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Systematisation Approach: Handling Insufficient Data Quality

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Abstract

Current megatrends such as globalisation and digitalisation are increasing complexity, making systems for well-founded and short-term decision support indispensable. A necessary condition for reliable decision-making is high data quality. In practice, it is repeatedly shown that data quality is insufficient, especially in master and transaction data. Moreover, upcoming approaches for data-based decisions consistently raise the required level of data quality. Hence, the importance of handling insufficient data quality is currently and will remain elementary. Since the literature does not systematically consider the possibilities in the case of insufficient data quality, this paper presents a general model and systematic approach for handling those cases in real-world scenarios. The model developed here presents the various possibilities of handling insufficient data quality in a process-based approach as a framework for decision support. The individual aspects of the model are examined in more detail along the process chain from data acquisition to final data processing. Subsequently, the systematic approach is applied and contextualised for production planning and supply chain event management. Due to their general validity, the results enable companies to manage insufficient data quality systematically.

Keywords

Data Quality; Insufficient Data; Production Planning; Supply chain event management; SCEM

1. Introduction

Efficient execution of business processes in increasingly complex value chains is based on data-driven and automated decision making. A key success factor here is suitable data quality as a basis. While companies are increasingly collecting data in large volumes and increasing the number of data-based decisions, problems with data quality often lead to reduced acceptance among decision-makers. This is not surprising, since these very decision makers are regularly not involved in the process of data collection or at least not responsible for it. In order to counteract this decoupling of the decision-making basis (data) and the decision-makers, we develop in this paper a structured approach to consider data quality relevant aspects in relation to the decision to be made. The model provides a descriptive basis for improving decision quality and acceptance.

2. State-of-the-art

Data quality is commonly defined as data being fit for use by the data consumer [1] following the commonly used definition from quality management [2]. In the context of data-based decision-making, the data consumer relates to the model using the data as an input. Fitness for use therefore relates to the suitability

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of the data for the model to work as intended. Although the definition clearly states that data quality can only be measured for a specific intended application, most research follows a data-centric generic approach not considering the respective application.

Extensive research has been conducted on describing data quality and its aspects, usually referred to as data quality dimensions [1]. However, this research is not suitable from a decision-maker's perspective as the dimensions are receivable at most, but not directly to be influenced. In the domain of production planning and control, Günther et. al propose a method to assess data quality [3] but without a specific focus on the improvement. Therefore, a more process based seems to be reasonable. Miller and Mork present a value chain for big data [4] which provides a framework for the life cycle of data for decision making but lacks the data quality aspect.

Multiple models for managing data quality in companies have been developed. English presents a method for Total Data Quality Management consisting of data definition quality, an information quality assessment, nonquality information costs and reengineering and improvement aspects [5]. Some work has been conducted on applying the concepts of quality function deployment (QFD) in the domain of data quality. Wang et. al. [6] use the house of quality to correlate a desired quality with data engineering aspects. Pinto [7] describes the application of QFD concepts in database planning. Vaismann develops an approach specifically for designing databases for decision support systems [8]. However, all approaches assume a desired data quality can be defined a priori and all approaches remain data-centric.

Overall, a research gap was identified in data quality research from a decision-maker's perspective. Models for a process-oriented view on the quality of input data for decision making can contribute to better decisions and a better acceptance of decisions.

3. Research questions and approach

This work aims to provide decision-makers with a universally applicable structured approach to handle the fact of data being insufficient in real world scenarios. We formulate the main research question for this paper as follows: How can the quality of input data be considered in data-based decision-making?

We follow a research approach in three steps. First, we conduct a systematic literature review [9] and examine strategies for handling insufficient data quality. In a second step, we develop a model based on the extracted handling strategies. Finally, we present two cases from the domain of supply chain event management and production planning, in which we apply the structured approach of handling insufficient data quality in decision-making.

4. Examining strategies for handling of insufficient data quality

The initial search within scopus results in 63 articles. After scanning the title and abstract of the results, 45 remain. Relevant work in the context of this paper should be defined as those containing at least one specific approach to deal with insufficient data in decision-making. Therefore, results with a mere focus on the measurement of data quality were not ranked as relevant. Applying these criteria yields a total of 13 relevant articles we examined in detail. We structured those articles in three different categories: Data source and accessibility, Data manipulation and Data usage and model (table 1). Following this, we describe our findings from the studies and extract the relevant aspects for handling the insufficient data quality.

Table 1: Structured literature

Data source and accessibility	Data manipulation	Data usage and model
Arnold et al. [10]	Reuter et al. [11,12]	Altendorfer [13]
Brauer et al. [14]	Lingitz et al. [15,16]	Busert et al. [17]
Büscher et al. [18]		Herold [19]
Gustavsson [20]		Krishnamurthy [21]
Messner et al. [22]		

4.1 Data source and accessibility

Arnold et al. highlight the relevance of correct data from production, which are still regularly based on manual data capture [10]. They propose a combined approach of using new sensor technologies such as Bluetooth Low Energy for location or Near Field Communication and applying data fusion concepts to improve the data quality of the target dimensions. Another approach focuses on the accessibility of data. In some cases data are available locally or databases are not connected. In this case connecting actual data sources to consumers can be a reasonable approach. Brauer et al. propose a Virtual Scheduling and Transportation Model to connect production scheduling and logistics tasks [14]. Büscher et al. present a similar data integration approach for the domain of production and factory planning [18]. Messner et al. propose a closed-loop approach to overcome integration issues and the factor of potential human errors [22]. Gustavsson studies the effects of organisational integration on data quality and shows, that a higher level of integration leads to less quality deficiencies [20].

4.2 Data manipulation

Data manipulation means taking the data as it is and no improvement of the data source. Reuter et al. present an approach based on data mining to deal with missing information and known inconsistencies in databases [11,12]. This provides improved data for the data-consuming decision model. Lingitz et al. use a simulation based evolutionary approach to predict expected values from historical data, which is a typical problem in production planning models like MRP [15,16].

4.3 Data usage and model

Altendorfer [13] shows the effect of information quality in terms of customer orders. While in theory a more detailed knowledge is preferrable, the overall costs in the examined model are only marginally influenced by data quality according to their findings. Another study shows a similar effect for demand information in pull production control systems [21]. While the integration of demand integration shows a significant impact, the actual quality of this data (i.e. variance) only has a marginal impact on system performance. If specific knowledge about the actual quality of data is available, Busert et al. suggest to model uncertainties by applying fuzzy logic [17]. However, this approach requires specific decision models, and it needs to be determined how fuzzy data leads to decisions. Another approach focuses just on the model by suggesting a model that is less data intensive. Therefore, it mitigates data quality issues by bypassing the nonquality data [19].

5. Conversion into a systematisation model

The necessary data quality for data-based decision-making is always application-specific. To determine this, a distinction can be made between two perspectives. The first perspective deals with the necessary data quality for decision-making (data quality requirement). This perspective is closely connected to the benefit of data quality, which continuously decreases with increasing data quality. In contrast to the data quality requirement, the second perspective looks at the available data and its quality (data quality availability). In the cost-benefit analogy, this reflects the cost side since the costs increase exponentially as the available data quality increases. Even if, ideally, the required and available data quality match, this is not automatically the case in practice. Accordingly, the goal of data-driven decision-making is to close the gap between data quality needs and availability. To enable this systematically, the following model illustrates the different strategies based on the data value chain from data collection to use.

The data value chain begins in the data source area with the process step gathering, which describes the recording and collection of the data. The next three process steps are in the integration area and are often described as the ETL process [23]. In the first step of the ETL process, the data is extracted from various sources and temporarily stored in a workspace (extract). In the second step, this temporary intermediate storage enables the necessary transformation of the data into uniform data formats and structures (transform). Finally, the data is loaded into the target system and the temporary storage is deleted again (load). Following the ETL process, the data is used so that decisions can be made based on analyses and evaluations (use). [24,4]

This value chain can now be used to classify the different approaches to dealing with insufficient data quality. These in turn can be categorised into four strategies (see Figure 1).

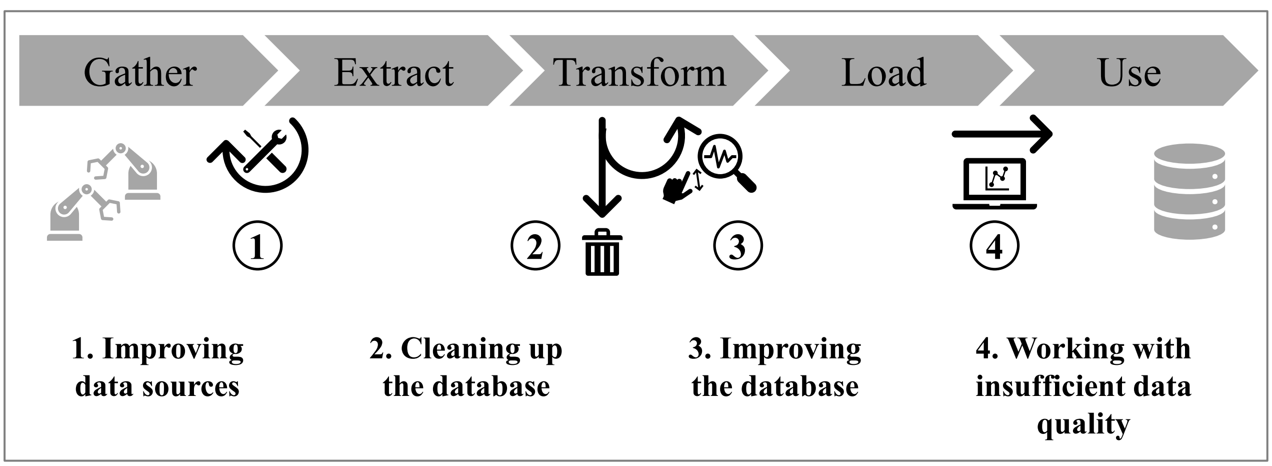

Figure 1: Strategies for handling insufficient data quality

The strategy "**Improving data sources**" can be assigned to the transition between gathering and extraction. This includes all approaches that improve data gathering from data sources. This may mean, for example, installing new sensors for data collection or recalibrating or reconfiguring the existing sensors. Another possibility is that the data collection processes are changed in such a way that the quality of the collected data is significantly improved. Unlike the other strategies, however, the focus here is not on the symptoms (insufficient data quality), but on tackling the causes (e.g., errors in data collection). This in turn means that the strategy only leads to improvements for future data sets and the insufficient data quality of the previous data sets remains.

The next two strategies can be assigned to the transformation step. Part of the transformation of the data stock into the standard data formats and structures is to check and improve the data quality. This means that if data with insufficient data quality is found during the transformation, the strategy "**Cleaning up the database**" can be applied, for example. Here, data records with insufficient data quality are filtered out of the data flow and not processed further. The remaining data flow then only contains corresponding data records with sufficient data quality.

The "**Improving the database**" strategy also filters out the records with insufficient data quality in the first step, but with a different goal. In contrast to the "do not consider further" in the previous strategy, the records with insufficient data quality are improved here. There are various methods for this improvement (excerpt)

- Replacement with other data: An improvement is possible by replacing data from other sources (e.g., reference data sets). External databases or internal sources can be used for the reference data. In addition, it is also possible to determine corresponding reference values from previous data sets.
- Derivation from other data: Furthermore, corrections for erroneous data can be derived from other data of the same data record or previous data records. In contrast to replacement, here values are determined by dedicated models and not simply taken over.
- Use of default values: In some cases, incorrect values can be replaced by default values. The condition is that a "meaningful" default value can be defined in advance for each situation.
- Removal of duplicates: Another method to clean up redundant data is to remove duplicates. Before removal, however, the redundant data must be consolidated. It should be noted that it would be wrong to use only the record with the most correct data and ignore the others.
- Splitting erroneous summaries: The opposite of the method "Removal of duplicates" is "Splitting erroneous summaries". Records that contain data on different real objects are split. The data set is thus split into two different data sets during the improvement.

Just like the selection of the right strategy, the selection of the methods presented here is also very dependent on the use case and the corresponding data.

The strategy "**Working with insufficient data quality**" can be placed in the transition to the process step use and describes the possibilities to consciously continue working with insufficient data quality. To make this possible, it is necessary to change the application context so that the existing data quality is sufficient for the necessary decision. This means that the requirements for the data quality are changed so that it is sufficient. For example, this can mean that the uncertainty regarding the data quality and the associated decisions is consciously dealt with for the use case and communicated accordingly. Another example would be that for specific use cases, robust algorithms are used in the decision-making process, which has lower data quality requirements.

It can be summarised that different approaches can be used to reduce the gap between required and available data quality. The strategies "Improving data sources", "Cleaning up the database" and "Improving the database" deal with improving the available data quality. In contrast, the strategy "Working with insufficient data quality" focuses on reducing the required data quality and thus closing the gap. The selection of the right strategy depends fundamentally on the use case and the associated decision-making process.

6. Case Studies

To evaluate the introduced model, we have examined two exemplary case studies from different fields of application following the Design Science Research Methodology [25]. First, the use case was briefly described before the different strategies of the model were applied and analysed.

6.1 Supply Chain Event Management

Event-based systems such as supply chain event management are used to reduce the complexity of our supply chains and support decision-making for the planning of production and the associated processes [26]. The data basis for supply chain event management are events, which describe every physical status change of objects in a standardised way (cf. EPCIS events) [27]. Based on this, supply chain event management comprises five core functions: The monitoring function tracks events across the supply chain and collects them in an event repository. The second function, reporting, describes the notification of critical deviations. The consequences of the deviations identified by the notification as well as possible reactions are analysed in the third function. The fourth function, Control, then selects and implements the best possible alternative course of action. The last function, measure, evaluates the reactions to improve the previous functional steps for future deviations. By reacting only to critical deviations, this is a management-by-exception concept. To ensure the functionality of event-based systems, special attention must be paid to data quality. [28,29] In practice, it turns out that the data quality of event data can vary greatly, so that a precise analysis of data quality availability and data quality needs is necessary [30,31].

For a systematic approach to improving the difference between data quality needs and data quality availability, the four main strategies can now be considered in detail:

- Improving data sources: In this use case, the event data is recorded by the various actors in the supply chain (e.g., 2nd tier supplier, 1st tier supplier, forwarder, etc.). In practice, it has been shown that this is precisely where the cause of poor data quality often can be found. In concrete terms, this can be, for example, an incorrectly set RFID gate or typing errors during manual recording. [30] The strategy of improving the data source is helpful in theory, but difficult to implement in practice. The reason for this is that the actors (e.g., manufacturers) who criticise the available data quality are not the same actors (e.g., suppliers) who record the data. Often the power relations are not such that the manufacturer can force the supplier to improve the data recording.
- Cleaning up the database: Cleansing the database of data records with insufficient data quality is a possible strategy in this case. This can avoid erroneous automatic reactions by the simulate and control functions, which in turn eliminates some overreactions and waste. The challenge here lies in determining the events with insufficient data quality in comparison to critical exception events, since the occurrences of the events are often similar, especially regarding the content-related data quality. According to the use case, it is particularly important to ensure that no critical exception events are sorted out, as otherwise the purpose of the overall system is not achieved.
- Improving the database: If events with insufficient data quality have been identified, they can also be improved depending on their appearance. Specifically, the approaches of Replacement with other Data can be used particularly well. On the one hand, data fields can be validated or completed by other IT systems. Another possibility is the correction of event data with the help of historical event data of the same or similar objects.
- Working with insufficient data quality: In contrast to data quality availability, when considering data quality requirements, the possible reactions must be considered, especially for the functions of simulating and controlling. The data quality requirement decreases for a system that is less sensitive

- regardless of whether the lower sensitivity results from the system modelling or the simulation algorithms used. However, if the system is too insensitive, it will no longer react to critical exceptional events, which is contrary to the concept.

The concrete consideration of the case study shows that the model with its systematisation approach of the strategies can be applied.

6.2 Production Planning

Production planning and control in companies has been supported for decades by data-based models in systems such as Enterprise Resource Planning, Manufacturing Execution Systems or Advanced Planning and Scheduling Systems. However, the underlying algorithms and model assumptions there are often based on very simplified assumptions, and the models are deterministic. This automatically results in a large number of potential data quality problems, as the studies analyzed have already shown.

In this case, the focus is on a company that uses detailed planning in production control and regularly fails to adhere to the specified order operation sequences and thus reschedules manually. According to the model, the following options for dealing with insufficient data arise:

- Improving data sources: In this case, detailed planning is system-supported, but the data basis is based on manual feedback from production. For reasons of cost and effort, this feedback is not carried out individually for each operation today; instead, standard times serve as the basis for planning. There is potential here to pursue this strategy and to develop a more detailed and qualitatively better data basis by means of detailed and automated recording of feedback data. However, this requires the introduction of new systems, which is time-consuming and associated with high costs. In this case, linking with further production data does not make sense, since new sensor technology would have to be purchased for this purpose and known and basic measures have not yet been exhausted. Even without the improved acquisition of live data, however, static optimization is conceivable. Since today's data are already default times, a check of the actuality is possible with a small effort and thus has the potential to improve the decision quality in the short term.
- Cleaning up the database: The quality of the data in the planning system is based on standard times, the data volumes are thus rather small. Individual data records are not expected to have a significant influence on the planning result. Nevertheless, a review of the input data and a correction of outliers can be implemented with little effort.
- Improving the database: Without a detailed collection of feedback data, the data basis for improving the data is not available. This strategy is therefore not very promising
- Working with insufficient data quality: The further the assumed data and models used deviate from reality, the less they contribute to good decision quality. Particularly in detailed planning with low granularity of the feedback data, less data-intensive alternatives thus present themselves. Following the lean concept, procedures such as Kanban can also be used here, depending on the concrete order and product structure. Here, significantly less information is required, and disadvantages such as supposedly larger inventories are not relevant in practice, because inadequate detailed planning regularly causes shortfalls. Other procedures in production control can also be suitable and achieve production with fewer exceptional situations due to lower complexity with lower data requirements.

7. Conclusion

In practice, it is evident that dealing with insufficient data quality for decision-making repeatedly leads to problems. Accordingly, this paper is the first to present an integrated approach for decision-making that takes a complete look at data quality from the data source to data use. In particular, the two perspectives of data quality needs and data quality availability were examined. A concretisation based on two use cases shows the basic usability of the model. However, there is a need for further research in the details, the further structuring, and the transfer to individual domains. It should be investigated how the individual strategies affect the individual domains, which strategies are the most promising and how they can be implemented in the best possible way.

Appendix

The structured literature search was conducted using the following search terms in scopus: TITLE-ABS-KEY (("data quality" OR "information quality") AND ("production planning" OR "production control" OR "manufacturing planning" OR "manufacturing control" OR "supply chain event management"))

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Biography

Tobias Schröer (*1991) has been working at the Institute for Industrial Management (FIR) at the RWTH Aachen since 2016, first as a project manager and since 2020 as head of the department Production Management. As such he leads a variety of applied research and consulting projects. In his research he focuses on the real-world applications of business software for operations in production and logistics.

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Prof. Dr.-Ing. Dipl.-Wirt.-Ing. Günther Schuh (*1958) is the director of the Institute for Industrial Management (FIR) at RWTH Aachen University, holds the Chair for Production Systems at the WZL, and is a member of the board of directors of the Fraunhofer Institute for Production Technology IPT in Aachen. Professor Schuh is a member of several supervisory boards and boards of directors.

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