CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2023-2

5th Conference on Production Systems and Logistics

Identification of Text Mining Use Cases In Manufacturing Companies

Florian Clemens[1], Hasan Hüseyin Özdemir[1], Günther Schuh[1]

[1] *FIR an der RWTH Aachen, Aachen 52074, Germany*

Abstract

Manufacturing companies face the challenge of managing vast amounts of unstructured data generated by various sources such as social media, customer feedback, product reviews, and supplier data. Text mining technology, a branch of data mining and natural language processing, provides a solution to extract valuable insights from unstructured data, enabling manufacturing companies to make informed decisions and improve their processes. Despite the potential benefits of text mining technology, many manufacturing companies struggle to implement use cases due to various reasons. Therefore, the project VoBAKI (IGF-Project No.: 22009 N) aims to enable manufacturing companies to identify and implement text mining use cases in their processes and decision-making processes. The paper presents an analysis of text mining use cases in manufacturing companies using Mayring's content analysis and case study research. The study aims to explore how text mining technology can be effectively used in improving production processes and decision-making in manufacturing companies.

Keywords

Data Mining; Text Mining; Manufacturing Company; Use Case Modelling; Text Data;

1. Introduction

1.1 Problem definition

Text mining technology, a branch of data mining, offers a promising solution to extract valuable insights from text data, helping manufacturing companies make informed decisions and improve their operational processes [1]. However, despite the potential benefits, many manufacturing companies struggle to implement relevant text mining use cases due to certain obstacles.

One challenge is the lack of technical expertise and infrastructure needed to successfully integrate text mining technology [2]. Implementing text mining solutions requires specialized knowledge and resources that might not be readily available within the company, making it a significant barrier [4,3].

Additionally, manufacturing companies often find it difficult to identify use cases. Figuring out which aspects of their business processes can benefit from text mining technology and how to use it effectively poses a considerable hurdle [5,6]. Without a clear understanding of the potential use cases, manufacturing companies may be hesitant to invest in text mining solutions or fail to maximize their benefits.

1.2 Objective and project description

The objective of the research project VoBAKI (IGF-Project No.: 22009 N) is to enable SME to independently identify text mining use cases and internal skill gaps regarding the development and implementation of text mining applications. To achieve this, the project is structured in five steps. The results are elaborated in cooperation with a user committee that is composed of 18 companies of different industries and sizes (see Table 1)

DOI: https://doi.org/10.15488/15241
ISSN: 2701-6277
publish-Ing.

Table 1: User committee

Branch	Number of Employees	SME
Manufacturing	11 – 50	x
Manufacturing	51 – 250	x
Manufacturing	11 – 50	x
Manufacturing	11 – 50	x
Manufacturing	11 – 50	x
Manufacturing	11 – 50	x
Manufacturing	251 - 500	
IT & Service	251 - 500	
IT & Service	< 10	x
IT & Service	11 – 50	x
IT & Service	251 - 500	
IT & Service	> 5000	
IT & Service	11 - 50	x
IT & Service	501 - 5000	
Consulting	< 10	x
Consulting	501 - 5000	
Consulting	11 - 50	x
Consulting	< 10	x

First, the project examines text mining use cases and regarding objectives of manufacturing companies to implement them. Second, the project identifies tasks in the lifecycle of text mining applications and determines the specific skills required for the execution of these tasks. Third, potential sourcing strategies will be described and evaluated with respect to their practical relevance for manufacturing companies. Eventually, the results of the project will be combined in an approach for the specific identification of skill gaps and the selection of the proper sourcing strategy to close these gaps.

This paper presents the interim results from the first step of the project. It proposes an analysis of potential text mining use cases in manufacturing companies, employing case study research and Mayring's content analysis. The objective of this study is to explore how text mining technology can be effectively employed to enhance production processes and decision-making in manufacturing companies. By identifying and examining practical text mining use cases, this research aims to provide manufacturing companies with valuable insights and guidance for implementing text mining technology. The outcomes of this study have the potential to help companies facilitate the identification of relevant use cases that align with their specific operational requirements.

1.3 Structure of the paper

Chapter 2 presents a systematic literature review regarding text mining use cases in manufacturing companies and derives the research gap. Chapter 3 displays the research approach to identify and describe text mining use cases. Chapter 4 describes the results achieved. Eventually, chapter 5 sums up the results presented in the paper.

2. Related Work

2.1 Text mining in manufacturing companies

Text mining, also known as text data mining or text analytics, is a computational technique that involves the extraction of meaningful information and patterns from large collections of textual data [7]. It encompasses a range of methods and algorithms for processing, analysing, and understanding unstructured text [8]. By utilizing natural language processing (NLP), statistical modelling, and machine learning techniques, text mining aims to uncover insights, discover relationships, and derive valuable knowledge from text-based sources such as documents, articles, social media posts, emails, and more [7,8]. However, to assess the status of use case diagrams for text mining use cases in manufacturing companies a systematic literature review was conducted. The research question "What are the current text mining use cases represented as use case diagrams?" and the inclusion criteria were defined. The following inclusion criteria were established. The text includes the terms "text mining" and "use case" or "use case diagram" and the text includes the term "text mining use case". Subsequently, the keywords "text mining AND use case diagram AND manufacturing company" were utilized to search for relevant papers in the IEEE Xplore, arXiv and google scholar databases. Table 2 shows an overview of the results of the searches:

Table 2: Results of the systematic literature review

Database	Search results
arXive	0
IEEE Xplore	0
google scholar	23

The systematic literature search using Google Scholar yielded 23 results, while IEEE Xplore and ArXiv yielded 0 results. However, none of the papers met the inclusion criteria. That is why the research was extended through unsystematic literature search which results are summarized below.

Shotorbani et. al. propose a new method for organizing and mining information in the growing volume of online manufacturing data. It suggests using K-means for document clustering and Latent Dirichlet Allocation (LDA) for topic modelling. Through experiments, the authors demonstrate that this combined approach enables automated annotation, classification of manufacturing webpages, and extraction of valuable patterns, leading to improved information search and organization in the manufacturing domain. [9] Sutanto et. al. introduce a novel framework for a complaint management system aimed at quality management. The framework utilizes text mining and potential failure identification to support organizational learning. Customer email complaints serve as input, and the most frequent complaints are visualized through a Pareto diagram. The framework involves three main parts: creating a defect database, text mining customer complaints, and matching the results with the defect database to present them in a Pareto diagram. The proposed method is illustrated through a case study, showcasing its applicability. The framework enables companies to interpret customer complaints, identify most common defects, and take anticipatory actions to prevent potential failures in the future. This approach is the first of its kind in this domain. [10] Mishra et. al. discuss the growth of manufacturing processes driven by advancements in procedure and computer technology. It highlights the increasing volume and variety of unstructured data generated in today's digital manufacturing compared to flexible manufacturing in the past. This data can be utilized to improve manufacturing processes, predict equipment failures, design equipment, and explore new technologies. However, managing and extracting valuable information from this vast amount of data pose challenges. Traditional methods like keyword search are insufficient for efficient information retrieval. The paper focuses on unsupervised machine learning techniques for text mining in manufacturing processes to address these challenges. [11] Biegel et al. use process monitoring by sensors on machine tools and combine them with text mining methods to detect anomalies in the manufacturing process. As text data information recorded by the machine operators about the existing machine parameters and corresponding process states were used as text data. [12] Hrcka et al. analyse production data in the form of text documents and forms in the automotive industry. They combine shutdowns with responsible employees to gain approaches for improving the production process. Thereby, the focus of the implementation is more on technical implementation than on business benefits. [13] Ansari et al. show that AI-assisted evaluation of digital shift of digital shift logs can increase Overall Equipment Efficiency (OEE), using an example from the automotive industry, can be increased. The digital shift employees were analysed with the help of text mining methods. evaluated. Based on these logs, the following three functions were implemented: A downtime prediction for aggregates, a dynamic word recommendation for documentation to improve the quality of the data, and a selection of the most suitable technician for troubleshooting. As a result, the machine running time by more than 6%, reduced the average fault detection time and thereby increasing the overall OEE by over 5%. [14] Li et al. use text mining methods to analyse unstructured accident reports from Chinese coal mines to identify risks in coal production. Based on over 700 accident reports, 78 risk factors were identified, which were assigned to six main categories. The main risks identified were lack of management, lack of training and over-supervision. [15] Wang et al. analyse 245 weakly structured accident reports from the Chinese cement industry using text mining methods. They identified four types of accidents and 35 causes of accidents, which in turn were classified into five categories. These were then combined to produce recommended actions for safety management. [16] Müller et al. combine NLP methods and clustering to identify the problems most frequently reported by a ticket system. Improvement projects can then be derived from the problem topics found. During validation on the field, the results were found to be representative. [17] May et al. have analysed fault descriptions digitally recorded by machine operators using NLP methods and classification methods to improve the accuracy of downtime estimation. In addition, the results of the different combinations of methods were compared. [18] In addition to the publications described above, there are a number of non-scientific texts and websites that provide lists of text mining applications and therefore should not remain uncited [21,20,19,22].

2.2 Research gap

The review of existing literature has highlighted a significant gap in comprehensive studies that specifically tackle the challenge of identifying text mining use cases for manufacturing companies. Current research predominantly emphasizes the technical dimensions of text mining algorithms, data preprocessing techniques, and broader methodologies for text mining. However, a noticeable lack exists when it comes to in-depth investigations into distinct use cases.

Hence, bridging this research gap demands a concerted effort to explore and document the array of text mining use cases in manufacturing, framed within the context of use case diagrams. This endeavour would not only contribute to the existing pool of knowledge but also extend practical guidance to organizations embarking on the integration of text mining into their enterprise.

3. Approach and Methodology

This chapter describes the approach adopted to elaborate the research results on text mining use cases within the context of manufacturing companies. The process involved three key stages, including content analysis using Maying's method, case studies with experts of the companies of the user committee, and the exemplary application of the use case modelling technique complemented by literature research (see Figure 1).

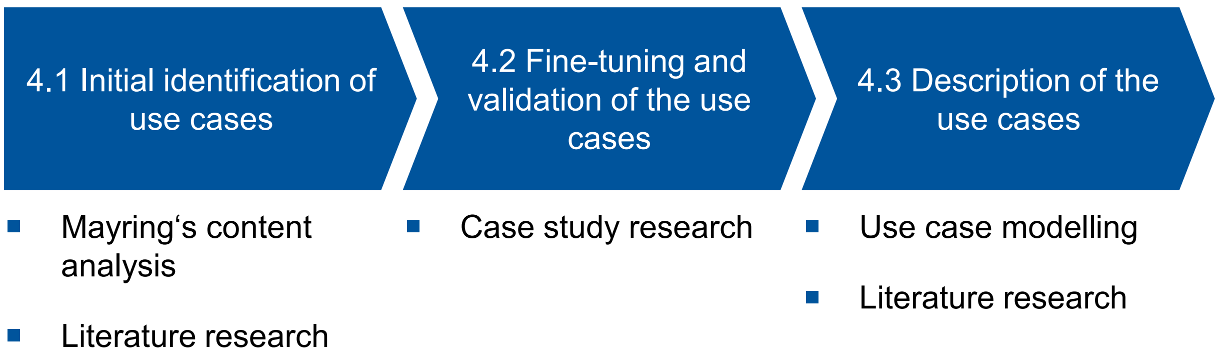


Figure 1: Approach

The research was commenced by conducting a comprehensive content analysis utilizing Maying’s approach (see chapter 4.1). The objective was to systematically examine textual data related to manufacturing companies, thereby identifying, and categorizing potential text mining use cases. This initial step provided a foundation for understanding the varied scenarios where text mining techniques could be applied in manufacturing companies.

The next crucial phase involved engaging in case studies with experts from companies of the user committee (see chapter 4.2). The preliminary list of use cases obtained from the content analysis served as a starting point for interviews with these experts. During the case studies, the list of use cases was fine-tuned based on the insights and feedback provided by the knowledgeable participants. A use case was considered identified if it was already implemented, planned for implementation, or known by the experts of the respective companies. This validation process helped ensure the relevance and applicability of the preliminary list of use cases.

The final step of the research encompassed a comprehensive description of some of the validated use cases through the application of the use case modelling technique (see chapter 4.3). Although the models are not the core result of the research, they show manufacturing companies that implementation is much easier with the help of such models. The step involved creating detailed representations of each use case, outlining the specific actions and expected outcomes. The use case models serve as a valuable tool for understanding the practical implications of text mining in manufacturing settings. Moreover, supplementary literature research was conducted to enrich the understanding of each use case.

4. Text mining use cases

4.1 Results from Mayring’s content analysis

In Appendix 7.1, the paper presents a detailed account of the primary findings from the content analysis. These findings not only laid the groundwork for subsequent case studies but also illuminated the diverse landscape of potential applications for text mining methods within manufacturing companies. In total, the content analysis identified a remarkable 17 distinct use cases. These findings can be assigned to different business areas.

Customer engagement:

- **Offer segmentation and proposal**: Tailoring product offers to individual customer segments, enhancing personalization and faster processing of offers.
- **Customer segmentation**: Gaining a deeper understanding of customer demographics and preferences for targeted marketing.

Production and logistics

- **Preparation of shipping documents**: Streamlining logistics and ensuring accurate order fulfilment.
- **Assistance with picking**: Providing support and guidance to warehouse staff in selecting items for order fulfilment, ultimately optimizing the picking process in manufacturing companies.

Documentation:

- **Evaluation of documents**: Analysing documents for compliance, accuracy, and decision-making.
- **Information extraction from documents**: Automating data extraction from unstructured documents, improving data access.

Customer support and service:

- **Chatbot**: Providing instant customer support and assistance through AI-powered chatbots.
- **Assignment of customer inquiries**: Efficiently routing customer queries to appropriate personnel.

Marketing and product management:

- **Creation of product descriptions**: Generating compelling product descriptions for marketing materials.
- **Flexible marketing**: Adapting marketing strategies based on real-time data and insights.
- **Summary of customer reviews**: Extracting key insights from customer feedback to inform product development.

Security and Strategy:

- **Early detection of cyberattacks**: Identifying potential cybersecurity threats before they escalate.
- **Prediction of market developments**: Forecasting market trends and adjusting strategies accordingly.

Human resources and employee engagement:

- **Identification of employee needs**: Understanding employee needs for better retention and satisfaction.
- **Control of recruitment strategy**: Optimizing recruitment efforts based on market and organizational trends.
- **Early detection of health Risks**: Monitoring employee health and well-being to mitigate risks.

Customer relationship management:

- **Management of customer cooperation**: Enhancing customer relationships and collaboration.

These findings underscore the transformative potential of text mining in processes of various business areas of manufacturing companies. From improving customer engagement to bolstering security and risk management, these use cases showcase the relevance of text mining in today's business landscape. Furthermore, they provide a rich foundation for future research and case studies, enabling organizations to harness these insights for sustainable growth and competitiveness.

4.2 Results from the case studies

The validation and refinement of the results from Mayring's content analysis were integral to ensuring the accuracy of text mining use cases within the context of business processes in manufacturing companies. The engagement of subject matter experts, carefully selected from both manufacturing companies and IT-service providers for manufacturing, added a layer of real-world validation and practicality to the initial findings. This process not only confirmed the relevance of some use cases but also uncovered new insights that had not been initially captured in the content analysis.

The 12 expert interviews provided a platform for in-depth discussions and knowledge exchange. These discussions involved presenting the findings from Mayring's content analysis, as outlined in Appendix 7.1. Importantly, these expert interviews allowed for a critical examination of the proposed use cases and their alignment with actual industry practices.

As a result of these expert interviews and discussions, several changes and adjustments were made to the original longlist of text mining use cases (see Appendix 7.2). These changes are summarized as follows:

Changed and newly identified use cases:

- o **Assistance to the preparation of offers**: The experts validated this use case, emphasizing the importance of text mining in tailoring offers to meet customer needs effectively and create them faster based on former offers.
- o **Automated document processing and management**: While the original use case of "Evaluation of Documents" was not entirely confirmed, the experts highlighted the significant role of text mining in processing and managing digitized documents, including classification and analysis.
- o **Proposal of solutions for troubleshooting**: This new use case emerged from the interviews, focusing on the generation of solutions based on error codes in machinery.

Use cases not confirmed:

- o **Assistance with picking**: This use case was not confirmed as text-based, as it involves speech-based interactions in warehouse logistics.
- o **Information extraction from documents**: The experts clarified that reading paper documents like invoices primarily relies on image recognition rather than text mining.
- o **Flexible marketing, early detection of cyberattacks, early detection of health risks, management of customer cooperation, and control of recruitment strategy**: These use cases could not be confirmed as text mining use cases based on current industry practices.

The refinement of the longlist through expert interviews led to a final longlist containing 11 validated text mining use cases (see Appendix 7.2), ensuring that only those with practical applicability were retained for further consideration. The integration of expert-driven enhancements with the initial content analysis findings provided a more comprehensive understanding of the text mining use cases relevant to manufacturing companies. In conclusion, the validation process not only confirmed the value of certain use cases but also demonstrated the need for a nuanced understanding of text mining applications within the manufacturing industry. This research, founded on both data-driven content analysis and expert insights, contributes significantly to the body of knowledge in this field.

4.3 Description of text mining use cases in manufacturing companies

This chapter provides an exemplary in-depth analysis of two use cases of the case studies using the use case modelling technique.

Customer Segmentation

Understanding which customer groups are interested in specific products and determining their value is crucial [23,24]. This process is known as customer segmentation, where the customer base is divided into distinct segments based on characteristic features (see Appendix 7.3) [25]. This segmentation enables more personalized marketing campaigns, better customer analysis, and improved control of sales and marketing activities [26]. Customer segmentation involves five essential steps, regardless of the chosen method [26]. Firstly, the target group must be defined around which the segmentation efforts will revolve. The starting point may vary depending on the product or marketing strategy being considered. Next, the criteria for dividing the target group into segments must be determined. [23–25] In the main analysis phase, various data sources such as customer surveys, online data, and social media evaluations are used to gain valuable insights. Text mining techniques can be employed to extract valuable information from unstructured data like customer feedback, reviews, and social media posts. Using this information, customers are classified and grouped into distinct segments based on their characteristics and preferences. Finally, the impact of these customer segments on marketing and product development is evaluated. [24,26] Customer segmentation not only enables the recognition of specific customer needs but also allows for tailored marketing concepts. It serves as a foundation for product development and overall company strategy, supporting the further growth and optimization of the business. [25] By effectively leveraging text mining, businesses can gain deeper insights from vast amounts of textual data, leading to more informed decisions and better customer understanding.

Identification of employee needs

One of the essential pillars of successful personnel and organizational development in a company is employee surveys to identify employee needs (see Appendix 7.4). These surveys collect information that is then processed and evaluated through a reflective process involving both employees and management. The objective of employee surveys is to develop and implement measures that enhance success within the organization. There are two types of success factors: general success factors and company-specific success factors. [27] In general, there are three methods for conducting employee surveys: distributing paper questionnaires, conducting online surveys through the intranet, and using a Tele-Dial system or Audience-Response system for projecting questions onto a screen and obtaining responses. The trend clearly favours online surveys due to their high acceptance among employees. This preference is driven by the benefits of high data quality, automation capabilities, and time efficiency in data collection and analysis. After conducting the survey, data analysis occurs in six stages: data input, data quality check and validation, generating key performance indicators, analysing patterns and correlations, contrasting with benchmarks, and creating a comprehensive analysis report. [27] Text mining can be applied during the data analysis process to extract valuable insights from unstructured data sources, such as open-ended responses in the survey, employee feedback, and comments. Text mining techniques can help identify sentiment, themes, and topics that are not easily captured through structured data analysis. Integrating text mining in the analysis can provide deeper and more nuanced understanding of employee sentiments and concerns, enriching the overall insights gained from the survey.

5. Conclusion

In conclusion, this research paper presents a validated longlist of text mining use cases specifically tailored to manufacturing companies. Through the synergy of Mayring's content analysis and real-world case studies, this study yields practical insights. The detailed exploration of two specific use cases underscores the relevance of these technologies and highlights their impact on critical business areas. These findings demonstrate how text mining can be instrumental in optimizing processes, enhancing decision-making, and fostering innovation within manufacturing companies. In essence, this research paper serves as a guide for professionals seeking to increase efficiency and innovation within their manufacturing operations, as the manufacturing industry continues to embrace digital transformation.

6. Acknowledgements

We would especially like to thank the user committee for attending several interviews and providing us with insights and feedback that helped to shape our research. Moreover, we would like to express our gratitude to the Federal Ministry for Economic Affairs and Climate Action for their support of VoBAKI (IGF-Project No.: 22009 N). The project is supported by Federal Ministry for Economic Affairs and Climate Action based on a decision of the German Bundestag.

7. Appendix

7.1 Results of the literature analysis according to Mayring

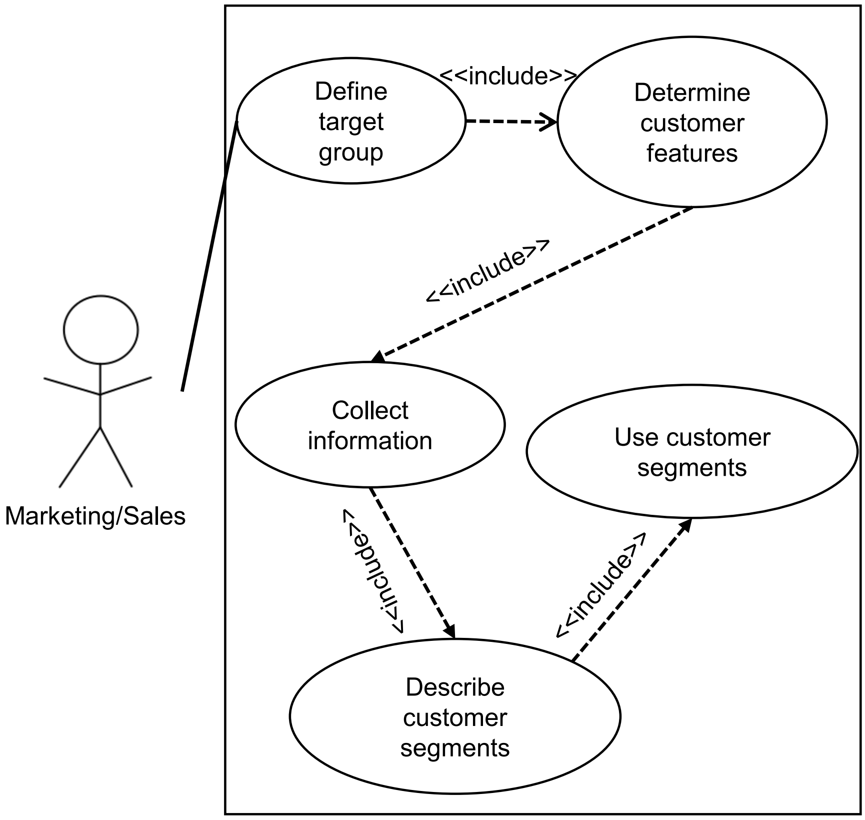
Results Mayrings's content analysis
Assignment of customer inquiries
Assistance with picking
Chatbot
Control of recruitment strategy
Creation of product descriptions
Customer segmentation
Early detection of cyberattacks
Early detection of health risks
Evaluation of documents
Flexible marketing
Identification of employee needs
Information extraction from documents
Management of customer cooperation
Offer segmentation and proposal
Prediction of market developments
Preparation of shipping documents
Summary of customer reviews

7.2 Results of the case studies (final longlist)

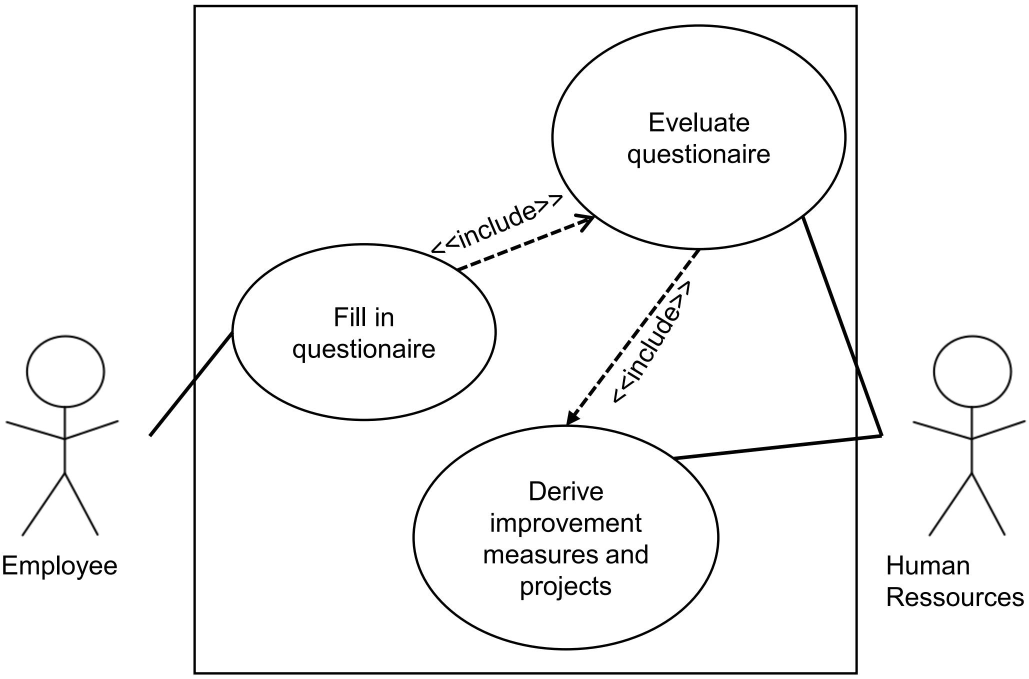
Results Mayrings's content analysis	Validated or added through case studies (final longlist)
Assignment of customer inquiries	Assignment of customer inquiries
Assistance with picking	
Chatbot	Use of data-based chatbots
Control of recruitment strategy	
Creation of product descriptions	Creation of product descriptions
Customer segmentation	Customer segmentation
Early detection of cyberattacks	
Early detection of health risks	
Evaluation of documents	Automated document processing and management
Flexible marketing	
Identification of employee needs	Identification of employee needs
Information extraction from documents	
Management of customer cooperation	
Offer segmentation and proposal	Assistance to the preparation of offers
Prediction of market developments	Prediction of market developments

Preparation of shipping documents	Preparation of shipping documents
Summary of customer reviews	Summary of customer reviews
	Proposal of solutions for troubleshooting

7.3 Use case diagram "Customer segmentation"



7.4 Use case diagram "Identification of employee needs"



References

[1] Hippner, H., Rentzmann, R., 2006. Text Mining. Informatik Spektrum 29 (4), 287–290.

[2] Lundborg, M., Guli, I., 2021. Künstliche Intelligenz im Mittelstand, Siegburg, 22 pp.

[3] La Justicia de Torre, C., Sánchez, D., Blanco, I., Martín-Bautista, M.J., 2018. Text Mining: Techniques, Applications, and Challenges.

[4] Hassani, H., Beneki, C., Unger, S., Mazinani, M.T., Yeganegi, M.R., 2020. Text Mining in Big Data Analytics. BDCC 4 (1), 1.

[5] Bernd W. Wirtz, Jan C. Weyerer, Carolin Geyer, 2019. Artificial Intelligence and the Public Sector—Applications and Challenges. International Journal of Public Administration 42 (7), 596–615.

[6] Quirin Demlehner, Daniel Schoemer, Sven Laumer, 2021. How can artificial intelligence enhance car manufacturing? A Delphi study-based identification and assessment of general use cases. International Journal of Information Management 58, 102317.

[7] Cohen, K.B., Hunter, L., 2008. Getting started in text mining. PLoS computational biology 4 (1), e20.

[8] Jo, T., 2019. Text Mining: Concepts, Implementation, and Big Data Challenge, 1st ed. 2019 ed. Springer International Publishing; Imprint: Springer, Cham, 1 online resource (XIII, 373 pages 236 illustrations, 148 illustrations in color.).

[9] Shotorbani, P.Y., Ameri, F., Kulvatunyou, B., Ivezic, N., 2016. A Hybrid Method for Manufacturing Text Mining Based on Document Clustering and Topic Modeling Techniques, in: Nääs, I., Vendrametto, O., Mendes Reis, J., Gonçalves, R.F., Silva, M.T., Cieminski, G. von, Kiritsis, D. (Eds.), Advances in Production Management Systems. Initiatives for a Sustainable World, vol. 488. Springer International Publishing, Cham, pp. 777–786.

[10] Astanti, R.D., Sutanto, I.C., Ai, T.J., 2022. Complaint management model of manufacturing products using text mining and potential failure identification. TQM 34 (6), 2056–2068.

[11] Devendra Kumar Mishra, Arvind Kumar Upadhyay, Sanjiv Sharma, 2021. Text mining in manufacturing process using unsupervised techniques of Machine learning. Materials Today: Proceedings 47, 6679–6681.

[12] Biegel, T., Jourdan, N., Madreiter, T., Kohl, L., Fahle, S., Ansari, F., Kuhlenkötter, B., Metternich, J., 2022. Combining Process Monitoring with Text Mining for Anomaly Detection in Discrete Manufacturing. SSRN Journal.

[13] Hrcka, L., Simoncicova, V., Tadanai, O., Tanuska, P., Vazan, P., 2017. Using Text Mining Methods for Analysis of Production Data in Automotive Industry, in: Silhavy, R., Senkerik, R., Kominkova Oplatkova, Z., Prokopova, Z., Silhavy, P. (Eds.), Artificial Intelligence Trends in Intelligent Systems, vol. 573. Springer International Publishing, Cham, pp. 393–403.

[14] Ansari, F., Kohl, L., Giner, J., Meier, H., 2021. Text mining for AI enhanced failure detection and availability optimization in production systems. CIRP Annals 70 (1), 373–376.

[15] Li, S., You, M., Li, D., Liu, J., 2022. Identifying coal mine safety production risk factors by employing text mining and Bayesian network techniques. Process Safety and Environmental Protection 162, 1067–1081.

[16] Wang, B., Gong, Y., Zhou, J., 2023. Text mining and association rules-based analysis of 245 cement production accidents in a cement manufacturing plant.

[17] Müller, M., Alexandi, E., Metternich, J., 2021. Digital shop floor management enhanced by natural language processing. Procedia CIRP 96, 21–26.

[18] May, M.C., Neidhöfer, J., Körner, T., Schäfer, L., Lanza, G., 2022. Applying Natural Language Processing in Manufacturing. Procedia CIRP 115, 184–189.

[19] Silipo, R., 2020. From Words to Wisdom - Towards Data Science. Towards Data Science, April 12.

[20] Shankar Chauhan, D., 2023. Text Mining offers Powerful Techniques for Manufacturers to Reduce Accounts Receivables Risk | LinkedIn. https://www.linkedin.com/pulse/text-mining-powerful-techniques-manufacturers-reduce-accounts/. Accessed 19 July 2023.

[21] Dialani, P., 2019. Top 5 Business Use Cases of NLP and Text Mining. Analytics Insight, July 21.

[22] Team, E., 2022. 10 Practical Text Mining Examples to Leverage Right Now. expert.ai, May 13.

[23] Adobe Experience Cloud Team, 2023. 21 reale Beispiele für Kundensegmentierung. https://business.adobe.com/de/blog/basics/real-world-examples-of-customer-segmentation. Accessed 31 July 2023.

[24] Raddao, N., 2018. Potenzialorientierte Kundensegmentierung zur Optimierung des Leistungsportfolios in der Firmenkundenbank: Konzeption und Implementierung einer "efficient customization" am Beispiel von Genossenschaftsbanken. Peter Lang International Academic Publishing Group, Bern, 141 pp.

[25] Wuttke, L., 2023. Kundensegmentierung: Definition, Methoden und Vorgehen. datasolut GmbH, May 24.

[26] Survey Monkey, 2023. Kundensegmentierung: Modelle, Ablauf, Beispiele: Mit einer professionellen Kundensegmentierung können Sie den Erfolg Ihres Unternehmens steigern. https://www.surveymonkey.de/mp/kundensegmentierung-modelle-ablauf-und-beispiele/#:~:text=Unter%20Kundensegmentierung%20versteht%20man%20die,anpassen%20und%20nachhalti g%20Erfolge%20erzielen. Accessed 31 July 2023.

[27] Nürnberg, V., 2022. Mitarbeiterbefragungen: Durch Mitarbeiterbeteiligung mit Feedback zum Unternehmenserfolg, 2. Auflage ed. Haufe Group, Freburg, München, Stuttgart, 180 pp.

Biography

Florian Clemens (*1993) received his M. Sc. degree in industrial engineering at University Paderborn. He is a researcher at FIR at RWTH Aachen University since 2019 in the department Information Management, working on the transfer of AI to production.

Hasan Hüseyin Özdemir (*1995) received his B. Sc. Production Engineering at the RWTH Aachen University and is writing his master's thesis in the field of information management at the FIR of the RWTH Aachen.

Prof. Dr.-Ing. Dipl.-Wirt. Ing Günther Schuh (*1958) holds the Chair of Production Systems at the Machine Tool Laboratory (WZL), is a member of the Board of Directors at the Fraunhofer Institute for Production Technology (IPT), Director of the Institute for Industrial Management (FIR) at the RWTH Aachen University and head of the Production Technology Cluster. He is the founder of the Schuh & Co. group of companies based in Aachen, St. Gallen and Atlanta.