Strategic Foresight of Future B2B Customer Opportunities through Machine Learning

Daniel Gentner, Birgit Stelzer, Bujar Ramosaj, and Leo Brecht

> *Foresight of phenomenon, and power over them, depend on knowledge of their sequences, and not upon any notion we may have formed respecting their origin or inmost nature.*
>
> John Stuart Mill (1806–1873)
> Philosopher, political economist, and civil servant
> In *Auguste Comte and Positivism*

Within the strategic foresight literature, customer foresight still shows a low capability level. In practice, especially in business-to-business (B2B) industries, analyzing an entire customer base in terms of future customer potential is often done manually. Therefore, we present a single case study based on a quantitative customer-foresight project conducted by a manufacturing company. Along with a common data mining process, we highlight the application of machine learning algorithms on an entire customer database that consists of customer and product-related data. The overall benefit of our research is threefold. The major result is a prioritization of 2,300 worldwide customers according to their predicted technical affinity and suitability for a new machine control sensor. Thus, the company gains market knowledge, which addresses management functions such as product management. Furthermore, we describe the necessary requirements and steps for practitioners who realize a customer-foresight project. Finally, we provide a detailed catalogue of measures suitable for sales in order to approach the identified high-potential customers according to their individual needs and behaviour.

Introduction

During the last 20 years, the research field of strategic foresight has played an increasingly important role in corporate strategy. The dynamic environment of companies necessitates, on the one hand, rapid adoption of incremental changes and, on the other hand, radical reorientation towards new business opportunities, technologies, or markets (Rohrbeck, 2011). Strategic foresight aims to detect development lines and trend interruptions in customer needs, technologies, law, and lifestyle habits through different foresight approaches – earlier than competitors (Hamel & Prahalad, 1995).

Within the strategic foresight literature, technological trends have been a major object of investigation. Technology foresight can be defined as the capability of identifying and integrating new technologies (Birke, 2011; Stelzer, 2016). It enables corporate management to gain insights about future differentiating competencies and to secure the company's competitive advantages (Schuh & Klappert, 2011; Stelzer, 2016). Therefore, methods and processes have been developed, largely established, and applied.

As a result, increasing professionalization in customer foresight and proactive market orientation is considered as the next major evolutionary step for most corporate foresight systems (Rohrbeck & Gemünden, 2007; Voola & O'Cass, 2010). Customer foresight as part of strategic foresight (see Figure 1) deals with the identification of early customer needs. Consideration of these future needs in idea generation and validation of concepts is required for radical and disruptive innovation, which is an important prerequisite for innovation success (Rohrbeck & Thom, 2008; Trommsdorff & Steinhoff, 2007). In B2B industries in particular, great potential can be seen in this research field, as a single customer relationship is associated with significantly higher value than in B2C industries (Nenonen & Storbacka, 2016). Recent studies in B2B industries have shown that a continuous development of future beneficial customer assets carried out by strategic management influences firm performance in a significant positive way (Nenonen & Storbacka, 2014; Patatoukas 2011).

However, even today, customer foresight still shows a low capability level. Foresight tools, their application within companies, mechanisms to force acceptance and utilization, as well as a foresight friendly culture are still underdeveloped (Rohrbeck & Gemünden, 2007). In particular, B2B companies lag behind their B2C counterparts when it comes to analyzing an entire customer base in terms of future customer applications, needs, and affinity for new technologies (Gentner et al., 2017; Stein et al., 2013). Among common techniques, there are, on the one hand, socio-cultural trend analysis and megatrend studies, which focus on markets and therefore follow a macro customer level (Rohrbeck & Gemünden, 2007; Rohrbeck & Thom, 2008). In many B2B companies, mainly in the manufacturing industry, these techniques are still based on management heuristics and do not cover the complexity of customer relationships (Lilien, 2016; Nenonen & Storbacka, 2016). On the other hand, lead user studies, explorative interviews, diary research, day-in-the-life visits, and insight clinics (Arnold et al., 2010; Rohrbeck & Gemünden, 2007; Rohrbeck & Thom, 2008) force investigations to focus on a single-customer level and are often applied by single operative sales representatives (Keränen & Jalkala, 2014). This often leads to a lack of early insights into changes in market trends and inefficiencies in market development.

A quantitative customer foresight approach that integrates customer insights of an entire customer base in order to identify future customer needs does not exist. Furthermore, the combination of an individual customer level with a market view cannot be found in recent B2B literature (Hämäläinen et al., 2015).

One research stream that has the potential to drive the development and application of such quantitative foresight approaches is the identification of weak signals (Kim et al., 2013; Porter, 2005). Weak signals are conspicuities or rare events indicating future changes (Ansoff, 1984; Hiltunen, 2008). While nowadays their importance is widely recognized, research on detection models is not sufficiently taken into account (Kim et al.,

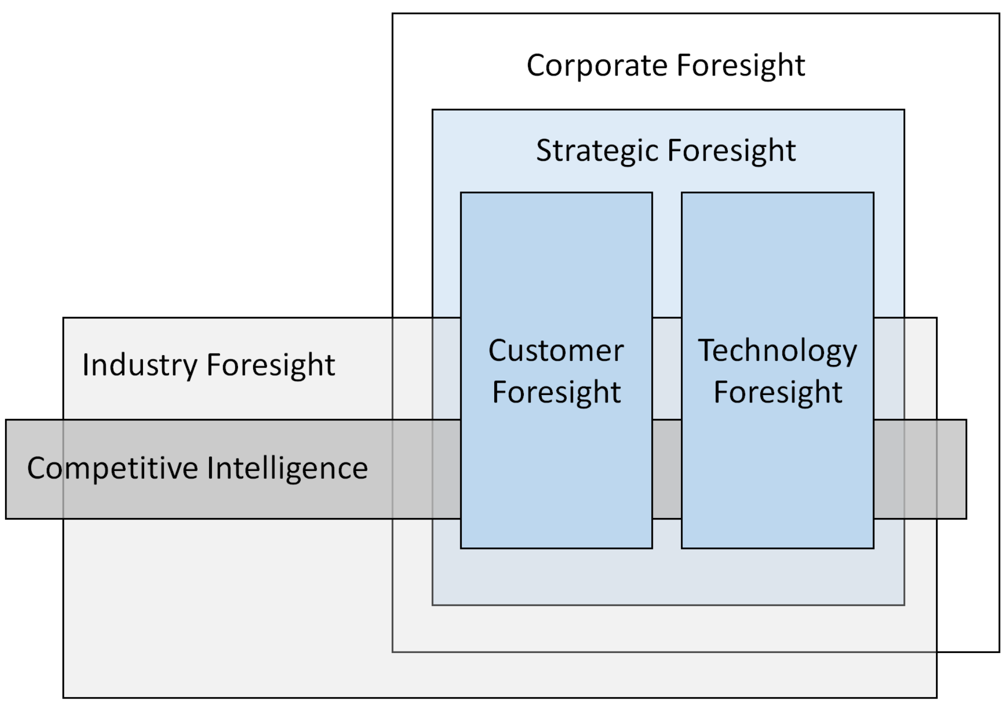

Figure 1. Customer foresight as part of strategic foresight (Adapted from Müller & Müller-Stevens, 2009 and Ramosaj et al., 2018)

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2013; Porter, 2005). In addition to qualitative detection approaches such as Delphi studies, futurists and information scientists increasingly use data mining (Nohuddin et al., 2011) to analyze collaborative knowledge (Boyd & Potter, 2003; Kim, 2013; Sureka et al., 2011). As described by Han and colleagues (2012), "machine learning investigates how computers can learn […] to recognize complex patterns and make intelligent decisions based on data". Research on the applicability of machine learning techniques such as nonlinear classification approaches or rule-based models has mainly been done within the field of technology foresight (Kim et al., 2013; Klerx, 2010; Schmidt & Hoyer, 2013; Stelzer et al., 2015). A common methodology used for machine learning projects is the so-called cross-industry standard process for data mining (CRISP-DM) (Wirth & Hipp, 2000). Its application within strategic decision making in B2B companies has been discussed by Niño and colleagues (2015).

Based on the situation described above and the current understanding, we will provide an answer to the following question: How can a strategic foresight team of a manufacturing company automatically identify weak signals within an existing customer base indicating customer groups with high future potential and need for a new technology?

We will show how to obtain a profile of high-potential customers due to their affinity and need for a new machine control sensor using data patterns out of two customer databases. Furthermore, we will highlight major obstacles, proceedings, and intermediate conclusions of a quantitative customer foresight approach following the CRISP-DM methodology. Finally, we will discuss in detail which measures to introduce in order to strategically develop the future most relevant markets and to manage a company's sales force most effectively.

Research Design

The empirical research comprised a single case study of a quantitative customer foresight approach within an international German manufacturer of full-line equipment for hydropower plants and related lifecycle services. The company had more than 19,000 employees and generated a sales volume of €4.3 billion ($6.4 billion CAD) in 2016. During a foresight project carried

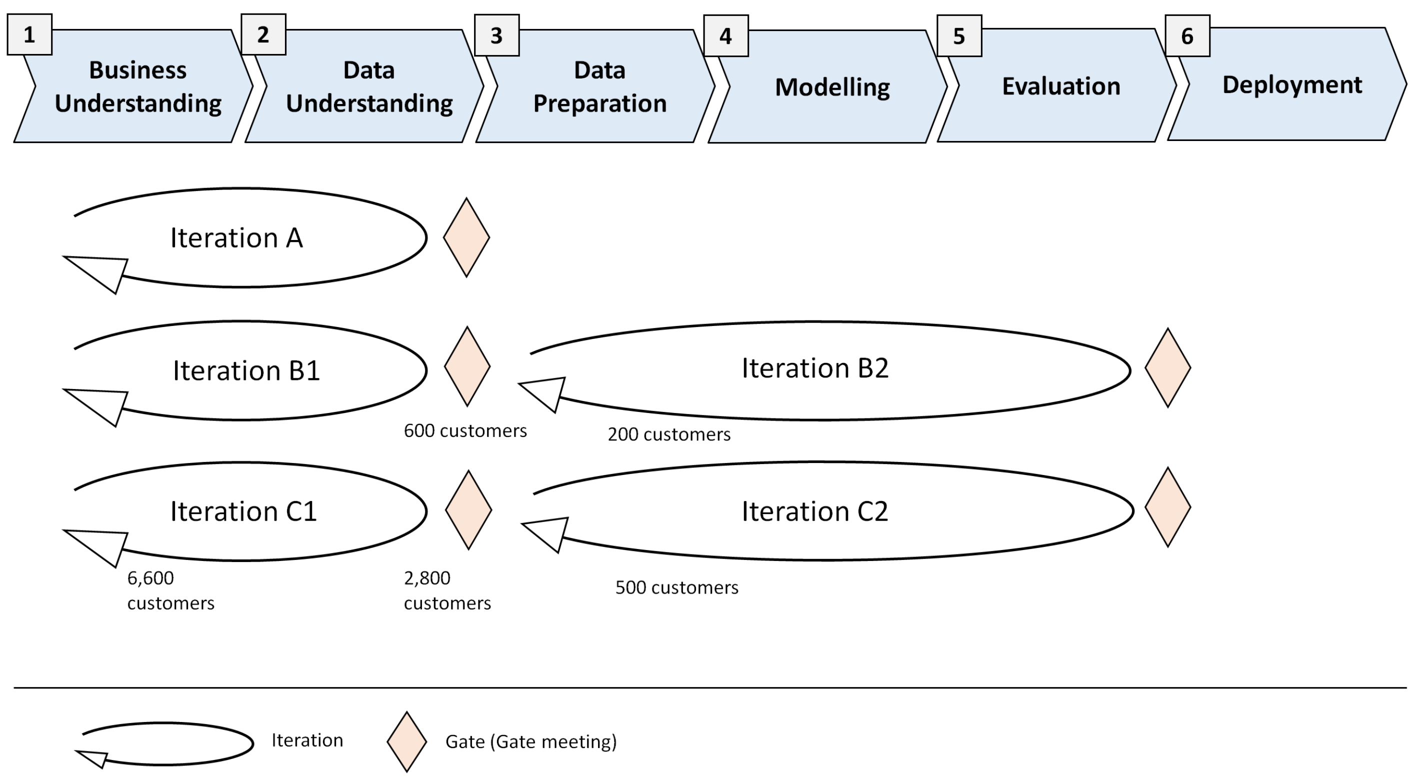

Figure 2. Project-specific iterations and gate meetings following the CRISP-DM methodology (based on Wirth & Hipp, 2000)

out from September to January 2018 in the strategic product management department, which was also responsible for the development of product and project business, approximately 2,800 worldwide customers, mostly powerhouse operators, were analysed through machine learning applications.

The data analysis followed the CRISP-DM methodology. Due to adjustments to the selection of variables, improvements in data quality, and an increase in the size of the dataset, several project-specific iterations were necessary. Therefore, the process steps *Business understanding* and *Data understanding* were run through three iterations, whereas the entire data-mining process was executed twice (see Figure 2). All statements within the present research contribution relate to the last two iterations (C1 and C2).

The case study was carried out using action research, which allows the researcher to gain academic knowledge by solving a practical problem (Hult & Lennung, 1980). In the present case study, action research enabled strong collaboration between the researchers and the organization, and it led to a systematic understanding of the object of investigation and the benefits of the implemented customer foresight approach for the company (Guertler et al., 2017; Lewin, 1946). The action research process used in the present case study is described by Susman and Evered (1978) as "a cyclical process consisting of five phases: diagnosing (identifying or defining a problem), action planning (considering alternative courses of action for solving a problem), action taking (selecting a course of action), evaluating (studying the consequences of an action), and specifying learning (identifying general findings)" (see Figure 3).

Customer Foresight Using the CRISP-DM methodology

As described above, in addition to the action research process, the CRISP-DM methodology serves as a guideline for the data-mining procedure conducted within the customer foresight project of the manufacturer of hydropower plant equipment. Therefore, we describe the analytic approach following the CRISP-DM steps. Within each step, major interactions between researchers and practitioners as well as major action research procedures are highlighted.

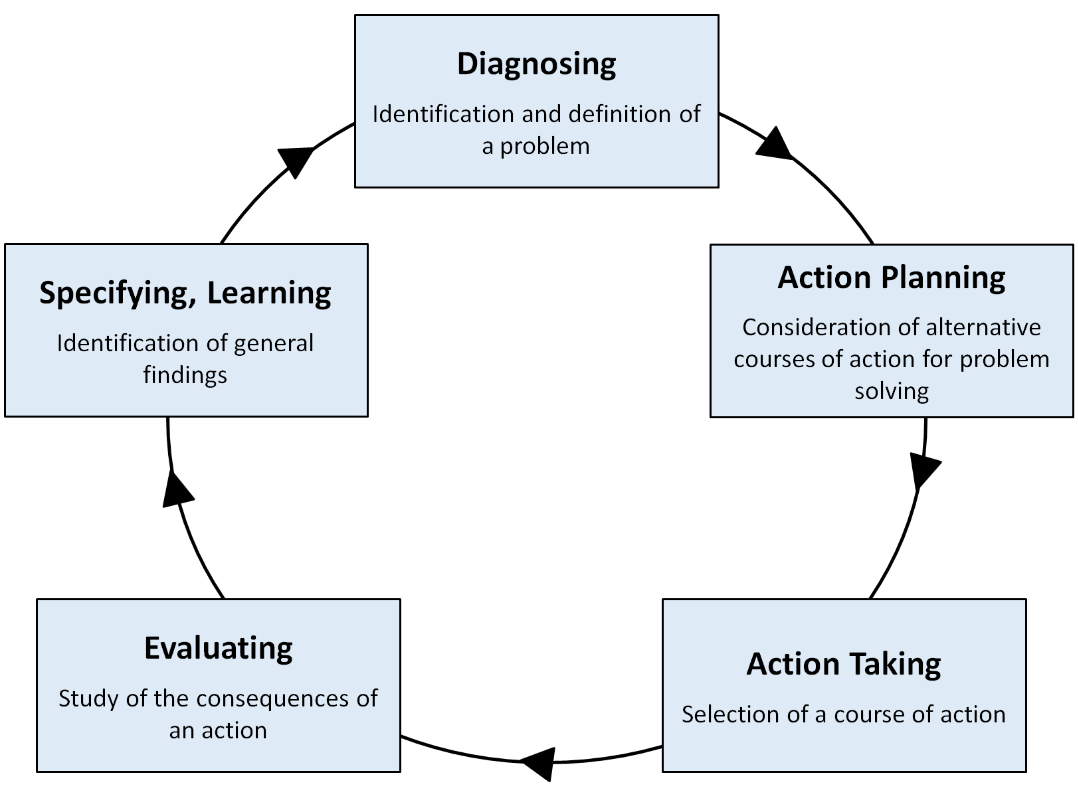

Figure 3. The cyclical action research process (based on Susman & Evered, 1978)

Business understanding
The product management team of the manufacturer of hydropower plant equipment was preparing the market launch of a new sensor. The innovative sensor allows the collection of condition data in turbines and the offer of associated unique maintenance services. The market launch was planned for 2018. For this purpose, we identified innovators and so-called early adopters from a global customer base with a total of approximately 6,600 customers during a customer foresight project. These customers usually showed high affinity for new technologies as well as deep product and operating knowledge. Due to their ability to generate awareness for their innovativeness, they are often suitable as reference customers (Rogers, 2003).

The company's assignments usually were large-scale projects that took several months to several years. These assignments were often initiated by the customer through a tendering process. Previously, the company lacked a quantitative information base for the strategic prioritization of such large-scale projects and related customers. By applying classification algorithms, we created a profile for the customers with the affinity and the need for new technologies. In addition, we used the profile to predict the customers' suitability for the sensor.

These project objectives were developed during an in-house meeting in the product management department as well as during two two-hour preliminary discussions between the scientific representative, a head of product management, and his staff. The meetings and discussions took place between the end of October and mid-November 2017. In terms of the action research method, these iterations were assigned to the subprocesses "diagnosing" and "action planning". Table 1 sums up main interactions and research results.

Data understanding
The process step data understanding consists of selection of attributes and granularity; evaluation of data quality; identification of multicollinearity; and outlier detection (Berthold et al., 2010), as described below:

1. Selection of attributes and granularity: For the analysis, two datasets were used: one obtained from the manufacturer's customer relationship management (CRM) system and another obtained from the enterprise resource planning (ERP) system. Both consisted of 23 customer- and product-related variables, such as country, outstanding opportunities, business segment, turbine type, generator type, capacity, degree of automation, as well as need for repair and education. The data showed different levels of granularity: some variables were related to single generators, whereas others were related to entire power plants or related customers. Therefore, the two databases were consolidated and transformed on a single-customer level. Some variables such as business segment or turbine type showed five to 10 specifications. Hence, each specification was transformed to a new variable, which was either

Table 1. Approach, roles, and results following the CRISP-DM subprocess: *Business understanding*

Approach (CRISP-DM)	Approach (Action Research)	Roles	Results
1. Problem identification (missing, quantitative information for the prioritization of calls for tenders) 2. Derivation of resulting analysis objectives	1. Introduction into the practical problem by the practitioners (Diagnosing) 2. Problem diagnosing by the scientific representative 3. Demonstration of applicable analytic methods by the scientific representative (Action planning) 4. Joint development of project objectives (Action planning) 5. Action planning through scientific representative and practitioners	• Head of Strategic Product Management • Product Manager • Scientific Representative	1. Defined analytics objective: Identification of customers with high suitability or need for a maintenance sensor and related services 2. CRISP-DM steps with major activities

classified on a binary basis or just defined as the total amount of related items, for example, number of turbines of a special type per customer. These variable splits led to an extension of the final dataset up to 66 variables. For two years, customers were judged qualitatively by responsible key account managers and sales staff for their product knowledge and operation experience as well as their affinity for new technologies. According to these criteria, the customers were classified into four categories from "basic" to "scientist". This pre-existing customer segmentation served as input for the target variable named "customer knowledge".

2. Evaluation of data quality: The final dataset showed a high missing value rate of 49%. Therefore, customers with more than 15 variables without record were removed. As a consequence, the dataset was reduced to approximately 2,800 customers.

3. Identification of multicollinearity: The proof of multicollinearity via Spearman correlation matrix and variance inflation factor (VIF) led to a reduction of the data set to 38 variables (Dormann et al., 2013).

4. Outlier detection: A calculation of studentized deleted residuals, Cook's distance, and leverage values did not indicate any anomalies (Cousineau & Chartier, 2010).

After a detailed data evaluation by the representative of science and the communication of the final results during iteration A and B, the evaluation for iteration C was briefly discussed during an online meeting in December 2017. A data report summarized the data evaluation approach as well as data-quality defects and adopted measures. The approach again covered the action research processes "diagnosing" and "action planning" (see Table 2).

Data preparation and Modelling

Out of the 2,800 customers within the final dataset, only approximately 500 were labelled by the target variable "customer knowledge". Within this dataset of labelled data, few customers had been classified as "scientists". For this reason, the original four specifications of the target variable had to be transformed into binary classes.

The data were prepared for the modelling process by intermediation of missing values and the adjustment of scales according to requirements of the machine learning algorithms used within the *Modelling* process step. The preparation was implemented by a data workflow in the open source software KNIME (knime.com/software) (Berthold et al., 2010).

The data, which until then have only been assessed in two-dimensional descriptive chars were analyzed by two classification algorithms implemented using KNIME. A resilient backpropagation multilayer neural network (Riedmiller & Braun, 1993) served as an example for nonlinear classification models and the C4.5 decision tree algorithm (Quinlan, 1993) was used as a rule-based classifier. Although neural networks are known for high prediction accuracy, decision-tree algorithms show very intuitive outcomes that can easily

Table 2. Approach, roles, and results following the CRISP-DM subprocess: *Data understanding*

Approach (CRISP-DM)	Approach (Action Research)	Roles	Results
1. Use of an existing qualitative customer segmentation according to customers' knowledge 2. Proof of available data according to relevant attributes and their granularity level, data quality, correlations, and outliers	1. Company in-house analysis of data availability (Diagnosing) 2. Joint evaluation of data availability by scientific representative and practitioners (Diagnosing) 3. Data consolidation by scientific representative 4. Action planning through scientific representative and practitioners under consideration of available database	• Head of Strategic Product Management • Product Manager • Scientific Representative • CRM System Administrators	1. Consolidated dataset with improved data granularity and quality 2. Result report about selected approach, data quality issues, identified multicollinearity, and outliers

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be interpreted by practitioners (Quinlan, 1993; Riedmiller & Braun, 1993).

In order to evaluate the prediction accuracy, the dataset of the 500 labelled customers was split into a training dataset (representing 80% of the data) and a test dataset (20%) through stratified sampling (Berthold et al., 2010; Stehman, 1996).

In this way, the remaining 2,300 unlabelled customers were classified according to their probability of being “scientist” or “basic”.

In order to increase prediction accuracy, a principal component analysis workflow was implemented. It reduced the dataset to 19 dimensions or principal components, which explained the major proportion of the variance (Wold et al., 1987).

Reasons for the transformation of the target variable as well as possible impacts were discussed within the product management department. The process steps *Data preparation* and *Modelling* were executed by the scientist. In the context of action research, executed activities were related to “Action taking”, “Evaluation”, and “Specifying, learning” (see Table 3).

Evaluation and Deployment
The highest prediction accuracy achieved during 10 workflow loops of the C4.5 decision-tree algorithm was 74.5%. This result was slightly higher than the one obtained from the neural network (73.2%). The application of a pruning procedure did not improve the results (Furnkranz, 1997). Table 4 shows the confusion matrix, which indicates instances in a predicted class versus instances in an actual class as well as the prediction accuracy, a percentage of correct classified customers (Story & Congalton, 1986).

Table 5 depicts extracts of the paths and major indicators (weak signals) and split values for “scientist” and “basic” customers as well as related prediction accuracy. The split values were falsified for reasons of data protection. The only indicator identified for “scientist” customers was “station size”. Customers with more than 4.5 large stations showed a high probability of being a “scientist” customer. Specific business segments such as “repair”, a certain range of revenue as well as a total amount of large stations less than 4.5 indicated a “basic” customer.

For the business development of the new sensor, these indicators (weak signals) were not sufficiently informat-

Table 3. Approach, roles, and results following the CRISP-DM subprocess: *Data preparation* and *Modelling*

Approach (CRISP-DM)	Approach (Action Research)	Roles	Results
1. Aggregation of specifications of selected, independent variables 2. Definition of the target variable 3. Creation of the analysis workflow through the KNIME open source software 4. Adaptation of data scaling 5. Replacement of missing values 6. Calibration of workflows 7. Feed-in of data and start of algorithms 8. Collection of result templates	1. Data preparation by the scientific representative (Action taking) 2. Communication of necessary dataset modifications to the representatives of product management (Evaluating / Specifying, learning) 3. Joint discussion about the impact of the proposed changes (Evaluating) 4. Initiation of change activities and preparation of the analysis by the representative of science (Action taking) 5. Data analysis by scientific representative (Action taking)	• Head of Strategic Product Management • Product Manager • Scientific Representative	1. List of necessary changes within the records 2. Catalogue of actions (approved by the practitioners) 3. Processed records 4. Analysis workflows 5. Result templates

ive. Although indicators for "basic" customers were very detailed and suitable for a customer profile, "scientist" customers were weakly characterized. Nevertheless, a comparison of the customer information gained with exiting qualitative profile data confirmed the results. Customers who were extremely comfortable with new technologies operated a group of several large power plants while customers with low technological affinity requested maintenance, repair, or operation of small plants.

In addition to the analysis of the 38 variables and in order to raise the prediction outcome, the principal components were used as input for the C4.5. They were applied to a training dataset, which consisted of the entire labelled database (500 customers). This procedure increased the prediction accuracy up to 78% due to the high data variance explained by the few principal components. The remaining 2,300 unlabelled customers were ranked according to their probability of being a "scientist" customer. As a result, 51 customers could be classified as "scientists". By taking a closer look at these companies, all showed a high level of product and operation expertise as well as technological affinity.

After the evaluation of the model results, the product management team was able to define the following actions suitable to fulfil the objective of the customer foresight project (see Business *understanding*):

- Analysis of identified "scientist" customers and exiting qualitative profile characteristics

Table 4. Confusion matrix and prediction accuracy of the test dataset by the C4.5 decision-tree algorithm (based on KNIME software version 3.0.1.)

Confusion Matrix			
Customer knowledge binary (to number) \ prediction (customer knowledge binary (to number))		0	1
	0	56	7
	1	19	20
Correct classified:		76	
False classified:		26	
Accuracy:		74.51%	
Error:		25.49%	

Table 5. Extracts of C4.5 decision tree paths, which are major indicators of customer knowledge and prediction accuracy (based on KNIME software version 3.0.1.)

Path	Prediction Customer Knowledge Binary (to number)	Number of Items (Customers)	Number of Correct Classified Items
"Segment" = "Repair" AND "Revenue" <= 2,326,435.627 AND "# Station size Large" <= 4.5	0	166	130
"Segment" = "Parts" AND "Revenue" <= 2,326,435.627 AND "# Station size Large" <= 4.5	0	78	58
...	...	...	...
"Revenue" > 2,326,435.627 AND "# Station size Large" <= 4.5	0	60	33
"# Station size Large" > 4,5	1	122	79

- Acquisition of reference customers for the new sensor out of the predicted "scientist" customers by sales department and product management

- Market analysis by the sales department and identification of further "scientist" customers not yet contained in the company's customer base

- Expansion of the profiles of "scientist" customers through personal interactions at the point of sales and resulting new insights, for example, about specific requirements, field of application, installed base, or potential

- Integration of the "scientist" customers in market tests

- Consideration of the identified requirements of the "scientist" customers in further product updates and variants

In addition, a catalogue of general key take-aways, long-term actions, and unused potential was formulated to help the manufacturer build on experiences made during this customer foresight project. Major aspects were:

- Improvement of data quality, especially the missing value rate through the provision of data, for example, via mandatory fields within the electronic sales reports of the CRM system

- Increase of data-mining expertise within indirect business departments

- Communication of the general potential of data mining via machine learning for strategic decision making

- Extension of qualitative market and customer knowledge through quantitative customer foresight, which combines detailed technical, product-related information with a customer and market view

- Effective, proactive sales support based on a quantitative customer prioritization

Although the evaluation of the model accuracy was executed by the scientific representative, the interpretation of the results, covered in a detailed final project report, as well as the deployment were realized by the product management team. The measures encouraged the communication of the foresight results to the sales department at an early stage of the deployment process. Following *Evaluation* and *Deployment,* the action research subprocesses were "Diagnosing", "Evaluating", as well as "Specifying, learning" (see Table 6).

Table 6. Approach, roles, and results following the CRISP-DM subprocess: *Evaluation* and *Deployment*

Approach (CRISP-DM)	Approach (Action Research)	Roles	Results
1. Analysis of the result templates of different analytic workflows and comparison of results 2. Interpretation of major outcomes in the context of the customer foresight objective 3. Derivation of measures 4. Communication of measures 5. Initiation of measures	1. Evaluation of the output templates by the scientific representative ("evaluating") 2. Interpretation of the results by science and practice ("evaluating" / "specifying learning") 3. Derivation of measures by science and practice ("specifying learning" / "diagnosing") 4. Communication of measures to other departments such as sales 5. Implementation of measures by responsible departments	• Head of Strategic Product Management • Product Manager • Scientific Representative • Sales Department	1. Result report 2. Catalogue of measures 3. Implementation plan including responsibilities

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Scientific Contributions

The results of our research provide scientific value in the field of customer foresight, which is illustrated by the following three aspects:

1. A quantitative and predictive customer foresight approach is shown, which completes existing qualitative applications in B2B industries by adding the identification of weak signals. The approach allows a systemic analysis through the consideration of influencing factors such as customer applications, needs, or new technologies (Schuh & Klappert, 2011). The volatility and variance of customer requirements can be tracked through customer-related variables such as customer knowledge.

2. The approach combines common applications that are either used on an operative single-customer level or on a strategic-market level in order to integrate all operative customer insights into one company-wide model for strategic decision making. On a single-customer level, the product–customer fit can be managed proactively, which increases sales effectiveness (Zallocco et al., 2009). On a strategic-market level, we address the research field by examining how to gain an early majority of customers by starting with few innovators in order to reach market success with new products (Moore, 2002).

3. Recent literature discussing the application of the CRISP-DM methodology for strategic decision making in B2B companies has been expanded by including the complete data-mining process. The present case study delivered detailed insights into the approach within each subprocess as well as responsible roles and achieved results. Due to the application of action research, a scientific project focus allows for a comparison between the present approach and all results to previous and future studies in the same research field.

Practical Implications

Strategic management, business development, product management, and sales in B2B companies will increase the efficiency and effectiveness of customer foresight and proactive market orientation by implementing the present case study results.

The company-specific project results consist of valuable weak signals that describe “basic” customers and separate this customer segment from so-called “scientist” customers. Furthermore, the patterns identified by the classification algorithms allow for the prediction of customer knowledge of 2,300 unlabelled customers. By doing so, another 51 “scientist” customers were identified. The results were equally important for business development, product management, and sales. All roles received a better understanding of potential users of a new machine control sensor.

The case study showed that open source software that is available in complete versions equipped with a powerful set of newest machine learning applications is suitable for a fast method launch within the organization. This enables the efficient execution of customer foresight on a quarterly basis, thereby ensuring a continuous awareness of weak signals and an updated customer prioritization. The implementation can be optimized by including the lessons learned following the CRISP-DM methodology. By focusing on those customers showing the highest future profitability and considering their needs within strategic decision making, an effective market development can be achieved that exceeds heuristic approaches.

In addition to previous studies, the present case study provides further evidence that the CRISP-DM methodology can yield complex customer foresight projects. An iterative approach and even agile sprints, for examples those executed by a Scrum team (Schwaber, 1997) can be easily realized. Furthermore, the applied machine learning techniques will provide a substantial gain of information resulting from a profound input of a company-wide customer base in a standardized and partially automated way. In particular, the manufacturing industry can benefit from the opportunity to combine detailed information related to technical products, applications, and requirements with profound customer and market insights. This reduces the risk of missing market requirements as well as mid-term customer- and technology-related trends.

Conclusion

The present single case study provided a holistic example of a successful customer foresight approach for the identification of weak signals. The following three insights gained during the foresight project led to further research questions and topics not yet covered within this context.

First, by using machine learning applications for customer foresight, existing markets and customer bases can be valuable objects of investigation. However, the detection of disruptive trends, which requires a radical reorientation of existing business models or market focus, is not yet guaranteed. Therefore, further research has to analyze methods and types of data which allow for this expansion of this market view.

Second, especially when considering the manufacturing industry, with its complex technical requirements and fields of applications, a question arises about the possible interactions between customer and technology foresight. How can a foresight team benefit from these customer- and product-related insights when detecting new technologies? One research topic dealing with this question within the product management and new product development literature is the so-called "loop closing". Loop closing makes the gap between two product lifecycles a subject of discussion. Researchers and practitioners try to close this gap by transferring product- and application-related market insights into ideation and early stages of the development process. In the future, these interactions could take place in an automated way (Ameri & Dutta, 2005; Kiritsis et al., 2003).

Finally, this study has shown vividly that the biggest obstacles of applying machine learning in indirect business departments of manufacturing companies are no longer the complex data resulting from profound customer relations and appropriate models suitable to dealing with those data. Particularly, the availability of high-quality data gained through these customer relationships will be the next issue to solve. This imposes new organizational requirements concerning cross-functional interactions, channel and data management, incentives, and responsibilities.

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