecycle, and across different functional departments leads to several potentials. For instance, value creation can be made more efficient, individualized and of higher quality, service-oriented, traceable, resilient and flexible. This allows to generate benefits in economic, ecological and social dimensions, relating to the Triple Bottom Line of sustainability [14], [15], [16]. Still the concept remains challenging to be set up in entire supply chains [17].

In its initial concept, Industry 4.0 was especially aiming for securing the competitiveness of the German manufacturing industry through increased productivity, proximity to customers, as well as higher resilience and flexibility, among other aspects [14]. This includes reshoring manufacturing activities back to the home country or building up new manufacturing capacities in the home country.

Comparable concepts have been launched worldwide to strengthen the respective domestic manufacturing industries, as several enterprises in the US have initiated the 'Industrial Internet Consortium', China has initiated the 'Internet Plus' or 'Made in China 2025' and South Korea the program 'Manufacturing Innovation 3.0' [18].

2.2. Reshoring

Throughout extant literature, several terms can be found to describe the geographical relocation of companies' activities. The term offshoring generally describes the relocation of activities from the home country to a foreign country. However, for the reversal of offshoring decisions, different terminologies can be found. Most researchers in this field, and especially most recent papers [19], [20] utilize the term reshoring, which is used in the remainder of this paper.

Reshoring represents a relatively young research field in contrast to offshoring [21], [22], [23]. Besides empirical evidence from the US [21], [22], several papers published from Europe can be found, whereby empirical evidence is generally rare [24], [19], [25], [20]. In general, the phenomenon of reshoring seems to increase [26], [24], while a large-scale trend with high amounts of activities reshored cannot be seen or clearly distinguished yet [27].

Several authors claim that offshoring and reshoring face the same considerations regarding a geographical and governance dimension [28], [29]. These include strategic management theories, such as transaction cost economics and the re-source-based view, that are linked to the manufacturing location decision [30], [31], [32]. In the context of reshoring, transaction costs of offshoring strategies are compared with the transaction costs of potential reshoring [33]. The resource-based view describes firms as possessing a bundle of resources that help them to develop a competitive advantage [34], [35]. When a company is not able to exploit the resources of the host country, it might also opt for reshoring. In practice reshoring is often a result from failed or unsatisfying offshoring results concerning costs or market motivations [23], [20], having a long-term effect on the companies' competitiveness [36]. The increased trust by reshoring can also be represented by the positive impact of reshoring on the shareholder wealth [37]. Further authors consider the consumer perspective [38],

'nearshoring' instead of long-distance offshoring [39], general 'deinternationalization' trends when referring to manufacturing [40], relating to perspectives from strategic operations management [1], [2].

Wiesmann et al. [41] conclude that due to the long-term implications of reshoring decisions they should be based on a dynamic decision model that considers the global dynamics, the host country, the home country, the supply chain and firm-specific properties.

2.3. Related Work and Research Question

In general, empirical evidence on reshoring is scarce [42], while a large number of reshoring drivers are discussed in literature [24], [43], [44], [20]. Only few studies are attributed to the topic of Industry 4.0 and reshoring yet [13], [45], [12], [7]. These studies provide an overview of potential reshoring drivers in the context of Industry 4.0, but not how those can be clustered, working out possible relationships. In response, this paper attempts to close this scientific gap by investigating the research question, how German manufacturing enterprises can be clustered and further classified in concerns to their reshoring incentives.

3. Research Design

Unsupervised learning is used as data-driven clustering method to find groups of enterprises, which differ in regard to their reshoring incentives. On the basis of these clusters, manufacturing enterprises are further classified by the combination of an intra class variance analysis and a priori knowledge. The quantitative study is used to support generalizations about the reshoring phenomenon by objective and accurate results. The data collection is based on a survey of 94 German companies with at least partially offshored production.

3.1. Clustering and Classification

Unsupervised learning through k-means clustering is performed to detect groups with a following intra class variance analysis in combination with a priori knowledge classifying manufacturing enterprises in reference to their reshoring incentives.

Due to the novelty of reshoring and its limited as well as specialized research [13], [45], [12], [7], a general classification of manufacturing companies concerning their reshoring incentives is preferable as baseline. While most classification tasks are exclusively based on theoretical prior knowledge in the form of labels, this paper uses unsupervised learning to keep the possibility open to identify unlabelled data and recognize structure in a data-driven way [46]. This paper adopts the unsupervised k-means clustering algorithm, which is the most common clustering algorithm. This algorithm aims to maximize the internally homogeneity as well as the externally heterogeneity between the subsets. In this application, K-means aims to cluster companies that answered very similar to their questionnaires, while also optimizing to keep companies with different answers in different clusters. K-means, as a partitional algorithm, finds every subset simultaneously as a partition of the whole sample [47]. The k-means algorithm works by choosing arbitrary centers in the data and assigning the individual data points to these centres with the smallest distance to them. With each iteration the centres are recalculated on the base of the minimum internal distance until centre stabilisation is reached [48]. To explore the optimal number of clusters, the elbow method is performed, which illustrates the relationship of quality and complexity by increasing the number of clusters [49]. The specification of the exact number of clusters is supported by a variance analysis of 100 experiments.

On the basis of the data-driven generated clusters, the features determining a subgroup are analysed to solve a classification problem. Therefore, an intra class variance analysis with enrichment through a priori knowledge is applied.

3.2. Data Collection

To build on the current state of research, the questionnaire and sample of Müller, Dotzauer, and Voigt [13] is used and extended by almost twice as many observations, resulting in 94 companies. The questionnaire includes the drivers for reshoring found in literature and the importance of Industry 4.0 for German as well as individual companies to reshore. Therefore, the framework provided by Fratocchi et al. [20] and a 5-point Likert scale are used.

The sample consists of manufacturing companies with at least partial offshore production from five different industrial sectors. Electrical and mechanical engineering are most strongly represented with 28 enterprises each. Further, 15 consumer goods, 14 automotive and 9 metal industry companies are included in the sample. The enterprises are additionally separated by size in regard to their annual turnover and number of employees, defined by § 267 (1-3) German Commercial Code. About two thirds are large, 18 medium and 15 small companies.

3.3. Data Preprocessing and Analysis

Data preprocessing is performed in terms of standardization and feature selection. To explore the optimal number of clusters, the elbow method is applied and the result is adjusted according to robustness requirements. In this case, high robustness is achieved if, over several tests, the cluster distribution remained similar.

Since training data quality is decisive for the validity of the output, data preprocessing starts with handling missing data points. Since negligibly few data points are not raised, the blanks are interpreted as indecisiveness and set to the scale mean value of three. Furthermore, the features are standardized to a mean of zero and a standard deviation of one to avoid overvaluation of individual variables [50]. That should particularly counteract the problems arising of the sensitivity of the initial center choice, which come along with the k-means algorithm [47].

Data preprocessing is completed by feature extraction and selection. Dimension reduction reduces noise, unnecessary complexity or bias through redundant information [50]. However, since the original feature space does not lead to efficiency problems and the different dimensions cover the different reshoring incentives found in literature so far, dimensionality reduction is not applied for the final data analysis. In order to check the results against bias and the assumptions made, the state-of-the-art scientific process of feature extraction is additionally performed. Therefore, a correlation analysis with a threshold of 0.55 correlation between two features is carried out. Based on that, the relevant features are classified through an intra class variance analysis and a priori knowledge. It is noticeable, that using this method only linear dependencies are considered [51].

The result of the data preprocessing is used for the data analysis. In reference to the baseline paper from Müller, Dotzauer, and Voigt [13] the dataset gets clustered into two groups by the k-means algorithm. To compare the result with the data driven detected number of groups of manufacturing enterprises, that differ in concern to their reshoring incentives, the elbow method is used. However, to get clusters, that also meet robustness requirements, the optimal number of subsamples is additionally checked experimentally by a variance analysis. Therefore, clustering is performed 100 times with each number of clusters within the elbow curve ($K = \{2 \ldots 15\}$). Based on that, robustness is checked in terms of intergroup variance, so that the number of clusters get determined by the result of the elbow method with low variance, leading to stable clusters.

These resulting clusters are the basis for the classification problem. The most informative features are detected by an intra class variance analysis and, in combination with a priori knowledge, classes are built, which identify the different groups of manufacturing enterprises in concern to their reshoring incentives.

4. Results

The sample includes 58 different features, while the compared feature extraction process leads to a reduction to 36 features. Related to the baseline [13], a two-class clustering problem is analyzed first. The results are very robust clusters, which divide the training data into groups with 49 and 45 observations. These subgroups differ the most in regard to the prioritization of uncertainty regarding political/economic developments, rising labour costs in low-wage countries, political stability/ planning security in Germany, legal certainty in Germany, high communication and coordination costs and better control and monitoring possibilities. Therefore, with two clusters the reshoring incentives are mainly focused on legal certainty and cost minimization, whereas Industry 4.0 related incentives only play a minor role. Further, the investigated dependence of the own reshoring intention of manufacturing enterprises on improvement of innovation skills, political incentives (government support), utilization or testing of new technologies, faster time to market as well as less communication and coordination costs [13] could not be supported with statistical significance based on the extended data by linear regression.

However, the main focus of this paper is to investigate the optimal clusters of manufacturing enterprises in a data-driven way with regard to their reshoring incentives and further to classify them. Using the elbow method, approximately five or six clusters optimize the trade-off between information content and complexity both in the main sample with all features and in the reference sample. The robustness test shows a clear preference to five cluster in both cases, which fixed the decision of the most reasonable number of clusters.

The size of the individual subsets given by the k-means algorithm is also found experimentally on a basis of 100 iterations. As a result, the dataset containing all features is clustered into five groups, including seven to 28 observations. Similarly, the sample with the reduced feature space is separated into nine to 29 manufacturing enterprises per cluster. To detect which features determine the individual groups, the quantile with the lowest intragroup variance is analyzed. The 15 (total feature space) and nine features (extracted feature space) of each subset get ranked in regard to their divergence to the mean. The five most influential features in terms of great deviation per subgroup are shown in Table 1 for the not-extracted sample and in Table 2 for the extracted one.

As illustrated in Table 1, cluster three and four are distinguished by features that are above-average importance, whereas cluster two and five are distinguished by features that are above-average unimportance and that cluster one includes both types of features.

Extending the two-class problem to a five-class problem, the claim of the baseline paper, that “innovators” differ in reference to their reshoring incentives can be supported by cluster three. The reshoring decision of these innovators is based on the extend of flexibility, utilization of new technologies and domestic research and development.

The counter part of this innovation class is the traditional class, illustrated in cluster five. Domestic innovations, research or technology as well as improved customer orientation through customer proximity are not perceived as an advantage of reshoring by them.

Furthermore, a lack of trust and sustainability is decisive for reshoring [13]. This claim is supported by cluster four, which mentions the loss of know-how, legal certainty in Germany and sustainability aspects as the most important reshoring incentives.

This class of trust and sustainability concerns also has a counter class, which has no trust issues in reference to reshoring. Neither increasing instability in the offshoring country, cultural differences nor product piracy are notable advantages of reshoring for them.

Table 1: Cluster Determining Features - Total Feature Space (58 Features)

Cluster	n	Features	μ	σ2
1	28	Attractiveness of Germany through I4.0 (general)	0,336	0,691
		Time from product development to placement	0,219	0,716
		Greater flexibility/higher responsiveness	-0,378	0,698
		Faster time-to-market	-0,260	0,713
		Customer service through geographic proximity	-0,208	0,682
2	25	Increasing instability due to crises	-1,034	0,603
		Loss of proximity to the customer	-0,777	0,658
		Cultural differences	-0,756	0,720
		Product piracy	-0,747	0,641
		Plagiarism	-0,723	0,685
3	20	Greater flexibility/higher responsiveness	0,838	0,384
		Exploiting or trying out new technologies	0,836	0,539
		Customer service through geographical proximity	0,780	0,535
		Proximity to domestic research and development	0,756	0,683
		Utilisation of capacities in the home country	0,743	0,723
4	14	Loss of know-how	1,218	0,527
		Legal certainty in Germany	1,079	0,547
		Sustainability Aspects	1,069	0,573
		Insufficient sustainability	1,043	0,584
		Lack of flexibility/low responsiveness	1,022	0,513
5	7	Customer orientation through customer proximity	-1,885	0,408
		Improvement of innovative capacity	-1,873	0,447
		Exploiting or trying out new technologies	-1,715	0,427
		Proximity to domestic research and development	-1,711	0,476
		Customer service through geographical proximity	-1,584	0,448

Cluster one is the largest, with approximately 30% of observations and its features do not lead to a clear classification. While they take German's Industry 4.0 strategy and shorter time from product development to placement as reshoring incentives seriously, greater flexibility or improved customer service through geographic proximity have a subordinated role in their reshoring decision.

Table 2 illustrates the key features in regard to reshoring incentives for five clusters of German manufacturing enterprises, where the feature space is reduced by data preprocessing. Since highly correlated features are excluded, every received feature represents its own topic so that they cannot be summarized into superordinate classes. Therefore, the classification is carried out more expedient by the generalist approach of this paper with the whole feature space as stated in the research design. However, the results of Table 2 can be used for very specific classification of manufacturing enterprises in regard to their reshoring incentives and as baseline for the most informative features of that topic.

5. Discussion

Based on the findings in section 4, German manufacturing enterprises can be clustered in reference to their reshoring incentives. Performing a robustness checked elbow-method for both applications, with and without pre-feature extraction, five clusters can robustly be found. By using these clusters, the research question, how manufacturing enterprises can be clustered in reference to their reshoring incentives, is qualitatively and quantitatively investigated. These clusters enable the classification of the observations, so that cluster two represents

Table 2: Cluster Determining Features - Extracted Feature Space (36 Features)

Cluster	n	Features	μ	σ2
1	29	Proximity to domestic R&D	0,485	0,687
		Rising wage costs abroad	0,443	0,710
		Better control and monitoring facilities	0,439	0,665
		Avoidance of exchange rate risks	0,410	0,628
		Avoiding cultural differences	0,406	0,703
2	21	Lack of flexibility/low responsiveness	0,921	0,567
		Lack of infrastructure abroad	0,879	0,617
		Difficult control/monitoring	0,878	0,527
		Better control and monitoring facilities	0,775	0,560
		Political/economic development uncertainty	0,768	0,604
3	20	Better control and monitoring facilities	-0,871	0,735
		Incentives from politics or state support	-0,663	0,772
		Total cost of offshoring higher than expected	-0,621	0,760
		Political stability/planning security in Germany	-0,608	0,760
		Legal certainty in Germany	-0,591	0,747
4	15	Better quality at home	0,561	0,434
		Rising raw material/material costs abroad	-0,989	0,655
		High storage and transport costs	-0,486	0,707
		Loss of proximity to the customer	-0,455	0,681
		Attractiveness of Germany through I4.0 (own ent.)	-0,436	0,655
5	9	High communication and coordination costs	-1,730	0,513
		Separation of design/production (less innovation)	-1,551	0,000
		Insufficient sustainability	-1,420	0,474
		Lack of infrastructure abroad	-1,404	0,678
		Lack of/high turnover of qualified personnel	-1,178	0,713

the class no-trust and no-sustainability, cluster three represents the class innovation, cluster four represents the class trust and sustainability and cluster five represents the class no-innovation. Thereby, using the entire feature space, four of the five clusters can be classified, so that the research question, how manufacturing enterprises can be classified in concerns to their reshoring incentives is answered in the main. However, the object of comparison (based on the extracted feature space) cannot support the classification problem.

The resulting classes illustrate that the importance of innovation as well as trust and sustainability are decisive for the separation of German manufacturing enterprises in regard to their reshoring incentives. The focus on innovation capability supports the finding that reshoring is driven essentially by Industry 4.0 of Müller, Dotzauer, and Voigt [13], Strange and Zucchella [45], Ancarani and Di Mauro [12] as well as Dachs, Kinkel, and Jäger [7], since the German high-tech concept is based on the interconnection of state-of-the-art innovations in terms of the IoT. Additionally, as discussed within the theoretical background, the horizontal and vertical interconnection across entire value chains allows for generate benefits, also in social and ecological dimensions [14], [15], [16], so that the demand for trust and sustainability are additionally motivated by Industry 4.0. The aim, to connect the physical and the virtual world needs to face the challenge of isolated companies and negative externalities, that apprehend a loss of know-how or inequitable cost and benefit distribution.

These findings add to the current body of knowledge in terms of methodology and content. The data-driven approach enables insight into previously unsupervised structures of the reshoring phenomenon and contribute to the understanding of the influence of Industry 4.0 on manufacturing location decisions.

6. Implications and Further Research

The main contribution of this paper is to cluster and classify German manufacturing enterprises in regard to their reshoring incentives. Using unsupervised learning in terms of the k-means algorithm for this purpose provides novelty, since the current state of reshoring research do not include unsupervised learning methodology. This data-driven approach enables the investigation of unknown relationships within the reshoring phenomenon while confirming objectivity. Validity is supported through the comparison to the baseline paper from Müller, Dotzauer, and Voigt (2017) as well as to the approach using an additional feature extraction phase. Generalizations for German manufacturing enterprises are possible through the sample homogeneity, despite the limitation in reliability caused by few observations (94 companies) and a single country.

Therefore, it is future suggested to extend the sample size. Additionally, other clustering methods should be applied to detect groups of enterprises that differ in their reshoring incentives. Since the k-means algorithm is the most common clustering algorithm, this paper provides a suitable baseline for further investigations. It is recommended to investigate a hierarchical algorithm instead of a partitional algorithm, which may produce more accurate results due it´s higher complexity without facing the problem of a too large data set.

Further, the motives and drivers behind reshoring could be further differentiated depending on the type of manufacturing processes used for each product. Thereby, a deeper understanding and a more differentiated perspective could be established of which manufacturing processes are most relevant and relate to which kind of drivers.

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