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Research Article

Quantifying Data-Driven SMEs: Scoring Factors and a Timeline for Better Decisions

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Abstract

This research builds on our earlier findings regarding the challenges SMEs, particularly in the crafts sector, face when adopting data-driven strategies. While large enterprises successfully utilize AI and data technologies, SMEs often encounter significant barriers to implementation. Building on these insights, this study identifies critical factors in the data-driven domain that can significantly enhance decision-making in German SMEs. The proposed scoring model aims to empower SMEs by enabling them to assess their data capabilities, identify weaknesses, and implement targeted improvements. Through a systematic literature review, the study highlights the most influential factors shaping data-drivenness in SMEs. Using the Design Science Research (DSR) methodology, we developed a refined scoring model and a chronological framework that integrate these factors to guide and improve data utilization. This research ultimately contributes to a deeper understanding of how SMEs can adopt data-driven strategies to foster innovation, optimize operations, and remain competitive in a dynamic market environment.

Keywords: data-driven decision-making, scoring model, chronological framework, German SMEs

Introduction

In our previous work, "Enabling German SMEs and Crafts through Data-Driven Innovation: Developing a Scoring Model and Chronological Framework for Enhanced Decision-Making", we proposed a scoring model and chronological framework to aid in the development of data-driven strategies tailored for German SMEs and craft businesses, which account for 99.6% of all enterprises in Germany (Eickelmann et al., 2024; European Commission, 2023). While larger corporations have successfully harnessed Artificial Intelligence (AI), Machine Learning (ML), and Big Data for innovation and operational efficiency (Manyika et al., 2011; Alghamdi & Agag, 2023), our research explored whether similar approaches could be effectively adopted in smaller organizations. We identified several barriers that German SMEs face in adopting data-driven practices, such as limited resources, inadequate data infrastructure, and

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low employee competence (Popovic et al., 2012; Gehrmann, 2020).

To address these challenges, we developed a scoring model and a chronological framework to assess the level of data-drivenness within SMEs and crafts. The scoring model provided a flexible tool to evaluate and enhance data-driven decision-making, enabling businesses to overcome specific challenges and improve their data utilization. Companies that implemented data-driven strategies reported a 5-6% improvement in productivity and performance compared to those that did not adopt such practices (Brynjolfsson et al., 2011; Kopanakis et al., 2016). Furthermore, the chronological framework helped assess the current status of data utilization, offering a clear pathway for adopting and improving data-driven processes.

Building on these insights, this paper continues to explore how German SMEs, particularly in the crafts sector, can overcome the unique challenges they face in adopting data-driven strategies. Our research aims to identify and prioritize the key factors that impact data-drivenness, ultimately enabling SMEs to make more informed decisions and stay competitive in an increasingly data-centric world.

While existing models such as Gartner's Data and Analytics Maturity Model (Gartner, n.d.) and Deloitte's People Analytics Model (Deloitte, 2016) focus on large enterprises, they do not fully address the specific challenges faced by SMEs, such as employee competence and knowledge transfer. Our comprehensive approach offers a more tailored methodology, along with AI-based recommendations, designed to improve the strategic and operational decision-making within SMEs.

The following sections of this paper are structured as follows: First, we present the methodology used to develop our scoring model, detailing the systematic literature review process and the key factors identified. This is followed by the results section, where we describe the critical factors and provide insights into their significance in assessing data-drivenness within SMEs. Subsequently, we introduce our proposed chronological framework and the scoring model for evaluating data capabilities in SMEs. Finally, we conclude by discussing the implications of our findings, the practical applications of the scoring model, and directions for future research.

Methodology

To develop a scoring model for assessing data-drivenness in German SMEs, particularly in the crafts sector, we conducted a systematic literature review (SLR) using the database ScienceDirect (Tranfield et al., 2003). Our search focused on identifying key factors that influence data-driven decision-making in SMEs.

ScienceDirect was selected as the primary database due to its extensive collection of peer-reviewed journals and articles, particularly within the fields of technology, business, and data science. Those areas of interest are closely aligned with the scope of this research. Additionally, the strong coverage of European studies made it particularly relevant for examining German SMEs. However, it is important to note some limitations in using only ScienceDirect for this literature review. While the database offers high-quality academic literature, it may lack access to certain industry-specific reports. Hence, defining a general model, the industry specificity was not of high importance, so our achieved results are still highly relevant for our research goal.

We used the following keywords: "data-driven decision-making," "scoring model," "smart decision-making," and "German SMEs," while reviewing articles published within the last 10 years, with a focus on studies providing relevant insights into the adoption of data-driven strategies by SMEs. From these keywords, we constructed specific search strings such as "data-driven decision-making" AND "scoring model" and "smart decision-making" OR "data-driven decision-making" AND "scoring model" OR "German SMEs" to refine our focus and retrieve relevant literature.

In the initial search phase, articles were retrieved using the specified keywords. After that, we defined our inclusion and exclusion criteria. Articles older than 10 years were automatically excluded to assess only state of the art developments. Also, articles that focused on large enterprises needed to be ignored in this context to leverage the focus on SMEs. For the inclusion side, we defined that articles that thematized data-driven decision making especially focused on SMEs should be weighted high. Particularly studies on the design, test, or validation of frameworks that propose such approaches were of the highest interest in this context. More Studies were excluded if they did not address key factors such as data infrastructure and employee competence, focused primarily on non-SME contexts or industries, or lacked practical applications and real-world insights. From the initial pool, 60 articles were identified, and, after screening, 20 were selected for detailed analysis. The findings from these studies formed the basis for developing our scoring model, which integrates critical factors such as data infrastructure, employee competence, and data integration, enabling SMEs to improve their data-driven decision-making processes.

To define the chronological framework after uncovering the key factors from the literature, we conducted the second and third steps of the Design Science Research approach (Brocke et al., 2020; Deng & Ji, 2018). The reasoning behind that was to define the objectives of our proposed solution and the first design of the proposed framework.

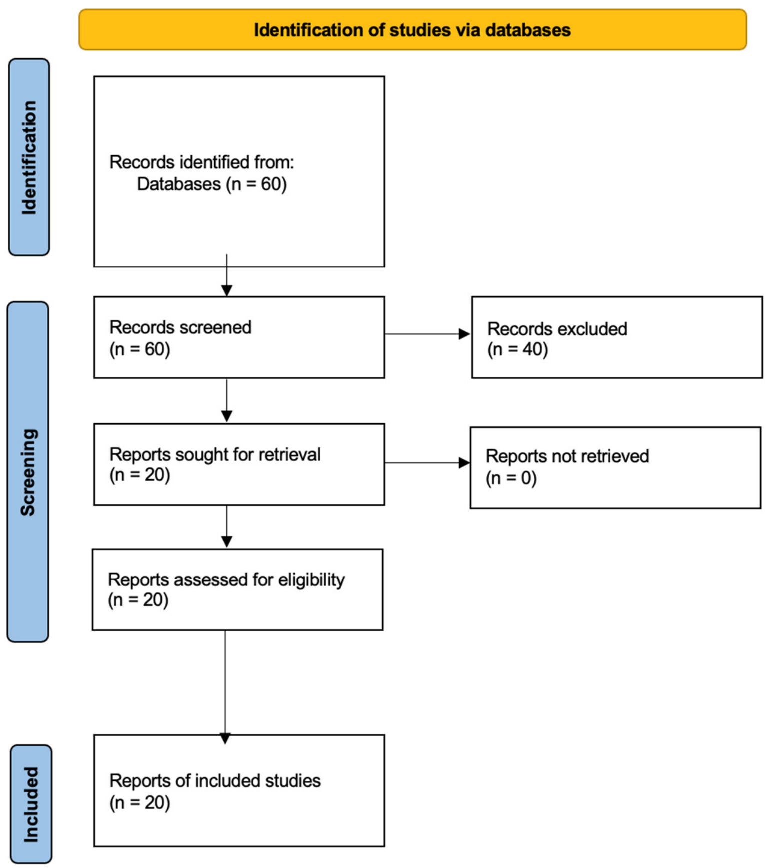

Figure 1: PRISMA Flow Diagram for the Systematic Literature Review Process. Adapted from Page, M. J., et al. (2021). "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews." *BMJ*, 372, n71. Licensed under Creative Commons Attribution 4.0 International (CC BY 4.0, https://creativecommons.org/licenses/by/4.0/).

Results

As proposed, we developed a chronological framework to assess data-drivenness in German SMEs, using the DSR approach and supported by a systematic literature review. First, defining the key factors of data-drivenness was essential to gain the fundamental knowledge needed to design the framework. Through the screening of 20 research papers on various topics within the data science domain, we identified nine key factors, or data-drivenness dimensions. These studies demonstrated how data-drivenness can be recognized in different contexts by examining how data are gathered, collected, analyzed, and ultimately utilized.

While equal weights are assigned to all key factors to ensure balance, we acknowledge that the weighting system may evolve in future iterations. Further development of the model could lead to adjustments in the weights, reflecting the varying significance of each factor based on empirical evidence.

The nine identified key factors are: Data Availability and Quality, Data Infrastructure, Employee Data Competence, Data-Driven Decision Making, Analytical Capabilities, Data Integration, Compliance, Data Interoperability, and Knowledge Transfer. It is important to note that "Knowledge Transfer" is the only external key factor. When knowledge is brought into the company, it must be translated into data, and when data leave the company, they must be interpreted as knowledge, providing context, and understanding.

Although this research primarily identifies general challenges facing SMEs in adopting data-driven strategies, the impact of these challenges may vary across industries. For example, data infrastructure tends to be more critical in sectors like manufacturing and logistics, where large volumes of data need to be processed in real-time, while compliance plays a more significant role in finance and healthcare due to stringent regulatory requirements. In the crafts sector, where digital infrastructure is often less developed, factors like employee competence and knowledge transfer may present more immediate challenges. Recognizing these sector-specific nuances will be essential in further refining the model and tailoring it to different industries. Since this paper focuses on the design stage of the DSR approach, the next phase will involve testing and validating the model to empirically assess how these key factors behave in various sectors. This testing phase will provide the necessary data to confirm whether sector-specific adjustments are needed to finalize the model.

To give a wider inside into the definition of our scoring model, the key factors or data-drivenness dimensions will be presented in the following sub parts of the results section. As we cannot list all relevant insides because it would break the frame of the discussion, we just pick out selected examples where the key factors played a significant role.

Data Availability and Quality

Data availability, especially high-quality data, was identified as the foundational factor for effective decision-making. Many studies emphasized the need for reliable and accessible data to support sound business decisions. For instance, in B2B banking, particularly in green finance, the availability and quality of data are essential for making well-informed financial decisions (Chang et al., 2024). Likewise, in smart city development, the accessibility of real-time data ensures the efficient management of urban systems (Sarker, 2022). In the realm of smart production planning, the accuracy of forecasts heavily relies on the quality of the data available (Saad et al., 2021). Collaborative innovation in SMEs also depends on the availability of reliable data for fostering innovation (Thomas et al., 2021). As a result, data availability and quality were recognized as one of the nine critical factors in the scoring model.

Data Infrastructure

A well-developed data infrastructure emerged as another critical factor. This infrastructure is essential for the collection, storage, and processing of data, enabling organizations to make data accessible and actionable. For example, in smart bridge maintenance, large volumes of sensor data must be efficiently processed through a strong infrastructure to support decision-making (Jiang et al., 2023). Similarly, smart manufacturing benefits from a robust infrastructure that allows data from various operational stages to be integrated, enhancing production efficiency (Wan et al., 2024). In NLP-based decision-making, data infrastructure supports the processing of large datasets for timely and accurate insights (Sawant & Sonawane, 2024). Thus, data infrastructure plays a pivotal role in the successful implementation of data-driven strategies.

Employee Data Competence

The ability of employees to handle data was extracted as another significant factor. Skills and the capability of employees to interpret and utilize data effectively is essential for the success of any data-driven initiative. In NLP-based decision-making, for example, employee competence in data analysis and usage of the correct methods is critical for extracting valuable insights from large volumes of textual data (Sawant & Sonawane, 2024). Without specified knowledge, the interpretation of results can be seen in weak or even wrong decision making. Another example is the field of smart bridge maintenance, employees must interpret sensor data and employ maintenance and monitoring technology to make informed decisions about structural integrity (Jiang et al., 2023). Similarly, within SMEs, employee skills in utilizing data are key to driving innovation and ensuring that strategic decisions are grounded in reliable data (Thomas et al., 2021). Because of the competence variable seen in different sectors, it was important to include employee data competence into our model. Hence, it was not directly mentioned but could be translated from the data competence and skills that are needed from researchers to employees working with and producing data in SMEs.

Data-Driven Decision Making

The importance of data-driven decision-making is widely acknowledged, as it enables businesses to base their strategies and operations on data insights rather than intuition. As this key factor has a two-fold role as an input but also an output factor in the wider context of data-drivenness of SMEs, it is of very high importance. As it is used in a broad area of different fields, here are mentioned the most illuminating examples from our literature review. Wan et al. (2024) described data-driven decision making as important regarding the field of smart manufacturing optimizing production processes and minimizing inefficiencies. In the same industrial context but the domain of smart production planning, real-time data-driven decisions significantly improve operational accuracy and resource allocation (Saad et al., 2021). As mentioned before for another key factor in B2B banking, smart decisions fostered by data understanding play an even bigger role as this sector more and more relies on data-driven decisions to ensure accurate financial risk assessments and facilitates the identification of business opportunities (Chang et al., 2024). Smart cities' research utilizes data-driven decision-making to enhance the efficient management of urban infrastructure (Sarker, 2022). All these examples underscore the importance of data-driven decision making, as a dimension in this scoring model, as well as the result that should be improved by expanding the knowledge an organization has about its own data-drivenness.

Analytical Capabilities

Like employee competence, the analytical capabilities of an organization are important to get an overview about the implications of the data provided by multiple sources. If on an individual level or as a collective skill by the whole staff, analytical capabilities are essential for interpreting complex data and transforming them into actionable insights. From an automation point of view, it can also be argued that good analytical capabilities of decision-support systems are necessary. As a practical domain, there should be mentioned the smart packaging industries. There, very high analytical capabilities are needed to enhance the organization's decision power by big data application (Kabadurmus et al., 2023). In our review, we also found that in NLP-based decision-making, these capabilities allow organizations to process and make sense of large volumes of textual data, leading to more informed decisions that, from that knowledge, can be generated (Sawant & Sonawane, 2024). Therefore, analytical capabilities were identified as a key element in supporting data-driven decision-making.

Data Integration

Data integration emerged as a critical factor in allowing organizations to combine data from various sources and generate a comprehensive view for decision-making. Given its importance, data integration was included as a key factor in our model. It is also possible to view data integration as information generation and in the last instance as knowledge creation. The integration of different data analytics techniques as well as the communication between these technologies are of extreme importance because this unlocks the potential to combine the recognition of different kinds of data patterns. For instance, Mende et al. (2022) show that the combination of deep learning and rule-based systems provides the strength of both approaches in the domain of visual inspection in production. The combined use of both approaches can cancel out weaknesses and leverage the strength of both approaches simultaneously. Deep learning and other machine learning approaches are powerful in handling large datasets and automatically extract patterns, while performing weak when there are limited data. They also are prone to inaccuracy in that case. In contrast to that, rule-based systems are very effective in dealing with specific rules and domain knowledge provided by experts. But they are limited by the rules they were given and their inability to learn from data and adapt new patterns outside of the predefined rules. By the integration of different approaches to handle data, there can be made significant process for data-drivenness.

Expanding on the example made above, companies should aim to improve the integration of various data types and data analytics models to increase their ability to expand their data-drivenness and professional data development. Hence, we involved this key factor in our scoring model.

Compliance

Compliance with various regulatory and industry standards plays a crucial role in ensuring that companies maintain trust with stakeholders and avoid potential legal consequences. In the case of German manufacturing SMEs, as analyzed by Steinhöfel et al. (2018), compliance with sustainability reporting frameworks, such as the Global Reporting Initiative (GRI), was a significant focus. The GRI framework is commonly used to guide companies in disclosing their economic, environmental, and social impacts. For companies that adhere strictly to GRI 'in accordance' standards, the study showed a higher level of conformity compared to those using GRI for orientation or those not using the framework at all. Compliance with GRI standards reflects a company's commitment to transparency and accountability in sustainability practices, which can enhance its reputation among stakeholders.

However, compliance does not stop at GRI standards alone. Data compliance, especially under regulations such as the General Data Protection Regulation (GDPR), is becoming increasingly critical for companies operating in the digital age. The ability to safeguard personal and sensitive data is not only a legal necessity but also a crucial factor in maintaining customer trust. For SMEs, navigating these complex regulations can be challenging, but failure to comply with data privacy laws can result in severe penalties, as well as reputational damage.

Beyond these forms of compliance, companies may also need to align with other industry-specific standards or certifications. For example, many manufacturing companies opt for ISO certifications, such as ISO 14001, which focuses on environmental management systems (DIN EN ISO 14001, n.d.). This type of compliance allows companies to demonstrate their commitment to sustainable practices and continuous improvement in environmental performance. Similarly, compliance with labor laws and ethical sourcing guidelines can further enhance a company's standing in both the marketplace and the communities in which it operates.

Consultants and analysts working with SMEs need to evaluate compliance from a holistic perspective. It's not only about meeting legal requirements but also about understanding the broader impact compliance can have on a company's strategy, operations, and stakeholder relationships. In this context, compliance serves as both a protective mechanism against risks and an opportunity to align business practices with sustainability and ethical standards, providing a competitive advantage in increasingly conscientious markets. Especially in saturated market economies like Germany, the focus of many Stakeholders slides to compliance matters and can guarantee a company's reputation. This is increasingly getting important for SMEs as well.

Data Interoperability

The ability of systems to exchange and process data referred to as data interoperability was identified as vital for enabling seamless collaboration across different platforms and technologies. Data interoperability, particularly with the use of knowledge graphs (KGs), plays a pivotal role in streamlining complex data interactions across various systems and platforms. In the context of manufacturing, knowledge graphs provide a structured, semantic approach to handle large, diverse datasets. They enhance data exchange by connecting unstructured data from multiple sources, revealing hidden insights and improving decision-making capabilities. KGs help manufacturers address challenges such as data fragmentation and heterogeneity by offering a unified view of processes, equipment, and tasks, thus facilitating better production scheduling and process optimization (Wan et al., 2024).

Knowledge graphs, though, are not the only data domains where interoperability is from immense importance. In all data related operations, there needs to be interoperability to form some form of data core that can be translated in different data formats.

Knowledge Transfer

Lastly, knowledge transfer emerged as a key factor in maintaining a competitive edge, especially in collaborative environments. Additionally, Thomas et al. (2021) highlighted the importance of knowledge transfer in collaborative innovation networks, where the dissemination of data-driven insights between partners fuels creativity and technological advancement. In many domains, knowledge transfer is vital as the data driven models developed in a certain research domain cannot be found in the research and development department of an SME. There are data-driven models from natural science contexts that contain models that are hard to develop inhouse if the research and development department of an SME does not have the needed financial and human capital support. For instance, Bwambale, Abagale, and Anornu (2023) developed a data-driven model for optimizing irrigation, helping SMEs in agriculture improving water efficiency. This shows the contrast between SMEs and big corporations because a big farming company would eventually have the possibility to fund the needed labs and researchers to conduct the experiments and develop such a model. For SMEs, it is vital to include research models from knowledge institutions and adapt and transition the knowledge into their own data infrastructure as well as knowledge management. In this scoring model, knowledge transfer is viewed as an essential assessment.

Factors Interdependencies

In addition to identifying the key factors, we also acknowledge that these factors do not operate in isolation. Interdependencies likely exist between them, and understanding these relationships will be the focus of future research to further refine the model and enhance its accuracy.

Chronological Framework for Assessing Data-Drivenness

The chronological framework we proposed is designed to guide consultants or analysts in evaluating the overall data-drivenness of SMEs. This framework allows for a structured assessment of the nine key factors identified in our scoring model, ensuring that each factor is rated consistently and comprehensively. When a consultant assesses an SME, they are expected to rate each of these factors through interviews, surveys, focus groups, or workshops within the company. We recommend conducting structured to semi-structured surveys and interviews with closed-ended questions to obtain a clear and consistent assessment of the factors in question. More contextual data should be gathered through workshops and focus groups, which naturally offer a more open environment. These focus groups or workshops should involve department heads, IT personnel and consultants, and executives of SMEs. The goal is to reveal gaps in data-drivenness and identify areas for improvement.

The assessment begins with input from the CEO and other executives, gathering insights into the strategic level of data integration within the organization. The consultant then moves to operational personnel, those directly involved with the application of data strategies, to compare their perspectives with those of the executives. This multi-level approach helps uncover gaps or consistencies in the perception and implementation of data-driven practices across the organization.

Each key factor including Data Availability and Quality, Data Infrastructure, Employee Data Competence, Data-Driven Decision Making, Analytical Capabilities, Data Integration, Compliance, Data Interoperability, and Knowledge Transfer will be rated on a 0 to 6 scale. A score of 0 represents the complete absence or weakness in each area, while a score of 6 indicates the highest level of capability and integration within that key factor. Once all the individual scores have been assigned, they are summed up to calculate the overall Data-Drivenness Score. This overall score reflects the company's or organization entity's collective capability across all nine factors. We propose the following interpretation for the summed score:

Low: 0-17; Medium: 18-35; High: 36-54

Dividing the scale into three categories - Low, Medium and High - helps to simplify the assessment process and provide clear benchmarks or evaluating a company's data-drivenness. This structure allows for easier identification of areas where the company is excelling, where it meets basic standards and where critical improvements are needed. By evaluating each key factor independently and then combining the scores, the consultant can provide a clear and structured analysis of the company's data capabilities. The final Data-Drivenness Score offers a comprehensive view of the organization's strengths and areas for improvement in its journey toward becoming a fully data-driven enterprise.

This scoring approach provides both a detailed snapshot of each key factor and a holistic view of the company's overall data maturity. The framework also ensures consistency while allowing for flexibility in the consultant's interpretation of scores based on the context of each individual business. As a fictional example, table 1 can give insights on how the data-drivenness score could look like in a real setup.

Table 2: Example of a Fictive Company's Data-Drivenness Score

Key Factor	Executive Rating (0-6)	Personnel Rating (0-6)	Average Rating
Data Availability and Quality	5	4	4.5
Data Infrastructure	3	2	2.5
Employee Data Competence	2	3	2.5
Data-Driven Decision Making	4	5	4.5
Analytical Capabilities	1	2	1.5
Data Integration	6	5	5.5
Compliance	3	4	3.5
Data Interoperability	2	1	1.5
Knowledge Transfer	4	3	3.5
Overall Data-Drivenness Score			29.5

To provide further insides into the interpretation of the assessment, an explanation of this fictional example is given here. The example reveals strong performance in data availability and quality, alongside proficiency in data-driven decision-making and data integration, indicating that the company has well-established processes in these areas. However, notable weaknesses are found in data infrastructure, employee data competence, and analytical capabilities, which highlight challenges in effectively processing and utilizing data. Moderate scores in compliance and knowledge transfer suggest that improvements can be made in meeting regulatory requirements and in the sharing of insights within the organization. With an overall data-drivenness score of 29.5, the company is positioned in the medium range, suggesting a solid foundation but also signaling the need for further development in several areas to fully capitalize on data for decision-making.

As defined earlier, the chronological framework guides consultants or analysts in evaluating the overall data-drivenness of SMEs through structured assessments of the key factors. To close the gap in the identified weaknesses, qualitative methods such as workshops and focus groups, as previously outlined, are necessary to uncover underlying issues and provide comprehensive consultancy. These approaches will involve key stakeholders, ensuring a thorough examination of the gaps and tailored strategies for improvement.

Conclusion

In this paper, building on our previous research where the first step was already accomplished, we have completed the second and third steps of the Design Science Research (DSR) approach, focusing on the development of a chronological framework to measure data-drivenness in German SMEs, particularly in the crafts sector. Our findings suggest that SMEs face unique challenges, such as limited data infrastructure, employee data competence, and knowledge transfer, which larger enterprises may not encounter to the same extent because they have larger monetary and timely resources available.

By identifying nine critical key factors: Data Availability and Quality, Data Infrastructure, Employee Data Competence, Data-Driven Decision Making, Analytical Capabilities, Data Integration, Compliance, Data Interoperability, and Knowledge Transfer, we provide SMEs with a comprehensive model to assess and improve their data-driven capabilities. The scoring model developed offers an actionable tool for evaluating data utilization in SMEs and helps them benchmark their current practices against desired outcomes.

The chronological framework, paired with our scoring model, serves as a flexible tool for consultants and analysts working with or for SMEs. This tool not only measures data-drivenness but also provides a pathway to enhance decision-making processes by guiding SMEs through targeted improvements in critical areas and enhance their capabilities to manage highly important data. Moreover, the results from this model indicate that SMEs with higher data-drivenness and data-maturity should experience improved competitiveness and performance.

However, there are several limitations to this research, including the focus on ScienceDirect as the primary database, which may have excluded industry-specific reports, and the general model, which may not fully address sector-specific nuances within SMEs. Future research could validate and refine the model further by applying it in specific sectors and incorporating diverse data sources.

Future research should focus on further validation of the scoring model through practical applications in different sectors beyond crafts, as well as exploring how AI-based recommendations could be integrated into the framework to offer more dynamic, real-time solutions for SMEs. Yet, this must be validated empirically. Therefore, it is planned to conduct multiple qualitative studies within German SMEs to test, validate, and iteratively even improve the presented scoring model embedded into the chronological framework. Expanding the scope to include international SMEs could also provide valuable cross-contextual insights into how data-drivenness evolves across different business environments. By tackling these unique challenges and enhancing data capabilities, German SMEs, especially in the crafts sector, could become more competitive in the increasingly digital global market.

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